Over a Century of Economics Research Collaboration

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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. We find rising collaboration, reflected by an increasing number of authors per paper and an increasing share of multi-author papers. Collaboration across institutions declined in the 20th century but increased in the 21st century, while collaboration across economists with different experience levels remained stable over time. In studying the benefits and costs of collaboration, we identify a key benefit: Larger research teams have written an increasingly higher proportion of highly cited papers. Using COVID as a natural experiment that shifts collaboration costs, we find a polarizing effect: Some researchers retreated and worked more by themselves, whereas others formed larger teams (i.e., of four or more authors).

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

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1 Introduction

Economics research papers have undergone a significant transformation over the past almost 140 years. Articles in the inaugural issue of the *Quarterly Journal of Economics* in October 1886 averaged fewer than 10 pages. Today, papers typically span 40 pages (often restricted by journal rules). Researchers have also documented that the average number of authors on an economics paper has increased in recent decades (McDowell and Melvin, 1983; Barnett, Ault, and Kaserman, 1988; Hudson, 1996; Hamermesh, 2013; Jones, 2021).[1] Despite ample evidence of increased collaboration, there is limited agreement among researchers regarding the underlying drivers of this shift.[2] Explanations of collaboration patterns have mostly been descriptive, with few attempts to formally test the sources of rising teamwork among academic economists.

In this paper, we set out to accomplish two goals. First, we document more comprehensive—i.e., more longitudinal and more granular—facts about research collaboration to establish a wider and deeper understanding of this phenomenon. Whereas prior papers tend to focus on recent decades when studying collaboration patterns, our investigation expands this analysis to the beginning of modern economics research in the late 19th century. Taking advantage of our uniquely assembled dataset, which links publications and author affiliations over time, we are able to document unprecedented collaboration patterns among economists at different academic institutions and varying levels of experience and shed light on additional dimensions of research collaboration.

Second, we explore potential drivers of collaboration. We seek to understand the choice an economist faces when writing a paper: working alone or collaborating with others. The trade-off can be summarized by the benefits associated with the improved quality of the paper as a result of collaboration versus the costs associated with the joint production of a paper. We seek to understand how variation in the benefits and costs over time can result in changes in collaboration patterns.

A key obstacle is the lack of quality data. Previous work often relies on datasets of limited quality, which have been compromised by misclassification, inaccuracies, and omissions. In some cases, the excessive inclusion of economics papers likely resulted in a dataset only loosely related to core economics research.[3] In other cases, author affiliations can be outdated or even missing from commonly used data sources such as Research Papers in Economics (RePEc) and the Web of Science (WoS). To anchor our analysis in quality data, we meticulously assemble a database of economics research papers and author information. We start from 64 journals representative

[1] In addition, Guimera, Uzzi, Spiro, and Amaral (2005) and Wuchty, Jones, and Uzzi (2007) document increased collaboration in many fields across both the natural sciences and the social sciences.

[2] Increases in collaboration have been attributed to the increased specialization of research areas (Hunter and Leahey, 2008); improvements in communication technology (Jones, Wuchty, and Uzzi, 2008; Xie, 2014); and the rising complexity of problems that require interdisciplinary solutions (Falk-Krzesinski et al., 2011; Milojević, 2014).

[3] For example, Jones (2021) counts articles from over 3,000 journals as economics-focused.

of economics research, including general-interest and field-specific journals. We compile bibliographic data from published papers in these journals via OpenAlex, a large bibliographic catalog of research papers. We also include economics working papers from the Social Science Research Network (SSRN) and the National Bureau of Economic Research (NBER). This comprehensive database provides a consistent definition of economics papers and academic economists, which enables us to address our research questions within a standardized environment. Our dataset consists of not only publications and working papers, but also author affiliation information over time. Because a researcher may move from one institution to another, accurately capturing affiliations is especially important in our study of inter-institutional collaboration.

Our empirical findings reveal that research collaboration first started to increase in the 1950s, before which more than 95% of the economics publications were single-author. We find a secular trend toward more collaboration arriving in waves: a consistent decline in sole authorship with increased shares of two-author papers since the 1950s and 1960s, of three-author papers since the 1970s, and of four-author papers since the 2010s. The proportion of multi-author papers and the average number of authors on those papers rose over time. A more granular view reveals that inter-institutional collaboration decreased in the 20th century and increased in the last 25 years, which reflects greater cooperation across institutions.[4] Conditional on the number of authors on papers, experience assortativity—whether researchers tend to work with those with comparable levels of experience—remained unchanged for much of our sample. These results extend and expand prior findings to a broader set of papers (working and published) and go further back in time. They also reveal new dimensions to collaboration.

Next, we investigate the drivers of these patterns by considering the benefits and costs of collaboration. The costs encompass all factors that contribute to the overall expense of producing a paper—time, opportunity costs, and financial resources. One important benefit is the increased impact, or "return," of the paper, for which we use the trailing 5-year citation count as the empirical proxy. We define a homerun paper as a publication whose trailing 5-year citation count is in the top decile of all economics papers published in the same year. Regressions of indicator variables of homerun papers on time fixed effects, controlling for other paper characteristics, show that returns to multi-author papers changed over time.[5] While single-author papers were the most likely to be highly cited in the 1950s, two-author papers were the most likely in the 1960s, 1970s, and 1980s. Three-author papers were the most likely in the 1990s and 2000s, only to be overtaken by four-plus-author papers in the 2010s. Evidently, returns to collaborative work have increased over time.

[4] Jones, Wuchty, and Uzzi (2008) find that research is increasingly inter-institutional. Using a longer sample, we find an earlier decrease in inter-institutional collaboration before a recent increase.

[5] Notably, having an author from a top institution significantly increases the likelihood of a homerun paper.

We investigate whether changing benefits may be a driving force in research collaboration. Economists may recognize the increasing returns to multi-author papers and respond by writing more papers in teams. We test this hypothesis through a statistical model with the fraction of n-author papers as the dependent variable and lagged shares of homerun papers as independent variables. Using the seemingly unrelated regressions of Tomz, Tucker, and Wittenberg (2002), we find that researchers tend to assemble into teams of four or more authors following higher returns, while they do not respond much to increased returns to two-author or three-author papers.

We consider the COVID pandemic as a natural experiment with an immediately large impact on the cost but a limited effect on other aspects of paper production. While there may be changes to returns or to idiosyncratic preferences of collaboration, we assume that they are on average small relative to changes in costs, given the sudden onset of the pandemic. We find positive deviations from trend in the shares of single-author papers as well as those of papers with four or more authors during COVID, which indicates that the pandemic had a polarizing effect: While some researchers retreated and worked more by themselves, others took advantage of the novel productivity tools and normalized remote work culture to team up with more people. We find little evidence of changes during COVID for collaboration across institutions and across experience levels.

The rest of the paper is organized as follows. After a review of the literature, Section 2 describes the construction of our unique database of author and paper information. Section 3 documents patterns of collaboration. Section 4 introduces the framework to understand collaboration patterns and conducts empirical tests of possible channels, and Section 5 concludes. Tables and figures are presented at the end of the main text, and additional tables and figures are collected in the appendices.

1.1 Literature Review

Our paper contributes to three strands of the literature: (i) documenting facts related to research collaboration, (ii) empirically testing the mechanisms of research collaboration, and (iii) identifying the effects of COVID on productivity and collaboration.

Several papers document a rise in research collaboration across scientific fields. Wuchty, Jones, and Uzzi (2007) illustrate an increase in the number of authors on a research paper for both the natural sciences and the social sciences. Uzzi et al. (2013) compare the research output of teams and those of individuals and find that teams generate more creative ideas. As research fields become increasingly specialized, researchers tend to train longer and receive their doctoral degrees later (Jones, 2009, 2010). These studies tend to measure collaboration intensity by the number of authors and offer a broad view of trends across disciplines, with less focus placed on the composition of research teams.

Some studies focus on the economics profession, often zooming in on a select few journals over a relatively short (usually less than 30 years) period of time (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). Whereas previous work performs textual analysis on published papers (Hamermesh and Oster, 2002; Hamermesh and Kosnik, 2024; Kosnik, 2023, 2022; Kosnik and Hamermesh, 2024), we mainly rely on papers' bibliographic information. Compared with prior work, we provide more comprehensive documentation of publication and collaboration patterns spanning almost 140 years. Our detailed dataset allows us to account for variables such as author seniority, institutional rankings, and location of affiliation at a finer level.

In contrast to the abundant descriptive studies of research collaboration, there is less focus on empirical tests of formal hypotheses in the literature. Sheng (2020) empirically investigates a pairwise coauthor formation model of Jackson and Wolinsky (1996), and acknowledges the difficulty to analyze and estimate more complicated collaboration patterns in a network. With a focus on the physical sciences and patents, Ahmadpoor and Jones (2019) find that teams tend to assemble among authors with similar citation levels, which provides corroborating evidence for positive assortative matching. In a comprehensive survey, Liu et al. (2023) classify empirical work into categories: (i) to discover and estimate empirical regularities and (ii) to identify the underlying mechanism. The authors discuss significantly more papers in the former category than the latter. Our paper adds to each of these categories, with an emphasis on making progress in the latter.

A number of papers examine the effects of COVID on workplace behavior (Butler and Jaffe, 2021; Bayhan et al., 2022; Ford et al., 2021; Yang et al., 2022; Dong et al., 2023; Jain et al., 2024). Survey-based research highlights a differential impact of the pandemic on genders, which suggests heightened challenges for women, especially those with caregiving responsibilities (King and Frederickson, 2021; Liu et al., 2022; Sinatra et al., 2023). Heo et al. (2022) collect more than 2,000 surveys from 100 countries and identify delays in STEM research that relies on labs and fieldwork, a disproportionate burden on female scientists, and reduced opportunities for informal collaboration due to the shift to virtual conferences. Whereas previous work tends to focus on COVID itself as the event of interest, we treat it as a laboratory to examine how costs can change collaboration patterns, using the onset of the pandemic as an experiment to test our framework.

2 Data

We obtain paper-level information from the bibliometric database OpenAlex, which includes publications from 1886 to 2023 and Social Science Research Network (SSRN) working papers from its inception in 1994 to 2023. 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 considered to be 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.[6] Publications are available since 1886, when the *Quarterly Journal of Economics* was founded. We refer to all 64 journals as "EC64," and the top-5 general interest journals (*American Economic Review*, *Econometrica*, *Journal of Political Economy*, *Quarterly Journal of Economics*, and *Review of Economic Studies*) as "top-5." 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.

We record the year papers are published or posted to working paper repositories.[7] Since the dating is precise only up to the year, we define the pre-COVID period as all years through 2019 and the post-COVID period as 2021 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 COVID pandemic by filtering out any papers whose title includes "COVID," "coronavirus," or "sars-cov-2." We also 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. In our analysis, a paper's "major affiliation" is defined as the most frequently occurring affiliation among its authors.

2.1 Author Affiliation Records

Author affiliation through time is necessary for studying collaboration patterns across institutions. Existing datasets typically do not contain a time series of affiliation information for each author. Furthermore, available affiliation from bibliographic catalogs may be incorrect or stale. This is particularly pronounced for working papers, since repositories such as SSRN often only retain the latest affiliation information and overwrite past positions, even for works posted while the author was in those positions.[8] To overcome this issue, we construct author-affiliation records using

[6]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 and Moktan, 2020; Ham, Wright, and Ye, 2021). 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).

[7]The date of many papers appears as January 1 in OpenAlex, which makes it difficult to more precisely determine the time of publication or posting.

[8]For example, suppose that author A was affiliated with institution I from 2005 to 2010 and institution J from 2011 to 2020. If author A posted a working paper on SSRN in 2008 (while at institution I), but the information was not

published papers, which contain the affiliation on the date of publication. By chaining together multiple publications, we are able to construct a panel of author affiliations. Our approach follows the framework proposed by Lin et al. (2023) for completing institutional data from Microsoft Academic Graph (MAG)—a large database that contains scientific publication records, citation relationships, and author information. However, MAG stopped its updates in December 2021.

The non-profit organization OurResearch launched an open-access bibliographic database to continue MAG called OpenAlex, which has since been used extensively in academic research. As of March 2024, OpenAlex includes metadata for over 200 million papers and books, 13 million authors, and over 100,000 institutions. Given its comprehensive coverage, many universities have used OpenAlex to track the progress of their research.

To construct author-affiliation records for working papers, we obtain all articles indexed in OpenAlex that have been published in the EC64 journals. We extract relevant paper information from OpenAlex to construct records of each economist's affiliation and fill any gaps using the steps described below. To process author-affiliation data with missing records, we implement the following procedure. First, we identify active years: For each author-affiliation pair, we determine the range of years with records. Second, we forward fill missing years: For each affiliation, forward fill in any missing years between the first and last recorded years. This technique replaces missing values with the last observed non-missing value, which ensures continuity in the data. Third and finally, we retain the most recent forward-filled entry: For years that contain only filled records, we retain the most recent forward-filled entry. This approach ensures that the data reflect the latest known affiliation information.

By implementing these steps, we can achieve a consistent and up-to-date representation of affiliations over time, effectively addressing gaps due to missing records. Our methodology of affiliation construction relies on authors having active publication histories. For authors who do not have publications beyond 2018, we forward fill their 2018 affiliation through 2023. For any authors whose affiliation is still missing after this step, we include affiliation information from working papers posted in 2018 or later. Our approach yields a 98% complete panel of author affiliation records.[9]

To verify the quality of our constructed data, we cross-check with manually collected information on the education and career history of tenure-track faculty members of MIT. For the years in which an affiliation was present, our data construction yields an 85.6% match rate. In addition, we check our dataset against the education and career histories of 200 award-winning economists

scraped until 2018, it is more than likely that OpenAlex would record that this paper was published with author A from institution J instead of institution I. We exclude affiliation records for NBER and IZA, due to the inter-institutional nature of these organizations.

[9] The only authors who do not have affiliations from this construction are those who do not have affiliations listed on their working papers and have no publications.

collected by Freeman et al. (2024), and the results show a 76.3% match rate.[10]

2.2 Paper-Year Records

Along with author affiliation records, our dataset includes paper and author information. We construct a dataset of paper-year records that include title, publication year, and journal/repository, as well as authors and their affiliations. We obtain available information from OpenAlex, incorporate author affiliation, and construct additional variables necessary for our analysis. For a paper i published in year t in journal/repository j, we form the following outcome variables of interest:

- (Num_{ijt}) Number of authors on the paper
- Inter-institutional collaboration variables
  - ($Intra_{ijt}$) Intra-institutional collaboration dummy: An indicator variable that equals 1 if all authors share a common institution.
  - (pct_maj_{ijt}): The fraction of authors from the major institution—i.e., the most common affiliation for paper i.
- Experience variables
  - (pct_jun_{ijt}) Fraction of junior economists: percentage of authors who are economists and whose first EC64 paper was published 0 to 9 years ago.
  - (pct_sen_{ijt}) Fraction of senior economists: percentage of authors who are economists and whose first EC64 paper was published 10 or more years ago.

Authors of NBER working papers must be linked to author profiles from OpenAlex in order to populate the author affiliation records that we construct from EC64 papers. In lieu of unique identifiers that we can map between the two databases, we adopt a fuzzy matching algorithm similar to that used by Bremer (2023) that seeks to identify similar elements from different datasets while allowing for some small degree of imperfect matching. We fuzzy match author names from NBER working papers with those from our author affiliation records and retain pairs of names with a Jaro-Winkler distance with $p = 0.1$ smaller than 0.05 (Cohen et al., 2021). When applied to 31,356 working papers from 1973 to 2023, 24,563 papers (77.4%) have fully matched author identifiers, 6,591 papers (20.8%) have partial matches, and 567 papers (1.8%) are unmatched.

[10] The main reasons for mismatches are the lack of publications and the lag of publications, which results in erroneous institutions for years when authors switch institutions. Another reason is that sometimes coauthors' institutions were recorded.

However, many of the authors posted NBER papers before their first EC64 publication with non-missing affiliations. As a result, when merging with our author affiliation records, 11,931 papers (38.0%) 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 of the four sets of papers. Although working paper repositories are a more recent occurrence, given that NBER paper series started in 1973 and the SSRN in 1994, the numbers of papers on these platforms (31,356 and 217,226) approach those of published papers in the top-5 journals and EC64 (35,109 and 238,787), respectively. The average number of authors per paper is higher for working papers than for publications, due to the more recent nature of repositories. There is a great deal of collaboration across institutions in all types of papers. In particular, 77.4% of NBER working papers are written by teams across institutions. There is also a large share of younger economists in published papers: More than 60% of authors in multi-author papers have fewer than 10 years of experience publishing papers.

3 Stylized Facts in Economics Research Collaboration

In this section, we document a set of stylized facts that characterize research collaboration among academic economists. Since the COVID pandemic began in 2020—which had a significant impact on collaboration patterns—we first focus on data before 2019 to study secular trends over time, and we reserve 2020 onward for analysis specific to COVID.

3.1 Number of Journals, Papers, and Authors

Figure 1(a) plots the number of considered journals over time. While the number of journals hovered below 10 prior to the 1950s, many more journals were introduced between 1960 and 2000, and our set of 64 journals was almost complete by the early 2000s. Figure 1(b) plots the number of published and working papers over time. While the number of papers published in the top-5 journals rose steadily over time, the rate of increase of publications among all 64 journals is markedly higher, which indicates faster expansion in top-field and other general-interest journals. NBER working papers grew at a similar rate compared with EC64 publications. Since its founding in 1994, the SSRN has hosted an increasingly large number of papers, with a rate of growth that dwarfs publications or NBER working papers. This dramatic increase stabilized around 10,000 papers per year in 2012, then spiked in 2020.

In Figure 2, we show over time (i) the number of active economists, who are assumed to be active between their first and last EC64 publication years; (ii) the number of publishing economists who published in EC64 in a given year; (iii) the number of new economists, who published in EC64 for the first time in that year; and (iv) the cumulative number of economists, who were tracked from their first EC64 publication year. The three flow measures—the numbers of active, publishing, and new academic economists—have increased substantially, and they have increased more rapidly in the post-WWII era. The cumulative number of economists reaches nearly 120,000.

Figure 3 highlights the evolution of the number of authors on a research paper over time. Single-author papers dominated prior to 1950. At that time, it was also exceedingly rare to have papers with three or more authors. The absolute number of single-author papers continued to rise until 1990, from which point we have seen a steady decline for more than 30 years. The popularity of multi-author papers appears to exhibit waves: Beginning in the 1950s, there was a noticeable increase in the number of two-author papers. There was a clear increase in the number of three-author papers in the 1980s, and papers with four or more authors became more common in the 2000s. In subsequent analyses, we group papers with four or more authors into one category of 4+ authors; fewer than 10% of papers had four or more authors until 2010.

Figure B1 illustrates similar patterns when we focus on papers published in the top-5 journals. Multi-author papers in these journals became more common at approximately the same time as in EC64 papers. Publications in the top-5 journals exhibit a more extreme shift toward a greater number of collaborators, however, as shown by the sharp decline in single-author papers from 400 per year in the 1970s to fewer than 100 per year in the 2010s.[11]

Given the relatively small sizes of journals and papers and the near unanimity of single-author papers before 1950, from now on we focus on patterns from the 1950s. Figure 4 shows that much of this growth may be attributed to the rising number of papers with three or more authors. Figure 5 presents the same breakdown by the number of authors in each set of papers. In Figure 5 it is clear that the share of papers with three or more authors has increased in all samples.

We quantify changes in the composition of research papers 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 $n = 1, 2, 3, 4+$. The variable α_s captures the difference in the number of authors across distinct outlets.

Table 3 provides the results for estimating Equation (1). Column (1) shows that the share of single-author papers decreased by an average of 1.04 percentage points for each year that passed. Column (2) indicates that two-author papers also tended to decrease over time, falling by an average of 0.45 percentage points per year. Columns (3) and (4) show increasing shares of three-

[11] There was a sharp increase in papers in *Econometrica* in the 1970s. Also, until 2017, the May issue of the *American Economic Review* each year included papers presented at the American Economic Association's annual meeting that January, which increased the overall paper count for top-5 journals.

and four-or-more-authored articles, which grew by an average of 0.89 percentage points and 0.59 percentage points per year, respectively. NBER, SSRN, and top-5 dummy variables suggest that working papers and the most selective published papers tend to have more authors compared with the universe of EC64 publications. To see if there is any discrepancy across the four sets of papers, we repeat our analysis by estimating Equation (1) separately for each set of papers in Table A1. While there exists some variation in point estimates across datasets, we continue to observe the salient pattern whereby *economics research production has shifted from an individual exercise to a team effort*.

3.2 Collaboration across Institutions

As research teams become larger over time, do their compositions change? The first dimension we examine relates to whether researchers mainly work with colleagues at their home institutions who are in close physical proximity or with those from other institutions. On the one hand, to the extent that the increase in the number of authors on articles is primarily a result of better collaboration tools and lower communication hurdles, we might expect to see more frequent cooperation across institutions over time. On the other hand, if rising collaboration is more a product of an increasingly competitive publication environment, we do not necessarily expect to see changes in teamwork across institutions.

We study two variables related to inter-institutional collaboration. First, we compute the proportion of inter-institutional papers—defined as those with at least one author who is affiliated with a different institution—of all multi-author papers. Second, we compute the share of authors at the major institution—defined as the most common affiliation on a paper—of inter-institutional papers. Figure 6 plots the time series of the fraction of inter-institutional papers. Focusing on the period since 1950, we observe that the fraction of papers that involve cross-institutional cooperation declined from about 90% of all multi-author papers in 1950 to 60% in 2000. This negative trend subsequently reversed, rising to 75% by 2023.[12]

Working papers from NBER and SSRN tend to contain more inter-institutional collaboration compared with published papers. The fraction of inter-institutional SSRN papers hovers around 80% for the entire period, and the share of inter-institutional NBER papers increases over time.

Figure 7 shows that, among inter-institutional papers, the fraction of authors from the majority institution on a paper has decreased over time. This trend is the most salient for publications from EC64 journals and top-5 journals. Working papers, on the other hand, show little to no decrease in the concentration of authors from the same major institution. This pattern suggests that growing

[12]In comparison, Jones, Wuchty, and Uzzi (2008) examine collaboration from 1975 to 2005 and find that scientific research is increasingly conducted across universities. The difference in findings may be due to our expanded sample period and our particular focus on economics research rather than across fields.

collaboration may not simply be driven by former colleagues who have moved to new institutions, but rather by collaborators at multiple institutions.

We quantify the magnitude of inter-institutional collaboration by estimating trend models for the fraction of inter-institutional papers and the share of authors from the major institution:

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

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

where $Inter_{ist}$ is an indicator variable that is 1 if all authors of the paper have a common institution 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 presents results estimated from 2001 to 2019 using Equation (2). Column (1) indicates a significantly positive trend of 0.17 percentage points per year. Working papers have statistically and quantitatively higher fractions on average when compared with published papers in EC64 journals, and the top-5 journals have a lower fraction on average. Columns (2) and (3) separately examine the trends for working papers and publications, which reveal that the increase in inter-institutional collaboration is much more evident for publications. The trend coefficient is eight times larger for publications (an average of 0.42 percentage points increase per year) than for working papers (0.05 percentage points per year). SSRN papers have a lower fraction of inter-institutional papers compared with NBER papers.

The dependent variable in Panel B of Table 4 is the share of authors in the major institution. Column (1) shows a significantly negative trend in this period of -0.09 percentage points per year. Working papers tend to have a lower share of authors from the same majority institution, with NBER working papers having the lowest average (3.76 percentage points lower than EC64 papers). Papers in the top-5 journals also tend to have a lower share than the EC64 publications. Columns (2) and (3) show that the trend is flatter for working papers than publications, with point estimates of -0.07 percentage points and -0.14 percentage points, respectively. Across the board, it appears that papers are becoming less dominated by team members from one institution.

3.3 Collaboration across Experience Levels

A research team can also be viewed based on the composition of members' experience levels. We separate authors into three groups: (i) *junior*: an author whose first EC64 publication was nine or fewer years prior to the publication; (ii) *senior*: an author whose first EC64 publication was 10 or more years prior to the publication; and (iii) *non-economist*: an author who has never published a paper in EC64. Using these categories, we evaluate whether researchers tend to work with others with similar or different experience levels. A partnership between two researchers of similar experience levels may indicate a more horizontal relationship, such as a combination of distinct expertise, while teamwork across experience levels may suggest a more vertical one, such as a mentor-mentee relationship.

Figure 8 presents the shares of two-author publications among EC64 journals by collaboration type: two juniors, one junior and one senior, and two seniors. From 1950 onward, the share of papers written by two junior economists initially rose into the 1970s, but then declined. The share of papers by one junior and one senior economist has consistently been around 40%, and the fraction of papers produced by two senior collaborators increased in the 1980s and has remained stable at around 20% since. Overall, the split among the three categories has remained relatively stable over time.

Figure 9 plots the share of collaboration types among SSRN working papers. In addition to the three types we can define for publications, we can further construct two categories that involve non-economists (authors who have never published in EC64 journals). This figure exhibits trends similar to those in Figure 8: A stable share of junior-senior and senior-senior collaboration, and a decreasing share of junior-junior papers. We also observe a growing proportion of working papers by an economist and a non-economist, which suggests an increase in interdisciplinary collaboration.[13] Figures 10 and 11 show the results when we expand the analysis to all EC64 publications. We continue to observe relatively stable shares of entirely senior, entirely junior, and mixed papers over time.

We estimate trend models for collaboration across experience levels:

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

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

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. Independent variables use the same notation as in Equation (1).

Table 5 presents the results of these estimates and demonstrates a decline in papers written by only junior collaborators and a much smaller change for papers written only by senior collaborators. Point estimates in Column (1) demonstrate that among SSRN working papers, those with exclusively junior authors tend to decline by 0.65 percentage points per year, whereas those with exclusively senior authors decline at only 0.13 percentage points each year. We observe a similar pattern of overall decreases in experience assortativity for NBER working papers and publications in EC64 journals or top-5 journals.

[13] This observation could also be due to expansion of the economics profession and more collaboration between PhD students (who have yet to publish in the 64 journals) and their mentors.

4 Drivers of Collaboration

We have documented research collaboration patterns among academic economists. The natural next step is to explore the potential drivers of such trends. What factors are associated with changes in the number of authors or the composition of a research team? Our investigation seeks to address these questions next.

Consider a simple random utility model (McFadden, 1974) in which the economist's utility from a project is comprised of benefits, costs, and taste. Based on these three factors, the economist decides to either work alone to produce a single-author paper or collaborate with other economists to produce a multi-author paper. Let b^s denote the per-author benefit of a single-author paper and b^m that of a multi-author paper. Let c^s and c^m denote the per-author cost of production of single-author and multi-author papers, respectively. Individual researchers may also have idiosyncratic preferences for working by themselves or with others, captured by ε^s and ε^m. The decision for an author j can then be summarized as follows. She would prefer to write a multi-author paper over a single-author paper if

$$b_j^m - c_j^m + \varepsilon_j^m > b_j^s - c_j^s + \varepsilon_j^1 \Rightarrow (b_j^m - b_j^s) + (\varepsilon_j^m - \varepsilon_j^s) > c_j^m - c_j^s. \tag{6}$$

That is, if the additional benefits of collaboration and preferences for collaboration outweigh the additional costs of collaboration.

This model provides two directions for exploration: benefits and costs. Benefits seek to capture the quality and impact of a paper. Costs encompass all factors that contribute to the production of a paper; these include time cost, opportunity cost, and financial cost. All else equal, researchers presumably would like to write high-quality papers that are well regarded by the profession and have an impact. Similar to Jones (2021), we use the trailing 5-year citation count as the empirical proxy for the return of a paper. Because the number of researchers and papers changes over time, two equally influential papers written at different points in time may receive different numbers of citations. To provide a fair comparison across time, we compare citations with other papers published in the same year, and define highly influential papers as those that rank in the top decile of their respective cohorts.[14]

We use the model as a guide to understand the empirical patterns in collaboration. If costs (and idiosyncratic preferences) were held constant, then collaboration patterns must be entirely due to returns. If instead returns were held constant, then any changes in collaboration patterns must arise due to variations in the relative costs of working alone and working with coauthors, provided that preferences are truly idiosyncratic. In reality, neither returns nor costs can be held constant, and the

[14]The return to a paper may be defined in other ways. For example, Heckman and Moktan (2020) define relative returns as the additional hazard rate for successful tenure.

relative degree of their variation may also differ. On the one hand, we can use publication records over a prolonged period absent shocks to costs to study the effect of returns on the number of coauthors on a paper. We explore these directions in the following subsections. On the other hand, if there are drastic and differential shocks to the cost of producing each type of paper while the returns are relatively constant, we can study the relationship between these shocks and the share of multi-author papers. We use COVID as a natural experiment.

4.1 Changes in Returns to Collaboration

We capture the return to a research paper through its impact on the profession, using as proxies based on the number of citations it receives. Jones (2021) homes in on the citation counts of a paper and documents that multi-author economics papers, relative to single-author papers, have a higher likelihood of being highly cited. We follow Jones (2021) to focus on highly cited papers among teams of different sizes, with the difference that we focus on trailing 5-year citations rather than cumulative citations. Our measure favors papers whose impact is recognized relatively quickly—a desirable trait in the competitive landscape of academia, where promotions and prestige are often tied to the recent impact of one's work. We also evaluate the impact of the number of authors at multiple points over many decades. Let i denote the paper, j the journal, t the year, and n the number of authors. Let the number of n-author papers in journal j in year t be M_{njt}. We construct the following variables linked to the impact of papers.

Homerun HR_{nijt} is an indicator variable that denotes whether paper i is a *homerun paper*, defined as a paper whose trailing 5-year citation count is among the top decile of all EC64 papers published in the same year. *Relative n-author impact* is the ratio between the share of n-author papers that are homerun and the share of single-author papers that are homerun:

$$RNI_t = \frac{\sum_i HR_{Nijt} / \sum_j M_{Njt}}{\sum_i HR_{1ijt} / \sum_j M_{1jt}}.$$

This is a comparison between the homerun conversion rate of n-author papers and that of single-author papers. *Relative n-author returns* is the ratio between the share of all homerun papers that are n-author and the share of homerun papers that are single-author:

$$RNR_t = \frac{\sum_i HR_{Nijt} / \sum_{i,n} HR_{nijt}}{\sum_i HR_{1ijt} / \sum_{i,n} HR_{nijt}} = \frac{\sum_i HR_{Nijt}}{\sum_i HR_{1ijt}}.$$

This is a comparison between the contribution to all homerun papers from n-author collaborations and individual work.

We study the time variation and driving factors of the above variables to understand differential returns from writing single-author and multi-author papers.

4.1.1 Predicting a Homerun Paper

We estimate the relative returns of having multiple authors on a paper using the specification in the following equation:

$$100 \cdot HR_{nijt} = \alpha + \sum_{n} \beta_n \mathbb{1}\{Num_{ist} = n\} + \gamma X_{ijt} + \kappa_t + \phi_j^F + \phi_j^J + \varepsilon_{nijt}, \tag{7}$$

where β_n's are n-author fixed effects, κ_t captures year fixed effects, ϕ_j^J are fixed effects for the journal, ϕ_j^F are fixed effects for the field, and X is a vector of binary control variables.[15]

Table 6 reports results from Equation (7). Column (1) controls for paper characteristics including inter-institutional collaboration, author experience and institutional rank, whether one author is affiliated with a US institution, and whether the collaboration is international. The strongest predictor for whether a paper will be highly cited is having an author from a top-10 institution, followed by having an author from a top 11-30 institution. Other characteristics have relatively small effects on the probability of becoming a homerun paper, with authors from US institutions, the number of authors, and international collaboration also having some explanatory power. Controlling for characteristics, articles with multiple authors are more likely to become homerun papers. Two-author and three-author papers are 2.36% and 2.94% more likely, compared with single-author papers, to be highly cited, while four-plus-author papers do not show a significant difference. Column (2) includes the same control variables as Column (1) plus year fixed effects. Four-plus-author papers now show a statistically significant increase in the likelihood of becoming a homerun paper compared with single-author papers. Column (3) further adds fixed effects for fields (see Table 1 for the categorization of fields and journals), and Column (4) includes journal fixed effects. We observe similar estimates in these columns, with similar economic magnitudes across two-, three-, and four-plus-author articles when controlling for latent differences across journals. Table A2 repeats the analysis, excluding publications in top-5 journals. While some point estimates change, the overall patterns remain unchanged. We also re-estimate the model without the interaction term between the experience level of an author and their institutional ranking, and change the indicator variable for author institutional ranking to whether the majority of authors on a paper belong to a

[15]Control variables include the following: whether a paper has a senior author, has an author from a US institution, has an author from a top-10 school, has a senior author from a top-10 school, has an author from a top 11-30 school, has a senior author from a top 11-30 school, involves inter-institutional collaboration, and involves international collaboration.

certain ranking. Table A3 shows that the results also remain largely unchanged.

An alternative measure of a paper's impact is its percentile among the trailing 5-year citations of all papers published in the same year. Whereas HR_{nijt} is a binary variable based on whether a paper is in the top decile of citations, this alternative measure is a continuous variable with larger values indicating more impact. All independent variables are identical to those in Equation (7). Table A4 exhibits estimates similar to those in Table 6: More impactful papers are associated with authors from US institutions, top-10 institutions, top 11-30 institutions, and multiple authors. Interestingly, whether a paper includes international collaborators appears to be a stronger driver for its citation percentile than it is for the likelihood of becoming a homerun paper. Unsurprisingly, we see the same pattern in Table A5, in which the dependent variable is citation counts.

4.1.2 Time-varying Returns to Multi-authored Papers

The preceding results show that research teams of different sizes can have different probabilities of creating impactful work. We further investigate whether these probabilities change over time, and whether teams of a certain size consistently outperform teams of other sizes. We re-estimate Equation (7) to obtain the likelihood of becoming a homerun paper by two-, three-, and four-plus-author papers over 10-year intervals. Figure 13 illustrates the likelihood of becoming a homerun paper for different-sized teams, compared with a benchmark of single-author papers. For example, a two-author paper is 2.5% less likely to become highly cited than a single-author paper in the 1950s, but 2% more likely in the 1960s.

There appears to be several waves of change in the type of research that is most likely to become a homerun paper. In the 1950s, single-author papers were the most likely to be highly cited, followed by two- and three-author papers. Four-plus-author papers are 5% less likely to be highly cited compared with single-author papers. In the 1960s and 1970s, two-author papers overtook single-author papers to become the most likely to be highly cited. Three-author papers also became more likely to be highly cited compared with single-author papers in the 1970s. By the 1980s, two- and three-author papers were both 3%-4% more likely to be highly cited compared with single-author papers, while four-plus-author papers continued to have less impact. Since the 1960s, the likelihood of multiple authors producing impactful papers has consistently exceeded that of single-author papers. In particular, three-author papers became the most likely to be highly cited in the 1990s and 2000s, while four-plus-author papers became the most likely in the 2010s (5% higher than single-author papers).

The patterns in Figure 13 reveal that there have been increasing returns to working in larger teams. Over time, larger teams became more effective at producing high-impact research. The timing of each successive wave of the highest-cited papers appears to coincide with the change in the shares of each type of paper (Figure 5). We plot the fraction of n-author papers along with the fraction of homerun papers written by n-author teams in Figure 14. The former can be viewed as the "popularity" of specific-sized teams and the latter as the "success." For teams of all sizes, popularity and success track each other closely. Single-author papers show a steady decrease in both popularity and success over time. Two-author papers have seen a resurgence in popularity and success since the 1960s, compared with relatively steady shares from 1900 to 1960. Three- and four-plus-author papers experienced both a surge in popularity and success in the 1980s and 2000s, respectively.

4.1.3 Do Returns Drive Popularity?

Figure 14 suggests a close relationship between the success of a multi-author paper and how common it is. On the one hand, economics researchers may respond to increasing returns to larger teams by writing more multi-author papers. On the other hand, stronger researchers who work more often in teams can yield a greater fraction of highly influential multi-author papers. In this section, we investigate these possibilities.[16]

We explore whether economists collaborate more in response to increasing returns to collaborative work. We estimate the following model:

$$S_{n,t} = \alpha_n + \beta_{0,n} t + \beta_{1,n} HRS_{n,t-5} + \gamma_n S_{n,t-5} + e_{n,t}, \tag{8}$$

where $S_{n,t} = M_{njt}/(\sum_n M_{njt})$ is the share of n-author papers in year t, and $HRS_{n,t-5}$ is the share of n-author papers that are in the top decile of trailing 5-year citations in year $t-5$. The choice of a 5-year lag aligns with our choice of a 5-year trailing citation count.[17]

If we estimate Equation (8) for papers with different numbers of authors, their shares add up to 1: $\sum_{n=1,2,3,4+} S_{n,t} = 1$. In this way, information present in one regression (for one set of papers) may be related to coefficients in another regression. We tackle this issue by adopting the methodology of Tomz, Tucker, and Wittenberg (2002), who provide a simple way to estimate models under the seemingly unrelated regression framework with multiple categories of outcomes. We create the following variables for $n = 2, 3, 4+$: $LRS_{n,t} = \ln(S_{n,t}/S_{1,t})$, $LRI_{n,t} = \ln(RI_{n,t})$, and $LRR_{n,t} = \ln(RR_{n,t})$.

Computing the relative share of papers (to the share of single-author papers $S_{1,t}$) and taking logarithms breaks the constraint that the sum of all shares must be 100%. First, we examine whether having higher returns to collaboration in general would promote more collaboration by

[16]Recent papers—e.g., Carrell, Figlio, and Lusher (2024) and Hill and Stein (2025)—have shown that researchers respond to incentives in terms of publishing.

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

estimating

$$\Delta LRS_{m,t} = \alpha_m + \beta_{0,M} t + \beta_{1,m} LRI_{m,t-5} + \gamma_2 LRS_{m,t-5} + e_t, \tag{9}$$

where $\Delta LRS_{m,t} = LRS_{m,t} - LRS_{m,t-1}$ is the first difference of log shares. The estimates are presented in Table 7 and are positive across the board. Even though none are statistically significant, the positive estimates suggest that increasing returns could contribute to more collaboration in economics. The small sample size is likely the reason for the large standard errors. To further examine whether specific types of collaborations have this relationship, we estimate the following system of equations using the SUR framework:

$$\begin{cases} \Delta LRS_{2,t} = \alpha_2 + \beta_{0,2} t + \beta_{1,2} LRI_{2,t-5} + \gamma_2 LRS_{2,t-5} + e_t \\ \Delta LRS_{3,t} = \alpha_3 + \beta_{0,3} t + \beta_{1,3} LRI_{3,t-5} + \gamma_3 LRS_{3,t-5} + e_t \\ \Delta LRS_{4,t} = \alpha_4 + \beta_{0,4} t + \beta_{1,4} LRI_{4,t-5} + \gamma_4 LRS_{4,t-5} + e_t, \end{cases} \tag{10}$$

where $\Delta LRS_{n,t} = LRS_{n,t} - LRS_{n,t-1}$ is the first difference of log shares. We are interested in the coefficient associated with the relative n-author impact from 5 years ago, $LRI_{n,t-5}$. A positive coefficient would indicate that researchers tend to assemble teams following their relative impact in the preceding period.

Table 8 provides the results. The top two panels, on two- and three-author papers, show little support for the idea that economists form teams in response to larger team impact. In comparison, the bottom panel, for four-plus-author papers, offers evidence that researchers assemble in larger teams in response to higher returns. Across the four alternative specifications in the columns, the coefficient on $LRI_{4,t-5}$ remains consistently positive and significant, with a similar economic magnitude. The coefficient of $LRS_{n,t-5}$ can be interpreted as a kind of peer effect. A positive coefficient here would suggest that economists who observe that more collaborations are more likely to collaborate in the future. In both Table 7 and Table 8, the coefficients are small and insignificant, which lends weight to our assumption of stable preferences for collaboration over time. We also estimate the system from Equation (10) with relative n-author returns, $LRR_{n,t}$, in place of $LRI_{n,t}$. Table A6 shows results similar to those in Table 8. Whereas researchers respond to higher returns for larger teams of four or more members, they do not appear to do so for smaller teams of two or three people.

4.2 COVID as a Natural Experiment

The onset of the COVID pandemic swiftly impacted daily life. In-person events quickly dwindled and, in many cases, were halted completely. The result was an immediate change in the costs associated with doing research, which increased the difficulty of face-to-face communication and collaboration. Because few people anticipated the pandemic (likely true for most academic researchers in economics), the return to a paper likely did not shift as quickly as costs did, and the impact a particular paper has on the profession likely persisted. Furthermore, since COVID was a rare event, economists lacked prior experience in dealing with such an occurrence, and it is unlikely that the profession adjusted the standards with which papers are viewed. Therefore, we treat COVID as a natural experiment that, in relative terms, primarily changed the costs of collaboration.

Assuming that the relative returns of multi-author papers and the distribution of individual preferences for collaborative work remained relatively constant before and after COVID, we can attribute changes to the shares of multi-author papers in the post-COVID era to changes in costs.[18] We provide an overview of some of the challenges and opportunities of COVID, which form the basis for our hypotheses regarding changes in research collaboration.

4.2.1 The Impact of COVID

The COVID pandemic potentially had an immediate impact on the following channels. We separately list those that may have raised the costs of collaboration and those that served to lower costs. The following channels likely increased the costs of collaboration. *(i) Disruption of research activities.* Field experiments came to a halt, and in-person access to labs and offices was suspended. There was also increased mental drain related to the pandemic, which may have reduced motivation and research productivity. *(ii) Strain on funding and resources.* The pandemic led to financial strain for many funding agencies and research institutions. Some projects, especially those not directly related to COVID, experienced budget cuts or delays in funding. *(iii) Cancellation of research activities.* The cancellation of academic conferences, workshops, research visits, and meetings limited opportunities for researchers to interact face-to-face, which in some cases is crucial for establishing and maintaining collaborative relationships.

The following channels may have reduced the cost of collaboration. *(i) An aggregate shift toward virtual collaboration.* The pandemic accelerated the adoption of virtual collaboration tools, which allowed researchers to continue to cooperate through online platforms. Video conferences, cloud-based collaboration tools, and virtual events became more commonplace and culturally accepted, and rendered collaboration easier and eliminated travel time. Virtual collaboration also reduced the cost of inter-institutional collaboration relative to working with an in-person colleague. *(ii) Increased open science and data sharing.* There was a notable shift toward open science, with researchers sharing data and findings more freely and rapidly than before the pandemic. Pre-print

[18] It is also possible that changes in the composition of papers is due to changes in taste. For example, Heckman and Moktan (2020) assert that single-author papers are assigned higher weight than multi-author papers in tenure decisions. This is outside the scope of our paper, which focuses on the returns and costs of paper production.

servers such as SSRN and arXiv saw a surge in usage, which facilitated faster dissemination of research results and enabled collaborative efforts to build on emerging knowledge without the delays associated with traditional publishing. *(iii) Cancellation of non-research activities.* The cancellation of activities related to teaching and services allowed researchers additional free time for research, but the cancellation of other non-research activities, such as childcare, may have reduced their productivity. How they affected the relative costs of collaboration is unclear.

COVID may also have a long-term impact on the costs of collaboration. Determining the long-term impacts is more difficult than determining the short-term impacts, since other factors can confound the initial impact of the pandemic. The mass adoption of new collaborative tools decreased the costs of collaboration, and their prevalence has persisted after the pandemic. Researchers had different outside options during the work-from-home era compared with afterward. For example, suppose that COVID limited the capacity of researchers to work on single-author papers due to the increased mental load of handling a health crisis. This would cause an immediate negative shock to the feasibility of single-author papers and encourage more researchers to work in teams. As the effect of COVID diminished, those with a strong preference for individual work would revert to solo work.

Combining the perspectives above, we evaluate the net effect of COVID on collaboration patterns to understand how costs can influence teamwork.

4.2.2 The Effect on the Number of Authors

Empirically, COVID had a significant impact on collaboration. Figure 1 demonstrates that the economics profession experienced a positive shock in both the number of working papers and publications in 2020. In 2021, the number of SSRN and NBER working papers experienced negative growth (but not publications in the top-5 and EC64, as expected).

Because the fraction of multi-author papers exhibits a time trend, changes during COVID may simply be attributed to a secular shift over time. As such, we must control for the time trend when evaluating the effect of COVID and estimate

$$100 \cdot \mathbb{1}\{\#_{ist} = n\} = \beta_0 + \sum_{c=2020}^{2023} \mathbb{1}\{t = c\} + \beta_1 t + \varepsilon_{ist} \tag{11}$$

separately for working papers and EC64 publications.

Tables 9 and 10 report the results. Yearly trend estimates in both tables show that single-author and two-author papers are on the decline, whereas three- and four-plus-author papers are on the rise. During the COVID pandemic, there appears to be a consistent decrease in two- and three-author publications and some increases in four-plus-author publications from 2020 through

2022. What is more striking is the magnitude and persistence of changes in publications. While the changes in working papers are large and immediate, they went away in 2023. On the other hand, while the deviations from trends are expected to be small in 2020, they persisted throughout 2023. Overall, these two tables present evidence that while some economists chose to collaborate with more colleagues during COVID, a considerable amount also shifted to working alone. These effects are immediate in pre-print works, and the pattern persisted through the publication process.

As a supplement, Figure 15 visualizes these deviations from the extended linear trends of 2000-2019. In summary, our estimates suggest a polarizing effect: After COVID, the share of two- and three-author working papers decreased, while the share of single-author papers and papers with four or more authors increased.

4.2.3 The Effect on Inter-institutional Collaboration

What is the net effect on cooperation across institutions? We focus on the share of papers that are inter-institutional and the share of authors who are at the major institution as our outcome variables of interest. Given that the estimated trends of institutional assortativity vary substantially by sample in Table 11, we also estimate deviations from the historical trend separately by sample. Similar to our preceding analysis, we estimate COVID period deviations for our outcome variables by adding indicator variables for post-COVID years, revising Equations (2) and (3) to

$$100 \cdot \mathbb{1}\{Inter_{ist}\} = \alpha_s + \sum_{c=2020}^{2023} \mathbb{1}\{t = c\} + \beta_1 t + \varepsilon_{ist}, \tag{12}$$

$$pct\_maj_{ist} = \alpha_s + \sum_{c=2020}^{2023} \mathbb{1}\{t = c\} + \beta_1 t + \varepsilon_{ist}. \tag{13}$$

Table 12 presents the results for inter-institutional collaboration. Columns (1), (2), and (4) show that SSRN and NBER working papers, as well as papers published in top-5 journals, exhibit little to no significant deviation from their pre-COVID trends. Column (3) suggests some increases in teamwork across institutions for publications in EC64 journals in 2022 and 2023.

Table 13 reports the results for the fraction of authors in the major institution in multi-author papers. SSRN papers show almost no change during COVID compared with the prior period, whereas NBER working papers and EC64 publications display some decline, albeit not always consistently across the COVID years. Taken together, there is limited evidence of a change in inter-institutional collaboration during COVID. In other words, researchers did not significantly alter the composition of their coauthors, even if they collaborated more.

4.2.4 The Effect on Experience Assortativity

Finally, we examine the effect of COVID on the experience assortativity of economics collaboration. We estimate a variation of Equations (4) and (5) for each of the samples:

$$100 \cdot \mathbb{1}\{pct_jun = 100\}_{ist} = \alpha_s + \sum_{c=2020}^{2023} \mathbb{1}\{t = c\} + \beta_1 t + \varepsilon_{ist}, \tag{14}$$

$$100 \cdot \mathbb{1}\{pct_sen = 100\}_{ist} = \alpha_s + \sum_{c=2020}^{2023} \mathbb{1}\{t = c\} + \beta_1 t + \varepsilon_{ist}. \tag{15}$$

Table 14 presents the results. Column (1) shows that SSRN working papers experienced significant decreases in all-junior collaborations and significant increases in all-senior collaborations. While the same cannot be said about NBER working papers, we see very little deviation in these statistics in publications, which is likely due to the delay in publication.

5 Conclusion

This paper seeks to expand our understanding of economics research collaboration along two dimensions. First, we document more granular collaboration patterns, including how economists with different experience levels work together, and offer more complete evidence on how collaboration across institutions has changed. Second, we study the potential drivers of collaboration patterns using a simple framework that allows us to compare the benefits of a paper to its costs of production. Changes in benefits and costs can generate different collaboration patterns over time.

We construct a novel dataset that combines published papers from 64 economics journals and working papers from SSRN and NBER. Our dataset provides both a consistent analytic environment and detailed author-level information. Similar to prior work, we find a significant trend of an increasing number of coauthors on research papers over time. The share of multi-author papers, whether as a fraction of working papers or publications, continued to rise over time. Teamwork across institutions has become more common, but only in the last 25 years. Researchers tended to work with others with similar experience and standing, such that the mix between senior and junior economists has remained unchanged in recent decades.

We document increasing returns to collaborative work over time. While single-author papers were the most likely to become highly cited in the 1950s, multi-author papers became increasingly more likely to be highly cited in subsequent decades, with four-plus-author papers as the most influential in the 2010s. We test the hypothesis that the prevalence of multi-author papers follows a rise in their academic influence, and find that researchers tended to respond to higher returns of larger teams but showed a limited response to rising returns of medium-sized teams.

Using COVID as a plausible exogenous shock to the cost of paper production, we find a polarizing effect on economics scholarship. While some researchers tended to work more by themselves, others collaborated more broadly during the pandemic than ever before. Inter-institutional collaboration remained largely unchanged in this period.

Although our work takes a step toward understanding research collaboration through variation in returns and costs, our empirical investigation imposes minimal structure and relies on reduced-form evidence. A more formal theoretical exploration of the mechanism of research collaboration should account for the empirical patterns in returns and costs, and provide an explanation for their observed changes over time. We leave this intriguing direction to future work.

Bibliography

Ahmadpoor, Mohammad and Benjamin F. Jones. 2019. "Decoding team and individual impact in science and invention." *Proceedings of the National Academy of Sciences* 116 (28):13885–13890.

Andrikopoulos, Andreas, Aristeidis Samitas, and Konstantinos Kostaris. 2016. "Four decades of the *Journal of Econometrics*: Coauthorship patterns and networks." *Journal of Econometrics* 195 (1):23–32.

Barnett, Andy H., Richard W. Ault, and David L. Kaserman. 1988. "The rising incidence of co-authorship in economics: Further evidence." *Review of Economics and Statistics* 70 (3):539–543.

Bayhan, Hasan Gokberk, Sinem Mollaoglu, Hanzhe Zhang, and Kenneth Frank. 2022. "Project team collaborations during time of disruptions: Transaction costs, knowledge flows, and social network theory perspective." *Construction Research Congress* :1012–1023.

Bremer, Leon. 2023. "Fuzzy firm name matching: Merging Amadeus firm data to PATSTAT." Tech. Rep. TI 2023-055/VIII, Tinbergen Institute. URL https://papers.tinbergen.nl/23055.pdf.

Butler, Jenna L. and Sonia Jaffe. 2021. "Challenges and gratitude: A diary study of software engineers working from home during COVID-19 pandemic." In *2021 IEEE/ACM 43rd International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP)*. IEEE, 362–363.

Cabral, Luís. 2020. "List of leading journals for economics faculty." Accessed: 2025-02-06.

Carrell, Scott E., David N. Figlio, and Lester R. Lusher. 2024. "Clubs and networks in economics reviewing." *Journal of Political Economy* 132 (9):2999–3024.

Cohen, Gregory J., Jacob Dice, Melanie Friedrichs, Kamran Gupta, William Hayes, Isabel Kitschelt, Seung Jung Lee, W. Blake Marsh, Nathan Mislang, Maya Shaton, Martin Sicilian, and Chris Webster. 2021. "The U.S. syndicated loan market: Matching data." *Journal of Financial Research* .

Dong, Xu, Victoria R. Nelson, Hanzhe Zhang, Young Anna Argyris, Sinem Mollaoglu, Kenneth Frank, Arnav Jain, Xiao Qiao, Joseph Thekinen, and Haochen Liu. 2023. "Does the transition to online meetings exacerbate or alleviate gender and racial inequities in student participation in project teams? Theory-guided machine-learning analysis of online collaborative work during the pandemic." Mimeo.

Falk-Krzesinski, Holly J., Noshir Contractor, Stephen M. Fiore, Kara L. Hall, Cathleen Kane, Joann Keyton, Julie Thompson Klein, Bonnie Spring, Daniel Stokols, and William Trochim. 2011. "Mapping a research agenda for the science of team science." *Research Evaluation* 20 (2):145–158.

Ford, Denae, Margaret-Anne Storey, Thomas Zimmermann, Christian Bird, Sonia Jaffe, Chandra Maddila, Jenna L. Butler, Brian Houck, and Nachiappan Nagappan. 2021. "A tale of two cities: Software developers working from home during the COVID-19 pandemic." *ACM Transactions on Software Engineering and Methodology (TOSEM)* 31 (2):1–37.

Freeman, Richard B., Danxia Xie, Hanzhe Zhang, and Hanzhang Zhou. 2024. "High and rising concentration of award-winning economists." Mimeo.

Guimera, Roger, Brian Uzzi, Jarrett Spiro, and Luis A. Nunes Amaral. 2005. "Team assembly mechanisms determine collaboration network structure and team performance." *Science* 308 (5722):697–702.

Ham, John C., Julian Wright, and Ziqiu Ye. 2021. "New rankings of economics journals: Documenting and explaining the rise of the new society journals." Mimeo.

Hamermesh, Daniel S. 2013. "Six decades of top economics publishing: Who and how?" *Journal of Economic Literature* 51 (1):162–172.

Hamermesh, Daniel S. and Lea-Rachel Kosnik. 2024. "Why do older scholars slow down?" *Economic Inquiry* 62 (1):488–499.

Hamermesh, Daniel S. and Sharon M. Oster. 2002. "Tools or toys? The impact of high technology on scholarly productivity." *Economic Inquiry* 40 (4):539–555.

Heckman, James J. and Sidharth Moktan. 2020. "Publishing and promotion in economics: The tyranny of the top five." *Journal of Economic Literature* 58 (2):419–470.

Heo, Seulkee, Alisha Yee Chan, Pedro Diaz Peralta, Lan Jin, Claudia Ribeiro Pereira Nunes, and Michelle L. Bell. 2022. "Impacts of the COVID-19 pandemic on scientists' productivity in science, technology, engineering, mathematics (STEM), and medicine fields." *Humanities and Social Sciences Communications* 9 (1):1–11.

Hill, Ryan and Carolyn Stein. 2025. "Race to the bottom: competition and quality in science." *Quarterly Journal of Economics* 140 (2):563–608.

Hudson, John. 1996. "Trends in multi-authored papers in economics." *Journal of Economic Perspectives* 10 (3):153–158.

Hunter, Laura and Erin Leahey. 2008. "Collaborative research in sociology: Trends and contributing factors." *American Sociologist* 39:290–306.

Jackson, Matthew O. and Asher Wolinsky. 1996. "A strategic model of social and economic networks." *Journal of Economic Theory* 71 (1):44–74.

Jain, Arnav, Faizan Shafique, Sinem Mollaoglu, Xu Dong, Hanzhe Zhang, Shimeng Dai, Kenneth Frank, Dorothy Carter, Anna Young Argyris, Annick Anctil et al. 2024. "Iterative development of dynamic student project team interventions." In *Construction Research Congress 2024*. 109–118.

Ji, Pengsheng and Jiashun Jin. 2016. "Coauthorship and citation networks for statisticians." *The*

Annals of Applied Statistics 10 (4):1779–1812.

Jones, Benjamin F. 2009. "The burden of knowledge and the 'death of the Renaissance man': Is innovation getting harder?" *Review of Economic Studies* 76 (1):283–317.

———. 2010. "Age and great invention." *Review of Economics and Statistics* 92 (1):1–14.

———. 2021. "The rise of research teams: Benefits and costs in economics." *Journal of Economic Perspectives* 35 (2):191–216.

Jones, Benjamin F., Stefan Wuchty, and Brian Uzzi. 2008. "Multi-university research teams: Shifting impact, geography, and stratification in science." *Science* 322 (5905):1259–1262.

Kalaitzidakis, Pantelis, Theofanis P. Mamuneas, and Thanasis Stengos. 2003. "Rankings of academic journals and institutions in economics." *Journal of the European Economic Association* 1 (6):1346–1366.

King, Molly M. and Megan E. Frederickson. 2021. "The pandemic penalty: The gendered effects of COVID-19 on scientific productivity." *Socius* 7:23780231211006977.

Kosnik, Lea-Rachel. 2022. "Who are the more dismal economists? Gender and language in academic economics research." *AEA Papers and Proceedings* 112:592–596.

———. 2023. "Additional evidence on gender and language in academic economics research." *Scientometrics* 128:5949–5968.

Kosnik, Lea-Rachel and Daniel S. Hamermesh. 2024. "Aging in style: Seniority and sentiment in scholarly writing." *Southern Economic Journal* 90 (4):1136–1164.

Lin, Zihang, Yian Yin, Lu Liu, and Dashun Wang. 2023. "SciSciNet: A large-scale open data lake for the science of science research." *Scientific Data* 10 (1):315.

Liu, Lu, Benjamin F. Jones, Brian Uzzi, and Dashun Wang. 2023. "Data, measurement and empirical methods in the science of science." *Nature Human Behaviour* 7 (7):1046–1058.

Liu, Meijun, Ning Zhang, Xiao Hu, Ajay Jaiswal, Jian Xu, Hong Chen, Ying Ding, and Yi Bu. 2022. "Further divided gender gaps in research productivity and collaboration during the COVID-19 pandemic: Evidence from coronavirus-related literature." *Journal of Informetrics* 16 (2):101295.

McDowell, John M. and Michael Melvin. 1983. "The determinants of co-authorship: An analysis of the economics literature." *Review of Economics and Statistics* 65 (1):155–160.

McFadden, Daniel. 1974. "The measurement of urban travel demand." *Journal of Public Economics* 3 (4):303–328.

Milojević, Staša. 2014. "Principles of scientific research team formation and evolution." *Proceedings of the National Academy of Sciences* 111 (11):3984–3989.

Nowell, Cliff and Therese Grijalva. 2011. "Trends in co-authorship in economics since 1985." *Applied Economics* 43 (28):4369–4375.

Schwert, G. William. 2021. "The remarkable growth in financial economics, 1974–2020." *Journal* *of Financial Economics* 140 (3):1008–1046.

Seltzer, Andrew J. and Daniel S. Hamermesh. 2018. "Co-authorship in economic history and economics: Are we any different?" *Explorations in Economic History* 69:102–109.

Sheng, Shuyang. 2020. "A structural econometric analysis of network formation games through subnetworks." *Econometrica* 88 (5):1829–1858.

Sinatra, Roberta, Sandra Sousa, Yanmeng Xing, and M. Szell. 2023. "The impact of COVID-19 on scientific productivity and collaboration." In *Proceedings of the 9th International Conference on Computational Social Science (IC2S2)*. Copenhagen, Denmark, 1–4.

Tilburg University. 2025. "Economics and Business Schools Research Ranking Sandbox." URL https://rankings.tilburguniversity.edu/sandbox/. Accessed: 2025-02-06.

Tomz, Michael, Joshua A. Tucker, and Jason Wittenberg. 2002. "An easy and accurate regression model for multiparty electoral data." *Political Analysis* 10 (1):66–83.

Uzzi, Brian, Satyam Mukherjee, Michael Stringer, and Benjamin F. Jones. 2013. "Atypical combinations and scientific impact." *Science* 342 (6157):468–472.

Wuchty, Stefan, Benjamin F. Jones, and Brian Uzzi. 2007. "The increasing dominance of teams in production of knowledge." *Science* 316 (5827):1036–1039.

Xie, Yu. 2014. "'Undemocracy': Inequalities in science." *Science* 344 (6186):809–810.

Yang, Longqi, David Holtz, Sonia Jaffe, Siddharth Suri, Shilpi Sinha, Jeffrey Weston, Connor Joyce, Neha Shah, Kevin Sherman, Brent Hecht et al. 2022. "The effects of remote work on collaboration among information workers." *Nature Human Behaviour* 6 (1):43–54.

Tables

Table 1: Journals by Field

* Numbers in parentheses indicate the ranks in Ham, Wright, and Ye (2021).

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 Paper Samples

	SSRN	NBER	Top Five	EC64
Coverage Years	1994-2023	1973-2023	1886-2023	1886-2023
Number of Papers	217,226	11,931	35,109	238,787
Number of Authors per Paper	2.3	2.4	1.5	1.8
Number of Unique Authors	104,148	4,978	22,001	119,324
% Inter-Institutional in Multi-Authored Papers	78.2%	77.4%	74.5%	74.8%
Avg % Junior in Multi-Authored Papers	48.9%	44.7%	61.4%	63.1%

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. 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 Yearly Trend in Number of Authors from 2001 to 2019

	(1)	(2)	(3)	(4)
	% 1 Author	% 2 Authors	% 3 Authors	% 4+ Authors
Yearly Trend	-1.04***	-0.45***	0.89***	0.59***
	(0.02)	(0.02)	(0.02)	(0.01)
NBER	-0.58	5.62***	-2.62***	-2.42***
	(0.60)	(0.63)	(0.49)	(0.24)
SSRN	-30.29***	-3.93***	22.26***	11.96***
	(0.34)	(0.38)	(0.32)	(0.20)
Top 5	-8.63***	4.46***	2.69***	1.47***
	(0.57)	(0.65)	(0.55)	(0.34)
Number of Papers	261,641	261,641	261,641	261,641

Note: SSRN papers include those with at least 33% economist authors. Results under a quadratic trend 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) All	(2) Working Papers	(3) Publications
Panel A		% Papers Inter-Institutional	
Yearly Trend	0.17***	0.05**	0.42***
	(0.02)	(0.02)	(0.04)
NBER	8.04***		
	(0.66)		
SSRN	8.38***	0.44	
	(0.23)	(0.64)	
T5	-1.54**		-1.47**
	(0.71)		(0.71)
Number of Papers	192,344	134,559	57,785
Panel B		% Authors in Major Institution	
Yearly Trend	-0.09***	-0.07***	-0.14***
	(0.01)	(0.01)	(0.02)
NBER	-3.76***		
	(0.20)		
SSRN	-3.63***	0.12	
	(0.10)	(0.18)	
T5	-1.15***		-1.15***
	(0.33)		(0.33)
Number of Papers	144,966	104,878	40,088

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. Models in panel A are estimated with only multi-authored papers. Models in panel B are further restricted to include only inter-institutional papers. Results under a quadratic trend are not qualitatively different. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: 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 6: Predictors of Homerun Papers, 1900-2018

	(1)	(2)	(3)	(4)
	% Likelihood of Becoming a Homerun Paper			
Number of Authors				
2	2.36***	2.92***	2.68***	3.81***
	(0.16)	(0.17)	(0.16)	(0.17)
3	2.94***	3.82***	3.28***	4.76***
	(0.24)	(0.24)	(0.24)	(0.24)
4+	0.52	1.28***	1.20***	3.49***
	(0.38)	(0.38)	(0.37)	(0.37)
$\mathbb{1}\{$Inter-Institutional$\}$	1.22***	0.49***	-0.33**	-1.54***
	(0.15)	(0.15)	(0.15)	(0.15)
$\mathbb{1}\{$Has Senior Author$\}$	-0.99***	-0.72***	-0.94***	-0.71***
	(0.15)	(0.15)	(0.15)	(0.15)
$\mathbb{1}\{$Has Top 10 Author$\}$	15.93***	15.95***	13.81***	11.04***
	(0.26)	(0.26)	(0.26)	(0.26)
$\mathbb{1}\{$Has Top 10 Senior$\}$	-0.72**	-0.82**	-1.00***	-0.72**
	(0.35)	(0.35)	(0.35)	(0.34)
$\mathbb{1}\{$Has 11-30 Author$\}$	7.80***	7.94***	6.80***	5.02***
	(0.27)	(0.27)	(0.26)	(0.26)
$\mathbb{1}\{$Has 11-30 Senior$\}$	-0.42	-0.47	-0.37	-0.42
	(0.36)	(0.36)	(0.35)	(0.35)
$\mathbb{1}\{$US Institution$\}$	0.67***	1.03***	2.64***	3.20***
	(0.15)	(0.15)	(0.15)	(0.16)
$\mathbb{1}\{$International Collab.$\}$	-0.02	0.79***	0.81***	0.71***
	(0.23)	(0.23)	(0.23)	(0.23)
Number of Papers	213,947	213,947	213,947	213,947
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 7: Estimated Correlations Between Returns and Popularity of Multi-Authored Papers, 1950-2018

	$\Delta LRS_{n,t}$			
$LRI_{n,t-5}$	0.0494	0.0488	0.0507	0.0515
	(0.0327)	(0.0519)	(0.0769)	(0.0835)
$LRS_{n,t-5}$		0.0006		0.0036
		(0.0365)		(0.0764)
Year			-0.0000	-0.0001
			(0.0016)	(0.0031)
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 8: Estimated Correlations Between Returns and Popularity of Multi-Authored Papers, 1950-2018

	$\Delta LRS_{2,t}$			
$LRI_{2,t-5}$	-0.0068	-0.0293	-0.0615	-0.0748
	(0.0258)	(0.0364)	(0.0485)	(0.0525)
$LRS_{2,t-5}$		0.0416		-0.0780
		(0.0416)		(0.0809)
Year			0.0017	0.0034
			(0.0010)	(0.0021)
	$\Delta LR3S_t$			
$LRI_{3,t-5}$	0.0043	-0.0353	-0.0634*	-0.0638*
	(0.0244)	(0.0341)	(0.0382)	(0.0387)
$LRS_{3,t-5}$		0.0499		-0.0583
		(0.0310)		(0.0627)
Year			0.0033**	0.0056*
			(0.0014)	(0.0029)
	$\Delta LRS_{4,t}$			
$LRI_{4,t-5}$	0.0690**	0.0744*	0.0666*	0.0712*
	(0.0347)	(0.0409)	(0.0387)	(0.0410)
$LRS_{4,t-5}$		0.0077		-0.0517
		(0.0508)		(0.0715)
Year			0.0011	0.0024
			(0.0016)	(0.0023)
Number of Years	61	61	61	61

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 9: 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	0.85**	-0.51	-2.59***	2.25***
	(0.38)	(0.51)	(0.49)	(0.37)
2021	2.43***	-2.17***	-3.63***	3.37***
	(0.42)	(0.54)	(0.53)	(0.42)
2022	2.99***	-1.47***	-3.99***	2.47***
	(0.43)	(0.55)	(0.54)	(0.42)
2023	0.80	0.62	-3.22	1.80
	(2.40)	(2.77)	(2.53)	(1.92)
Yearly Trend	-0.94***	-0.62***	0.91***	0.65***
	(0.02)	(0.02)	(0.02)	(0.01)
NBER	10.64***	2.09***	-8.55***	-4.18***
	(0.53)	(0.57)	(0.45)	(0.24)
Number of Papers	205,596	205,596	205,596	205,596

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

Table 10: Estimated Deviations in the Number of Authors from Linear Yearly Trends During COVID from 2001 to 2023, EC64 Papers

	(1)	(2)	(3)	(4)
	% 1 Author	% 2 Authors	% 3 Authors	% 4+ Authors
2020	1.37**	-2.49***	-0.87	1.98***
	(0.65)	(0.72)	(0.67)	(0.49)
2021	-0.58	-1.62**	-1.25*	3.45***
	(0.62)	(0.72)	(0.67)	(0.51)
2022	1.87***	-3.49***	-1.56**	3.18***
	(0.67)	(0.75)	(0.71)	(0.54)
2023	2.22***	-4.62***	-2.57***	4.97***
	(0.68)	(0.76)	(0.72)	(0.57)
Yearly Trend	-1.20***	-0.16***	0.87***	0.49***
	(0.03)	(0.03)	(0.02)	(0.02)
Number of Papers	109,806	109,806	109,806	109,806

Note: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Estimated Yearly Trend in Institutional Assortativity in Collaboration from 2001 to 2019

	(1)	(2)	(3)	(4)
Sample	SSRN	NBER	EC64	T5
Panel A		% Papers Inter-Institutional		
Yearly Trend	0.02	0.85***	0.38***	0.77***
	(0.02)	(0.11)	(0.04)	(0.12)
Number of Papers	130,126	4,981	53,159	4,626
Panel B		% Authors in Major Institution		
Yearly Trend	-0.06***	-0.18***	-0.13***	-0.35***
	(0.01)	(0.03)	(0.02)	(0.05)
Number of Papers	101,443	3,874	36,946	3,142

Note: SSRN papers only include papers with at least 33% economist authors. NBER papers only include those for which we could recover full author-affiliation information. Models in panel A are estimated with only multi-authored papers. Models in panel B are further restricted to include only inter-institutional papers. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Estimated Deviations in Inter-Institutional Collaboration from Yearly Trends During COVID from 2001 to 2023

	(1)	(2)	(3)	(4)
Sample	SSRN	NBER	EC64	Top 5
2020	0.85*	-0.24	0.88	-3.42
	(0.48)	(2.29)	(0.80)	(2.75)
2021	0.71	-2.60	0.19	-2.83
	(0.52)	(2.65)	(0.80)	(2.74)
2022	-0.08	2.26	1.95**	-5.26*
	(0.53)	(2.49)	(0.83)	(2.86)
2023	1.75***	-3.24	2.21***	-0.98
	(0.58)	(2.78)	(0.84)	(2.76)
Yearly Trend	0.02	0.78***	0.38***	0.77***
	(0.02)	(0.12)	(0.04)	(0.12)
Number of Papers	162,002	5,529	68,850	6,022
2019 Mean	78.22	85.28	72.51	75.24

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

Table 13: Estimated Deviations in the % Authors in the Major Institution from Yearly Trends During COVID from 2001 to 2023

	(1)	(2)	(3)	(4)
Sample	SSRN	NBER	EC64	Top 5
2020	-0.05	-0.21	-0.93**	-1.12
	(0.18)	(0.80)	(0.39)	(1.25)
2021	-0.02	0.30	-1.03***	1.06
	(0.20)	(0.90)	(0.38)	(1.25)
2022	0.21	-2.11**	-0.07	-0.25
	(0.20)	(0.99)	(0.40)	(1.26)
2023	0.32	1.58	-0.33	0.71
	(0.23)	(0.99)	(0.42)	(1.37)
Yearly Trend	-0.06***	-0.15***	-0.13***	-0.35***
	(0.01)	(0.03)	(0.02)	(0.05)
Number of Papers	126,593	4,366	48,687	4,164
2019 Mean	48.59	47.74	51.06	46.80

Note: SSRN papers only include papers with at least 33% economist authors. NBER papers only include those for which we could recover full author-affiliation information. Models are estimated with only multi-authored papers. 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 14: Estimated Deviations in Experience Assortativity in Multi-Authored Papers from Yearly Trends during COVID from 2001 to 2023

	(1) SSRN	(2) NBER	(3) EC64	(4) Top 5
	% Papers with All Junior Authors			
2020	-0.99**	-0.43	-1.80**	-0.44
	(0.43)	(2.09)	(0.80)	(2.51)
2021	-2.64***	0.49	-0.56	-2.80
	(0.44)	(2.36)	(0.79)	(2.43)
2022	-3.93***	1.73	-0.02	4.22
	(0.43)	(2.54)	(0.85)	(2.71)
2023	-7.18***	0.62	-0.98	-2.14
	(0.42)	(2.44)	(0.85)	(2.52)
Yearly Trend	-0.65***	-0.67***	-0.31***	-0.51***
	(0.02)	(0.11)	(0.04)	(0.11)
	% Papers with All Senior Authors			
2020	2.15***	3.03	1.24*	1.66
	(0.31)	(2.90)	(0.64)	(2.43)
2021	1.56***	5.58*	-0.11	-2.80
	(0.33)	(3.31)	(0.61)	(2.27)
2022	2.63***	-0.89	0.97	0.81
	(0.35)	(3.36)	(0.67)	(2.48)
2023	3.51***	-0.43	0.49	0.36
	(0.40)	(3.38)	(0.67)	(2.47)
Yearly Trend	-0.13***	-0.10	-0.07**	-0.07
Number of Papers	162,002	5,529	69,181	6,027

Note: SSRN papers only include papers 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figures

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

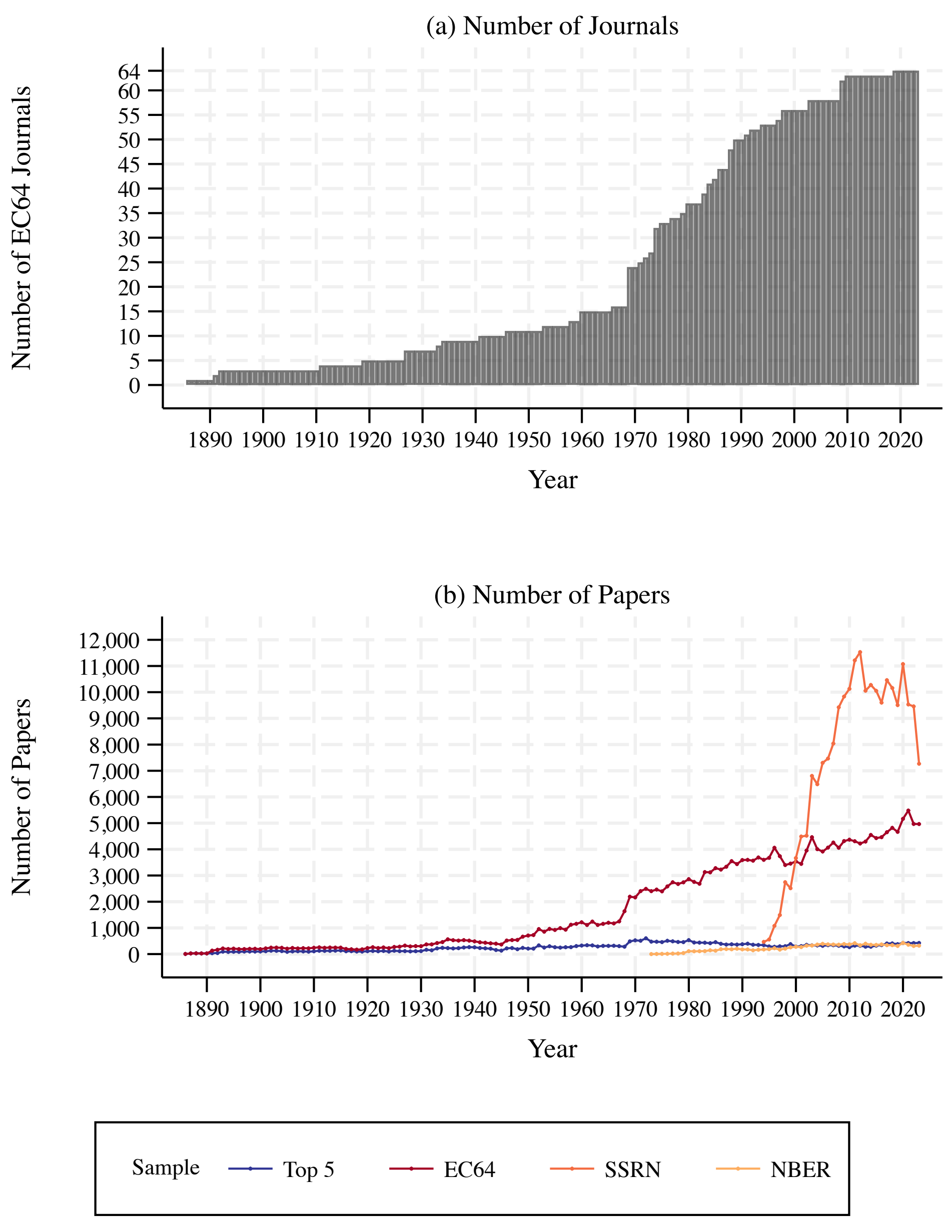
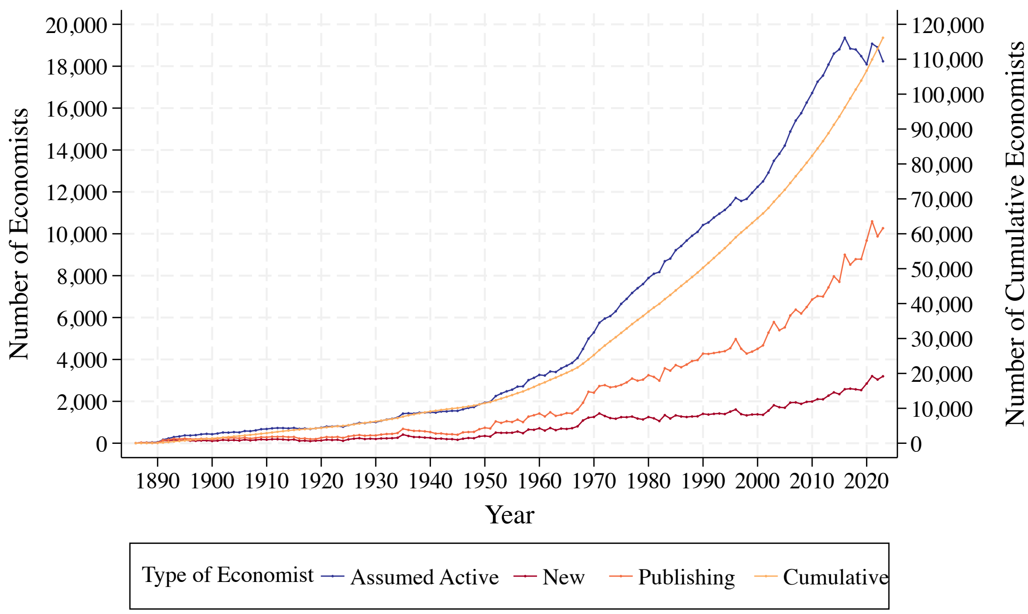


Figure 2: Number of Economists



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

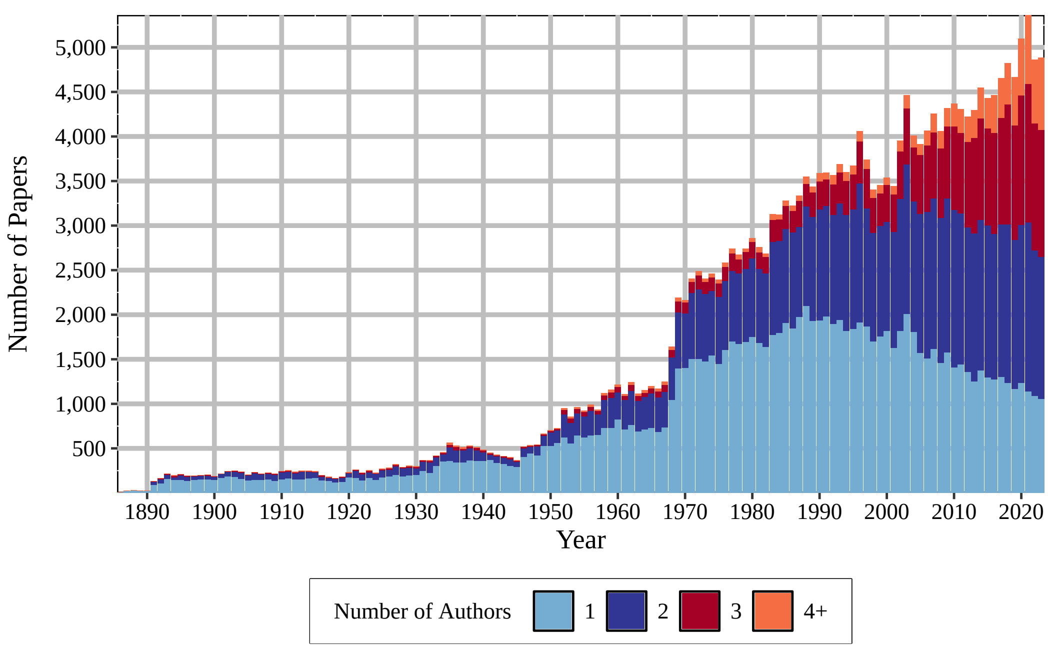


Figure 4: Multi-Author Papers Increased over Time

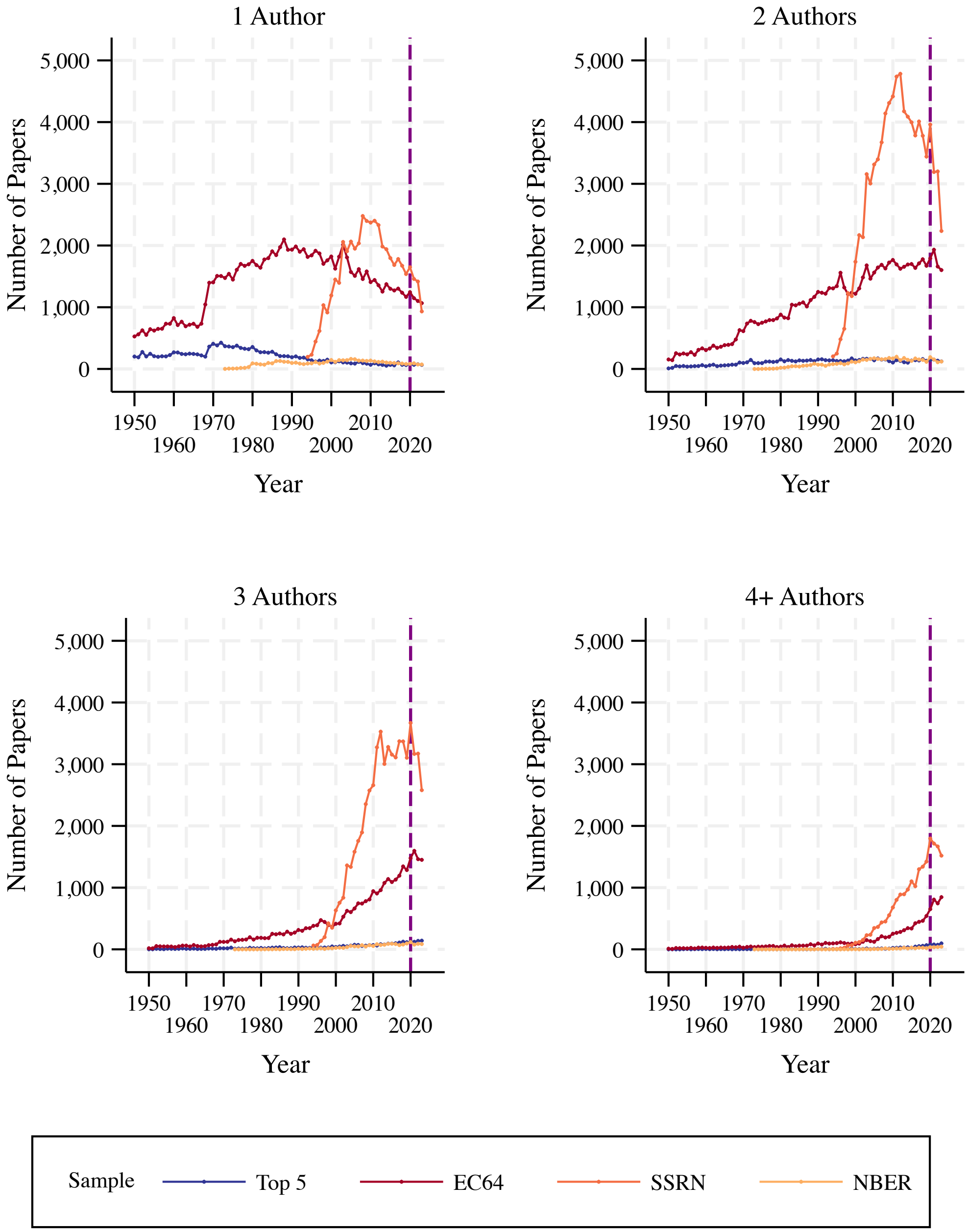


Figure 5: The Proportion of Multi-Author Papers Increased over Time

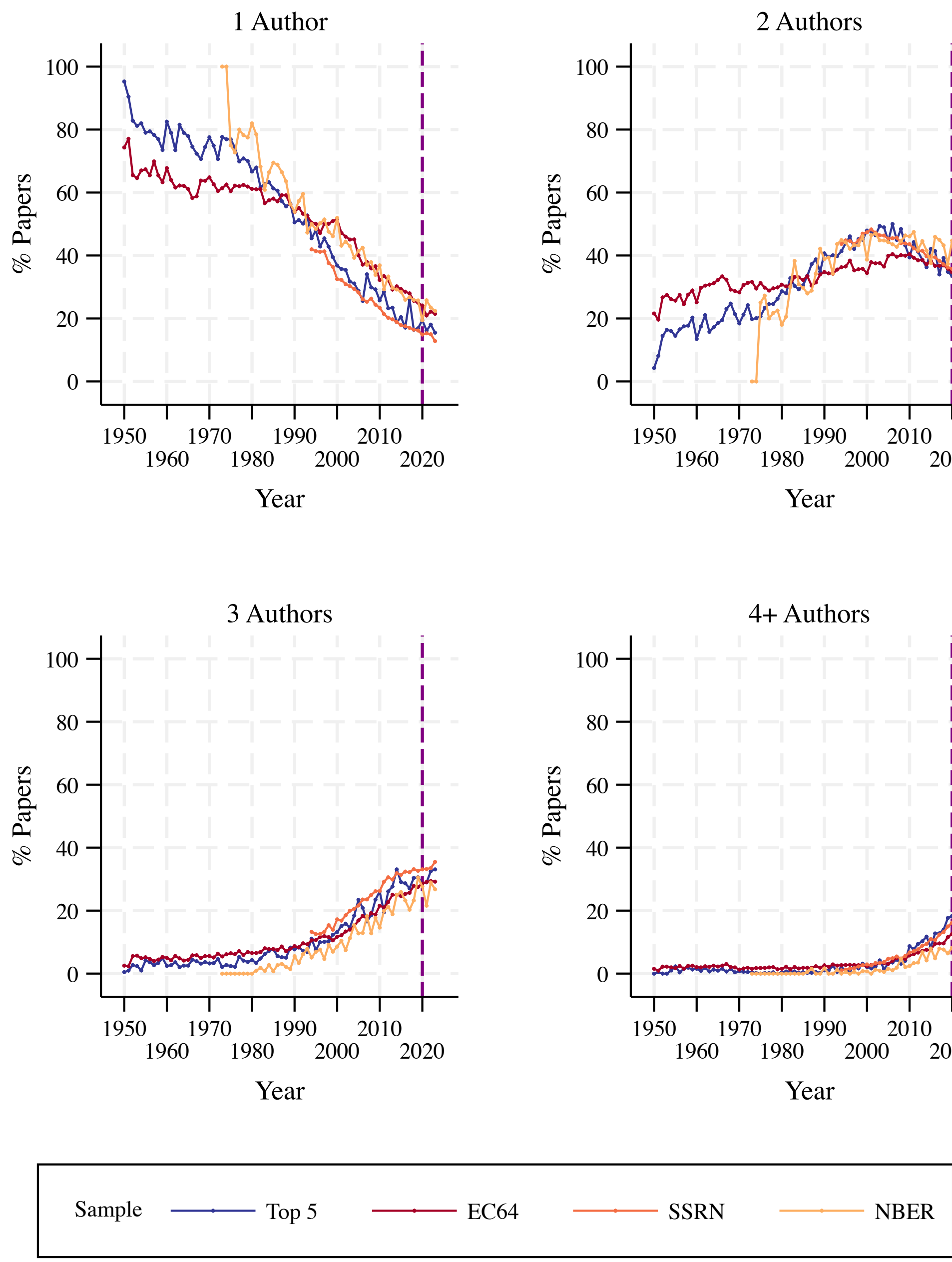
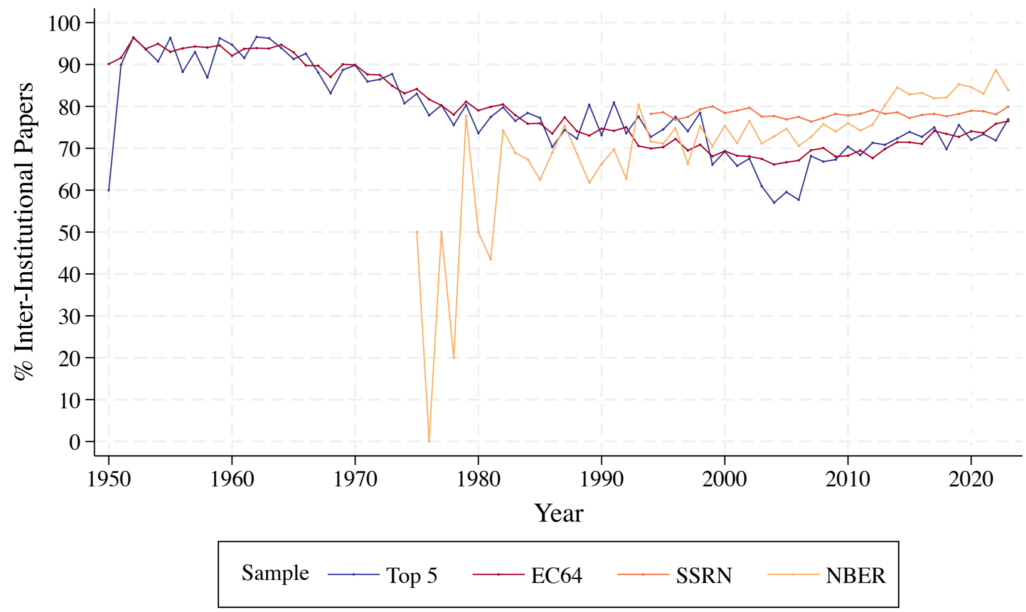
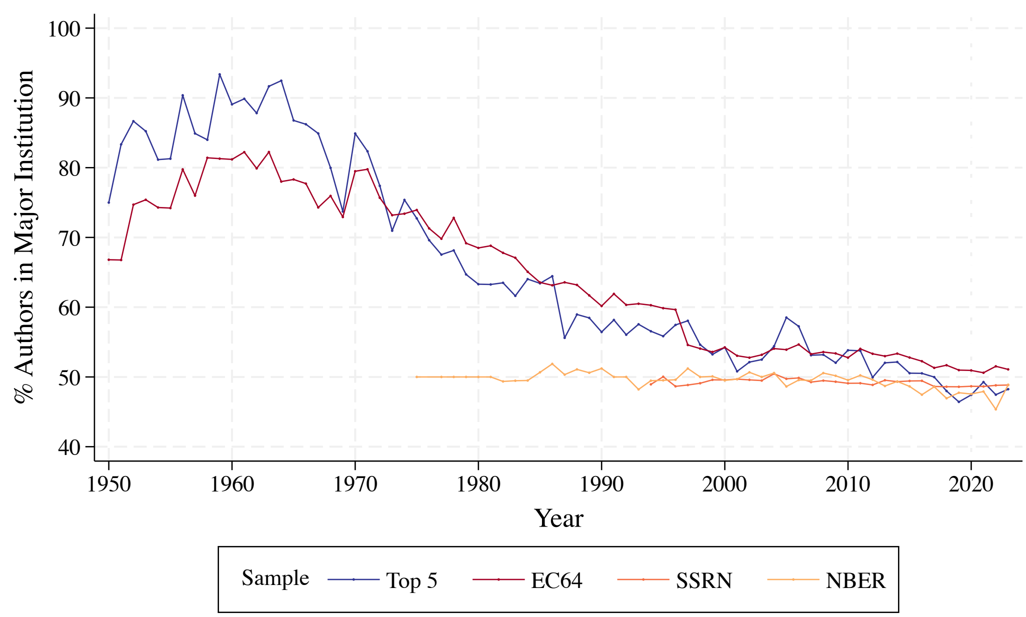


Figure 6: Trends in Inter-Institutional Collaboration



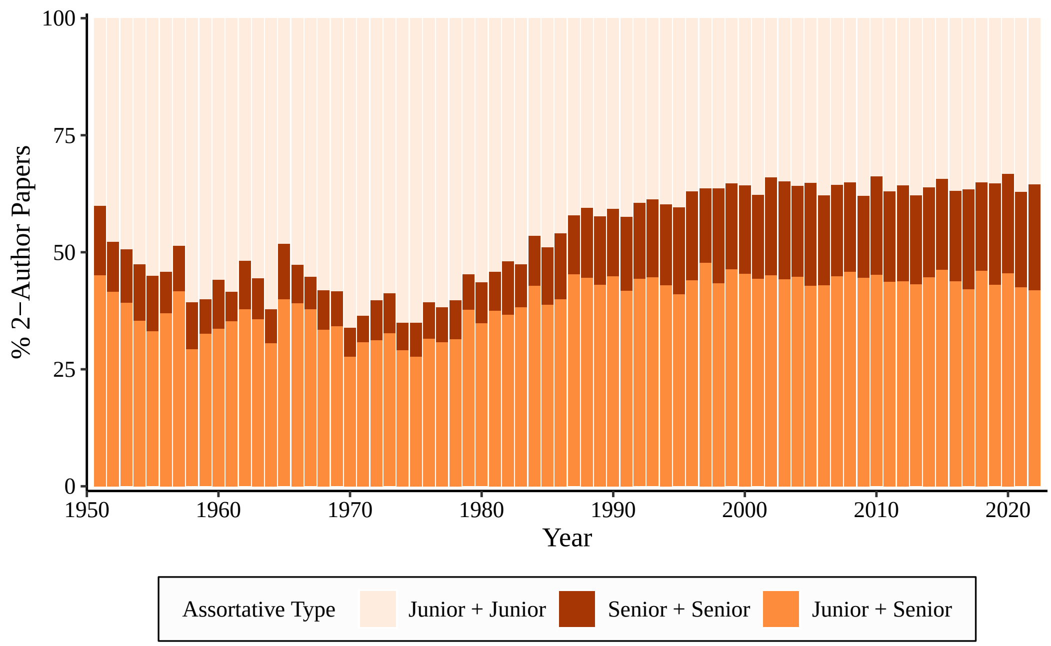
Note: A paper is inter-institutional if at least one author does not share an affiliation with another author.

Figure 7: Decrease in Institutional Concentration



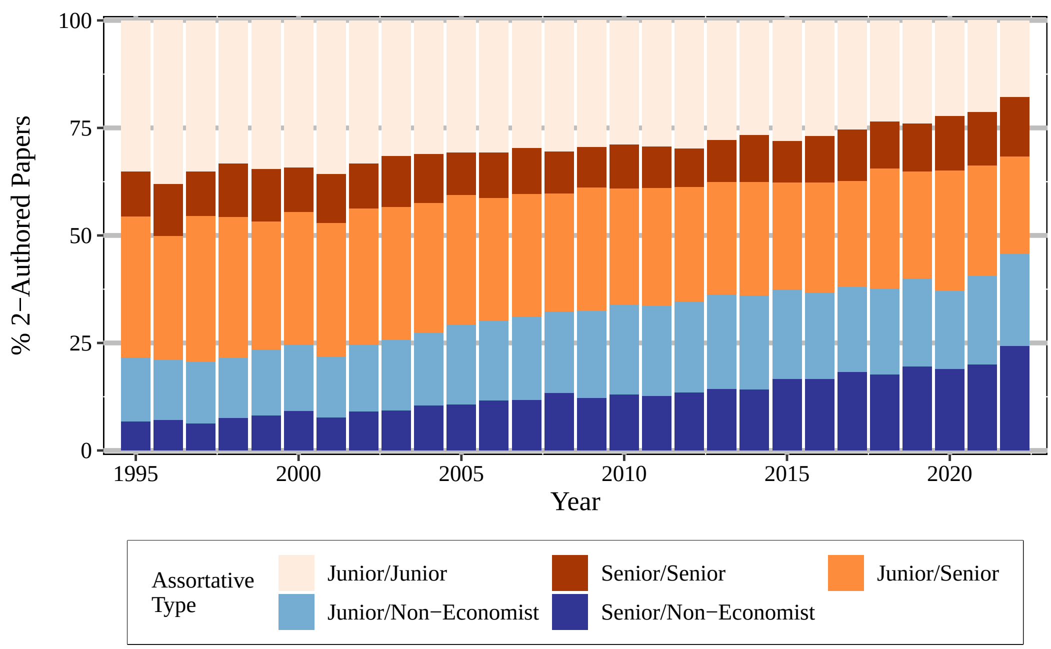
Note: An institution is a major institution if the highest number of authors on the paper are affiliated with said institution. Ties are irrelevant, given that our outcome is the share of authors.

Figure 8: Stable Pattern of Experience Assortativity in 2-Author EC64 Papers



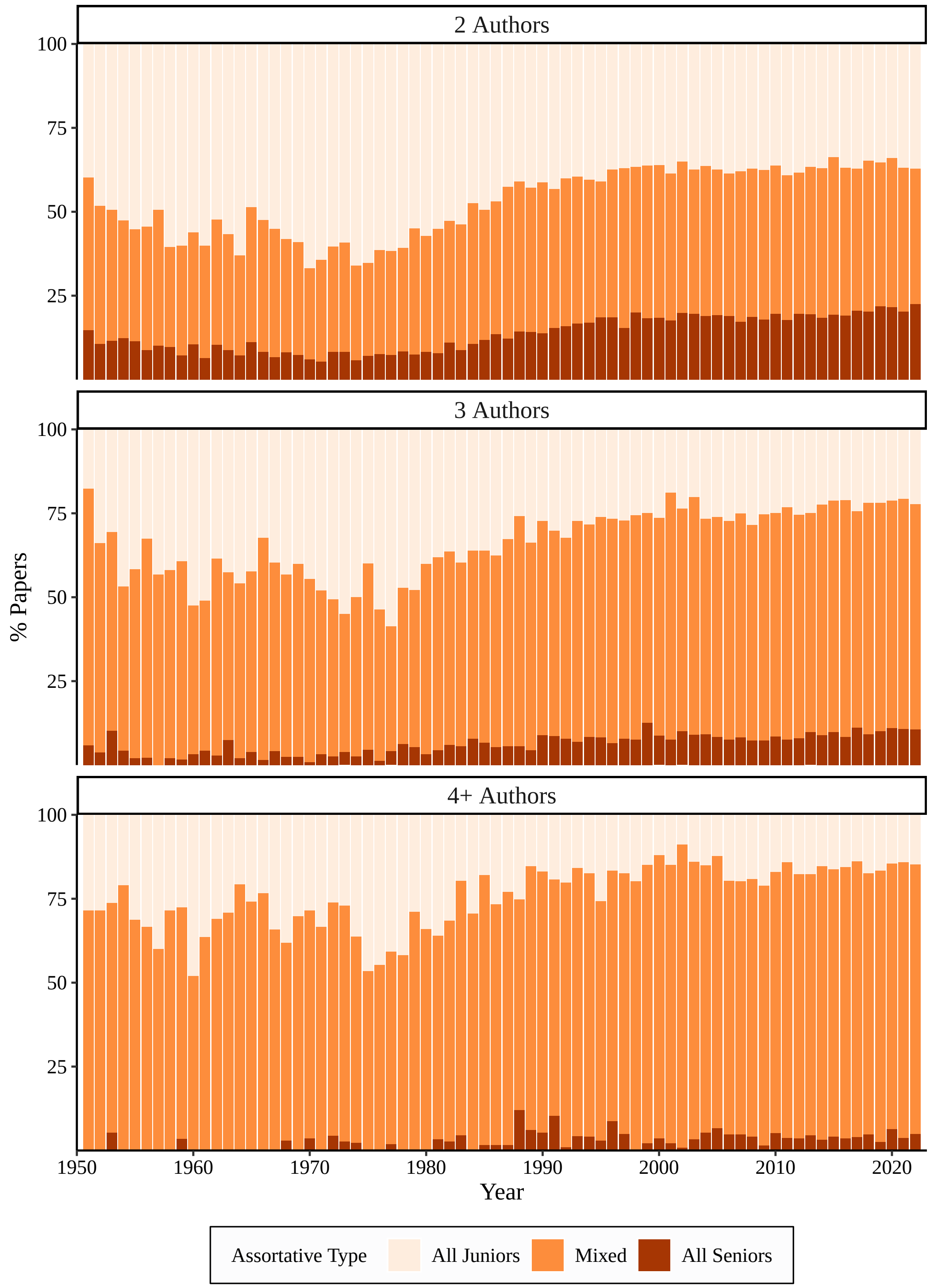
Note: An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. An economist is a junior if they are not a senior.

Figure 9: Stable Pattern of Experience Assortativity in 2-Author SSRN Papers



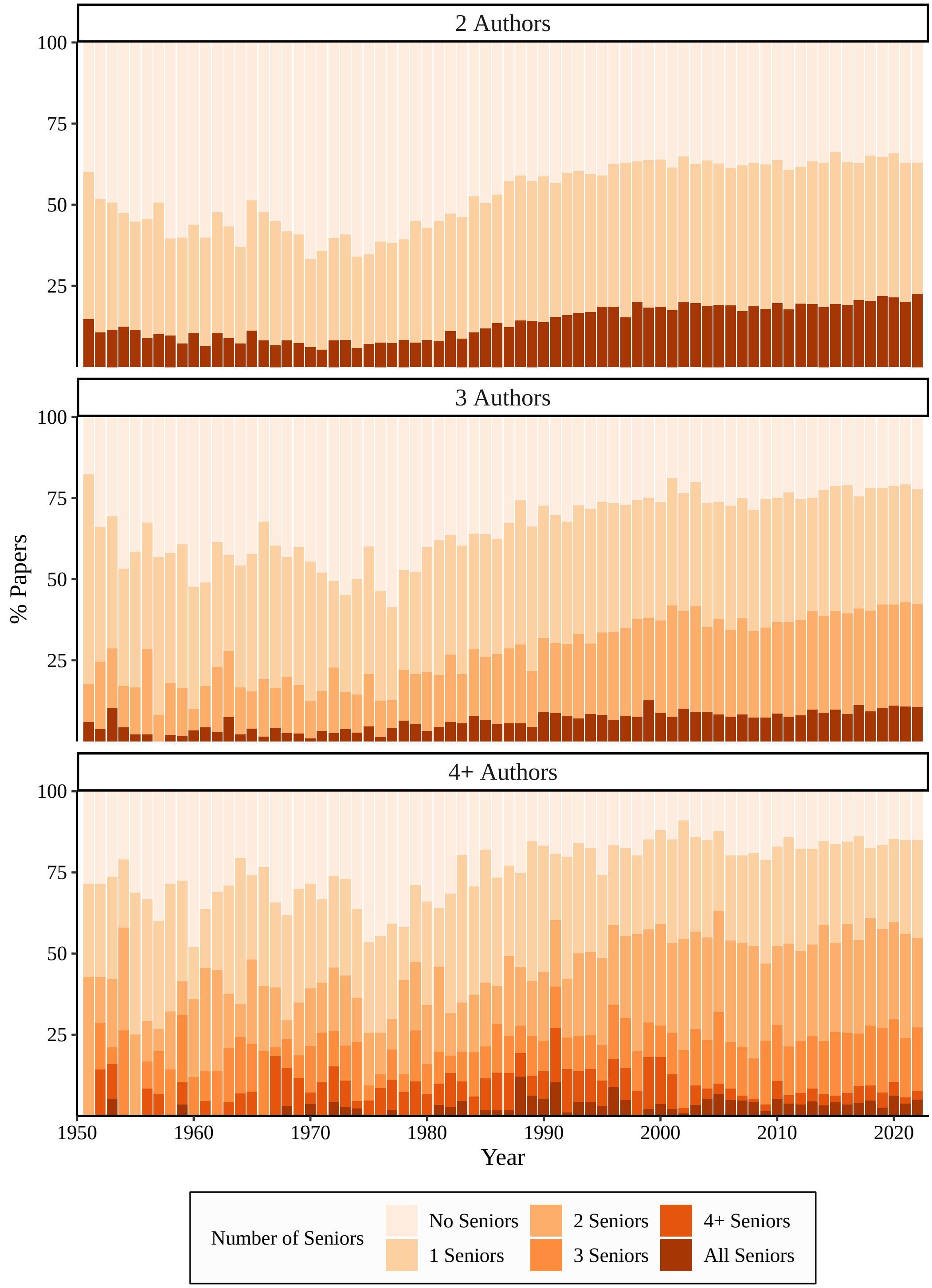
Note: An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. An economist is a junior if they are not a senior.

Figure 10: Experience Assortativity in EC64 Papers Conditional on Number of Authors



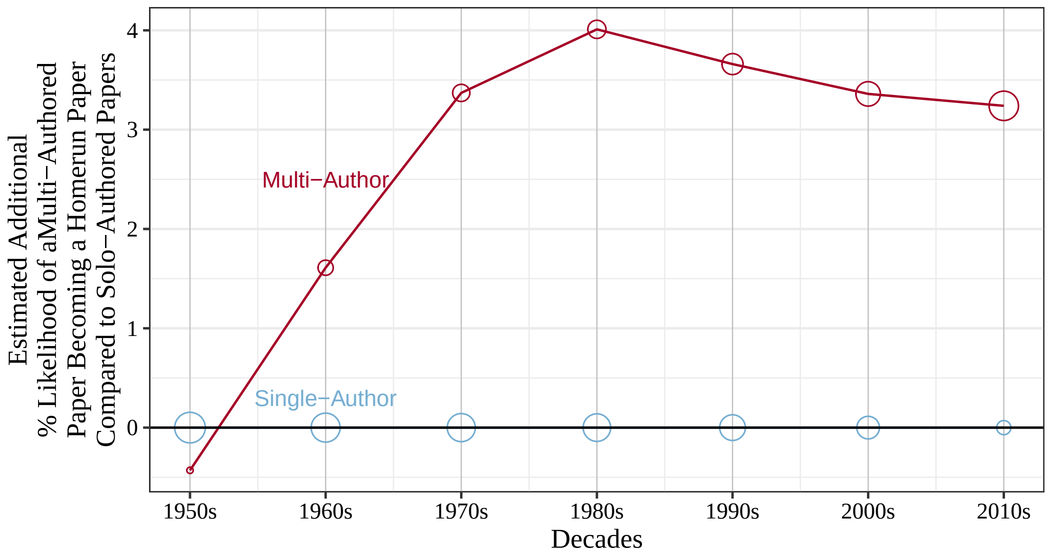
Note: An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. An economist is a junior if they are not a senior.

Figure 11: Experience Assortativity in EC64 Papers Conditional on Number of Authors



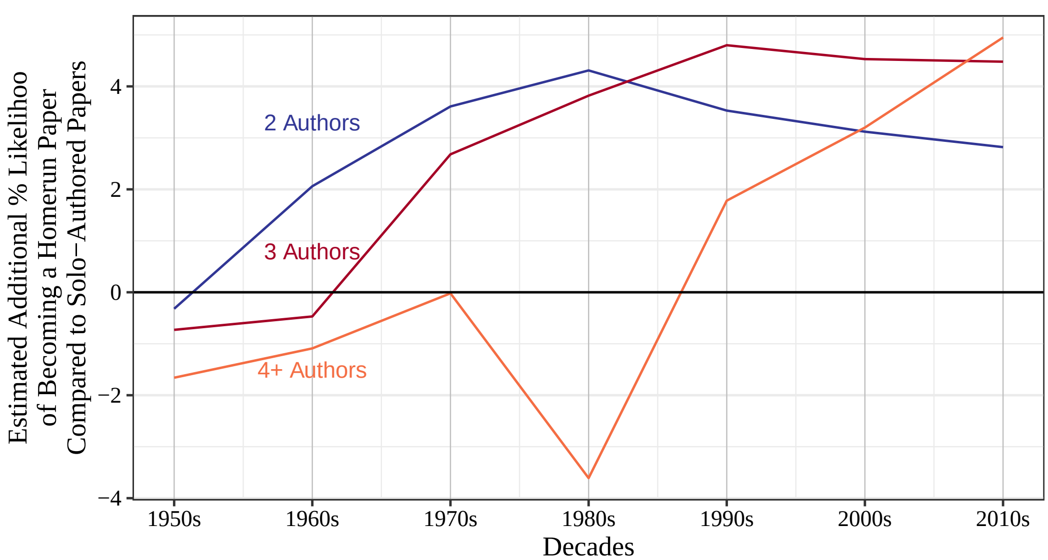
Note: An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. An economist is a junior if they are not a senior.

Figure 12: Evolution of Estimated Returns to Collaboration, 10-Year Periods



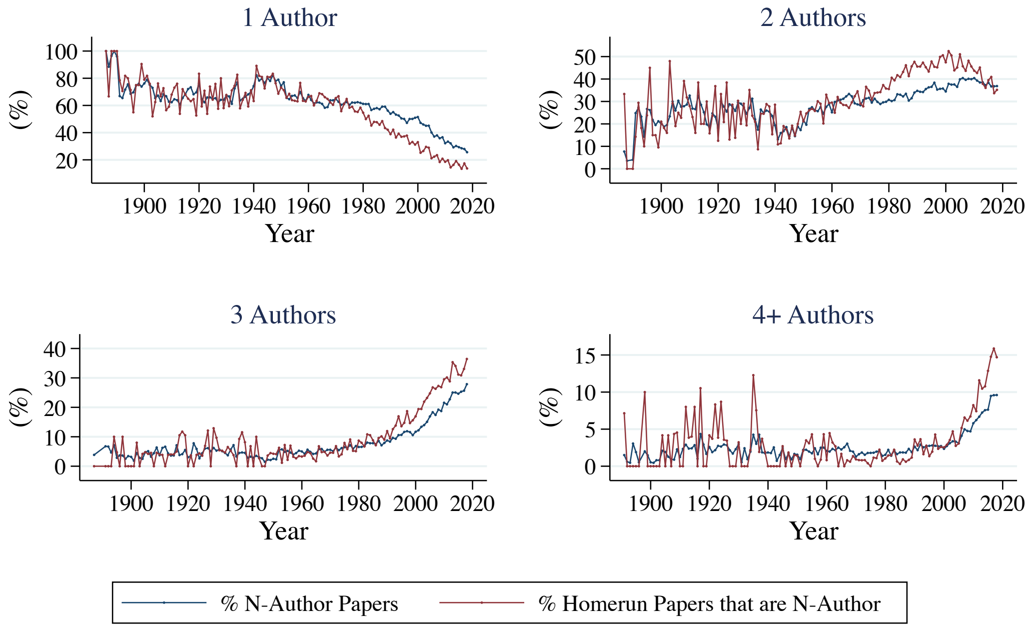
Note: We estimate Equation (7) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation in the top decile among EC64 papers published in the same year. Sizes of the circles correspond to the shares of N-Author papers that year.

Figure 13: Evolution of Estimated Returns to Number of Authors, 10-Year Periods



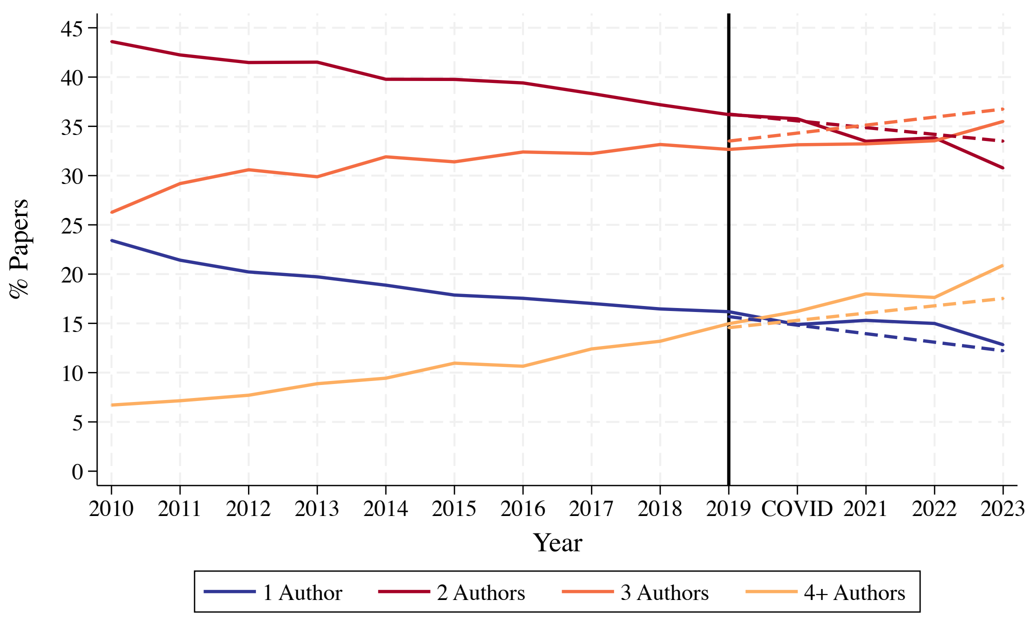
Note: We estimate Equation (7) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation in the top decile among EC64 papers published in the same year.

Figure 14: 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 15: Deviation from Linear Trend, Number of Authors, 2010-2023 SSRN Working Papers



Note: Dashed lines are linear predictions.

Appendix A Additional Tables

Table A1: 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	-0.93***	-0.64***	0.91***	0.66***
	(0.02)	(0.02)	(0.02)	(0.01)
Number of Papers	167,367	167,367	167,367	167,367
Panel B: *NBER*				
Yearly Trend	-0.73***	-1.41***	0.80***	1.33***
	(0.04)	(0.05)	(0.05)	(0.04)
Number of Papers	27,261	27,261	27,261	27,261
Panel C: *Top 5*				
Yearly Trend	-0.97***	-0.75***	0.91***	0.81***
	(0.10)	(0.11)	(0.09)	(0.06)
Number of Papers	6,258	6,258	6,258	6,258
Panel D: *EC64*				
Yearly Trend	-1.22***	-0.11***	0.87***	0.46***
	(0.03)	(0.03)	(0.03)	(0.02)
Number of Papers	81,270	81,270	81,270	81,270

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 A2: Predictors of Homerun Papers, Excluding T5 Papers, 1900-2018

	(1)	(2)	(3)	(4)
	% Likelihood of Becoming a Homerun Paper			
Number of Authors				
2	2.42***	2.81***	2.15***	2.46***
	(0.16)	(0.16)	(0.16)	(0.16)
3	2.74***	3.59***	2.41***	2.98***
	(0.22)	(0.23)	(0.23)	(0.23)
4+	0.58*	1.27***	0.52	1.59***
	(0.35)	(0.35)	(0.35)	(0.35)
$\mathbb{1}$\{Inter-Institutional\}	0.69***	-0.17	-0.57***	-1.24***
	(0.15)	(0.15)	(0.15)	(0.15)
$\mathbb{1}$\{Has Senior Author\}	-0.74***	-0.44***	-0.10	-0.10
	(0.14)	(0.14)	(0.14)	(0.14)
$\mathbb{1}$\{Has Top 10 Author\}	11.42***	11.47***	10.68***	8.96***
	(0.26)	(0.26)	(0.26)	(0.26)
$\mathbb{1}$\{Has Top 10 Senior\}	0.00	-0.11	-0.10	-0.12
	(0.35)	(0.35)	(0.35)	(0.35)
$\mathbb{1}$\{Has 11-30 Author\}	5.99***	6.16***	5.21***	4.06***
	(0.26)	(0.26)	(0.26)	(0.25)
$\mathbb{1}$\{Has 11-30 Senior\}	0.05	0.03	0.29	0.29
	(0.34)	(0.34)	(0.34)	(0.34)
$\mathbb{1}$\{US Institution\}	1.08***	1.47***	1.85***	2.06***
	(0.14)	(0.14)	(0.14)	(0.15)
$\mathbb{1}$\{International Collab.\}	-0.71***	0.50**	0.69***	0.49**
	(0.21)	(0.22)	(0.22)	(0.22)
Number of Papers	180,906	180,906	180,906	180,906
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: Predictors of Homerun Papers, 1900-2018

	(1)	(2)	(3)	(4)
	% Likelihood of Becoming a Homerun Paper			
Number of Authors				
2	2.34***	2.90***	2.68***	3.83***
	(0.16)	(0.17)	(0.16)	(0.17)
3	4.24***	5.12***	4.41***	5.69***
	(0.24)	(0.24)	(0.24)	(0.24)
4+	2.52***	3.27***	2.95***	5.00***
	(0.38)	(0.38)	(0.37)	(0.37)
$\mathbb{1}\{$Inter-Institutional$\}$	1.46***	0.74***	-0.11	-1.38***
	(0.15)	(0.15)	(0.15)	(0.15)
$\mathbb{1}\{$Has Senior Author$\}$	-1.18***	-0.93***	-1.17***	-0.92***
	(0.14)	(0.14)	(0.14)	(0.13)
$\mathbb{1}\{$Majority Author Top 10$\}$	15.89***	15.85***	13.58***	10.90***
	(0.20)	(0.20)	(0.20)	(0.20)
$\mathbb{1}\{$Majority Author 11-30$\}$	7.92***	8.04***	6.92***	5.04***
	(0.20)	(0.20)	(0.19)	(0.19)
$\mathbb{1}\{$US Institution$\}$	0.78***	1.14***	2.74***	3.33***
	(0.15)	(0.15)	(0.15)	(0.16)
$\mathbb{1}\{$International Collab.$\}$	0.01	0.83***	0.83***	0.71***
	(0.23)	(0.23)	(0.23)	(0.23)
Number of Papers	213,947	213,947	213,947	213,947
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. The 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: Predictors of Citation Percentile among Papers Published in the Same Year, 1900-2018

	(1)	(2)	(3)	(4)
	Citation Percentile (Higher = More Citations)			
Number of Authors				
2	5.33***	6.26***	5.38***	6.06***
	(0.15)	(0.16)	(0.15)	(0.16)
3	5.60***	7.15***	5.76***	7.14***
	(0.22)	(0.23)	(0.23)	(0.22)
4+	2.11***	3.51***	2.70***	5.33***
	(0.36)	(0.36)	(0.35)	(0.35)
$\mathbb{1}\{$Inter-Institutional$\}$	1.38***	0.24	-0.56***	-1.99***
	(0.14)	(0.15)	(0.14)	(0.14)
$\mathbb{1}\{$Has Senior Author$\}$	-2.42***	-2.00***	-1.70***	-1.33***
	(0.14)	(0.15)	(0.14)	(0.14)
$\mathbb{1}\{$Has Top 10 Author$\}$	14.26***	14.21***	12.05***	8.44***
	(0.25)	(0.25)	(0.24)	(0.24)
$\mathbb{1}\{$Has Top 10 Senior$\}$	-0.88***	-1.02***	-1.36***	-1.00***
	(0.33)	(0.33)	(0.33)	(0.32)
$\mathbb{1}\{$Has 11-30 Author$\}$	9.13***	9.28***	7.90***	5.48***
	(0.26)	(0.26)	(0.25)	(0.24)
$\mathbb{1}\{$Has 11-30 Senior$\}$	-0.67*	-0.70**	-0.57*	-0.60*
	(0.34)	(0.34)	(0.33)	(0.32)
$\mathbb{1}\{$US Institution$\}$	1.65***	2.23***	3.59***	4.96***
	(0.14)	(0.14)	(0.14)	(0.15)
$\mathbb{1}\{$International Collab.$\}$	3.54***	5.12***	4.51***	3.85***
	(0.22)	(0.22)	(0.22)	(0.21)
Number of Papers	213,947	213,947	213,947	213,947
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 A5: Raw Citation Count by Paper Characteristics, 1900-2018

	(1)	(2)	(3)	(4)
	Number of Citations			
Number of Authors				
2	1.39***	0.80***	0.76***	1.05***
	(0.03)	(0.03)	(0.03)	(0.03)
3	2.58***	1.51***	1.34***	1.68***
	(0.05)	(0.05)	(0.05)	(0.05)
4	2.21***	1.22***	1.14***	1.66***
	(0.08)	(0.08)	(0.08)	(0.08)
$\mathbb{1}\{$Inter-Institutional$\}$	-0.43***	0.25***	0.03	-0.31***
	(0.03)	(0.03)	(0.03)	(0.03)
$\mathbb{1}\{$Has Senior Author$\}$	0.09***	-0.14***	-0.21***	-0.17***
	(0.03)	(0.03)	(0.03)	(0.03)
Majority Author Top 10	3.46***	3.57***	3.03***	2.34***
	(0.04)	(0.04)	(0.04)	(0.04)
Majority Author 11-30	1.88***	1.85***	1.58***	1.12***
	(0.04)	(0.04)	(0.04)	(0.04)
$\mathbb{1}\{$US Institution$\}$	0.95***	0.59***	0.96***	1.12***
	(0.03)	(0.03)	(0.03)	(0.03)
$\mathbb{1}\{$International Collab.$\}$	1.45***	0.23***	0.27***	0.26***
	(0.05)	(0.05)	(0.05)	(0.05)
Mean Citation	2.7	2.7	2.7	2.7
Number of Papers	213,947	213,947	213,947	213,947
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 A6: Estimated Correlations Between Returns and Popularity of Multi-Author Papers, 1950-2018

	$\Delta LRS_{2,t}$			
$LRR_{2,t-5}$	0.0048	-0.0293	-0.0726	-0.0748
	(0.0151)	(0.0364)	(0.0496)	(0.0525)
$LRS_{2,t-5}$		0.0708		-0.0032
		(0.0716)		(0.0793)
Year			0.0032*	0.0034
			(0.0019)	(0.0021)
	$\Delta LRS_{3,t}$			
$LRR_{3,t-5}$	0.0111	-0.0353	-0.0617*	-0.0638*
	(0.0126)	(0.0341)	(0.0342)	(0.0387)
$LRS_{3,t-5}$		0.0852		0.0055
		(0.0599)		(0.0702)
Year			0.0056**	0.0056*
			(0.0024)	(0.0029)
	$\Delta LRS_{4,t}$			
$LRR_{4,t-5}$	0.0389*	0.0744*	0.0300	0.0712*
	(0.0222)	(0.0409)	(0.0295)	(0.0410)
$LRS_{4,t-5}$		-0.0667		-0.1230
		(0.0799)		(0.0928)
Year			0.0010	0.0024
			(0.0020)	(0.0023)
Number of Years	61	61	61	61

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 A7: Estimated Correlations Between Returns and Popularity of Multi-Authored Papers, 1950-2018

	$\Delta LRS_{2,t}$			
$\Delta LRR_{2,t-5}$	-0.1033***	-0.1165***	-0.1035***	-0.1176***
	(0.0399)	(0.0403)	(0.0399)	(0.0403)
$\Delta LR2S_{t-5}$		0.1711*		0.1648
		(0.1010)		(0.1016)
Year			0.0004	0.0003
			(0.0006)	(0.0006)
	$\Delta LRS_{3,t}$			
$\Delta LRR_{3,t-5}$	-0.0334	-0.0233	-0.0393	-0.0293
	(0.0363)	(0.0362)	(0.0368)	(0.0364)
$\Delta LRS_{3,t-5}$		-0.0318		-0.0633
		(0.1090)		(0.1122)
Year			0.0012	0.0013
			(0.0010)	(0.0010)
	$\Delta LRS_{4,t}$			
$\Delta LRR_{4,t-5}$	0.0790**	0.0643*	0.0748**	0.0623
	(0.0374)	(0.0386)	(0.0373)	(0.0386)
$\Delta LRS_{4,t-5}$		0.1737*		0.1495
		(0.1024)		(0.1040)
Year			0.0021	0.0018
			(0.0015)	(0.0015)
Number of Years	57	57	57	57

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 A8: 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	367	854	1,900	4,057	1,335
2	Harvard University	11	203	317	538	825	1,864	2,885	598
3	University of Chicago	9	27	118	205	681	1,434	2,493	742
4	University of California, Berkeley	0	1	7	145	498	1,408	2,060	549
5	Stanford University	1	12	44	73	570	1,323	2,057	554
6	London School of Economics and Political Science	0	3	66	328	593	980	1,921	587
7	New York University	0	5	13	152	336	1,044	1,857	519
8	Massachusetts Institute of Technology	0	6	0	170	611	1,188	1,543	322
9	University of Pennsylvania	9	11	16	97	420	1,274	1,645	349
10	Columbia University	4	46	66	241	287	902	1,599	452
11	Yale University	2	22	16	68	480	1,021	1,488	484
12	Princeton University	0	5	40	144	448	1,066	1,438	428
13	Northwestern University	3	5	4	55	208	1,124	1,340	291
14	Cornell University	4	33	42	91	282	916	1,319	337
15	University of Michigan–Ann Arbor	1	5	43	103	304	833	1,217	307
16	Duke University	0	0	25	111	155	590	1,185	330
17	University of Wisconsin–Madison	0	15	5	42	386	716	895	268
18	University of California, Los Angeles	0	0	2	100	250	793	915	192
19	University of Toronto	2	3	3	45	228	595	1,039	326
20	Institut Polytechnique de Paris	0	0	0	0	45	227	1,375	507
21	Univ of Illinois Urbana-Champaign	0	1	4	59	241	714	765	193
22	University of British Columbia	0	0	0	12	205	719	793	204
23	University of California, Davis	0	0	0	6	172	736	803	204
24	University of Oxford	0	0	15	31	65	242	1,164	389
25	University of Maryland, College Park	0	0	0	37	143	642	889	168
26	University of Minnesota	0	4	35	46	194	671	738	163
27	University of California, San Diego	0	0	0	0	89	504	961	278
28	Iowa State University	0	9	19	58	172	764	711	76

29	The Ohio State University	0	9	20	29	164	633	727	156
30	University of Rochester	0	0	3	22	264	764	547	129
31	University of Warwick	0	0	0	0	111	421	849	286
32	University of Southern California	0	0	0	26	60	464	844	263
33	University College London	0	0	1	23	71	248	951	299
34	Université Paris 1 Panthéon-Sorbonne	0	0	0	0	6	197	1,024	365
35	Michigan State University	0	0	0	39	261	461	618	159
36	Tel Aviv University	0	0	0	0	152	624	564	132
37	Carnegie Mellon University	0	0	6	2	181	545	589	112
38	University of Hong Kong	0	0	0	2	1	148	906	356
39	Tilburg University	0	0	0	0	1	376	829	173
40	Johns Hopkins University	13	27	8	113	215	305	454	215
41	Boston University	0	0	0	0	34	406	659	239
42	Pennsylvania State University	0	0	0	12	127	375	613	207
43	The University of Texas at Austin	0	0	0	9	64	400	628	211
44	Hebrew University of Jerusalem	0	0	0	9	285	458	449	101
45	Vanderbilt University	1	0	0	20	91	318	712	155
46	University of Virginia	0	0	10	50	130	341	568	170
47	Texas A&M University	0	0	0	0	114	503	489	126
48	University of Washington	0	3	7	44	249	359	437	119
49	University of Amsterdam	0	0	0	0	23	256	735	198
50	École des Ponts ParisTech	0	0	0	0	1	55	804	311

Table A9: 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	286	0	0	0	0	3	89	153	41
John J. Siegfried	233	0	0	0	0	25	58	144	6
Joseph E. Stiglitz	199	0	0	0	0	61	100	30	8
Daron Acemoğlu	183	0	0	0	0	0	21	141	21
F. Y. Edgeworth	182	70	90	22	0	0	0	0	0
Paul A. Samuelson	175	0	0	7	44	80	30	14	0
Stephen J. Turnovsky	174	0	0	0	0	47	76	46	5
Andrei Shleifer	164	0	0	0	0	0	66	86	12
Thomas J. Sargent	160	0	0	0	0	37	41	70	12
Jean Tirole	156	0	0	0	0	0	74	77	5
M. Hashem Pesaran	155	0	0	0	0	6	66	69	14
Harry G. Johnson	152	0	0	0	42	106	2	2	0
James J. Heckman	150	0	0	0	0	9	51	80	10
John A. List	150	0	0	0	0	0	3	129	18
Martin Feldstein	144	0	0	0	0	68	57	19	0
Bruce A. Babcock	141	0	0	0	0	0	48	92	1
Stanley L. Engerman	139	0	0	0	0	68	45	26	0
Drew Fudenberg	138	0	0	0	0	0	62	60	16
William J. Baumöl	135	0	0	0	32	50	43	10	0
René M. Stulz	131	0	0	0	0	0	65	56	10
Jeffrey G. Williamson	130	0	0	0	0	47	56	27	0
Richard Blundell	129	0	0	0	0	0	47	69	13
C. W. Guillebaud	121	0	6	36	41	38	0	0	0
Charles P. Kindleberger	117	0	0	2	27	45	40	3	0
Peter Temin	115	0	0	0	0	42	50	22	1
David Card	113	0	0	0	0	0	25	70	18
George J. Stigler	112	0	0	3	39	53	16	1	0
Larry Samuelson	112	0	0	0	0	0	52	52	8
Badi H. Baltagi	112	0	0	0	0	0	71	38	3
Sidney Pollard	110	0	0	0	10	41	59	0	0
W. Kip Viscusi	110	0	0	0	0	3	64	39	4
David K. Levine	110	0	0	0	0	0	46	49	15
Jagdish N. Bhagwati	110	0	0	0	3	60	43	4	0
David E. M. Sappington	109	0	0	0	0	0	52	50	7
Edwin Cannan	108	21	47	40	0	0	0	0	0
Philippe Aghion	107	0	0	0	0	0	32	67	8
Mark R. Rosenzweig	107	0	0	0	0	12	63	30	2
Randall Wright	106	0	0	0	0	0	36	60	10
Dermot J. Hayes	106	0	0	0	0	0	52	51	3
Robert J. Barro	105	0	0	0	0	36	44	19	6
Martin Bronfenbrenner	105	0	0	2	43	45	15	0	0
Richard Zeckhauser	105	0	0	0	0	24	42	39	0

Nicholas Crafts	104	0	0	0	0	16	64	22	2
Éric Ghysels	104	0	0	0	0	0	38	56	10
Eugene F. Fama	104	0	0	0	0	32	44	26	2
Joel Mokyr	103	0	0	0	0	19	54	27	3
William B. Walstad	103	0	0	0	0	2	52	48	1
Jean-Jacques Laffont	102	0	0	0	0	20	62	20	0
Frank H. Knight	101	0	4	52	44	1	0	0	0
Janet Currie	101	0	0	0	0	0	18	72	11

Table A10: 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	118	0	0	0	0	4	11	103	0
Frank H. Knight	93	0	4	50	38	1	0	0	0
Daron Acemoğlu	89	0	0	0	0	0	8	72	9
Joseph E. Stiglitz	88	0	0	0	0	39	40	8	1
Jean Tirole	75	0	0	0	0	0	37	33	5
James J. Heckman	71	0	0	0	0	9	24	34	4
George J. Stigler	70	0	0	3	32	29	5	1	0
William J. Baumöl	69	0	0	0	20	32	14	3	0
Paul A. Samuelson	68	0	0	6	24	31	6	1	0
Martin Feldstein	65	0	0	0	0	36	19	10	0
F. W. Taussig	62	13	35	14	0	0	0	0	0
Martin Bronfenbrenner	60	0	0	2	37	20	1	0	0
Franklin M. Fisher	59	0	0	0	5	42	10	2	0
Andrei Shleifer	57	0	0	0	0	0	15	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	9	23	16	4
Harry G. Johnson	50	0	0	0	9	39	0	2	0
Chester W. Wright	50	0	22	15	13	0	0	0	0
Drew Fudenberg	49	0	0	0	0	0	28	16	5
John A. List	49	0	0	0	0	0	1	44	4
H. J. Davenport	48	6	41	1	0	0	0	0	0
Gene M. Grossman	47	0	0	0	0	0	23	19	5
Thomas J. Sargent	47	0	0	0	0	13	16	17	1
Alvin E. Roth	47	0	0	0	0	4	22	20	1
David Card	46	0	0	0	0	0	14	26	6
Wesley C. Mitchell	46	10	31	3	2	0	0	0	0
Paul H. Douglas	46	0	4	33	8	1	0	0	0
Kenneth J. Arrow	45	0	0	0	19	21	3	2	0
Robert M. Solow	45	0	0	0	15	17	12	1	0
Mark R. Rosenzweig	45	0	0	0	0	3	24	16	2
Jacob Viner	44	0	1	37	5	1	0	0	0
Robert J. Barro	42	0	0	0	0	16	16	10	0
Richard Blundell	41	0	0	0	0	0	11	27	3
Robert E. Hall	40	0	0	0	0	10	13	16	1
Milton Friedman	40	0	0	3	16	14	6	1	0
Dale W. Jorgenson	40	0	0	0	0	26	10	4	0
Gary S. Becker	40	0	0	0	2	16	14	8	0
Arthur W. Marget	40	0	0	37	3	0	0	0	0
B. Douglas Bernheim	39	0	0	0	0	0	17	17	5
Boyan Jovanovic	39	0	0	0	0	2	22	12	3
Alberto Alesina	39	0	0	0	0	0	11	25	3

Ernst Fehr	37	0	0	0	0	0	6	27	4
Olivier Blanchard	37	0	0	0	0	2	22	13	0
Lawrence R. Klein	37	0	0	0	24	11	2	0	0
Debraj Ray	36	0	0	0	0	0	8	26	2
J. M. Clark	36	0	12	17	7	0	0	0	0
Parag A. Pathak	36	0	0	0	0	0	0	28	8
Donald W. K. Andrews	36	0	0	0	0	0	22	14	0
George A. Akerlof	36	0	0	0	0	8	19	9	0

Table A11: 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	72	398	662	3,446	10,232	27,771	44,672	11561
Great Britain	5	16	106	838	2,214	4,804	10,916	3405
Canada	3	8	13	134	800	2,702	5,044	1487
Germany	4	3	3	7	96	740	5,263	2337
France	1	2	1	21	125	949	4,330	1561
Italy	2	1	5	2	35	457	2,964	1317
Australia	0	1	11	44	288	868	2,449	1016
Netherlands	1	0	2	17	81	824	2,738	883
China	0	1	1	1	8	112	1,998	1946
Spain	0	0	0	2	9	434	2,695	810
Japan	0	0	1	6	138	596	1,787	538
Switzerland	0	0	1	1	32	280	1,855	806
Israel	0	0	0	7	247	898	1,296	313
Sweden	0	0	1	7	29	362	1,412	509
Belgium	0	0	0	3	54	442	1,257	358
Denmark	0	0	2	5	14	188	951	448
Singapore	0	0	0	6	7	76	992	448
Norway	0	0	0	2	51	210	878	372
Hong Kong	0	0	0	2	3	138	908	391
Austria	0	0	3	3	13	160	798	389
South Korea	0	0	1	24	23	170	760	254
India	0	1	4	31	148	271	440	211
Taiwan	0	0	0	2	7	109	467	144
New Zealand	0	0	0	4	44	143	410	88
Russia	0	0	0	2	3	81	391	191
Rest of World	2	3	13	51	352	1,222	4,859	2268

Appendix B Additional Figures

Figure B1: Number of Papers in Top-5 Journals, 1950-2023

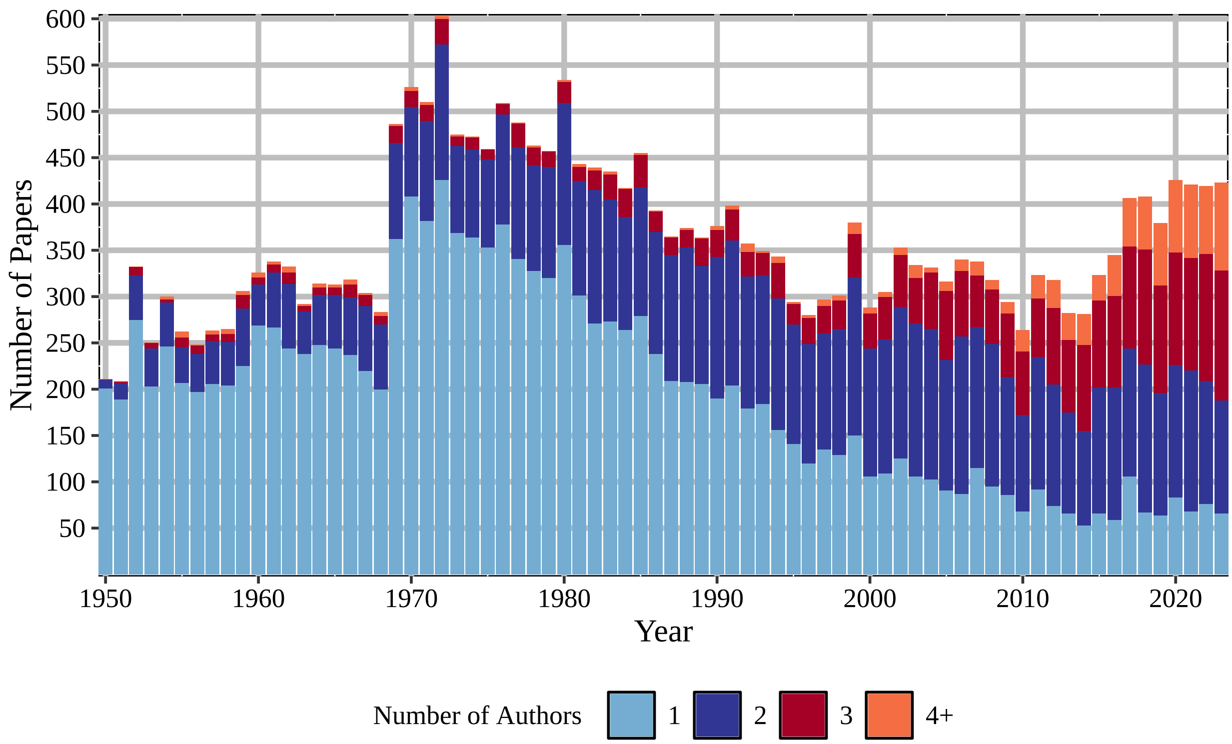
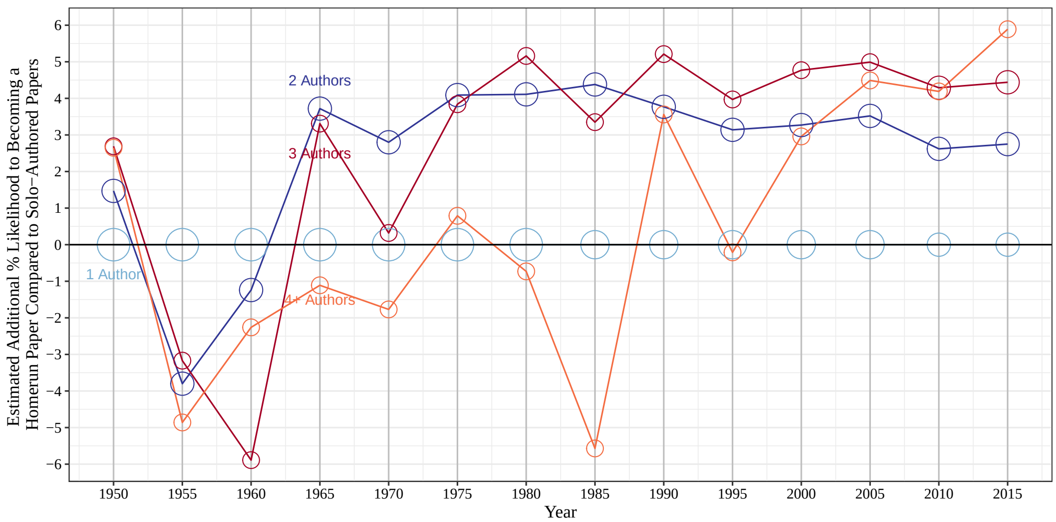
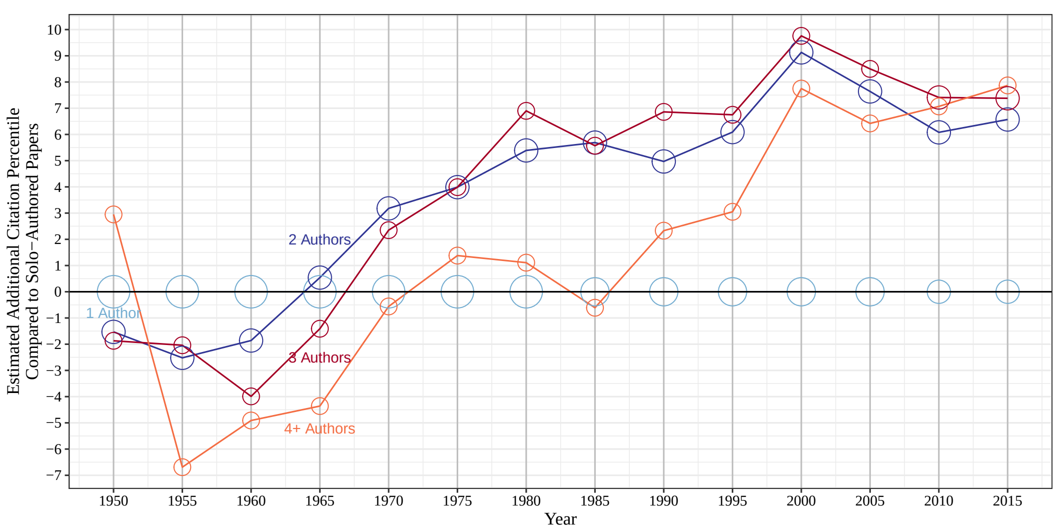


Figure B2: Evolution of Estimated Returns to Number of Authors, 5-Year Periods



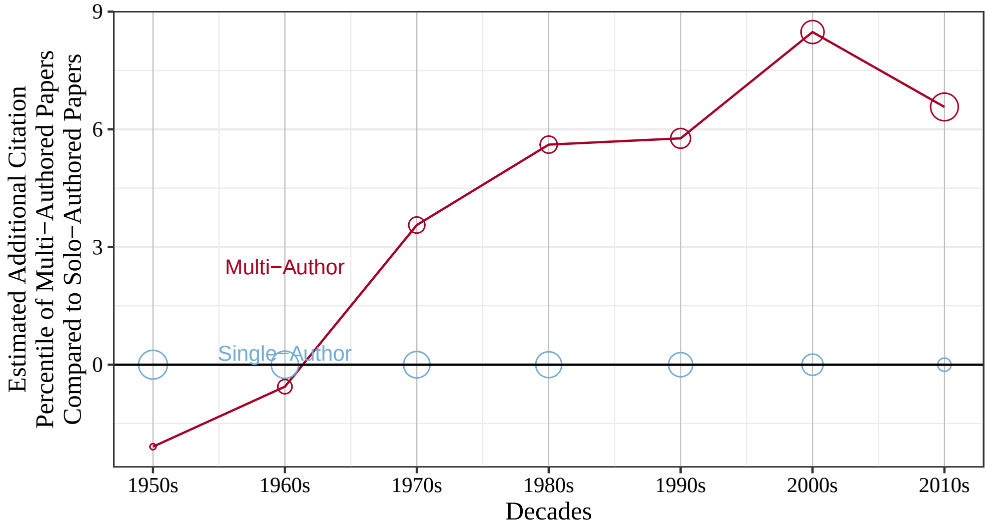
Note: We estimate Equation (7) for each quinquennial. Each tick on the x-axis represents the 5-year period starting that year. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in the same year.

Figure B3: Evolution of Estimated Returns to Number of Authors, Citation Percentile, 5-Year Periods



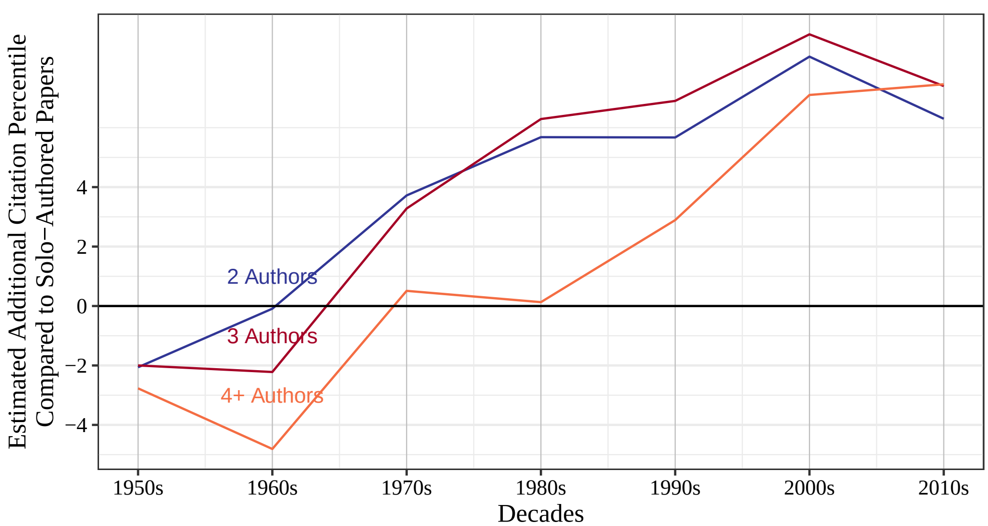
Note: We estimate Equation (7) for each quinquennial. Each tick on the x-axis represents the 5-year period starting that year. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in the same year.

Figure B4: Evolution of Estimated Returns to Multi-Authored Papers, Citation Percentile, 10-Year Periods



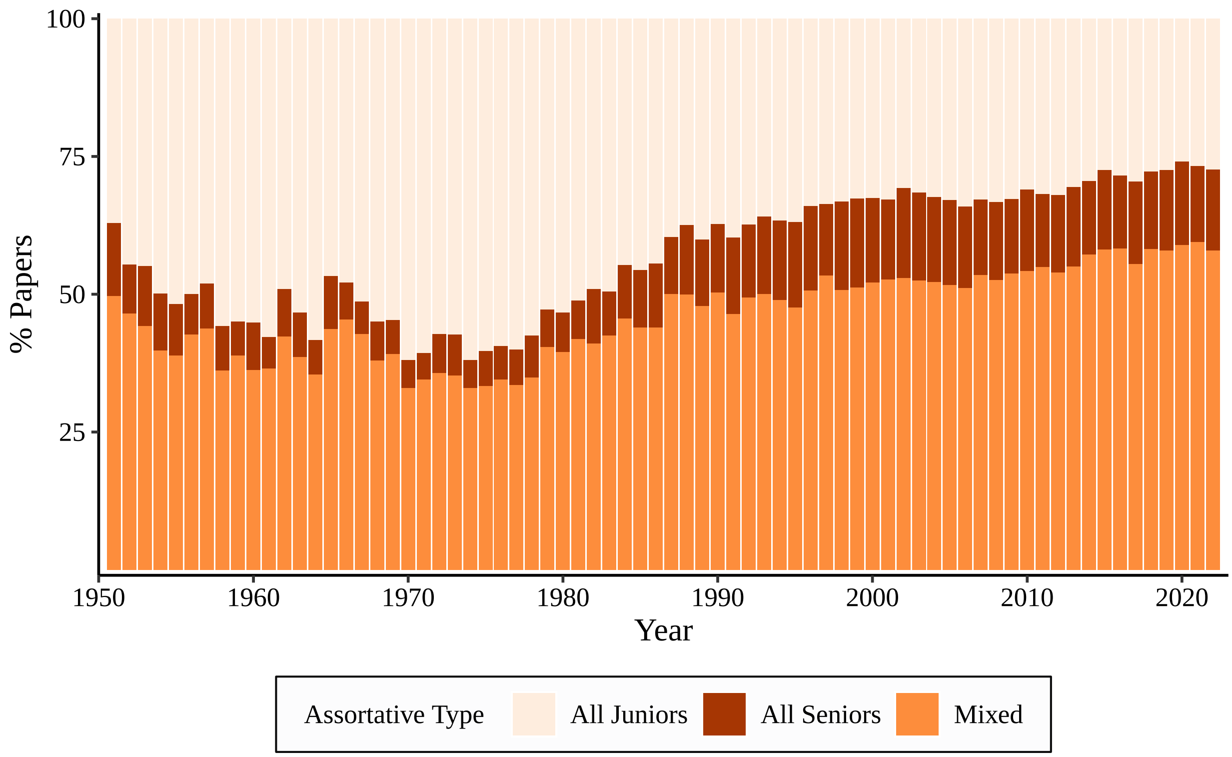
Note: We estimate Equation (7) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation count in the top decile among EC64 papers published in the same year. Sizes of the circles correspond to the shares of n-author papers that year.

Figure B5: Evolution of Estimated Returns to Number of Authors, Citation Percentile, 10-Year Periods



Note: We estimate Equation (7) 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 B6: 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 B7: Distribution of Authors by Number of EC64 Papers

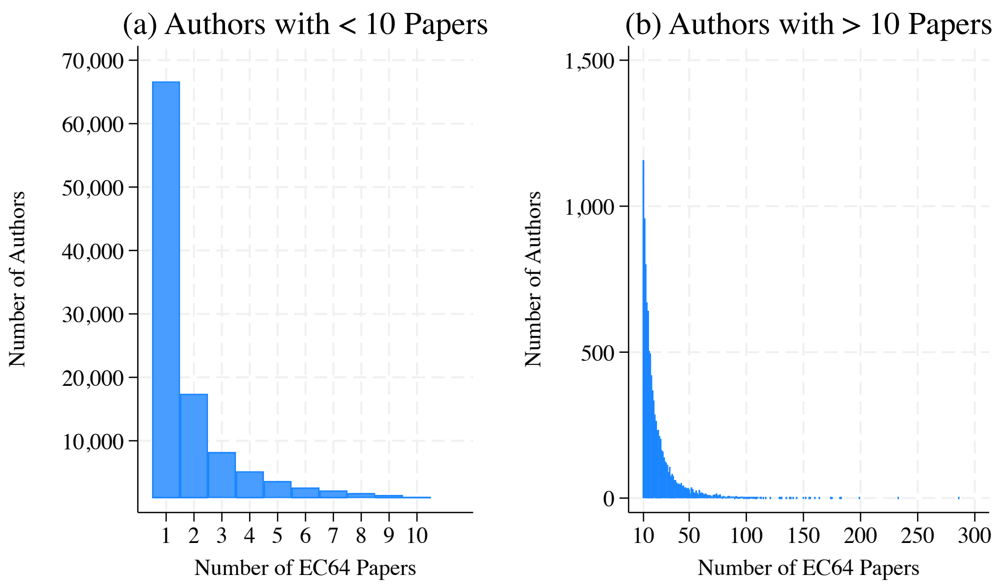


Figure B8: Distribution of Institutions by Number of EC64 Papers

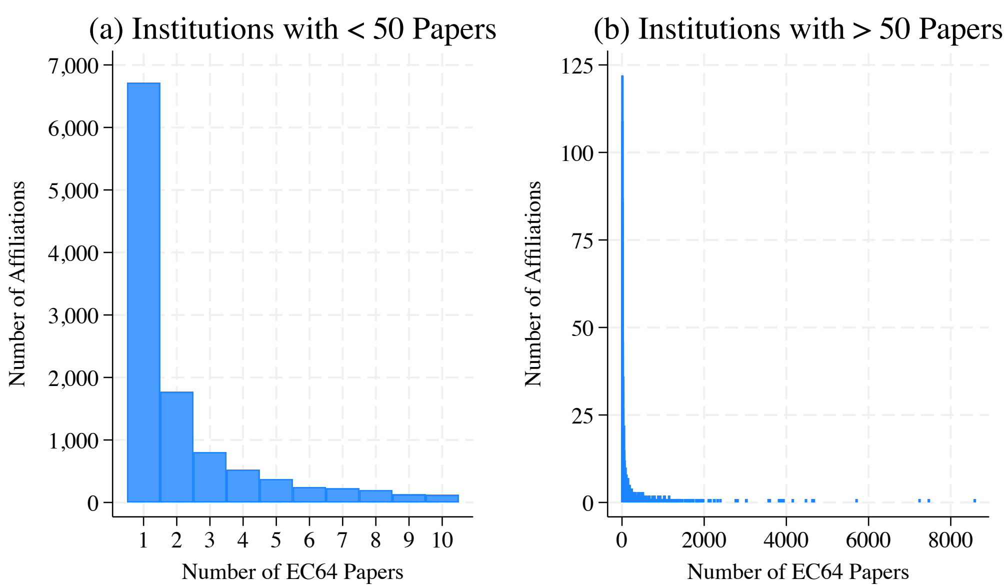


Figure B9: Evolution of Number of EC64 Publications from Top Countries

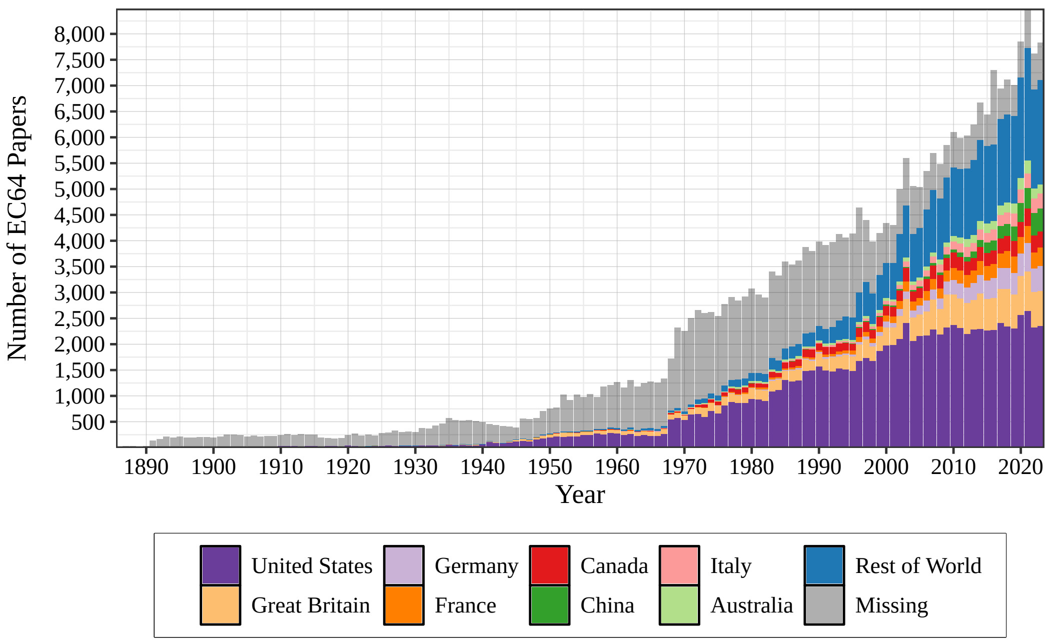
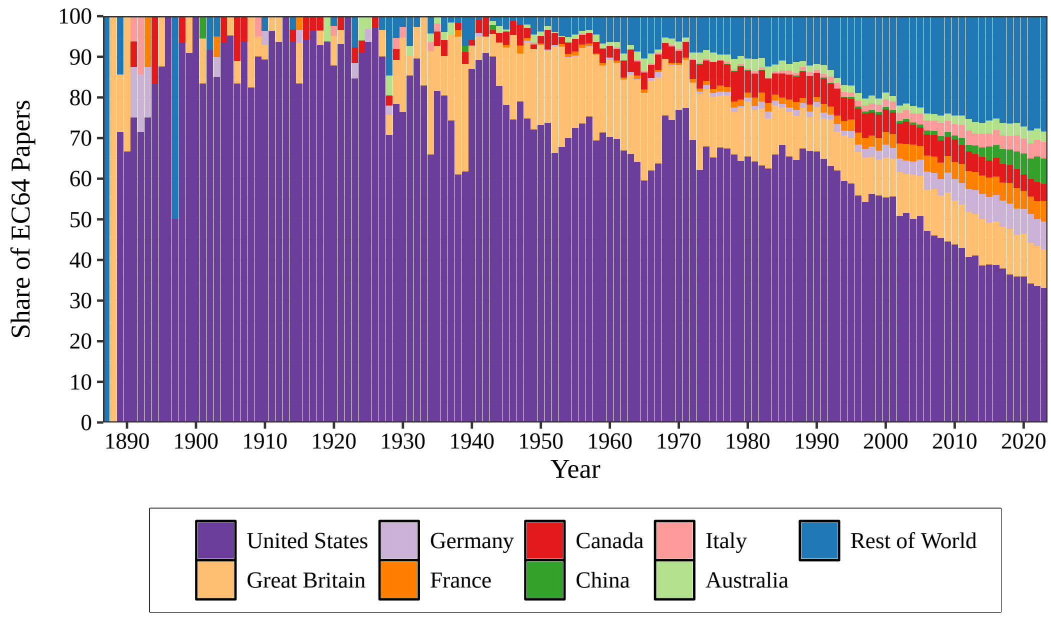
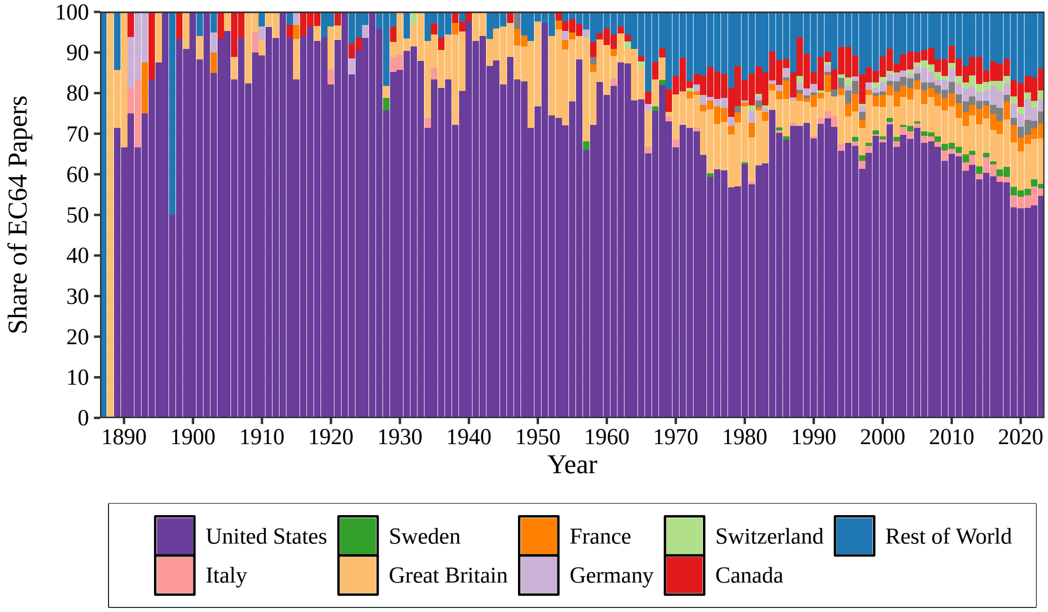


Figure B10: Evolution of Share of EC64 Publications from Top Countries



Notes: Only the top 8 producing countries from 2010 are shown in the graph.

Figure B11: Evolution of the Share of Top-5 Publications from Top Countries



Notes: Only the top 8 producing countries from 2010 are shown in the graph.

Figure B12: Distribution of Countries by Total Number of EC64 Papers

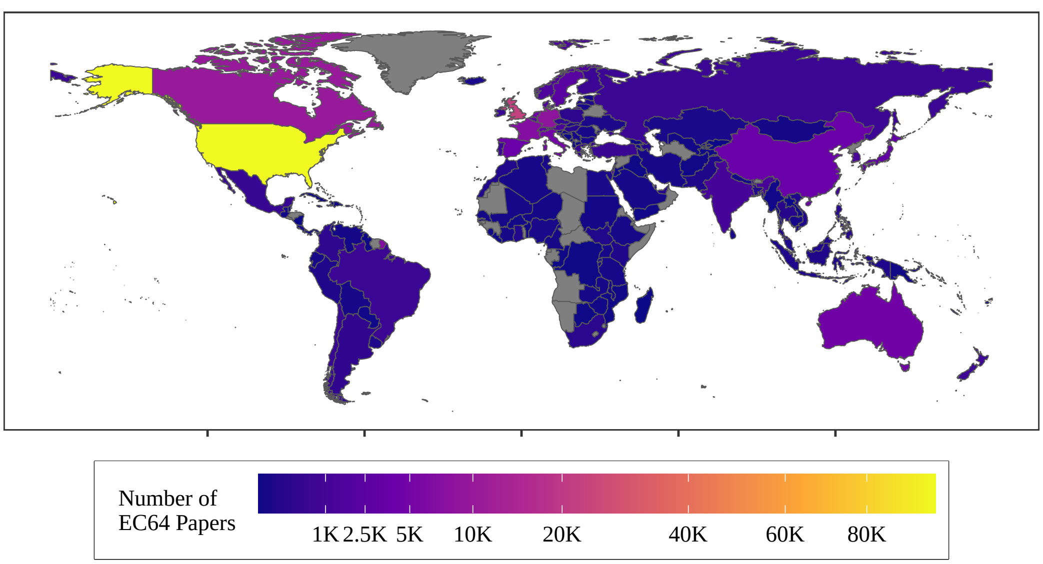
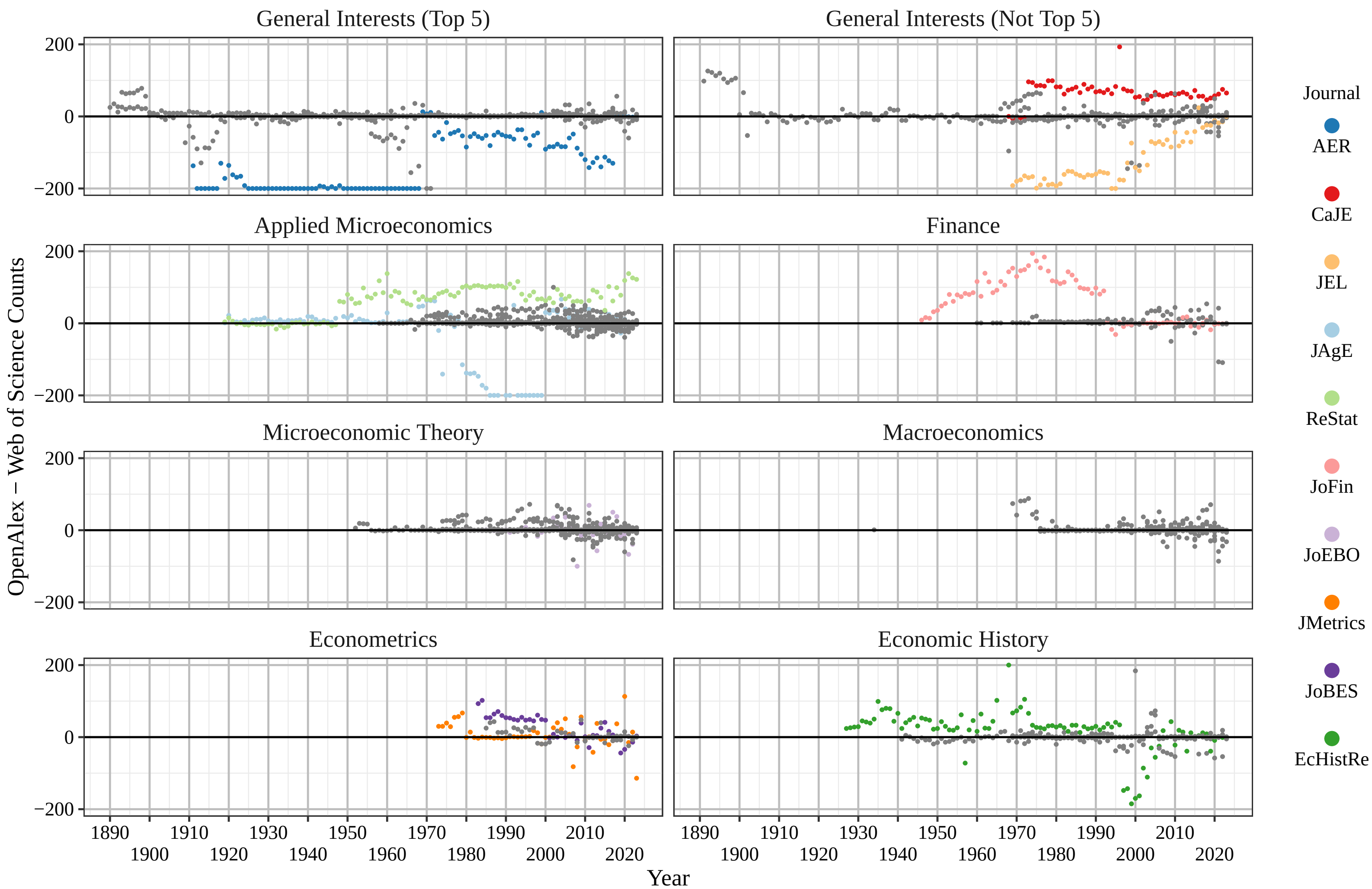


Figure B13: Differences Between OpenAlex and Web of Science Records by Field and Journal



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

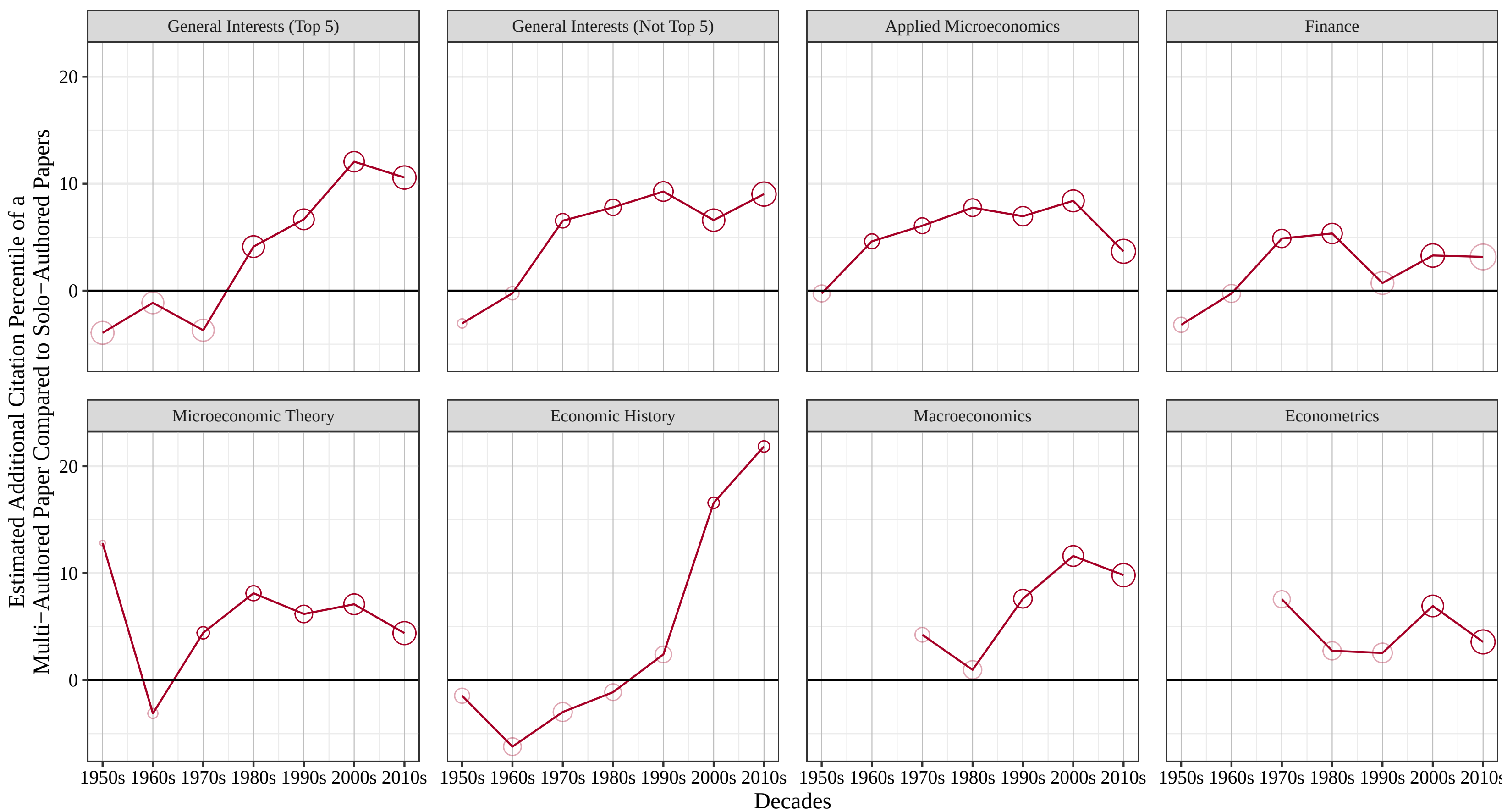
Figure B14: Evolution of Estimated Returns to Multi-Author Papers by Field, 10-Year Periods

Note: We estimate Equation (7) 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 B15: Evolution of Estimated Returns to Number of Authors by Field, 10-Year Periods

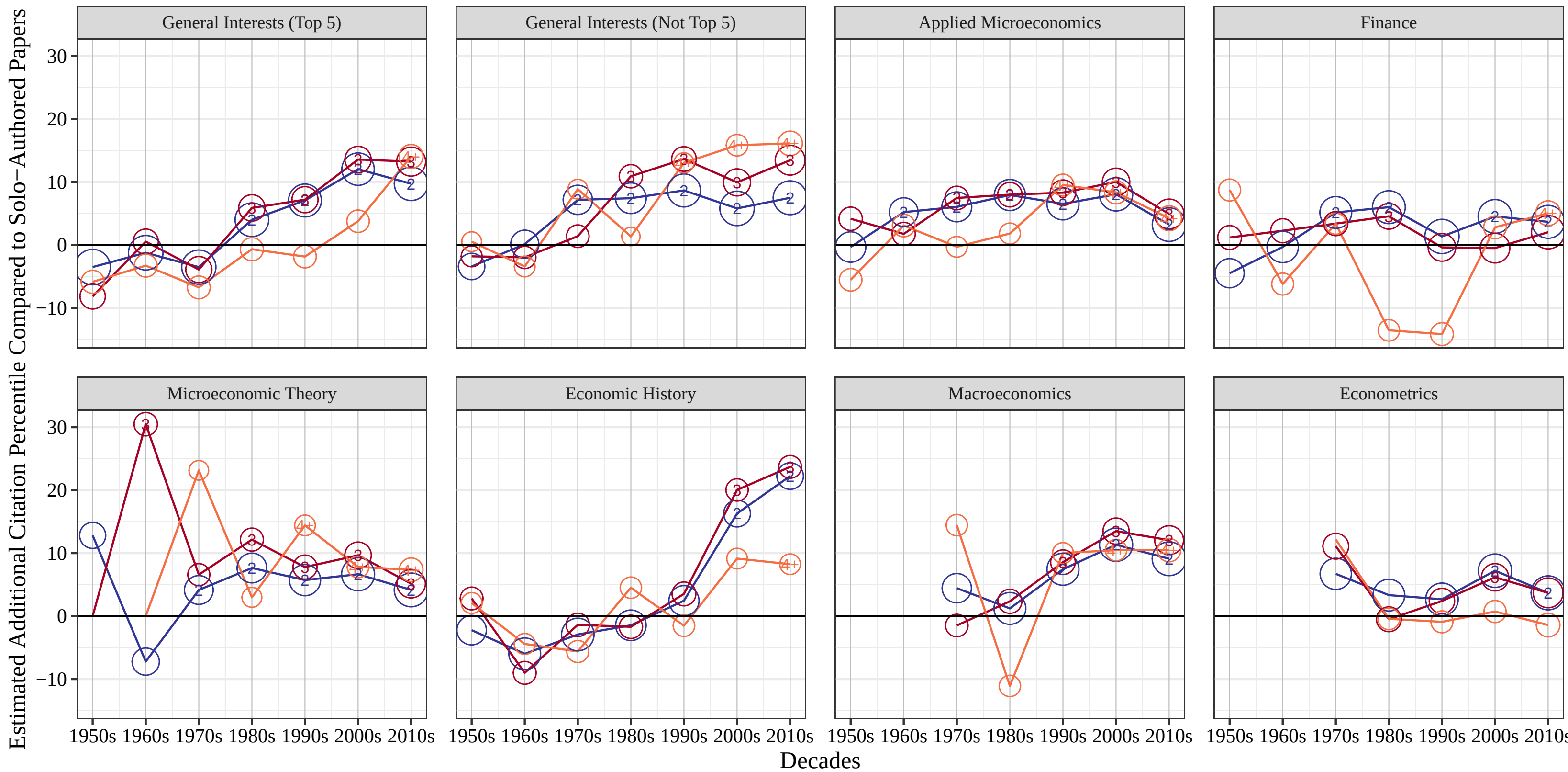
Note: We estimate Equation (7) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5-year citation in the top 10 percentile among EC64 papers published in that field in the same year. Sizes of the circles correspond to the shares of N-Author papers that year. Number of authors are noted in the center of the markers if the estimates are positive and statistically significant at the 5% level.

Figure B16: Evolution of Estimated Returns to Multi-Author by Field, 10-Year Periods



Note: We estimate Equation (7) 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 B17: Evolution of Estimated Returns to Number of Authors by Field, 10-Year Periods



Note: Estimating equation is equation (7) 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 tl markers if the estimates are positive and statistically significant at the 5% level.

Note: We estimate Equation (7) 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.