Over a century of economics research collaboration

Willy Chen[*] Xiao Qiao[†] Hanzhe Zhang[‡]

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

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

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

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Abstract

We study patterns of collaboration among 100,000+ academic economists using bibliographic information of 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-authored papers. Collaboration across institutions declined in the 20th century but increased in the 21st century, while collaboration across economists of different experience levels remained stable over time. Through 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 bigger (i.e., 4-or-more-authors) teams.

Keywords: collaboration, economics, COVID, working papers

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1 Introduction

Economics research papers have undergone a significant transformation over the past 100 years. Articles in the inaugural issue of the *Quarterly Journal of Economics* in 1886 averaged less than one page. Today, these papers typically span 40 pages. Researchers have 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 on the underlying drivers of this shift.[2] Explanations of collaboration patterns mostly remain descriptive, and few attempt 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—more longitudinal and more granular—facts about research collaboration to establish a wider and deeper understanding of this phenomenon. Whereas existing 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. Due to our uniquely assembled data that links authors' publications and affiliations over time, we also document unprecedented collaboration

[1] In addition, Guimera et al. (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 increased specialization of research areas (Hunter and Leahey, 2008), improvements in communication technology (Jones, Wuchty, and Uzzi, 2008; Xie, 2014), and rising complexity of modern problems that require interdisciplinary solutions (Falk-Krzesinski et al., 2011; Milojević, 2014).

patterns among economists of different academic institutions and experience levels to shed light on additional dimensions of research collaboration.

Second, we explore potential drivers of collaboration patterns. We seek to understand the choice an economist faces: working alone or collaborating with others. The trade-off can be summarized by the benefits associated with the improved quality of the paper from 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 challenge standing in the way of our research questions is a lack of existing quality data. Extant work often relies on data of limited quality, compromised by misclassifications, inaccuracies, and omissions. In some cases, overly inclusive classification of economics papers likely results in a dataset only loosely related to economics research.[3] In other cases, author affiliations can be stale or simply missing from commonly used data sources such as Web of Science (WoS) and Research Papers in Economics (RePEc). To anchor our analysis in quality data, we meticulously put together a database of economics research papers and author information. We start from 64 journals representative 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. In addition, we obtain Social Science Research Network (SSRN) economics working papers from OpenAlex and the National Bureau of Economic Research (NBER) working papers from its website. This comprehensive database provides a consistent definition of economics papers and academic economists, which enables us to address our research questions in a standardized environment. Our assembled data consists of not only publi-

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

cations 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 collaboration first increased in the 1950s, before which more than 95% of the economics publications were solo-authored. We find a secular trend toward more collaboration arriving in waves: a consistent decline in relative sole-authorship with increased shares of two-authored papers since the 1950s and 1960s, of three-authored papers since the 1970s, and of four-authored papers since the 2010s. The proportion of multi-authored papers as well as the average number of authors among these papers rose over time. A more granular view reveals that inter-institutional collaboration decreased in the twentieth century and increased in the last 25 years, reflecting 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 existing findings to a broader set of papers (working and published) going further back in time, as well as reveal new dimensions to collaboration.

Next, we investigate the drivers of these patterns by considering the benefits and costs of collaboration. One benefit is the increased impact of the paper, for which we use the trailing five-year citation count (compared to other papers in the same year) as the empirical proxy. The costs encompass all factors contributing to the overall expense of producing a paper, including time, opportunity costs, and financial resources.

[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.

We define a homerun paper as a publication whose trailing five-year citation count is in the top 10% among 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-authored papers changed over time.[5] While single-authored papers were the most likely to be highly cited in the 1950s, two-authored papers were the most likely in the 1960s, 1970s, and 1980s. Three-authored papers were the most likely in the 1990s and 2000s, only to be overtaken by four-plus-authored papers in the 2010s. Evidently, returns to collaborative work have increased over time.

We investigate whether the academic returns may be a driving factor in research collaboration. Our hypothesis is that economists respond to higher returns to multi-authored papers 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-authored or three-authored 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-authored papers as well as those of papers with four or more authors during COVID, indicating that the pandemic had a polarizing effect. While some researchers

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

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. In terms of collaboration across institutions and across seniority, we find little evidence of changes during COVID.

Our expanded and more granular empirical documentation of research collaboration patterns also encourages additional theoretical explanations. Stylized facts related to the cross-sectional variation in experience levels and institutional affiliation must be accounted for in newly proposed theories of collaboration.

After a review of the literature, the rest of the paper is organized as follows. Section 2 describes the construction of our unique database of author and paper information. Section 3 documents patterns of collaboration. Section 4 introduces the framework to understand collaboration patterns and conducts empirical tests of possible channels. 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 literature: (i) documenting facts in 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 outputs 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, offering 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 specific journal or a select few 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 the bibliographic information of the papers. Compared to previous work, we provide a 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 than extant work.

In contrast to the abundant descriptive studies of research collaboration, there is less of a focus on empirical tests of formal hypotheses in the literature. Milojević (2014) proposes a model of research teams to capture its cross-sectional distribution. 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, providing corroborating evidence for positive assortative matching. Sheng (2020) empirically investigates a pairwise coauthor formation model of Jackson and Wolinsky (1996), but it is difficult to analyze and estimate more complicated collaboration patterns in a network. In a comprehensive survey, Liu et al. (2023) classify empirical work into two 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 two categories, with an emphasis on making progress on 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, suggesting 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 reliant on labs and fieldwork, a disproportionate burden on female scientists, and reduced opportunities for informal collaboration due to the shift to virtual conferences. Whereas existing 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) from the beginning of the working paper series in 1973 to 2023 from its website. For publications, we consider papers published in 64 journals commonly considered to be the most prominent economics research outlets, including 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 publications among the 64 journals as "EC64," and the top five general interest journals (*American Economic Review*, *Econometrica*, *Journal of Political Economy*, *Quarterly Journal of Economics*, and *Review of Economic Studies*) as "top five." 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 where 33% or more of the authors are academic economists.

We record the year in which 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 our focus on economics research and provide a valid comparison before and after COVID, we exclude papers primarily about 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.

[6]The list of journals comes from the School of Economics at Shanghai University of Finance and Economics and is consistent with the top journals in various lists of ranking (Kalaitzidakis, Mamuneas, and Stengos, 2003; Heckman and Moktan, 2020; Ham, Wright, and Ye, 2021). We choose to base our selection of journals on it 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 1st in OpenAlex, making it difficult to more precisely determine the time of publication or posting.

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 issue 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 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 containing scientific publication records, citation relationships, and author information. However, MAG stopped its updates in December 2021.

The non-profit organization OurResearch proposed 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 metadata for over 100,000 institutions. Given its comprehensive coverage, many universities have used OpenAlex to track the progress of their research.

[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 in institution I), but the information was not scraped until 2018, then 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 the affiliation records for NBER and IZA, due to the inter-institutional nature of these organizations.

To construct author-affiliation records, we obtain all articles indexed in OpenAlex that are published in the 64 economics journals we consider. We pull relevant paper information from OpenAlex to construct records of each economist's affiliation and fill in any gaps using the steps described below. To process author-affiliation data with missing records, we implement the following procedure. First, identify active years: For each author-affiliation pair, determine the range of years with existing records. The first recorded year is `minyear` and the last is `maxyear`. Second, forward fill missing years: For each affiliation, forward fill in any missing years between `minyear` and `maxyear`. This technique replaces missing values with the last observed non-missing value, ensuring continuity in the data. Third and finally, retain the most recent forward-filled entry: For years that contain only filled records, retain the most recent forward-filled entry. This approach ensures that the data reflects 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 about the education and career history of tenure-track faculty members of MIT. For the

[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.

years that 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 collected in 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 including title, publication year, 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, the most common affiliation for paper i.
- Experience variables

[10]Main reasons for mismatches are the lack of publication and lag of publication, resulting in erroneous institutions for years when authors switch institutions. Another reason is that sometimes the coauthors' institutions were recorded.

– (pct_jun_{ijt}) Fraction of junior economists: the percent of authors that are economists whose first EC64 paper was published zero to nine years ago.

– (pct_sen_{ijt}) Fraction of senior economists: the percent of authors that are economists whose first EC64 paper was published 10 or more years ago.

Authors of NBER working papers need to be linked to author profiles from OpenAlex to populate 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 in Bremer (2023) that seeks to identify similar elements from different data sets 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, retaining 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. 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 the summary statistics of the four sets of papers. Although working paper repositories are a more recent occurrence, with the NBER paper series starting in 1973 and SSRN in 1994, the numbers of papers on these platforms (31,356 and 217,226) approach those of published papers in the top-five 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-authored 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 characterizing research collaboration among academic economists. As 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 plots the number of journals from 1886, when *Quarterly Journal of Economics* was first founded. Economics as a field has shown significant growth since 1886. While the number of journals hovered below 10 prior to the 1950s, many more journals were introduced between 1960 and 2000, resulting in almost our complete set of 64 journals by the early 2000s.

Figure 1 also plots the number of published and working papers over time. While the number of papers published in the top-five journals rose steadily over time, the rate of increase of publications among all 64 journals is markedly higher, indicating a faster expansion in top-field and other general-interest journals. NBER working papers grew at a similar rate compared to EC64 publications. Since its founding in 1994, SSRN has been hosting 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, until a spike 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 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 numbers of active, publishing, and new economists—these flow measures—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-authored 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-authored papers continued to rise until 1990, from which point we have seen a steady decline for more than 30 years. The popularity of multi-authored papers appears to take on waves: Beginning in the 1950s, there was a noticeable increase in the number of two-authored papers. There was a clear increase in the number of three-authored papers in the 1980s, and papers with four or more authors became more common in the 2000s. In subsequent analysis, 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-five journals. Multi-authored papers in these journals became more common at approximately the same time as did those of EC64 papers. Publications in the top-five journals exhibit a more extreme shift toward a greater number of collaborators, as shown by the sharp decline in single-authored papers from 400 per year in the 1970s to fewer than 100 per year in the 2010s.[11]

[11]Until 2017, the May issue of the *American Economic Review* each year includes papers presented at the

Given relatively small sizes of journals and papers and the near unanimity of single-authored 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. Trends in top-five papers may be difficult to see in Figure 4 because of the volume of papers, but it is clear in Figure 5 that the share of papers with three or more authors has increased in all samples.

We quantify changes in the composition of research papers through 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-authored papers decreased by an average of 1.04 percentage points for each year that passed. Column (2) indicates that two-authored 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- 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-five dummy variables suggest that working papers and the most selective published papers tend to have more authors compared

American Economic Association's annual meeting that January, increasing the overall paper count for top-five journals. Figure B2 presents the result without the *AER*, which shows the same patterns over time with fewer papers.

to the universe of papers published in EC64 journals. 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 that *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 may expect to see more frequent cooperation across institutions over time. On the other hand, if rising collaboration is more of 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 affiliated with a different institution—among all multi-authored papers. Second, we compute the share of authors in the major institution—defined as the most common affiliation on a paper—among 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 pertaining to cross-institutional cooperation declined from about 90% of all multi-authored papers in 1950 to 60% in

2000. This negative trend reversed in the most recent decades, rising to 75% by 2023. 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 the particular focus on economics research rather than across fields.

Working papers from NBER and SSRN tend to contain more inter-institutional collaboration compared to 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 major institution on a paper decreased over time. This trend is the most salient for publications from EC64 journals and top-five 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 collaboration may not simply be driven by old colleagues who 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. The independent variables are defined the same way as those in Equation (1).

Table 4 presents the 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 to published papers in EC64 journals, and the top-five 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 to 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-five 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 for 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 through 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-authored 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 been consistently 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 involving non-economists (authors who have never published in EC64 journals). This figure exhibits similar trends as 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 posted by an economist and a non-economist, which suggests an increase in interdisciplinary collaboration.[12] Figures 10 and 11 expand the analysis to all EC64 publications. We continue to observe relatively

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

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. The independent variables follow the same notation as that of Equation (1).

Table 5 presents the results of these estimates and demonstrates a decline in papers written by all junior collaborators, while there is a much smaller change for papers written by all 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 a smaller 0.13 percentage points each year. We observe a similar pattern of overall decreases in experience assortativity for NBER working papers and publications on EC64 journals or top-five journals.

4 Drivers of Collaboration

We have documented patterns of research collaboration of academic economists. The natural next step is to explore potential drivers of such trends. What factors are associated with changes in the number of authors or in 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-authored paper or collaborate with other economists to produce a multi-authored paper. Let b^s denote the benefit of a single-authored paper and b^m that of a multi-authored paper. Let c^s and c^m denote the per-author cost of production of single-authored and multi-authored 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-authored paper over a single-authored 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 of exploration: benefits and costs. The benefits seek to capture the quality and impact of a paper. The costs encompass all factors contributing to the production of a paper, including 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 leave an impact. Similar to Jones (2021), we use the trailing five-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.[13]

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 co-authors, provided that preferences are truly idiosyncratic. In reality, neither returns nor costs can be held constant, while the relative degree of their variation may differ. On the one hand, we can use publication records over a prolonged period absent of any shocks to costs to study the effect of returns on the number of co-authors 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, then we can study the relationship between these shocks and the share of multi-authored 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 a proxy the number of citations it receives. Jones (2021) hones in on citation counts of a paper and documents that multi-authored economics papers, relative to single-authored papers, have a higher likelihood of becoming 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 five-year citations rather than cumulative citations. Our measure favors papers whose impact is recognized relatively quickly, a

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

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 for if paper i is a *homerun paper*, defined as a paper whose trailing five-year citation is among the top 10% of all EC64 papers published in the same year. *Relative n-author impact* is the ratio between the share of n-authored papers that are homerun and the share of single-authored 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 rates of n-authored papers to that of single-authored papers. *Relative n-author returns* is the ratio between the share of all homerun papers that are n-authored and the share of homerun papers that are single-authored:

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

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

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

4.1.1 Predicting a High Impact, Homerun Paper

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

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

where β_n's are n-author fixed effects, κ_t capture 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.[14]

Table 6 reports the 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 to 30 institution. Other characteristics have relatively small effects on the probability of becoming a homerun paper, with authors from U.S. 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-authored and three-authored papers are 2.36% and 2.94% more likely, compared to single-authored papers, to be highly cited, while four-plus-authored papers do not show a significant difference. Column (2) includes the same control variables as Column (1), plus year fixed

[14]The control variables include the following: whether a paper has a senior author, has an author from US institution, has an author from one of the top 10 schools, has a senior author from top 10 schools, has an author from the top 11-30 schools, has a senior author from top 11-30 schools, involves inter-institutional collaboration, and involves international collaboration.

effects. Four-plus-authored papers now show a statistically significant increase in the likelihood of becoming a homerun paper compared to single-authored 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-authored articles when controlling for latent differences across journals. Table A2 repeats the analysis, excluding publications in the top-five 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 certain ranking. Table A3 shows that the results also remain largely unchanged.

An alternative measure of the impact of a paper is its percentile among the trailing five-year citations of all papers published in the same year. Whereas HR_{nijt} is a binary variable that turns on if a paper is in the top 10% of citations, this alternative measure is a continuous variable with larger values indicating more impact. All independent variables remain identical to those in Equation (7). Table A4 exhibits similar estimates as 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.

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 if 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-authored papers over 10-year intervals. Figure 13 illustrates the likelihood of becoming a homerun paper for different-sized teams, compared to a benchmark of single-authored works. For example, a two-authored paper is 2.5% less likely to become highly cited than a single-authored 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-authored papers were the most likely to be highly cited, followed by two- and three-authored papers. Four-plus-authored papers are a full 5% less likely to be highly cited compared to single-authored papers. In the 1960s and 1970s, two-authored papers overtook single-authored papers to become the most likely to be highly cited. Three-authored papers also became more likely to be highly cited compared to single-authored papers in the 1970s. By the 1980s, two- and three-authored papers were both 3-4% more likely to be highly cited compared to single-authored papers, while four-plus-authored papers continued to see less impact. Since the 1960s, the likelihood of multiple authors producing impactful papers has consistently exceeded that of single-authored works. In particular, three-authored papers became the most likely to be highly cited in the 1990s and 2000s, while four-plus-authored papers became the most likely in the 2010s (5% higher compared to single-authored 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-authored papers along with the fraction of homerun papers written by n-authored teams in Figure 14. The former can be viewed as the "popularity" of specific-sized teams, while the latter as the "success." For teams of all sizes, popularity and success track each other closely. Single-authored papers show a steady decrease in both popularity and success over time. Two-authored papers have seen a resurgence in popularity and success since the 1960s, compared to relatively steady shares from 1900 to 1960. Three- and four-plus-authored 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-authored paper and how common it is. On the one hand, economics researchers may respond to increasing returns to larger teams by writing more multi-authored papers. On the other hand, stronger researchers working more often in teams can mean a greater fraction of highly influential multi-authored papers. In this section, we investigate these possibilities.[15]

We explore whether economists collaborate more in response to increasing returns to collaborative works. We would like to 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. $HRS_{n,t-5}$ is the share of n-author papers that are in the top 10% of trailing five-year citations, in year $t-5$. The choice of

[15] 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.

a five-year lag aligns with our choice of a five-year trailing citation count.[16]

If we estimate Equation (8) for the papers with different numbers of authors, their shares add up to 1: $\sum_{N=1,2,3,4+} S_{n,t} = 1$. This way, information present in one regression (for one set of papers) may be related to coefficients in another regression. We handle 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 $n = 2, 3, 4+$: $LRNS_t = \ln(S_{n,t}/S_{1,t})$, $LRNI_t = \ln(RNI_{n,t})$, and $LRNR_t = \ln(RNR_{n,t})$.

Computing the relative share of papers (to the share of single-authored 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 estimating:

$$\Delta LRMS_t = \alpha_M + \beta_{0,M} t + \beta_{1,M} LRMI_{t-5} + \gamma_2 LRMS_{t-5} + e_t \tag{9}$$

$\Delta LRMS_t = LRMS_t - LRMS_{t-1}$ is the first difference of log shares. Subbing in M for n to indicate the shares are the general multi-author papers. 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 culprit of the large standard errors. To further examine whether specific types of collaborations have this relationship, we estimate the following system of equations using

[16]We estimate the same models with a six-year, seven-year, or ten-year lag, and the results do not change.

the SUR framework:

$$\begin{cases} \Delta LR2S_t = \alpha_2 + \beta_{0,2}t + \beta_{1,2}LR2I_{t-5} + \gamma_2 LR2S_{t-5} + e_t \\ \Delta LR3S_t = \alpha_3 + \beta_{0,3}t + \beta_{1,3}LR3I_{t-5} + \gamma_3 LR3S_{t-5} + e_t \\ \Delta LR4S_t = \alpha_4 + \beta_{0,4}t + \beta_{1,4}LR4I_{t-5} + \gamma_4 LR4S_{t-5} + e_t \end{cases} \tag{10}$$

where $\Delta LRNS_t = LRNS_t - LRNS_{t-1}$ is the first difference of log shares. We are interested in the coefficient associated with the relative n-Author Impact from five years ago, $LRNI_{t-5}$. 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-authored 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-authored papers, offers evidence that researchers assemble into larger teams in response to higher returns. Across the four alternative specifications in the columns, the coefficient on $LR4I_{t-5}$ remains consistently positive and significant, with a similar economic magnitude. The coefficient of $LRMS_{t-5}$ can be interpreted as a kind of peer effects. A positive coefficient here would suggest that economists seeing more collaborations are more likely to collaborate in the future. In both Table 7 and Table 8, the coefficients are small and insignificant, lending weight to our assumption of stable preferences for collaboration over time. We also estimate the system from Equation (10) with relative n-author returns, $LRNR_t$, in place of $LRNI_t$. Table A5 shows similar results as those from Table 8. Whereas researchers respond to higher returns of the largest teams (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 to costs associated with doing research, increasing the difficulty of face-to-face communication and collaboration while making it easier to work together virtually. 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 that a particular paper imparts on the profession likely persisted. Furthermore, since COVID was a rare event, economists lacked prior experience in dealing with a massive pandemic, and it is unlikely that the profession quickly adjusted the standard with which papers are viewed. Therefore, we treat COVID as a natural experiment which, in relative terms, primarily changed costs of collaboration.

Assuming that the relative returns of multi-authored papers and the distribution of individual preferences for collaborative work remained relatively constant before and after COVID, we can attribute changes to shares of multi-authored papers in the post-COVID era to changes in costs.[17] We provide an overview of some of the challenges and opportunities of COVID, which form the basis for our hypotheses regarding changes to research collaboration.

[17] 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-authored papers provide higher weight than multi-authored papers in tenure decisions. This is outside of our scope that focuses on returns and costs of paper production.

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 the opportunities for researchers to interact face-to-face, which for some people 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, allowing researchers to continue to cooperate through online platforms. Video conferences, cloud-based collaboration tools, and virtual events became more commonplace and more culturally accepted, making collaboration easier and eliminating 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 more rapidly than before the pandemic. Preprint servers such as SSRN and arXiv saw a surge in usage, facilitating faster dissemination of research results and enabling 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 may leave researchers additional free time for research, but cancellation of other non-research activities, such as childcare, may reduce the productivity of researchers. How they affect 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 adaptation of new collaborative tools serves to decrease the costs of collaboration, and their prevalence persists after the pandemic. Researchers retain different outside options during the work-from-home era compared to afterward. For example, suppose that COVID limited the capacity of researchers to work on single-authored papers due to the increased mental load of handling a health crisis. This would cause an immediate negative shock to the feasibility of single-authored 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 illustrates that the economics profession experienced a positive shock in both the number of working papers and publications in 2020. In 2021, the number of working papers on SSRN and NBER experienced negative growth (but not the publications in the top five and EC64, as expected).

Because the fraction of multi-authored papers contains a time trend, observed 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:

$$100 \cdot \mathbb{1}\{Num_{ist} = n\} = \beta_0 + \sum_{c=2020}^{2023} W_i \cdot \mathbb{1}\{t = c\} + \sum_{c=2020}^{2023} \mathbb{1}\{t = c\} + \beta_1 t + W_i + \varepsilon_{ist}, \quad (11)$$

where W_i is an indicator variable that is 1 if paper i is a working paper, and 0 otherwise.

Table 9 reports the results. The yearly trend variable shows that single-authored and two-authored papers are on the decline, whereas three- and four-plus-authored papers are on the rise. During the COVID pandemic, there appears to be a consistent decrease in three-authored publications and some increases in four-plus-authored publications from 2020 through 2023. What is more striking is the magnitude and persistence of change in working papers. Specifically, Column (1) shows that the share of single-authored working papers experienced positive and growing deviations from the negative trend from 2020 to 2023, while the share of single-authored publications was largely unchanged. In contrast, Column (2) shows that the share of two-authored working papers experienced negative and growing deviations relative to its trend from 2020 to 2023, while the share of two-authored publications was virtually unchanged. Column (3) shows that the share of all three-authored papers, whether published or working, experienced negative and growing deviations from the positive trend from 2020 to 2023. Column (4) shows that the share of papers with four or more authors experienced positive and growing deviations from the positive trend. As a supplement, Figure 15 visualizes these deviations from the extended linear trends of 2010-2019. In summary, our estimates suggest a polarizing effect: After COVID, the share of two- and three-authored working papers decreased, while the share of single-authored 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 in the major institution as our outcome variables of interest. Given that the estimated trends of institutional assortativity vary substantially by sample in Table 10, we estimate deviations from the historical trend separately by sample as well. Similar to our preceding analysis, we estimate the COVID period deviations for our outcome variables by adding indicator variables of 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 11 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-five 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 12 shows the results for the fraction of authors in the major institution in multi-authored papers. SSRN and top-five papers show almost no change during COVID compared to the prior period, whereas working papers on NBER and publications in EC64 journals display some decline, albeit not always consistent 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 co-authors, 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 13 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 papers, we see very little deviation of these statistics in publications, which is likely due to the delay between working paper and publications.

5 Conclusion

This paper seeks to expand our current understanding of economics research collaboration along two dimensions. First, we document more granular collaboration patterns, including how economists of different experience levels work together, and offer more complete evidence on how collaboration across institutions has changed. Second, we study potential drivers of collaboration patterns through 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, as well as working papers from SSRN and NBER. Our dataset provides both a consistent analytic environment and detailed author-level information such as affiliation data across time. Similar to existing work, we find a significant trend of an increasing number of co-authors on research papers over time. The share of multi-authored 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 most recent 25 years. Researchers tended to work with others with similar experience and standing, such that the mix between senior and junior economists remained unchanged in recent decades.

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

While our work takes a step toward understanding research collaboration through variation in returns and costs, our empirical investigation imposes minimal structure and mainly 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. We also do not take a stance on the optimality and sub-optimality of increasingly many authors, which may have different implications for the advancement of science (Wu, Wang, and Evans, 2019).

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.” *The 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." *The 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." *The 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." *The 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.

Wu, Lingfei, Dashun Wang, and James A. Evans. 2019. "Large teams develop and small teams disrupt science and technology." *Nature* 566 (7744):378–382.

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

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

General Interests	*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	31,356	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 only include papers with at least 33% economist authors. 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-institutionality, 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 at the year of publication if it had been nine or fewer years since their first EC64 publication. For the share of junior authors, NBER papers only include papers with at least one author that is an economist according to our definition. Only for NBER papers, if an economist posted on NBER before their first EC64 publication, they are a senior at the year of NBER posting if it had been 10 or more years since their first NBER posting. Non-economist authors on NBER papers are treated as juniors.

Table 3: Estimated Yearly Trend of 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 only include papers with at least 33% economist authors. 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 4: Estimated Yearly Trend of 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 only include papers with at least 33% economist authors. NBER papers only include papers for which we successfully recover affiliation information of all authors for the year they are posted. Models in panel A are estimated with only multi-authored papers. Models in panel B are further restricted to include only inter-institutional 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 5: Estimated Yearly Trend of 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 only include papers with at least 33% economist authors. NBER papers only include papers with at least one author that is an economist according to our definition. An economist is a senior at 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. Only for NBER papers, if an economist posted on NBER before their first EC64 publication, they are a senior at the year of NBER posting if it had been 10 or more years since their first NBER posting. Non-economist authors on NBER papers are treated as juniors. 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 in the top 10 percentile 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 at 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

		$\Delta LRMS_t$		
$LRMI_{t-5}$	0.0494	0.0488	0.0507	0.0515
	(0.0327)	(0.0519)	(0.0769)	(0.0835)
$LRMS_{t-5}$		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: $LRNS_t$ is the natural log of the ratio between the share of N-author papers and the share of single-authored papers in year t. $LRNI_t$ is the year t natural log of the relative N-author impact, which is the ratio between the share of N-authored 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 in the top 10 percentile among 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

		$\Delta LR2S_t$		
$LR2I_{t-5}$	-0.0068	-0.0293	-0.0615	-0.0748
	(0.0258)	(0.0364)	(0.0485)	(0.0525)
$LR2S_{t-5}$		0.0416		-0.0780
		(0.0416)		(0.0809)
Year			0.0017	0.0034
			(0.0010)	(0.0021)
		$\Delta LR3S_t$		
$LR3I_{t-5}$	0.0043	-0.0353	-0.0634*	-0.0638*
	(0.0244)	(0.0341)	(0.0382)	(0.0387)
$LR3S_{t-5}$		0.0499		-0.0583
		(0.0310)		(0.0627)
Year			0.0033**	0.0056*
			(0.0014)	(0.0029)
		$\Delta LR4S_t$		
$LR4I_{t-5}$	0.0690**	0.0744*	0.0666*	0.0712*
	(0.0347)	(0.0409)	(0.0387)	(0.0410)
$LR4S_{t-5}$		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: $LRNS_t$ is the natural log of the ratio between the share of N-author papers and the share of single-authored papers in year t. $LRNI_t$ is the year t natural log of the relative N-author impact, which is the ratio between the share of N-authored 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 in the top 10 percentile among 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 of Number of Authors from Linear Yearly Trend During COVID from 2001 to 2023

	(1)	(2)	(3)	(4)
	% 1 Author	% 2 Authors	% 3 Authors	% 4+ Authors
2020	-0.15	0.32	-1.14*	0.97**
	(0.61)	(0.68)	(0.64)	(0.47)
2021	-2.31***	1.50**	-1.54**	2.34***
	(0.57)	(0.67)	(0.63)	(0.49)
2022	0.04	-0.10	-1.89***	1.96***
	(0.61)	(0.70)	(0.67)	(0.51)
2023	0.24	-0.94	-2.93***	3.64***
	(0.61)	(0.70)	(0.67)	(0.54)
Working Paper ×				
2020	1.86***	-2.37***	-1.31*	1.82***
	(0.69)	(0.80)	(0.77)	(0.57)
2021	5.69***	-5.38***	-1.94**	1.63***
	(0.67)	(0.81)	(0.78)	(0.61)
2022	4.01***	-3.25***	-1.93**	1.18*
	(0.70)	(0.83)	(0.80)	(0.63)
2023	1.78	-0.62	-0.10	-1.07
	(2.46)	(2.84)	(2.59)	(1.99)
Working Paper	-11.55***	4.04***	6.13***	1.37***
	(0.19)	(0.21)	(0.18)	(0.11)
Yearly Trend	-1.04***	-0.45***	0.90***	0.59***
	(0.02)	(0.02)	(0.02)	(0.01)
Number of Papers	315,402	315,402	315,402	315,402
Sample Fixed Effects	×	×	×	×

Note: Working papers are the papers in the SSRN sample and the NBER sample. SSRN papers only include papers with at least 33% economist authors. NBER papers only include papers with at least one author that is an economist according to our definition. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Estimated Yearly Trend of 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 papers for which we successfully recover affiliation information of all authors for the year they are posted. 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 11: Estimated Deviations of Inter-Institutional Collaboration from Yearly Trend 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 papers for which we successfully recover affiliation information of all authors for the year they are posted. The 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 12: Estimated Deviations of % Authors in Major Institution from Yearly Trend 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 papers for which we successfully recover affiliation information of all authors for the year they are posted. The 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 of Experience Assortativity in Multi-Authored Papers from Yearly Trend 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 papers with at least one author that is an economist according to our definition. An economist is a senior at 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. Only for NBER papers, if an economist posted on NBER before their first EC64 publication, they are a senior at the year of NBER posting if it had been 10 or more years since their first NBER posting. Non-economist authors on NBER papers are treated as juniors. 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: The Number of Journals, Published Papers, and Working Papers, 1886-2023

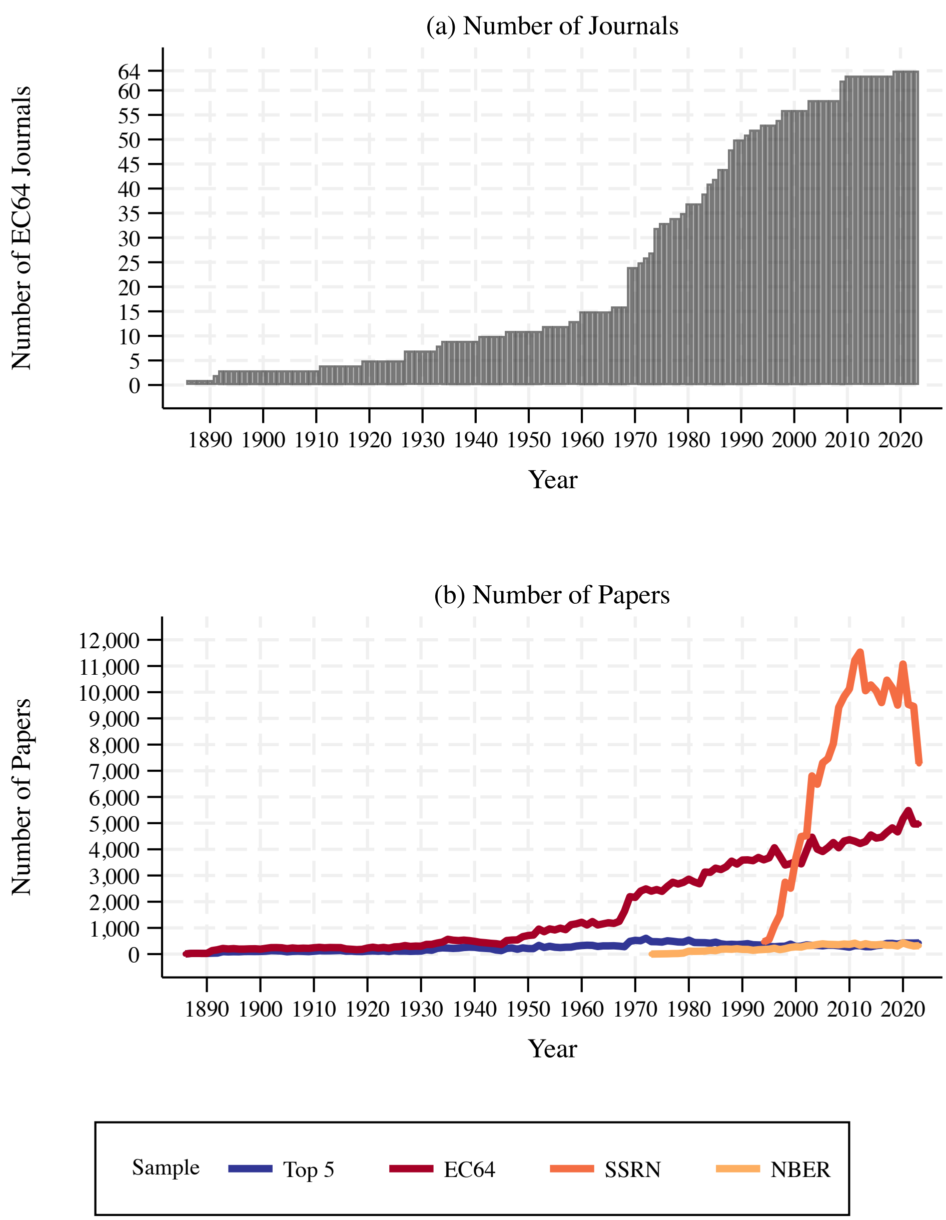
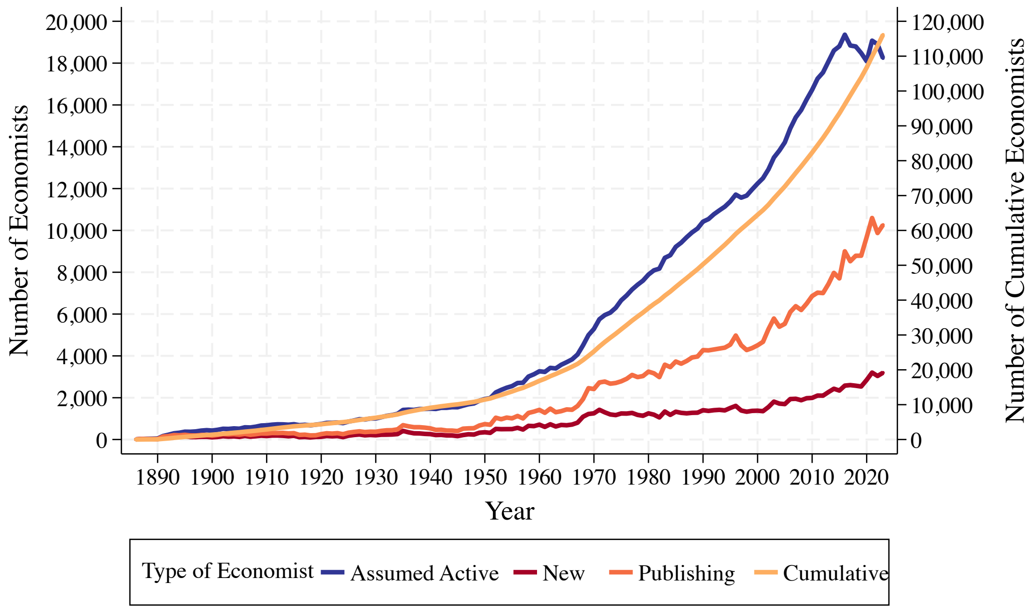


Figure 2: The Number of Economists in EC64



*Note: An economist is assumed **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: The Number of Authors on a Paper in EC64 Journals, 1886-2023

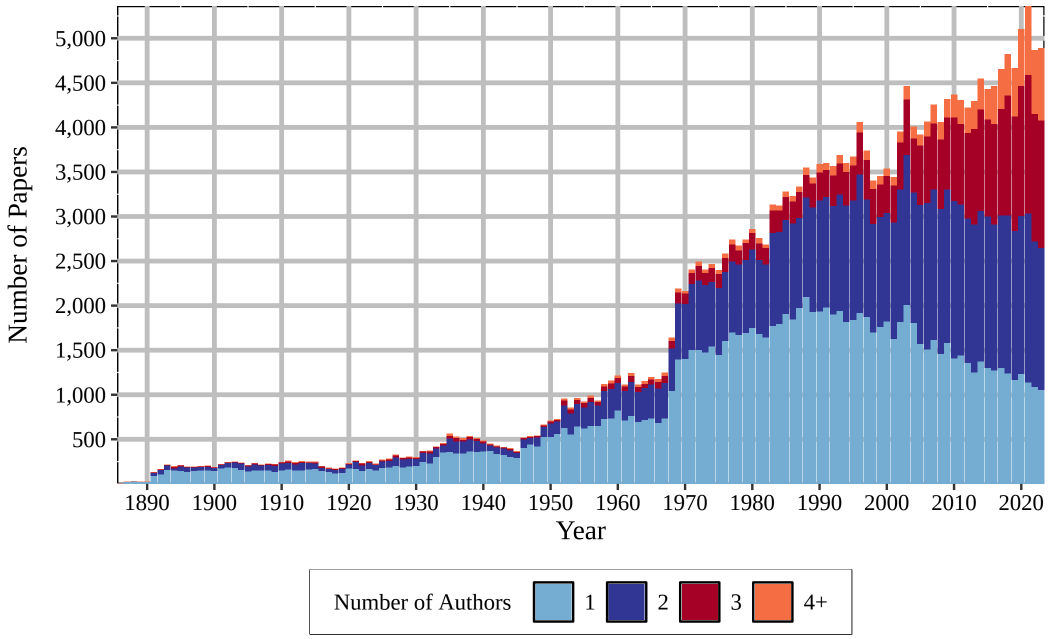


Figure 4: Multi-Authored Papers Increased Over Time

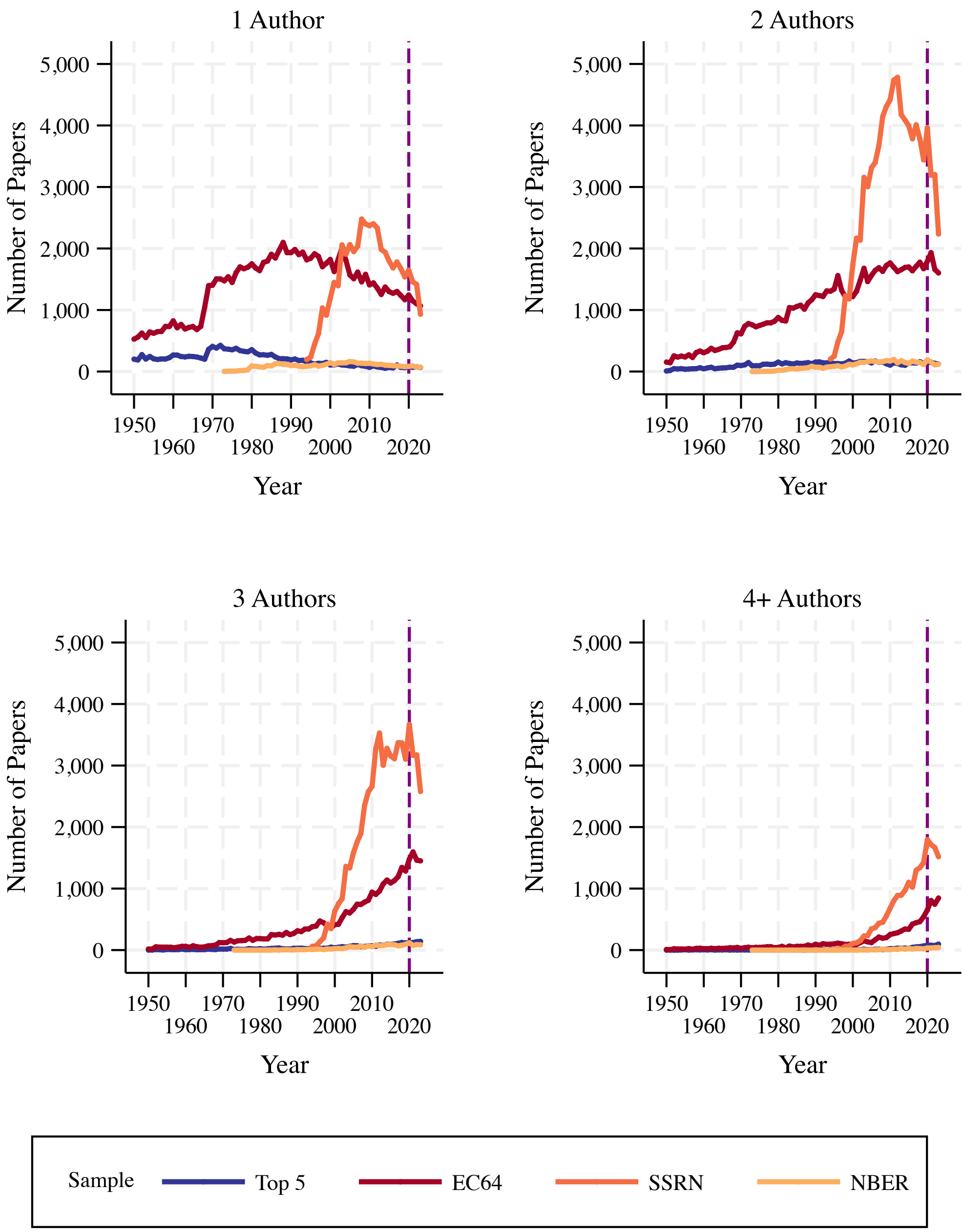


Figure 5: Proportion of Multi-Authored Papers Increased Over Time

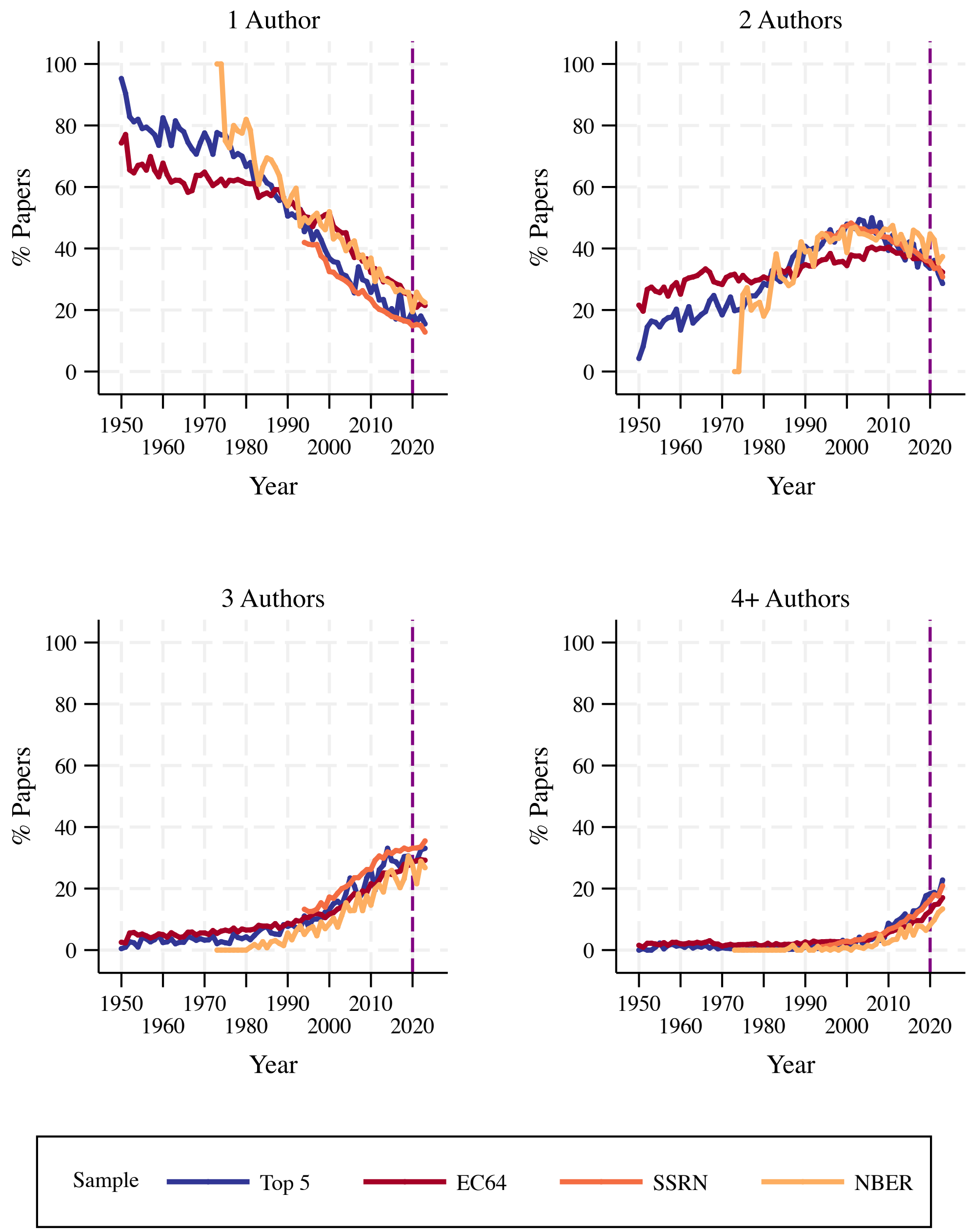
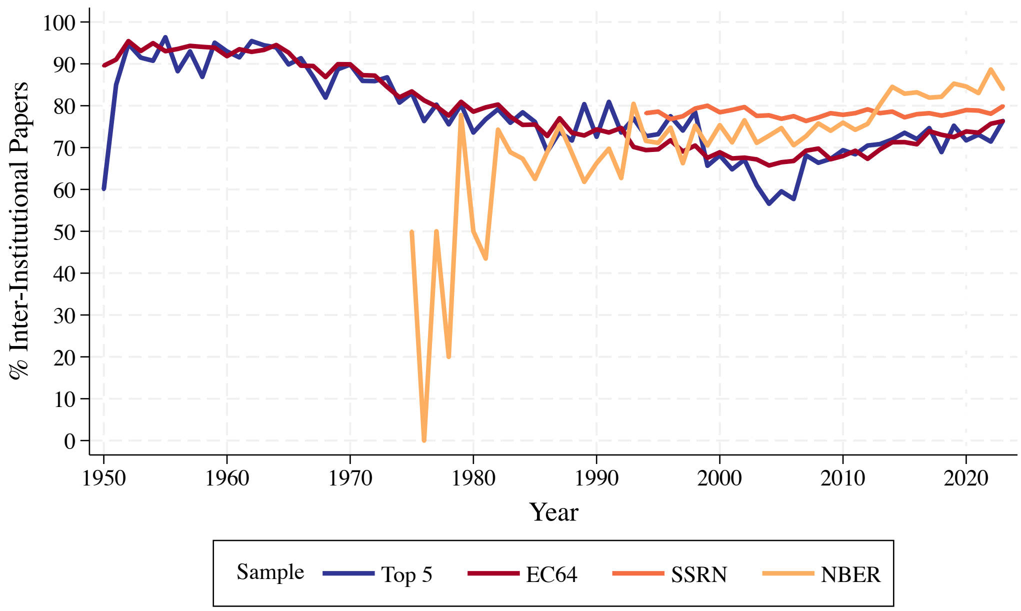
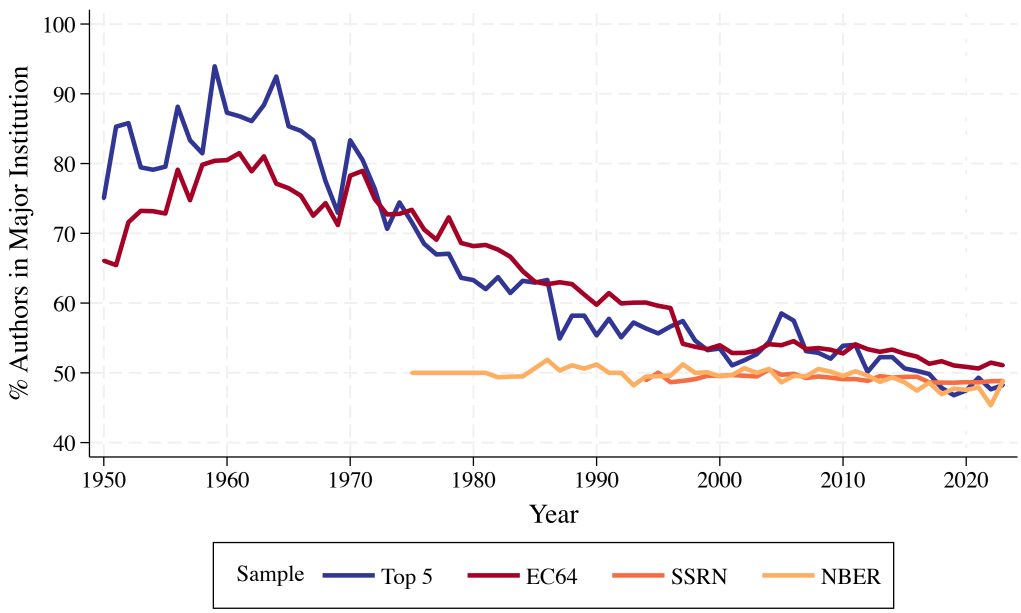


Figure 6: Trends in Inter-Institutional Collaboration



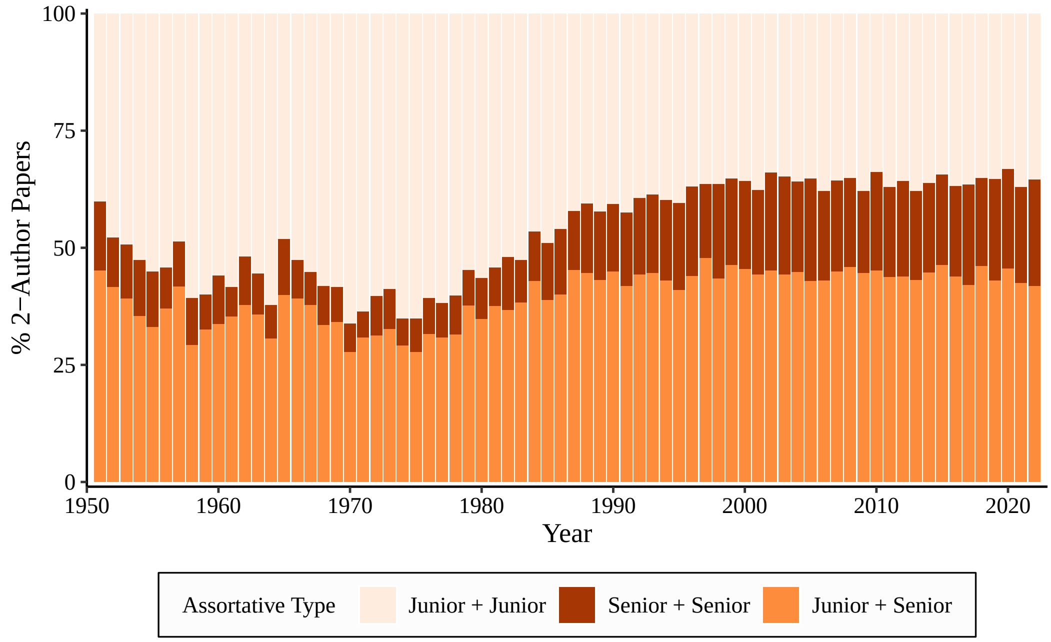
Note: A paper is inter-institutional if at least one author does not share an affiliation with another author.

Figure 7: Decrease in Institutional Concentration



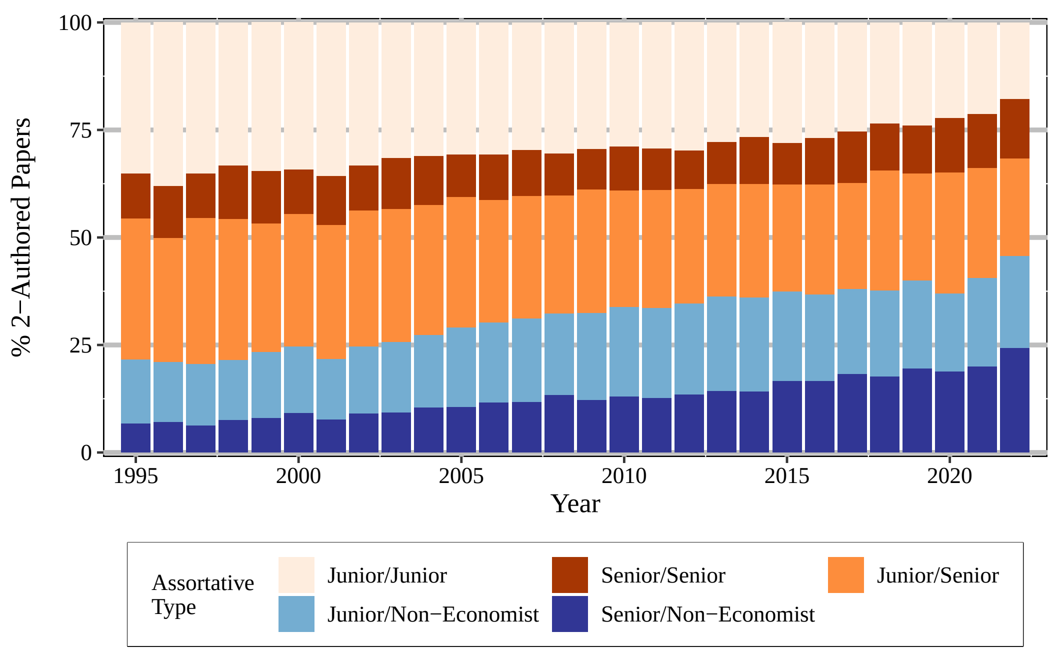
Note: An institution is a major institution if the most number of authors on the paper are affiliated with said institution. Ties are irrelevant given that our outcome is the share of authors.

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



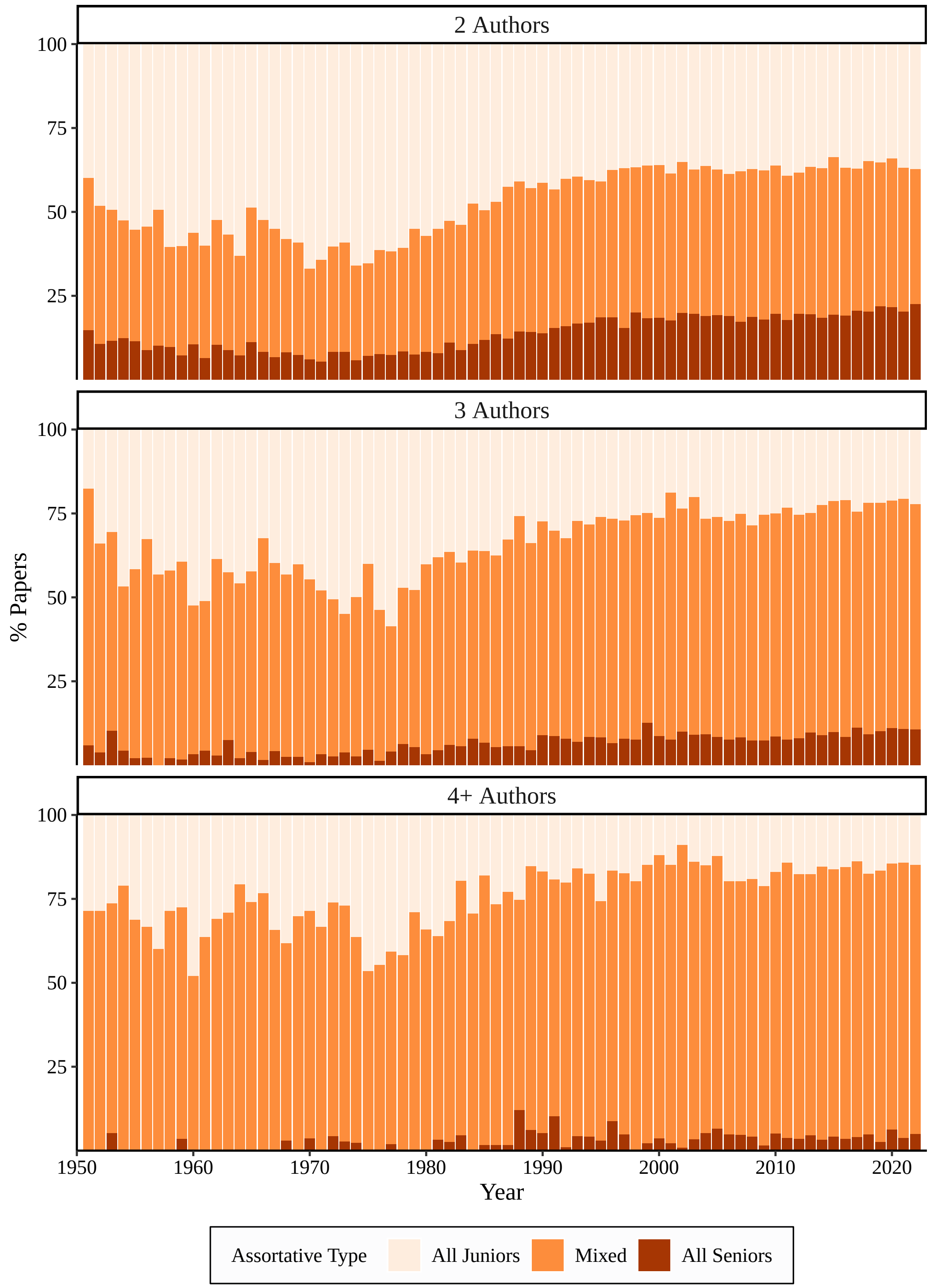
Note: An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. An economist is a junior if they are not a senior.

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



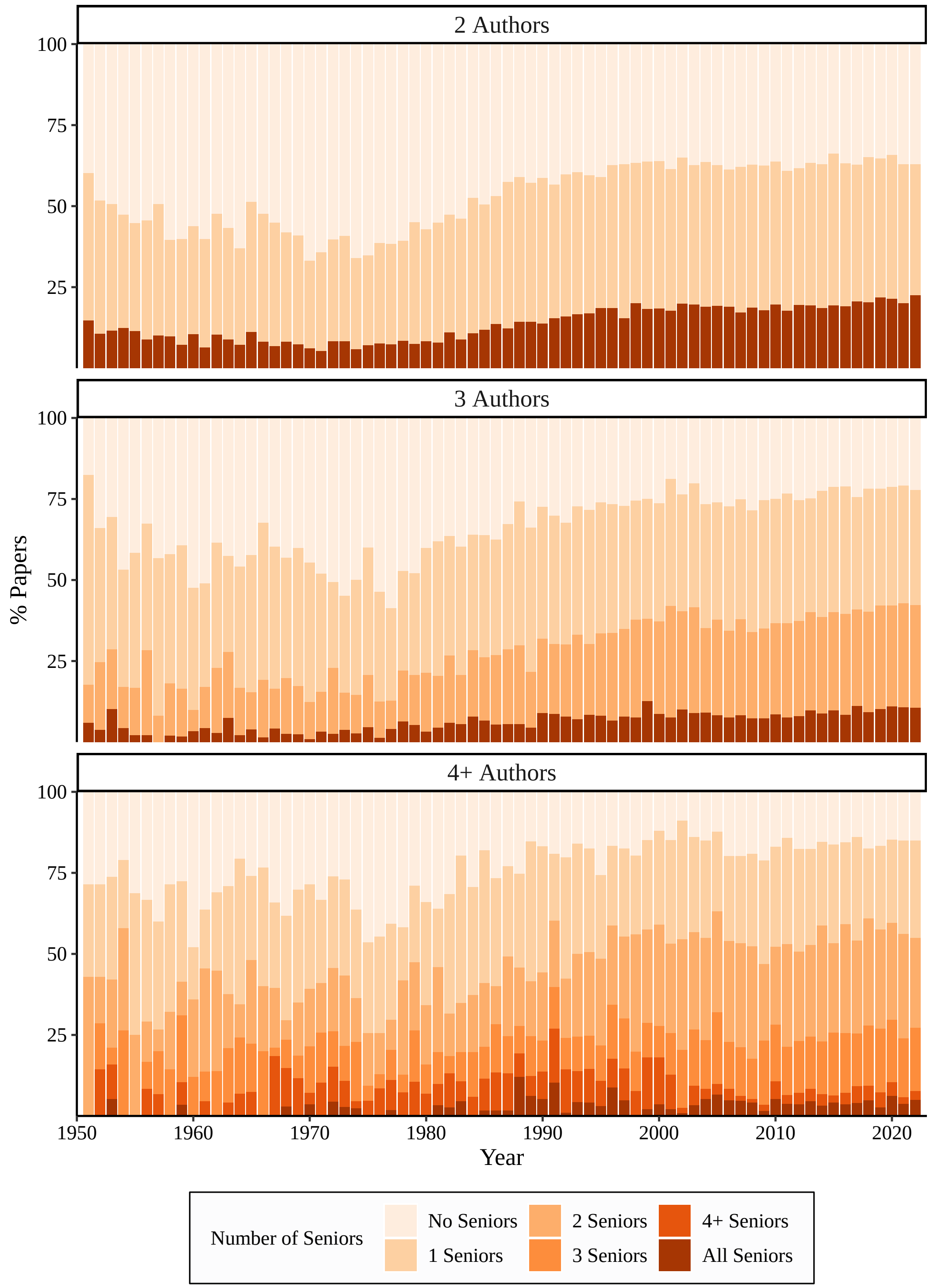
Note: An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. An economist is a junior if they are not a senior.

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



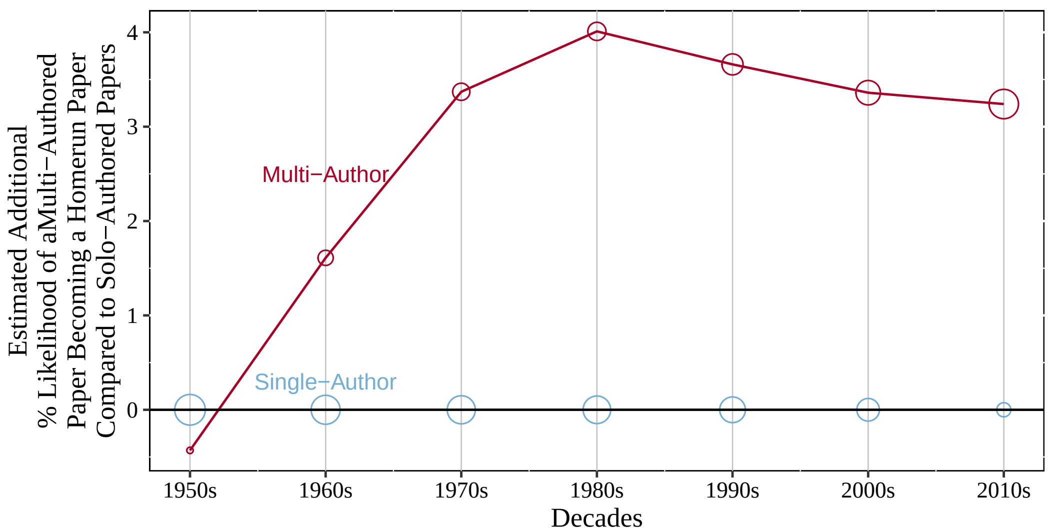
Note: An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. An economist is a junior if they are not a senior.

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



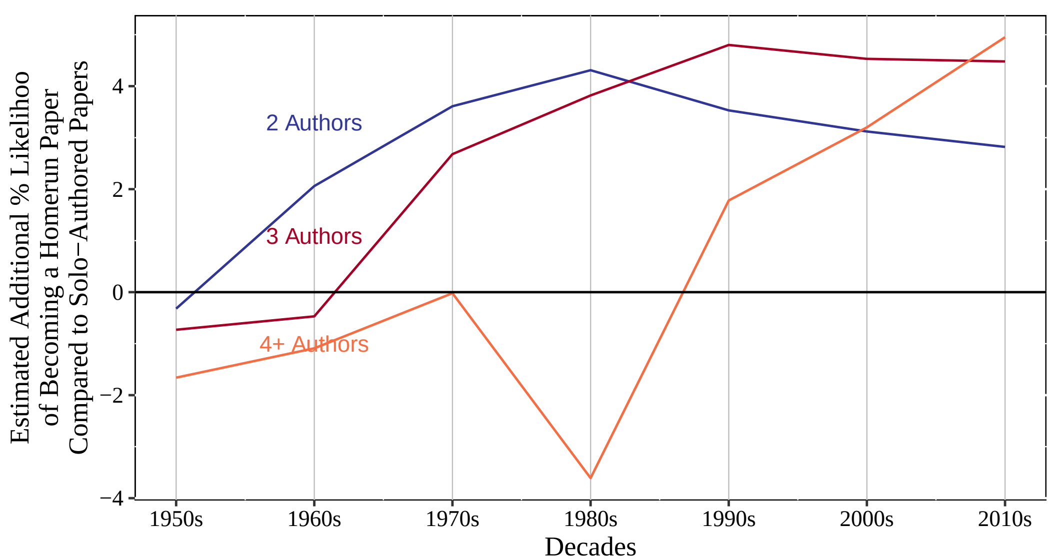
Note: An economist is a senior in the year of publication if it had been 10 or more years since their first EC64 publication. An economist is a junior if they are not a senior.

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



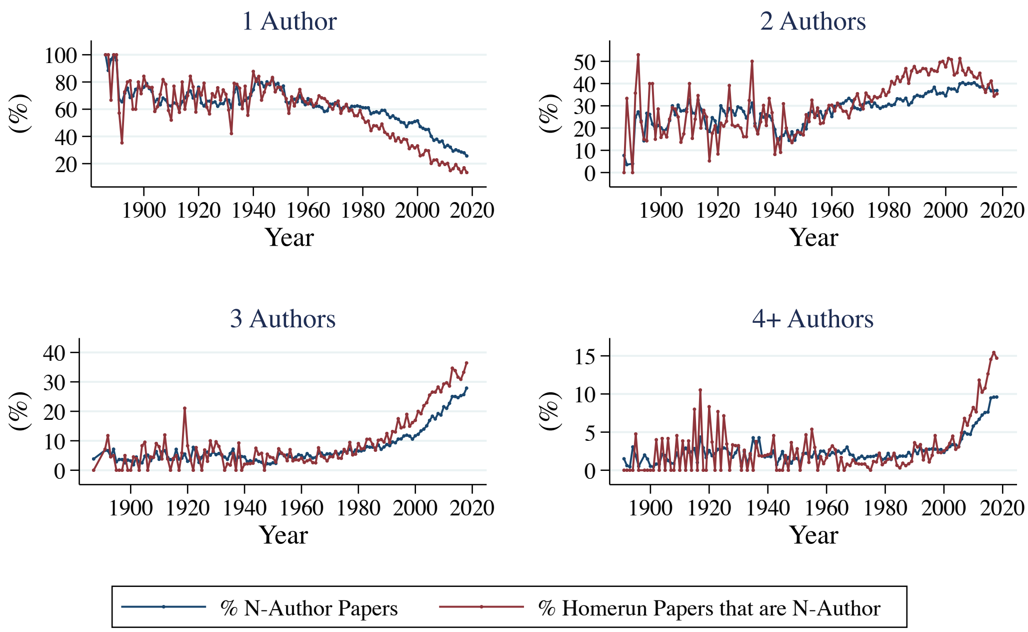
Note: Estimating equation is equation (7) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5−year citation in the top 10 percentile among EC64 papers published in the same year. Sizes of the circles correpond to the shares of N−Author papers that year.

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



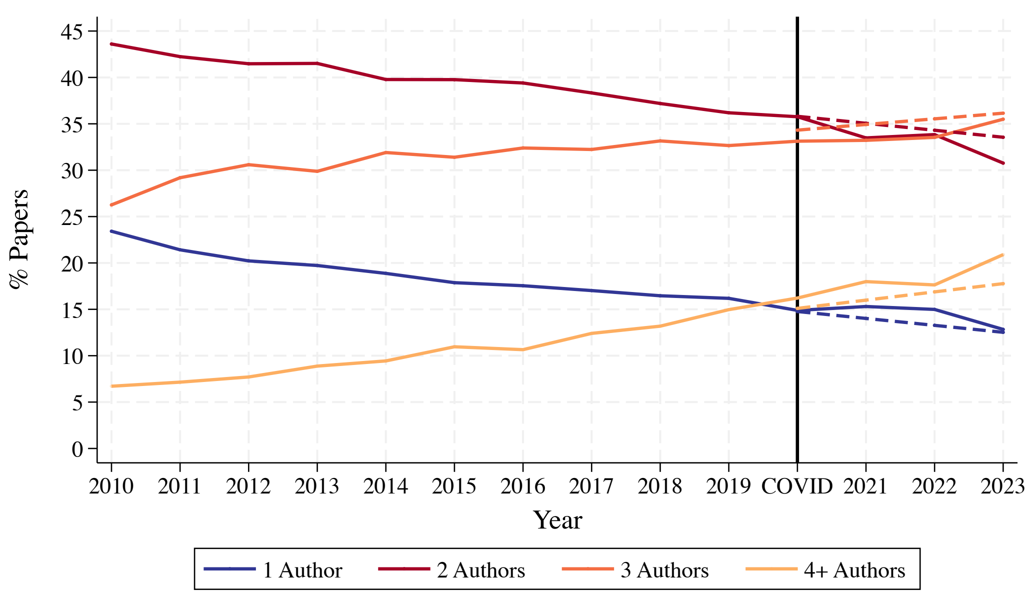
Note: Estimating equation is equation (7) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5−year citation in the top 10 percentile among EC64 papers published in the same year.

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 in the top 10 percentile among EC64 papers published in the same year.

Figure 15: Deviation from Linear Trend, Number of Authors, 2010-2023



Note: Dashed lines are linear predictions.

Appendix A Additional Tables

Table A1: Estimated Linear Yearly Trend of 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. 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 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 in the top 10 percentile 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 at 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)
$\mathbb{1}\{$Majoritys Author Top 10$\}$	15.89***	15.85***	13.58***	10.90***
	(0.20)	(0.20)	(0.20)	(0.20)
$\mathbb{1}\{$Majoritys 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 in the top 10 percentile 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 at 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: A homerun paper is a paper that has a trailing 5-year citation in the top 10 percentile 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 at 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: Estimated Correlations Between Returns and Popularity of Multi-Authored Papers, 1950-2018

		$\Delta LR2S_t$		
$LR2R_{t-5}$	0.0048	-0.0293	-0.0726	-0.0748
	(0.0151)	(0.0364)	(0.0496)	(0.0525)
$LR2S_{t-5}$		0.0708		-0.0032
		(0.0716)		(0.0793)
Year			0.0032*	0.0034
			(0.0019)	(0.0021)
		$\Delta LR3S_t$		
$LR3R_{t-5}$	0.0111	-0.0353	-0.0617*	-0.0638*
	(0.0126)	(0.0341)	(0.0342)	(0.0387)
$LR3S_{t-5}$		0.0852		0.0055
		(0.0599)		(0.0702)
Year			0.0056**	0.0056*
			(0.0024)	(0.0029)
		$\Delta LR4S_t$		
$LR4R_{t-5}$	0.0389*	0.0744*	0.0300	0.0712*
	(0.0222)	(0.0409)	(0.0295)	(0.0410)
$LR4S_{t-5}$		-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 in the top 10 percentile among EC64 papers published in that year. $LRNS_t$ is the natural log of the ratio between the share of N-author papers and the share of single-authored papers in year t. $LRNR_t$ is the year t natural log of the relative N-author return, which is ratio between the share of all homerun papers that are N-authored and 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 10 percentile among EC64 papers published in the same year. Robust standard errors in parentheses.

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

Table A6: Estimated Correlations Between Returns and Popularity of Multi-Authored Papers, 1950-2018

		$\Delta LR2S_t$		
$\Delta LR2R_{t-5}$	-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)
		$\Delta LR3S_t$		
$\Delta LR3R_{t-5}$	-0.0334	-0.0233	-0.0393	-0.0293
	(0.0363)	(0.0362)	(0.0368)	(0.0364)
$\Delta LR3S_{t-5}$		-0.0318		-0.0633
		(0.1090)		(0.1122)
Year			0.0012	0.0013
			(0.0010)	(0.0010)
		$\Delta LR4S_t$		
$\Delta LR4R_{t-5}$ (t-5)	0.0790**	0.0643*	0.0748**	0.0623
	(0.0374)	(0.0386)	(0.0373)	(0.0386)
$\Delta LR4S_{t-5}$		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: $LRNS_t$ is the natural log of the ratio between the share of N-author papers and the share of single-authored papers in year t. $LRNR_t$ is the year t natural log of the relative N-author return, which is ratio between the share of all homerun papers that are N-authored and 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 10 percentile among EC64 papers published in the same year. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B Additional Figures

Figure B1: The Number of Authors on a Paper, Top 5 Journals, 1950-2023

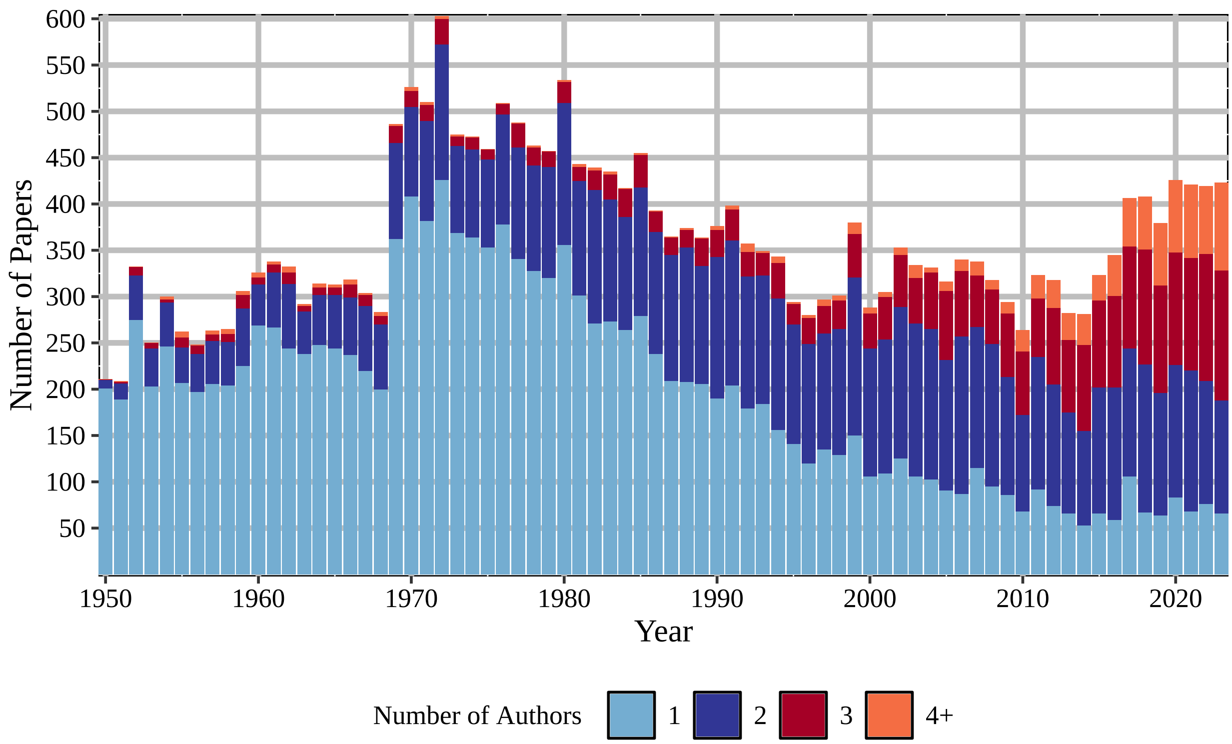


Figure B2: The Number of Authors on a Paper, Top 5 Journals Excluding *American Economic Review*, 1950-2023

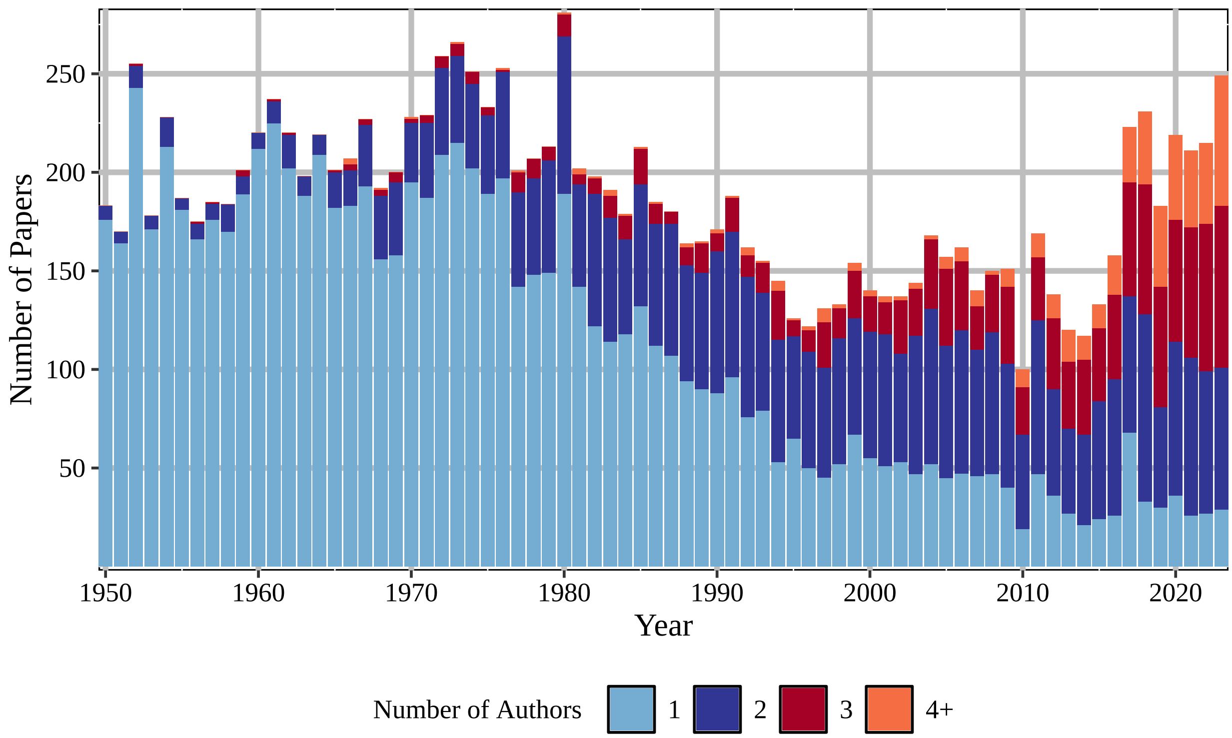
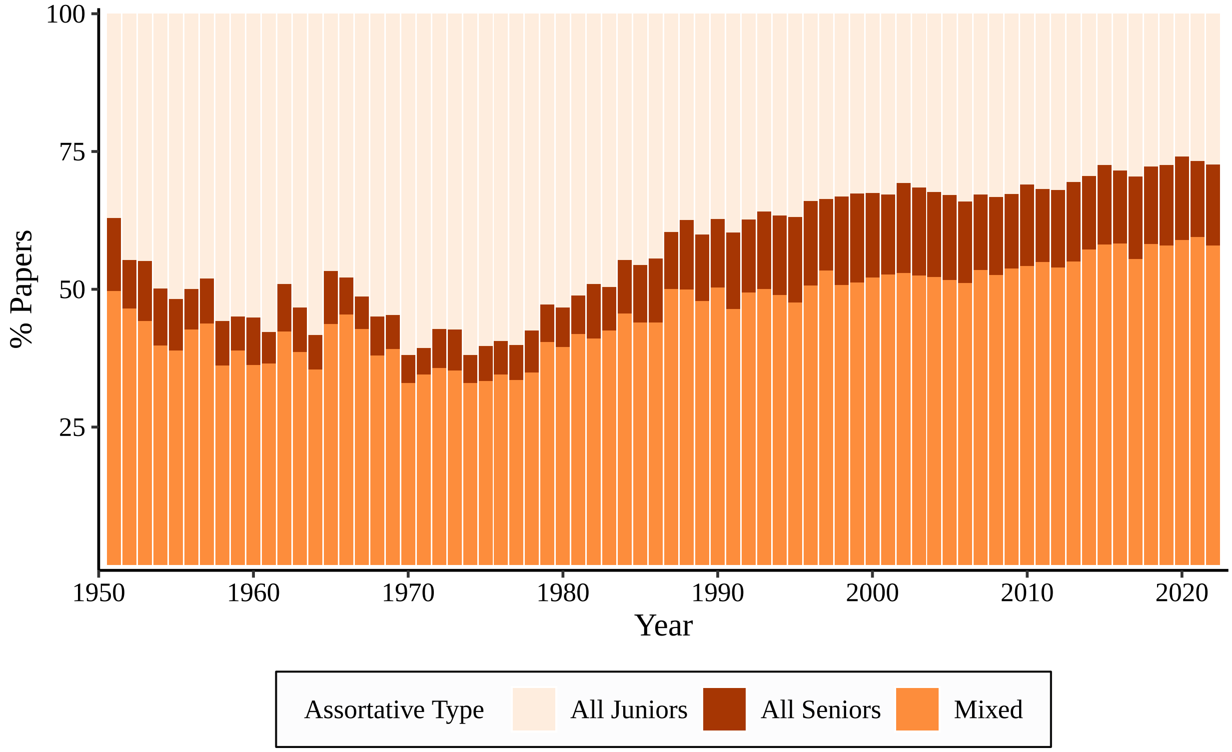


Figure B3: Evolution of Estimated Returns to Number of Authors, 5-Year Periods

Note: Estimating equation is 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 in the top 10 percentile among EC64 papers published in the same year.

Figure B4: Overall Decrease of Experience Assortativity in EC64 Papers



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

Figure B5: Distribution of Authors by Number of EC64 Papers

(a) Authors with < 10 Papers

(b) Authors with > 10 Papers

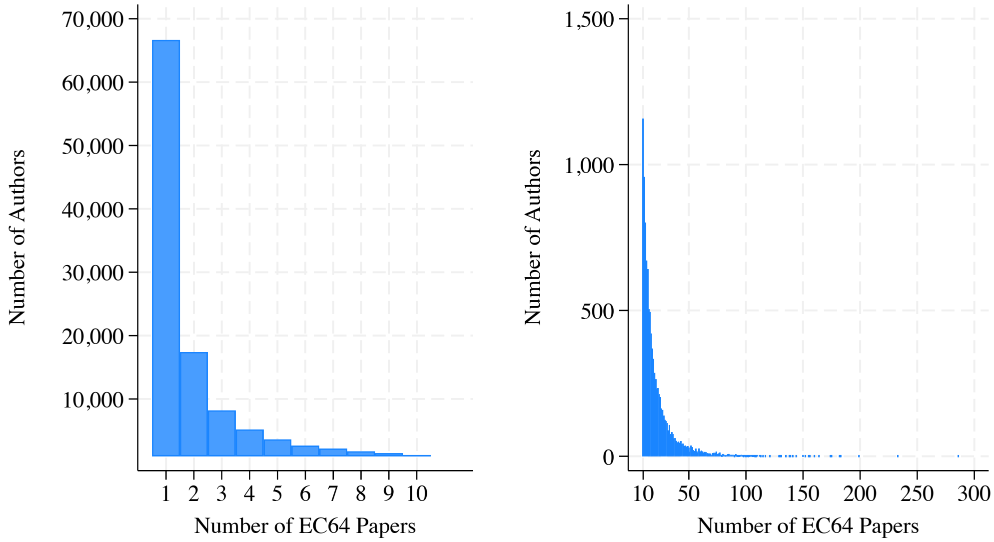


Figure B6: Distribution of Institutions by Number of EC64 Papers

(a) Institutions with < 50 Papers

(b) Institutions with > 50 Papers

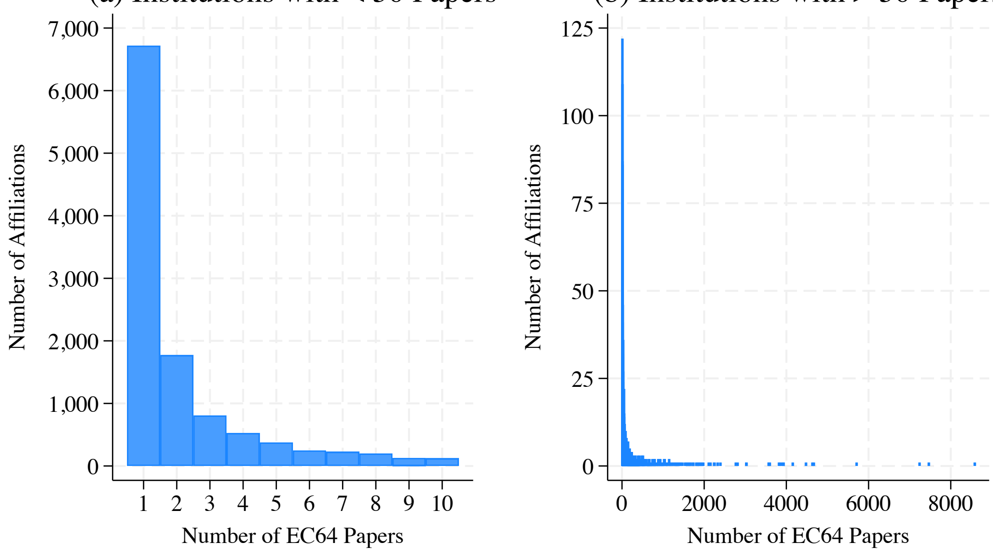
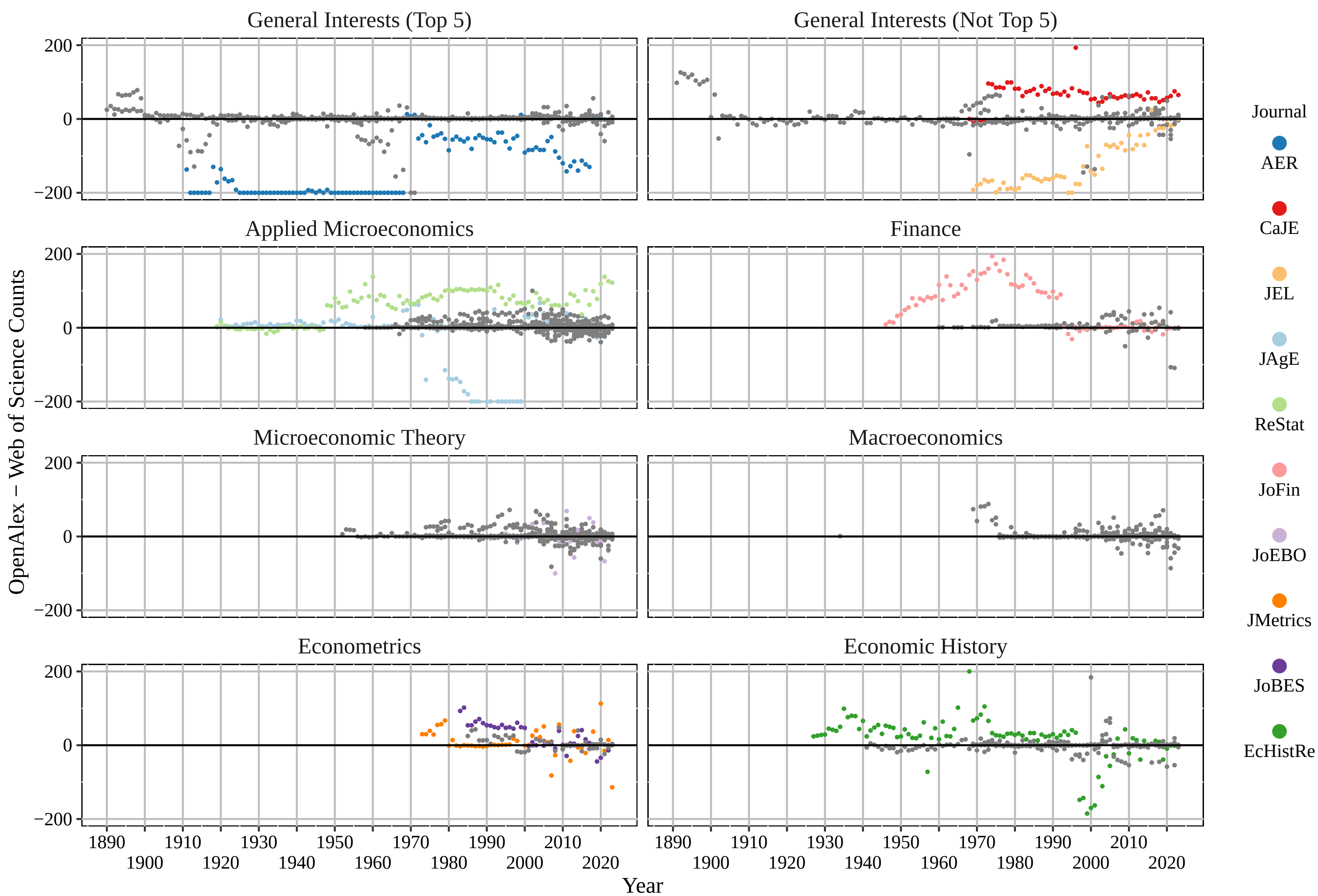
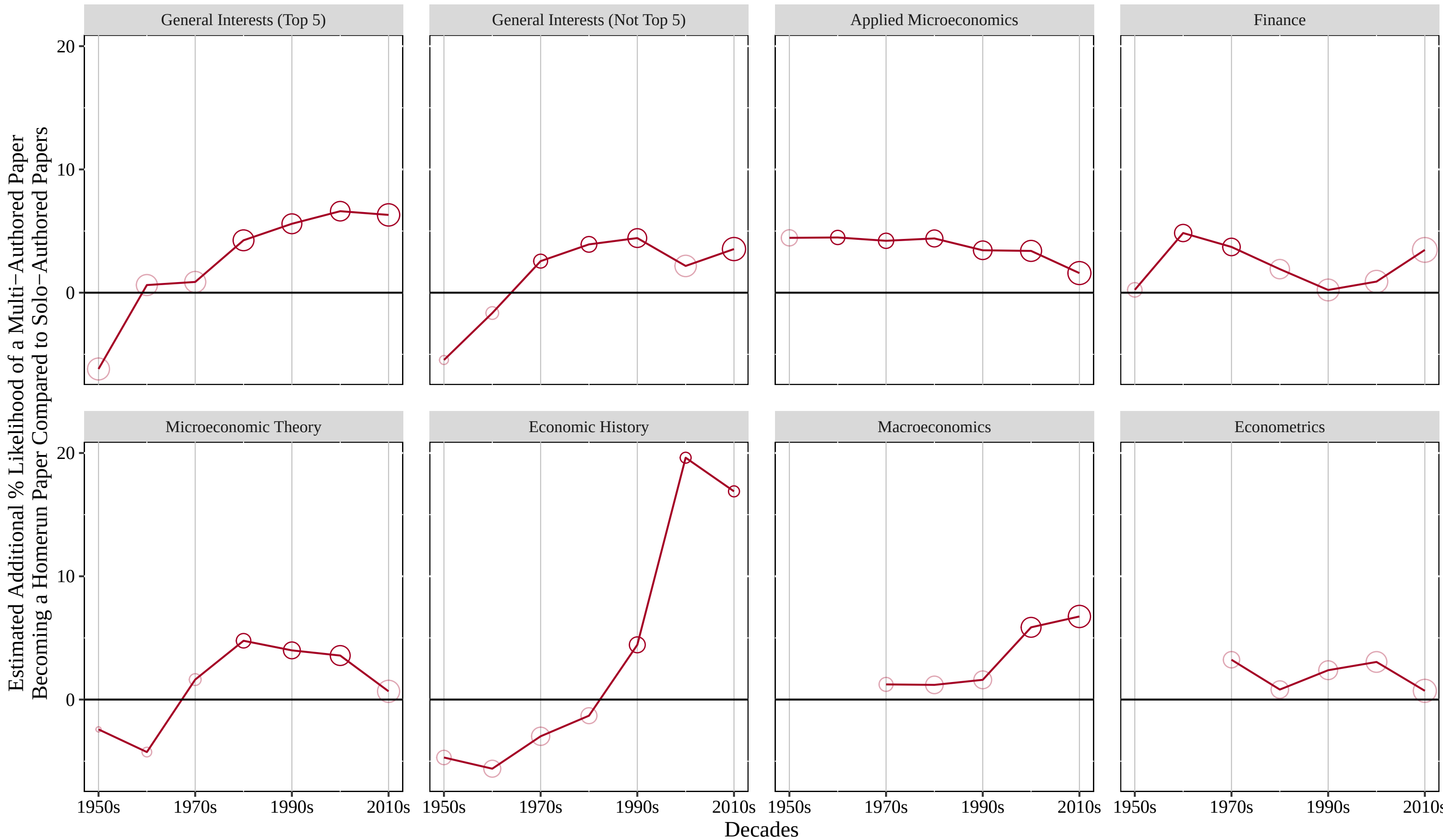


Figure B7: Differences Between OpenAlex and Web of Science Records by Field and Journal



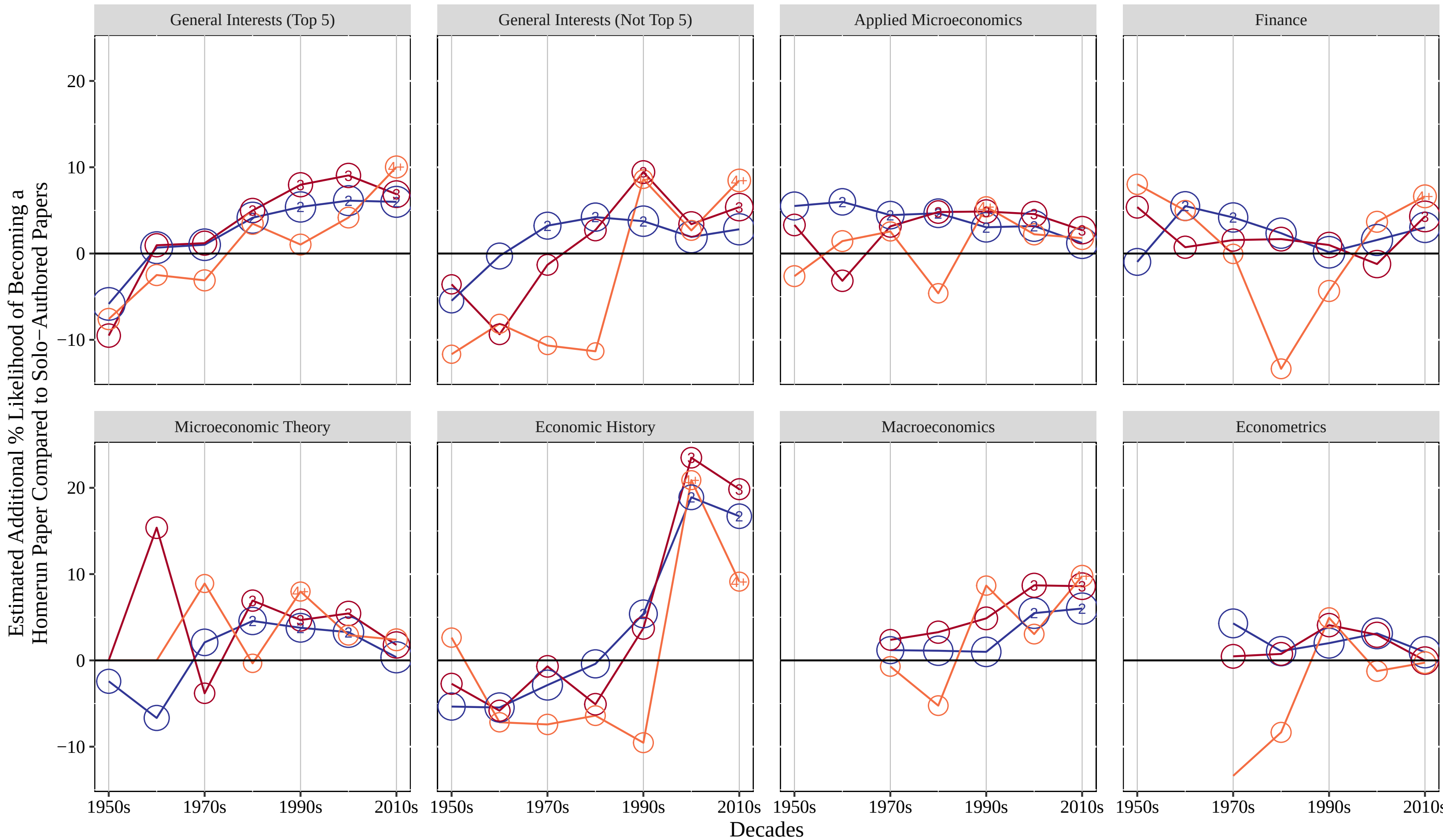
Note: The highlighted journals are journals with an average absolute difference greater than 25.

Figure B8: Evolution of Estimated Returns to Multi-Author by Field, 10-Year Periods



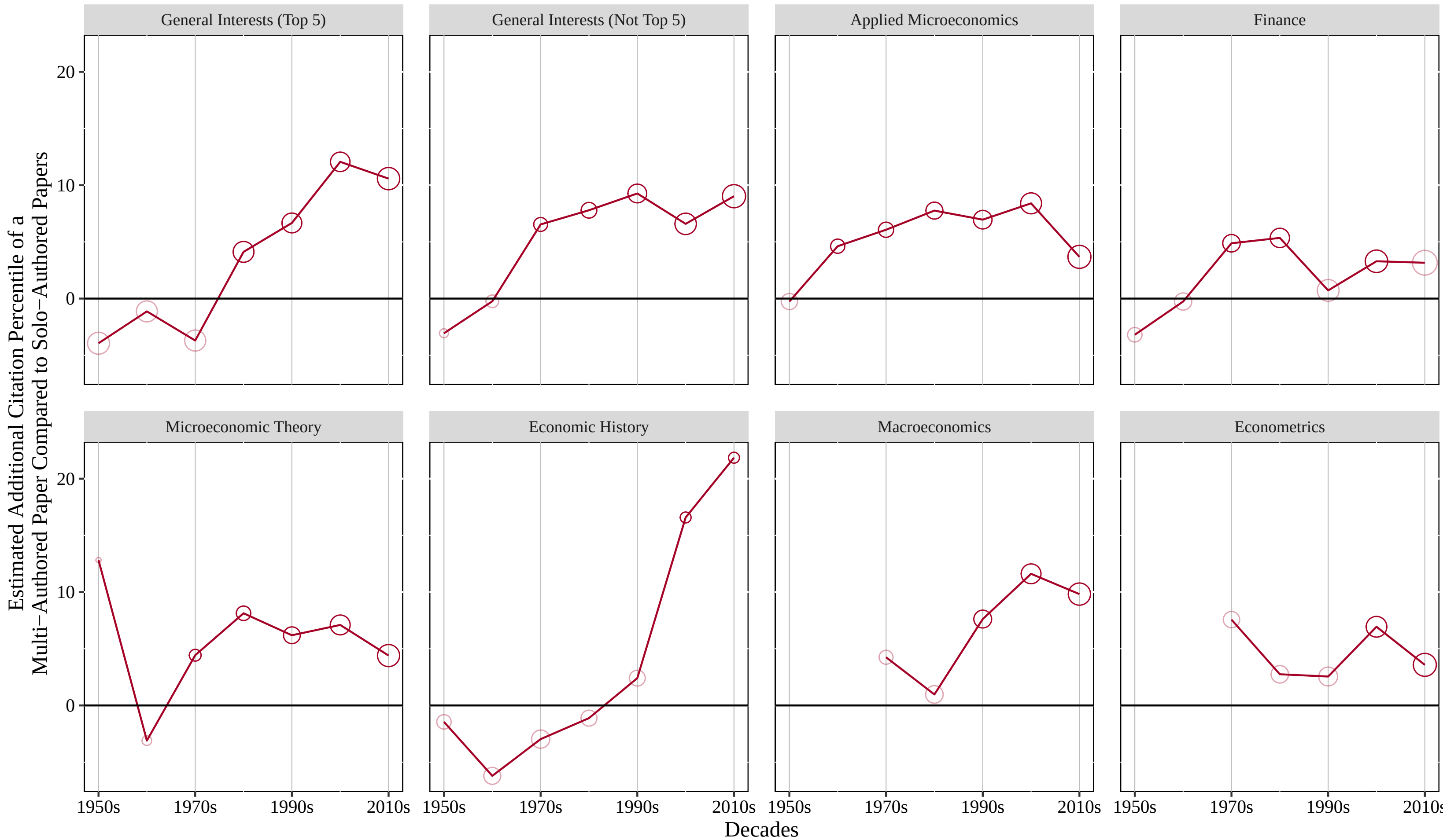
Note: Estimating equation is equation (7) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5−year citation in the top 10 percentile among EC64 papers published in that field in the same year. Sizes of the circles correpond to the shares of N−Author papers that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

Figure B9: Evolution of Estimated Returns to Number of Authors by Field, 10-Year Periods



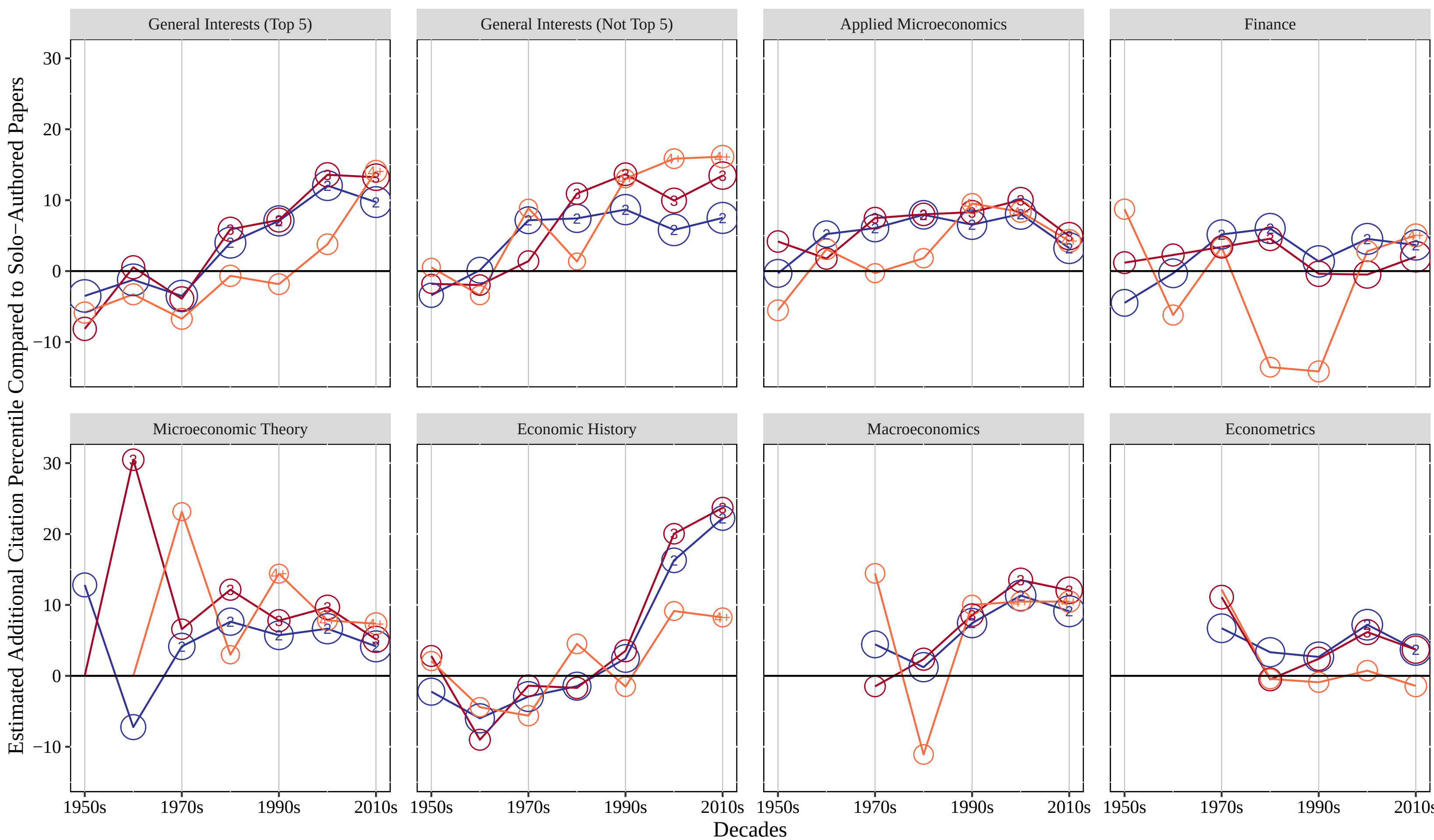
Note: Estimating equation is equation (7) with year and journal FEs for each decennial. A homerun paper is a paper that has a trailing 5−year citation in the top 10 percentile among EC64 papers published in that field in the same year. Sizes of the circles correpond to the shares of N−Author papers that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

Figure B10: Evolution of Estimated Returns to Multi-Author 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 correpond to the shares of N−Author papers that year. Number of authors are noted in the center of markers if the estimates are positive and statistically significant at the 5% level.

Figure B11: 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 correpond to the shares of N−Author papers that year. Number of authors are noted in the center of th markers if the estimates are positive and statistically significant at the 5% level.