# #Science: How Twitter Shapes Economic Research*

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**Abstract**

This paper provides the first causal evidence on the impact of Twitter usage on economic research. We link over 25,000 economists to their Twitter accounts, PhD cohorts, and detailed records of publications, citations, co-authorship networks, and research topics. To identify causal effects, we exploit plausibly exogenous variation in peer pressure to adopt Twitter arising from the research field composition of economists' PhD cohorts, and validate our instrument through placebo tests, pre-period balance checks, and event-study timing analyses. We establish four main findings. First, Twitter usage raises research output, with the average user producing approximately one additional paper every five years. Second, Twitter users receive an additional four citations per year, driven entirely by citations from other Twitter users.Third, Twitter users become significantly more likely to co-author with and cite the work of other economists on Twitter. Fourth, Twitter shapes the direction of research: adopters' work becomes increasingly similar to that of other platform users and increasingly dissimilar to that of non-users.

**Keywords**: Science of Science, Twitter, Research Productivity, Information Acquisition, Peer Effects, Herd Behavior

**JEL Codes**: D83, I23, I26, L82, L86, O31, O33,

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# 1 Introduction

Scientists build on existing research to advance the frontier of knowledge. In endogenous growth theory, the stock of existing ideas is a critical input for innovation and long-run economic growth (e.g., Romer, 1990; Jones, 1995), and disruptions to knowledge flows have been shown to substantially reduce scientific output (Iaria et al., 2018). In economics, researchers have traditionally relied on conferences, seminars, and informal exchanges with colleagues to stay abreast of developments in the field. Over the past decade, however, online social media have fundamentally reshaped these academic networks. Twitter, in particular, has emerged as a dominant platform for scholarly discourse, with the hashtag *#EconTwitter* serving as a prominent channel through which economists discover new work, signal their interests, and engage in real-time debate.

Despite the social media platform's growing prominence in the profession, little is known about how Twitter has affected knowledge production and scientific networks. The influence of social media on research likely operates through several, potentially opposing, mechanisms. On the one hand, Twitter may raise the visibility of research, lower the cost of finding collaborators, and help researchers identify which questions their peers consider important. On the other hand, it may divert attention away from deep research, amplify incentives to pursue short-lived trends, or contribute to inefficient herding behavior (e.g., Banerjee, 1992; Bikhchandani et al., 1992) in which economists converge on a narrow set of popular topics at the expense of broader scientific diversity. Hence, understanding the impact of social media on scientific research is essential for assessing how digital platforms reshape the incentives, networks, and ultimately the trajectory of scientific research. While a small number of studies have documented a positive correlation between papers' social media popularity and subsequent citations (Özkent, 2022; Sathianathen et al., 2020; Smith et al., 2019; Tonia et al., 2016), we lack causal evidence on the effects of social media on both the *productivity* and the *direction* of research.

In this paper, we provide the first causal evidence on these questions by examining the impact of Twitter on economic research from the platform's launch in 2006 through 2022. For our analysis, we construct a novel dataset linking over 25,000 economists to their Twitter accounts, PhD cohorts, and detailed records of publications, citations, co-authorship networks, and research topics. The starting point is RePEc, a comprehensive database of scholars and publications in economics. We link these records to personal Twitter accounts identified through a multi-step procedure combining information from researchers' professional websites, web searches, external datasets, and human validation. To capture peer networks, we collect PhD institutions and graduation years from research databases, faculty directories, publicly

available curricula vitae, and extensive web searches. Together, we assemble what is, to our knowledge, the largest existing database linking economists to their Twitter accounts and doctoral institutions.

The key empirical challenge in estimating the effect of Twitter on academic research is the endogeneity of the adoption decision. Researchers who join Twitter may differ systematically from those who do not in ways that also affect their research trajectories, and the direction of the resulting biases is a priori ambiguous. On the one hand, estimates could be upward-biased if more productive researchers are more likely to join Twitter. On the other hand, there could be a downward bias if researchers tend to adopt Twitter as they transition from research to policy or public engagement roles.

To overcome this challenge, we develop a novel instrumental variables strategy that exploits plausibly exogenous variation in peer pressure to adopt Twitter, arising from the research field composition of economists' PhD cohorts. Crucially, our instrument exploits variation in Twitter adoption only in fields in which the focal economist does not work, and relies on networks formed during doctoral training rather than on endogenously chosen professional connections. We validate the exogeneity of this instrument through placebo tests using shifted cohort assignments, pre-period balance checks, and event-study analyses based on the timing of peer pressure.

In our main specification, we instrument the number of years of Twitter usage with cohort-specific Twitter pressure in a two-stage least squares framework, controlling for PhD graduation year, PhD cohort size, PhD institution, and peer quality, as well as the economist's own research fields. Our approach estimates the local average treatment effect of Twitter use among economists who joined the platform due to peer pressure from their PhD cohort. We show that higher Twitter pressure significantly increases the likelihood of an economist to join Twitter. Specifically, a one-standard-deviation increase in Twitter Pressure is associated with 0.13 additional years on the platform, and the instrument significantly predicts both the extensive margin of adoption and the intensive margin of engagement. The key identifying assumption is that, conditional on controls, the research fields of one's PhD peers only affect researchers' outcomes through their effect on Twitter usage. We provide three tests in support of this assumption. First, we conduct a placebo test that reassigns each economist to the cohort graduating from the same institution fifteen years earlier, yielding estimates that are small and statistically indistinguishable from zero, which rules out the possibility that persistent institutional characteristics drive our results. Second, we show that our instrument is unrelated to scientific outcomes (publications and citations) before Twitter's launch, underlining that no pre-period differences in productivity drive our results. Third, event-study estimates show that adoption rises sharply only after the onset of peer pressure,

with no evidence of differential pre-trends, further reducing concerns that economists would have adopted Twitter even in the absence of peer pressure.

Our analysis proceeds in three parts. In the first part, we establish that Twitter usage increases both the quantity of publications and citations of economists. We estimate that Twitter users produce approximately one additional publication every five years, with gains present across the entire quality distribution of journals (i.e., from lower-ranked outlets to the Top 5). To put the most selective margin in perspective, the estimates imply that the average Twitter user accumulates roughly one additional Top 5 publication over the course of a 20-year period. Turning to citations, we find that the average Twitter user receives approximately four additional citations per year. A decomposition by the source of citations reveals that the entire increase is driven by citations from economists who are also Twitter users, while citations from non-users remain unchanged. This asymmetry is difficult to reconcile with a pure productivity channel and instead points strongly toward an additional visibility mechanism operating within the platform community. We validate these findings through placebo tests using shifted cohort assignments, which confirm that field compositions in other cohorts of the same institution produce no such results. Moreover, there are no pre-existing differences in productivity before the rollout of Twitter, and an event-study analysis shows that publication and citation gains materialize only after the onset of peer Twitter pressure.

We additionally explore heterogeneity in the returns to Twitter along two dimensions: gender and career age. First, while the effects on publications are positive for both men and women, male economists benefit significantly more in terms of citations, suggesting that, contrary to some popular narratives about social media as a leveling force (e.g., Qiu et al., 2024), Twitter may amplify rather than narrow existing gender disparities in the profession. Second, more experienced economists who completed their PhD before 2010 see substantially larger increases in both publications and citations. This pattern is consistent with established scholars being better positioned to convert platform visibility into academic recognition.

In the second part of the paper, we investigate the mechanisms behind the productivity gains by examining how Twitter reshapes co-authorship networks and the acquisition of knowledge about existing research. We find evidence of significant network restructuring. Twitter users slightly expand their set of co-authors, and these new collaborations are concentrated entirely among other economists on Twitter, with no corresponding increase in co-authorships with non-users. Moreover, Twitter users are able to attract higher-quality collaborators, as measured by their co-authors' publication records across all journal tiers. Turning to referencing behavior, we find that Twitter does not increase the total number of references economists include in their papers, but it shifts their composition. References

to work by other Twitter users nearly double, while references to work by non-users are unaffected. This compositional shift suggests that Twitter selectively expands economists' awareness of research circulating within the platform community rather than broadening their knowledge of the discipline as a whole.

Motivated by these findings, the third part of the paper asks whether the platform also influences the research questions economists choose to pursue. Using document embeddings of paper abstracts, we measure the similarity of each economist's work to that of other Twitter users and non-users, respectively. We find that Twitter adoption increases the similarity of an economist's research to that of other platform users by 0.11 standard deviations, while simultaneously decreasing similarity to the work of non-users by 0.50 standard deviations. These effects hold conditional on an economist's own research field, indicating that Twitter drives topical convergence within the platform community that goes beyond mere field selection. Together with the co-authorship and referencing results, these findings suggest that Twitter is drawing economists into a self-contained intellectual network in which members collaborate, cite each other's work, and converge on a shared set of research topics.

Taken together, our results suggest that Twitter has operated as a genuinely productivity-enhancing technology for economic research, facilitating the formation of high-quality collaborations, accelerating the diffusion of ideas, and increasing the visibility of economists' work. At the same time, the concentration of citation gains, co-authorships, and references among Twitter users, combined with the growing divergence in research topics between platform insiders and outsiders, raises important questions. If the topics that gain traction on Twitter systematically differ from those most valuable to the discipline or to society, the platform's influence on research direction could prove costly in the long run. Moreover, the finding that more experienced and male economists benefit disproportionately suggests that the returns to Twitter engagement are unevenly distributed, potentially reinforcing rather than disrupting existing hierarchies in the profession.

**Related literature** Our findings contribute to several strands of the literature. Most broadly, we contribute to the economics of science and innovation. A large body of work has studied the determinants of scientific productivity, including the role of patents and intellectual property rights (Scotchmer, 1991; Moser and Voena, 2012; Galasso and Schankerman, 2015), the geography of knowledge spillovers (Jaffe et al., 1993; Peri, 2005) the gains from collaboration (Wuchty et al., 2007; Jones et al., 2008), and the importance of access to frontier knowledge (Iaria et al., 2018). A closely related strand examines the role of peer networks in shaping scientific careers: Waldinger (2010, 2012) demonstrates that the quality of faculty and peers significantly affects PhD student outcomes, Azoulay et al. (2010) show that the premature

death of superstar scientists reduces their collaborators' output, and Borjas and Doran (2012, 2015) document both competitive and collaborative spillovers among mathematicians following the influx of Soviet émigrés. More recently, Hager et al. (2024) study how performance metrics shape the allocation of scientific talent. We contribute to this literature by identifying a previously unexplored channel through which the structure of scientific networks shapes both the quantity and the *direction* of research: the adoption of online social media platforms.

Second, we relate to the growing literature on the effects of social media. Research in this area has documented significant impacts of social media on political outcomes such as voting, polarization, and protests (e.g., Bond et al., 2012; Tucker et al., 2018; Enikolopov et al., 2020; Fujiwara et al., 2021), hate crimes (Müller and Schwarz, 2021, 2022), investment decisions (e.g., Müller et al., 2024) journalists (Hatte et al., 2021), as well as on well-being and mental health (e.g., Allcott et al., 2020; Braghieri et al., 2022).[1] Evidence regarding the effects of social media on academic research, however, is limited. A number of studies provide correlational evidence linking social media attention to subsequent citations (Eysenbach et al., 2011; Sathianathen et al., 2020; Smith et al., 2019). The two randomized studies we are aware of find conflicting results. Tonia et al. (2016) randomly promotes 130 articles on social media and finds no effect on downloads or citations, while Qiu et al. (2024) finds a positive effect of Twitter advertisement on job market outcomes, in particular for women. We advance this literature in two important ways: We provide the first large-scale causal evidence that social media usage affects scientific output and citations, and we are the first to show that social media shapes the *direction* of academic research, two dimensions that have not been explored in prior work.

Third, our findings speak to the theoretical and empirical literature on information acquisition and herd behavior. Models of social learning and informational cascades show how rational agents may disregard private information and follow the decisions of predecessors, potentially leading to inefficient herding (Banerjee, 1992; Bikhchandani et al., 1992). Subsequent theoretical work has studied how network structure mediates information aggregation and the speed of learning (Acemoglu et al., 2010, 2011). Empirically, herd behavior has been documented in a wide range of economic settings, from consumer product choice (Huang and Chen, 2006; Babić Rosario et al., 2016) to the investment decisions of professional fund managers (Scharfstein and Stein, 1990; Welch, 2000; Sias, 2004). Our finding that Twitter adoption leads economists to converge on a shared set of research topics, increasingly similar to those of other platform users and increasingly different from those of non-users, provides, to our knowledge, the first evidence of herding behavior among scientists, with potentially important implications for the diversity and long-run trajectory of scientific inquiry.

[1] See also Zhuravskaya et al. (2020) and Aridor et al. (2024) for a reviews.

# 2 Data

Our analysis draws on a novel database linking economists to their Twitter activity, academic output, and early-career peer networks. The database is, to our knowledge, the largest of its kind, covering over 25,000 economists with information on publications, citations, co-authorship networks, and research topics. We enrich the data with information on PhD institutions and graduation years, sourced from RePEc Genealogy, faculty directories, hand-collected CVs, and researchers' personal webpages. Further, we identify personal Twitter accounts through a multi-step procedure combining information from personal websites, targeted web searches, and existing external datasets. The following subsections describe each step in the data collection process.

## 2.1 Publication Data

The starting point of our data collection is RePEc (**Re**search **P**apers in **Ec**onomics), which provides a comprehensive online database of publications and author profiles in economics. RePEc is a decentralized, collaborative, non-profit initiative that aims to enhance the accessibility of research in economics and related fields. Established in 1997, RePEc aggregates research papers and metadata from over 2,000 participating archives. Publishers provide standardized, machine-readable files describing the works in their journals or working paper series, which are made accessible through various RePEc services. An advantage of RePEc is that it allows authors to create and maintain their personal research profiles, allowing them to link their work and track related statistics such as views and citations. In this way, RePEc can avoid errors in author disambiguation of papers that occur in other publication databases.

The database is organized in text files, an example of which is shown in Figure 1a. Parsing these files yields information on approximately 82,000 authors who produced more than 1.3 million publications and working papers. To exclude retired and deceased economists, we focus on the subset of 65,352 researchers who published at least one paper in our sample period (2006–2022). For each author, we observe current affiliation(s) and, where provided, links to their personal website and Twitter account, as well as a complete history of published and working papers. For each paper, the data record the title, abstract, names of all co-authors, the publishing journal or working paper series, and the date of publication. A subset of papers additionally includes author-assigned keywords, Journal of Economic Literature (JEL) topic codes, and Digital Object Identifiers (DOIs).[2] Finally, we observe the directed citation graph between papers.

[2]A DOI is a unique and persistent identifier widely used to link digital objects across different sources. See doi.org.

**Figure 1: Example of Linked Data Sources**

**(a) RePEc Data**

```
Name-First: Joshua
Name-Middle: D
Name-Last: Angrist
Name-Full: Joshua Angrist
Workplace-Name: Massachusetts Institute of Technology (MIT)
/ Economics Department
Workplace-Institution: RePEc:edi:edmitus
Workplace-Share: 60
Workplace-Name: National Bureau of Economic Research (NBER)
Workplace-Institution: RePEc:edi:nberrus
Workplace-Share: 40
Email: angrist@mit.edu
Homepage: http://web.mit.edu/angrist/www/
```

**(b) RePEc Geneology Data**

**RePEc Genealogy page for Joshua D Angrist**

This page traces who advised whom during graduate studies for Joshua D Angrist (RePEc Genealogy, EconPapers, IDEAS). You can help amend this and other pages of this project here. You can also look at the page's history.

**Graduate studies**

Joshua D Angrist got the terminal degree from Department of Economics, Princeton University, Princeton, New Jersey (USA) in 1989.

**Advisor**

1. Orley Ashenfelter (RePEc Genealogy, EconPapers, IDEAS)
2. David E. Card (RePEc Genealogy, EconPapers, IDEAS)

**(c) Twitter Data**




*Notes:* This figure visualizes three main data sources that we combine for our analysis. Panel (a) presents an example RePEc database file. Panel (b) shows a screenshot from RePEc Genealogy. Panel (c) shows a screenshot of a Twitter profile.

## 2.2 PhD institution and graduation year

As the second step of our data collection, we obtain information on economists' PhD institutions and graduation years to identify peers during doctoral studies, which we will use in our instrumental variable strategy. We collect information from four different sources.

1. *RePEc Genealogy:* We begin with the RePEc Genealogy project, which records PhD institutions and graduation years for a subset of authors with RePEc profiles. At the time of collection, the database included around 24,000 economists, even though only around 15,000 entries contain both variables.[3] We show an example of a RePec Geneology profile in Figure 1b.

2. *Hasselback Faculty Directories:* We supplement RePEc Genealogy with J. R. Hasselback's Faculty Directories, which provide hand-collected PhD institution and graduation

[3]For example, if someone listed a RePEc user as their advisor in RePEc Genealogy, the advisor's profile will be included in the Genealogy Project, but the advisor's graduation date might not be available.

year data for approximately 3,000 US-based economics faculty across 130 economics departments, compiled across five waves spanning 1999–2021, even though not all of them list PhD institutions and graduation years.[4]

3. *Curricula vitae:* We collect publicly available CVs from the personal websites identified either from the RePEc data or Google searches. Using a custom web scraper, we loop through all pages and subpages of economists' professional websites and identify links to CVs using a set of keywords commonly associated with academic CVs (e.g., CV, curriculum vitae). In cases where the automated collection fails, research assistants were instructed to locate and retrieve the files manually if available. Afterwards, we parse the documents using a large language model to extract relevant career information, including educational history and academic positions, along with associated dates. To rule out hallucinations from the large language model, we use a reverse-string-matching procedure to ensure that the extracted PhD information is indeed present in the CVs. For researchers who do not post a CV but provide career details in plain text on their website, research assistants record the information by hand. This procedure yields the PhD information for more than 9,000 economists, among them 7,700 in PDF format.

4. *LLM-augmented web retrieval:* For economists not covered by the preceding sources, we employ an LLM-augmented web search procedure using GPT-5.2 to recover additional PhD information. Specifically, we query the web search index for each researcher using their name and institutional affiliation, and prompt the model to identify and return links to webpages containing doctoral training information, such as departmental faculty pages, university archives, and professional profiles. The model then attempts to obtain PhD information from the web, always recoding both the extracted PhD information and the source URL, allowing for subsequent manual verification. This step further increases coverage among economists for whom CVs and genealogy records are unavailable.

We validate the consistency of the collected information by cross-checking the records for researchers who appear in multiple sources. Moreover, we ensure that names match across data sources and that each CV is linked to only one researcher. Finally, the data were manually validated by research assistants. In total, we recover both the PhD institution and the graduation year for 28,285 economists. To the best of our knowledge, this provides us with the largest existing database of economists and their PhD institutions.[5]

[4]We thank Advani et al. (2025) for providing the data matched to RePEc authors.

[5]For comparison, Koffi et al. (2024) hand-collect CVs for around 4,500 economists.

## 2.3 Twitter profiles

Given the absence of any complete, centralized directory linking economists to their online presence, the third step of our data collection involves identifying the personal Twitter accounts of economists through a five-step procedure using the following sources: (1) RePEc author profiles, (2) personal professional websites, (3) Google searches, (4) Twitter API profile searches, and (5) the dataset of Mongeon et al. (2023). The overall procedure is visualized in Appendix Figure A.1 and described below:

1. *RePEc profiles:* We begin by extracting all Twitter profiles that economists have registered directly on their RePEc profiles, yielding 3,256 verified links. The full list is publicly available at RePEc-registered economists on Twitter.

2. *Personal websites:* We identify personal websites both from researchers' RePEc profiles and through Google's Custom Search API, querying each researcher's first name, last name, and the keyword `economist`. We retain URLs from domains commonly associated with academic personal pages (Google Sites, WordPress, GitHub, etc.) or domains resembling the researcher's name, and manually validate each site before deploying a custom scraper to extract embedded Twitter profile links.

3. *Google searches:* We run additional Custom Search API queries restricted to Twitter.com using each researcher's first and last name, generating a large set of further candidate accounts.

4. *Twitter API:* We supplement the candidates from Step 3 using the Twitter Graph API, which was still active at the time of data collection, to search directly for profiles by name. Candidate accounts from Steps 3 and 4 are then filtered for name similarity and the presence of economics- or academia-related keywords in the profile biography.

5. *External datasets:* We incorporate the dataset of Mongeon et al. (2023), which links OpenAlex authors to Twitter profiles, matching approximately 6,500 of these profiles to our RePEc data.[6]

As a final step, we manually validate all matched Twitter accounts with the help of research assistants. The overall matching procedure is designed to minimize false positives in matching Twitter accounts to RePEc profiles: In addition to a similar name on the RePEc and Twitter profiles, we require clear evidence that the Twitter account belongs to the same person, based

[6]Much of our data collection predates the 2023 API restrictions that followed Twitter's change in ownership. For a small number of accounts identified thereafter, we supplement profile data from Garg and Fetzer (2025), who generously shared it with us.

on the RePEc profile or personal website. In particular, we instructed research assistants to look for a matching profile photo, a link between the Twitter account and the personal website, or a mention of the researcher's current academic position in the Twitter biography. We ensure that no Twitter account is linked to more than one author. For researchers with multiple accounts, we retain all of them.

In total, this procedure yields approximately 12,500 personal Twitter accounts, 7,311 of which belong to economists in our sample for whom full PhD information is available (Twitter user share = 25.8%). Despite the comprehensiveness of our collection effort, we may nonetheless fail to identify accounts that are not linked to an economist's professional identity, such as anonymous or pseudonymous accounts, as well as accounts of economists who registered on the platform but never actively used it to disseminate their work. Such "shadow" accounts are, however, arguably of limited relevance for the research outcomes we study, as these researchers' true usage of the platform is likely limited. Moreover, any resulting measurement error in Twitter adoption does not affect our IV estimates.

## 2.4 Outcome measures

We construct three sets of outcome variables that capture, respectively, economists' research output, co-authorship networks, and research topics. Each is described in turn below.

### Scientific Output

The first set of outcome variables captures standard measures of scientific output. For each economist, we count the number of publications both in total and separately by journal quality. As RePEc collects publication information based on a vast number of repositories covering working paper series, peer-reviewed, and unreviewed publications, we base our measure of scientific publication on the Top 200 journals based on RePEc's aggregate impact ranking.[7] We additionally distinguish between publication by quality based on the commonly used "Top 5" (QJE, AER, JPE, ECMA, RESTUD) and "Top General Interest" journals,[8] as well as the Top 50 and Top 100 journals. Moreover, we measure citations to publications in these journals until 2022, excluding citations from authors' own work.

[7] We provide the complete list of included Journals in Appendix Table A.1.

[8] The "Top General Interest" journals include the Top 5 plus the American Economic Journal (Applied Economics, Macroeconomics, Microeconomics, and Economic Policy), Economic Journal, Journal of the European Economic Association, and Review of Economics and Statistics.

### Scientific Network

In addition, we compile outcomes that capture connections between researchers. For each author, we measure the number of unique co-authors and the number of references. By combining these variables with information on when researchers joined Twitter, we can assess each researcher's connection to the Twitter network. Specifically, we measure the share of references to papers with at least one Twitter-using author, and the share of Twitter users among (unique) co-authors.

### Research Topics

Third, we characterize the topical similarity of research using document embeddings. Specifically, we represent each paper's abstract as a 50-dimensional vector using Doc2Vec (Le and Mikolov, 2014) and measure pairwise similarity between abstracts using cosine similarity. For each abstract, we then compute its average cosine similarity to the 100 most similar abstracts published in the same year, calculated separately for papers authored by Twitter users and non-users. This procedure yields two similarity measures for each paper: one capturing how closely an economist's research aligns with the work of others on Twitter, and one capturing alignment with the work of economists outside the platform. Together, these measures allow us to detect whether Twitter adoption shifts researchers' topical focus toward the concerns of the Twitter community and away from those of the broader discipline.

## 2.5 Sample Construction and Descriptive Statistics

Our main analysis covers the research output of economists over the period 2006–2022. This window spans almost the entire lifecycle of Twitter as a platform for academic discourse, from its launch in March 2006 through the acquisition by Elon Musk in October 2022, after which substantial platform changes, including the renaming to 𝕏 in March 2023, prompted a notable exodus of economists toward alternative networks such as BlueSky. For our instrumental variable strategy, which we describe in the next section, we additionally need to restrict our analysis to economists for whom we have information on the PhD institution and year. This allows us to use economists' academic network of researchers to identify causal effects.[9] Finally, we restrict to economists who completed their PhD between 1990 and 2022, which ensures that they are likely active at the end of our sample period.[10]

[9]This restriction also helps us to define a precise start year to include researchers in our data. Economists enter our sample in their PhD graduation year.

[10]The results are similar without this restriction.

Table 1 presents summary statistics for the cross-section of economists in our sample, where each observation represents an economist's average annual outcomes over the observation period. The typical economist publishes 0.46 papers per year, of which roughly one-third appear in Top 100 journals and fewer than one in forty in the Top 5. The average economist accrues 13.03 citations per year and collaborates with 0.69 co-authors.[11]

**Table 1: Summary Statistics**

| | Mean | SD | Min | Max | N |
|---|---|---|---|---|---|
| **General** | | | | | |
| PhD graduation year | 2007.89 | 7.88 | 1990 | 2022 | 28,285 |
| Twitter sign-up year | 2014.24 | 3.94 | 2006 | 2023 | 7,311 |
| Years on Twitter | 2.26 | 4.33 | 0 | 17 | 28,285 |
| Female | 0.27 | 0.44 | 0 | 1 | 22,064 |
| **Publications** | | | | | |
| All | 0.46 | 0.65 | 0 | 16 | 28,285 |
| Top 100 | 0.15 | 0.27 | 0 | 10 | 28,285 |
| Top General Interest | 0.02 | 0.08 | 0 | 4 | 28,285 |
| Top 5 | 0.01 | 0.06 | 0 | 3 | 28,285 |
| **Citations** | | | | | |
| All | 13.03 | 44.21 | 0 | 1651 | 28,285 |
| **Network** | | | | | |
| References | 16.25 | 27.87 | 0 | 580 | 28,285 |
| Unique co-authors | 0.69 | 1.02 | 0 | 18 | 28,285 |

*Notes:* Summary statistics at the scientist level, representing the average value across all active years between 1996 and 2022, starting from the year of PhD graduation. The sample includes only economists who graduated between 1990 and 2022 in cohorts with at least five recorded members.

# 3 Empirical Strategy

The key challenge in estimating the causal effect of Twitter use on research outcomes is the endogeneity of the adoption decision. Researchers may join Twitter for reasons that are correlated with their research trajectories but difficult or impossible to observe, rendering naive OLS estimates unreliable. The direction of the resulting bias is a priori ambiguous: For example, estimates could be upward-biased if more productive researchers are systematically more likely to join the platform, or downward-biased if researchers tend to adopt Twitter when transitioning away from research toward policy or public engagement roles.

[11]Throughout the paper, we always consider *unique* co-authors. I.e., if you co-author several papers with the same co-author, that co-author is counted only once.

To overcome this endogeneity, we propose a novel instrumental-variables strategy that exploits plausibly exogenous variation in *indirect* peer pressure to adopt Twitter, arising from the research-field composition of economists' PhD cohorts. In the following section, we describe the instrument's intuition, construction, validity, and first-stage estimates.

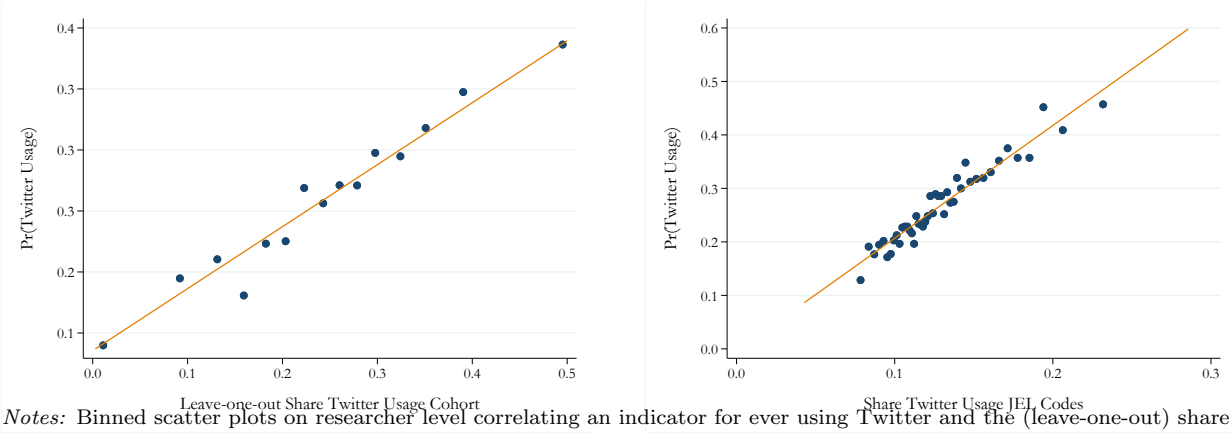
## 3.1 Peer Effects in Research Networks

Our strategy is based on the idea that the utility from using social media platforms increases in the number of peers using the same platform. Indeed, existing research shows that individuals' decisions to join social media platforms strongly correlate with their peers' usage (e.g., Aridor et al., 2024). In the context of academic research, two relevant networks are 1) classmates from the same PhD cohorts, who often form long-lasting connections that outlive the graduation, and 2) researchers in the same subfields of economics, whose collective interests and evaluations ultimately determine the academic impact and recognition of one's research.

Our data confirm that both Twitter usage in one's PhD cohort and in one's research field are good predictors of an economist's decision to join Twitter. Figure 2 Panel (a) presents a binned scatterplot of researchers' Twitter usage against the leave-one-out share of Twitter users in their PhD cohort (excluding the researcher themself). In Panel (b), we show a binned scatterplot of researchers' Twitter usage against the leave-one-out share of Twitter users in their respective research fields. In both cases, we find a strong, positive relationship between an economist's decision to join Twitter and adoption among peers.

**Figure 2: Motivational Evidence: Twitter Usage by Individual and in Network**

**(a) PhD Cohort** **(b) Research Field**




*Notes:* Binned scatter plots on researcher level correlating an indicator for ever using Twitter and the (leave-one-out) share of Twitter users in the PhD cohort (Panel (a)) and among the researchers with the same most frequent two-character JEL code (Panel (b)).

## 3.2 A Peer-Network Instrument for Twitter Adoption

We construct our instrument based on these key peer networks, exploiting two sources of variation to capture plausibly exogenous variation in individual Twitter usage: the composition of peers' research fields, and the intensity of Twitter adoption within those fields. Intuitively, researchers working in fields with high Twitter adoption face stronger incentives to join the platform as well.However, for a given researcher, adoption in fields outside their own should not directly affect their scientific outcomes, as they are not directly connected to those parts of the research network. Instead, it should only indirectly increase their research outcomes, through their peers' sign-up decisions (and ultimately their own). Therefore, the field-specific pressure to use Twitter that PhD colleagues face arguably shifts individual Twitter use without directly affecting outcomes such as research productivity, quality, or topics.

We instrument researchers' individual Twitter usage with a flexible prediction of PhD-cohort-level Twitter usage based solely on cohort members' research fields. This instrument closely relates to two key concepts in the literature on identification of causal effects in social networks. First, building on the long-standing literature on peer effects (e.g., Manski, 1993; Goldsmith-Pinkham and Imbens, 2013; Angrist, 2014), we exploit the fact that the characteristics of the members of one's PhD cohort can influence one's decisions. Second, we exploit the network structure of the academic research environment for identification using the indirect effect of "peers of peers" who are not peers themselves (e.g., Bramoullé et al., 2009; Lin, 2010; De Giorgi et al., 2010).

First, we identify PhD peers using information on researchers' doctoral institutions and graduation years, defining a PhD cohort as all scholars who graduated from the same institution within 5 years before or after the researcher's graduation.[12] Second, we identify the research fields of economists based on the JEL codes indicated in their research papers. In our baseline approach, we classify the relative weight of each economist's fields based on the share of each JEL code letter (i.e., A-Z, 20 distinct codes) among their research papers in their entire career. We average these shares across each PhD cohort to obtain the cohort-level composition of research fields. We predict the cohort-level Twitter shares as a function of cohort fields in the form:

$$\text{Twitter Share Cohort}_i = f(W_i) + \varepsilon_i, \tag{1}$$

where Twitter Share Cohort$_i$ denotes the leave-one-out share of Twitter users in economist $i$'s PhD cohort in 2022, and $W_i \in [0,1]^{20}$ denotes the corresponding leave-one-out vector

[12]This window is motivated by the typical duration of economics PhD programs, which averages five to six years, and is designed to capture the full set of doctoral peers an economist is likely to have interacted with during their studies. Our results are robust to alternative cohort window specifications.

capturing the weight of each JEL code letter in the cohort. We restrict the sample to PhD cohorts with at least five cohort members to ensure high accuracy in the measurement of field compositions. The predicted values Twitter $\widehat{\text{Share}}$ $\text{Cohort}_i$ thus capture the component of cohort-level Twitter adoption that is driven by the field composition of the PhD cohort, rather than by idiosyncratic adoption decisions of individual economists.

We estimate $f(\cdot)$ using a cross-fitted gradient-boosted random forest (XGBoost).[13] The XGBoost predictor captures the nonlinearities and interactions that likely characterize the relationship between research fields and Twitter usage.Moreover, rather than treating each field as a separate instrument, our approach combines all potential shifters into a single index, which avoids the finite-sample distortions that can arise in many-instrument IV settings and thus yields a more stable first stage. The leave-own-institution-out cross-fitting procedure ensures that predictions are unbiased. In particular, because the instrument assigned to economist $i$ is never estimated using observations from $i$'s own institutional environment, we eliminate any mechanical correlation ("overfitting bias") between the generated instrument and the structural error term. Therefore, cross-fitting is crucial for restoring the orthogonality condition required for consistent 2SLS estimation.

Our strategy offers three key advantages. First, by constructing the instrument from the Twitter adoption decisions of indirect peers rather than from the researcher or their immediate colleagues, we sidestep the reflection problem (Manski, 1993): since indirect peers do not directly influence the researcher, the mutual causation that confounds peer-effect estimation is broken by construction. Second, we exploit networks formed during doctoral studies rather than current professional networks. PhD cohort composition is determined prior to and independently of any career or research decisions, and remains fixed throughout an economist's career. This rules out the possibility that endogenous changes in network links or the strategic selection of colleagues could contaminate the instrument. Third, by controlling for researchers' own fields, we leverage variation in Twitter adoption exclusively in research fields in which the economist does not herself work. This ensures that the instrument is insulated from field-specific shocks, such as a surge of interest in a particular topic that might simultaneously drive Twitter adoption and research output, and thereby helps satisfy the exclusion restriction.

## 3.3 Estimation

After constructing the predicted Twitter adoption (Twitter $\widehat{\text{Share}}$ $\text{Cohort}_i$) in economist $i$'s PhD cohort, we standardize the variable to have zero mean and unit standard deviation, and

[13] As a robustness check, we also estimate the prediction function using a Ridge regression, adding interactions between all fields.

refer to it as *Twitter Pressure* hereafter. We estimate the effect of Twitter usage using the following two-stage least squares (2SLS) specification:

$$\text{Years on Twitter}_i = \omega + \lambda \, \text{Twitter Pressure}_i + \mathbf{X}'\gamma + \eta_i \tag{2}$$

$$y_i = \alpha + \beta \, \widehat{\text{Years on Twitter}}_i + \mathbf{X}'\theta + \varepsilon_i \ , \tag{3}$$

where $y_i$ denotes an outcome variable for researcher $i$ (e.g., academic output, citations, or research topics) in the period 2006 to 2022. The primary variable of interest is $\widehat{\text{Years on Twitter}}_i$ and captures the number of years an economist spent on Twitter until 2022.[14] In our regression, we additionally account for a large set of observable controls $\mathbf{X}'$: i) PhD graduation year fixed effects flexibly capture experience, ii) cohort size controls for the potential size of the initial research network, iii) measures the quality of the PhD institution and quality of PhD peers, respectively, by including the first principal component of the number of publications and citations, and iv) the top JEL code letter of researcher $i$, which captures any direct effect of economists $i$'s research field. We cluster standard errors at the PhD institution $\times$ graduation year level throughout.[15]

## 3.4 First Stage Estimates

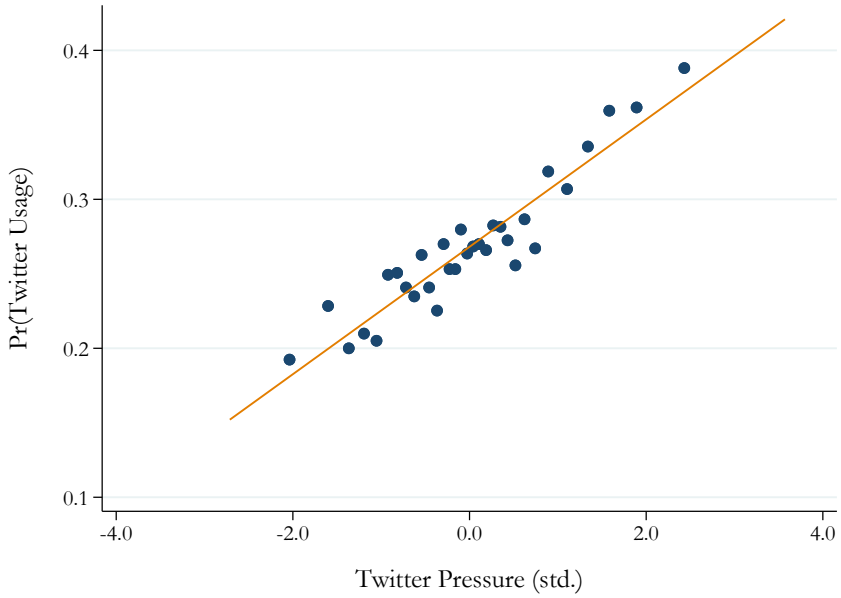
We begin by presenting graphical evidence for the relevance of our instrument in Figure 3, which plots the probability of Twitter adoption against standardized Twitter Pressure in a binned scatter plot. The figure reveals a strong, monotone, and approximately linear relationship between the field-composition-implied peer pressure to adopt Twitter and an economist's own probability of joining the platform.

Table 2 presents the first-stage estimates of the relationship between Twitter Pressure and years of Twitter usage. Column (1) includes only PhD graduation year fixed effects and a control for the size of the PhD cohort, yielding a coefficient of 0.201. Column (2) adds the controls for PhD institution quality, and Column (3) further includes controls for peer quality within the same PhD cohort. Column (4) adds research field controls, accounting for any residual variation in Twitter Pressure driven by field-specific adoption patterns, yielding a final coefficient of 0.135. Across all specifications, the estimate remains positive and significant at the one percent level. In our most demanding specification, a one-standard-deviation increase in Twitter Pressure is associated with approximately 0.135 additional years on the platform, a meaningful increase of 5.2% relative to the sample mean of 2.16 years.

[14] In alternative specifications, we also use an indicator for Twitter adoption, which captures the extensive instead of intensive margin of using Twitter.

[15] As we show later, the results are robust to alternative clustering schemes, including clustering by PhD institution alone, by graduation year alone, and at the individual level.

**Figure 3: First Stage: Network Twitter Pressure and Twitter Adoption**




*Notes:* Binned scatter plot on researcher level correlating an indicator for ever using Twitter with standardized cohort-level Twitter Pressure (excluding self).

**Table 2: First Stage: Network Twitter Pressure and Twitter Adoption**

| | Dep. Var.: Years of Twitter Usage | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Twitter Pressure (std.) | 0.201*** | 0.178*** | 0.178*** | 0.134*** |
| | (0.031) | (0.031) | (0.031) | (0.031) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 2.16 | 2.16 | 2.16 | 2.16 |
| $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* Regressions of the number of years of Twitter usage on standardized Twitter Pressure in PhD cohort (excluding self), controlling for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We also verify that our instrument predicts both the extensive and intensive margins of Twitter usage. On the extensive margin, we replace the dependent variable with an indicator for whether an economist ever joined Twitter. As reported in Appendix Table A.3, a one-standard-deviation increase in Twitter Pressure raises the probability of joining the platform by approximately 1.6 percentage points, representing an increase of around 5.9% relative to the sample mean, and the association is highly significant across all specifications. On the intensive margin, we define indicator variables for economists who used Twitter for at least 2, 5, 7, or 10 years and estimate the first stage separately for each threshold (see Appendix Table A.4). Across all thresholds, higher Twitter Pressure is associated with a significantly greater number of years on the platform, confirming that our instrument captures meaningful variation in the timing of Twitter adoption beyond the binary adoption decision.

## 3.5 Exclusion Restriction

As with any instrumental variables strategy, our approach requires the exclusion restriction to hold: variation in Twitter Pressure across PhD cohorts must affect economists' research outcomes exclusively through its impact on their own Twitter usage, and not through any direct channel. While this assumption is inherently untestable, we consider it plausible in our setting for at least three reasons.

First, our instrument is constructed from Twitter adoption in research fields other than the economist's own, and explicitly excludes information on Twitter usage within the economist's own PhD cohort. This double exclusion makes it highly unlikely that any individual economist could directly influence their own exposure to the instrument. Moreover, as we demonstrate below, Twitter Pressure is uncorrelated with economists' research productivity in the pre-Twitter period, providing direct empirical support for the validity of the exclusion restriction.

Second, we conduct a placebo test by shifting each economist's PhD graduation year back by 15 years, constructing a placebo instrument that captures the Twitter Pressure they would have faced had they graduated from the same institution earlier and therefore interacted with an entirely different peer group. For example, the placebo instrument assigns to an economist who graduated from Harvard in 2015 the Twitter Pressure corresponding to the 2000 Harvard cohort. Since this test requires observing individuals in the earlier placebo cohorts, it is necessarily restricted to economists who completed their PhD after 2010. The results are reported in Table 3. The placebo estimates are uniformly smaller than the baseline and statistically indistinguishable from zero, whereas our baseline IV estimates remain positive and significant at the 1% level throughout. This pattern is precisely what one would expect under the exclusion restriction: if an omitted institutional factor were simultaneously driving Twitter adoption and research outcomes, it should manifest equally in the true and placebo

instruments. The fact that it does not provides strong evidence that our instrument captures genuine peer-induced variation in Twitter adoption rather than confounded institutional characteristics.

**Table 3: First Stage: Placebo Network Twitter Pressure and Twitter Adoption**

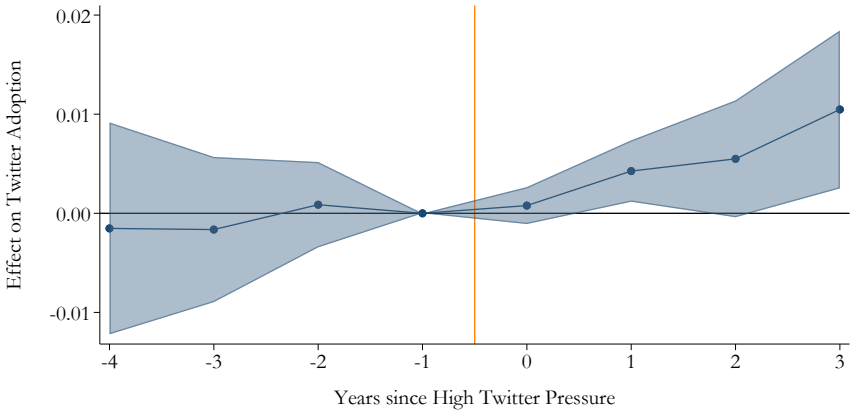
| | Dep. Var.: Years of Twitter Usage | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Twitter Pressure (std.) | 0.175*** | 0.173*** | 0.174*** | 0.128*** |
| | (0.047) | (0.047) | (0.048) | (0.048) |
| Placebo Twitter Pressure Pre. (std.) | 0.037 | 0.003 | 0.002 | -0.018 |
| | (0.047) | (0.048) | (0.049) | (0.048) |
| Observations | 10,162 | 10,162 | 10,162 | 10,162 |
| Mean of DV | 2.37 | 2.37 | 2.37 | 2.37 |
| $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* Regressions of the number of years of Twitter usage on standardized Twitter Pressure in PhD cohort (excluding self) as well as a placebo instrument, in which each researcher's graduation year is individually shifted back 15 years, for researchers graduating after 2010. Controls include the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Third, we examine the timing of our instrument's effect on Twitter adoption by estimating a staggered difference-in-differences specification in which researchers are treated once their Twitter Pressure turns positive, using the heterogeneity-robust estimator of De Chaisemartin and D'Haultfoeuille (2022). The resulting event-study estimates are shown in Figure 4. Two features of the figure are noteworthy. First, the pre-treatment coefficients are small and statistically indistinguishable from zero, supporting the parallel trends assumption and the notion that, in the absence of peer-induced Twitter pressure, economists would not have systematically differed in their propensity to adopt the platform. Second, the probability of joining Twitter rises sharply and significantly in the periods following the onset of positive Twitter Pressure.

Together, these three pieces of evidence, along with the additional validity tests we will provide later, suggest that our instrument provides plausibly exogenous variation in Twitter usage, which we will exploit in the following analysis to estimate the effect of Twitter usage on economists' research.

**Figure 4: Dynamic Effect of Twitter Pressure on Twitter Adoption**




*Notes:* Point estimates and 95 percent confidence intervals for the yearly effect of High Twitter Pressure on the indicator for using Twitter in the year, estimated using the heterogeneity-robust estimator by De Chaisemartin and d'Haultfoeuille (2020) in the author-year panel. High Twitter Pressure is an indicator that switches to 1 once Twitter Pressure becomes strictly positive.

### 3.6 Robustness

We verify the robustness of our first-stage estimates across several dimensions. First, Appendix Table A.5 shows that the instrument is robust to alternative definitions of the PhD cohort window, varying the bandwidth from ±3 to ±6 years around the researcher's graduation year, with no material impact on the estimates. Second, Appendix Table A.6 confirms that the results are virtually unchanged when replacing the XGBoost prediction function with a Ridge regression that includes both the shares of JEL code letters and their interactions, demonstrating that our findings are not sensitive to the choice of prediction model. Third, Appendix Table A.7 shows that the estimates are robust to alternative clustering schemes, including clustering by PhD institution, graduation year, or PhD cohort. Fourth, Appendix Figure A.2 presents a leave-one-institution-out analysis in which we sequentially exclude each PhD institution from the estimation sample, confirming that the first-stage relationship is not driven by any single institution and holds uniformly across the distribution of PhD-granting universities.

## 4 Effect of Twitter on Scientific Output

We begin by documenting the effect of Twitter usage on economists' research output. We first examine the impact on publication counts, both overall and across the quality distribution of journals, before turning to the effect on citations received. We then explore heterogeneity in these effects along two dimensions: gender and career stage.

## 4.1 Publications

Table 4 presents the second-stage estimates of the effect of Twitter usage on the average annual number of publications, using Twitter Pressure as an instrument for years on Twitter. The specifications mirror the structure of the first stage. Column (1) includes only PhD graduation year fixed effects and a control for the size of the PhD cohort. Column (2) additionally controls for the quality of PhD institutions. Column (3) further adds controls for the quality of PhD peers. Finally, column (4) includes research field controls. Across all specifications, we find that Twitter usage substantially increases economists' publication output. The estimates are positive and significant across all specifications. Given that the average number of years of Twitter usage (including non-users) is 2.16, the magnitude of the coefficient in column (4) implies that Twitter users, on average, published one additional paper every 5 years.

**Table 4: Effect of Twitter Usage on Number of Publications**

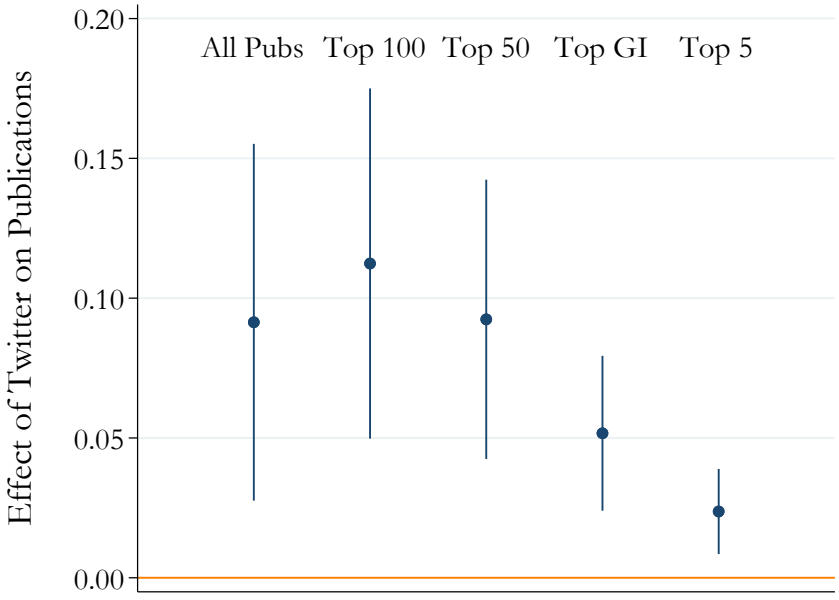
| | Dep. Var.: Nr. of Publications per Year | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Years of Twitter Usage | 0.088*** | 0.061*** | 0.056*** | 0.091*** |
| | (0.022) | (0.022) | (0.021) | (0.033) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 0.38 | 0.38 | 0.38 | 0.38 |
| F-Stat (KP) | 42.78 | 33.58 | 33.38 | 18.61 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by Twitter Pressure in PhD cohort, on the average number of publications per year. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of the average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A natural question concerns the distribution of quality of the additional publications generated by Twitter use: do the gains accrue disproportionately to lower-ranked journals with high acceptance rates, or do they extend to the most selective outlets? We study this question by replacing the dependent variable with publication counts in journals of progressively higher quality (i.e., the Top 100, Top 50, Top General Interest, and Top 5). The estimates are visualized in Figure 5 and reported in full in Appendix Table A.8. We find that Twitter usage is associated with an increase in publications across all quality tiers, with coefficients that generally decline with journal selectivity: 0.112 for the Top 100, 0.092 for the Top 50, 0.051 for Top General Interest journals, and 0.024 for the Top 5. While the

effects are naturally smaller in absolute magnitude for more prestigious outlets, they remain statistically significant throughout and are increasing in relative terms. To put the Top 5 estimate in perspective, it implies that the average Twitter user accumulates approximately one additional Top 5 publication over the course of 20 years. Taken together, these results suggest that Twitter use significantly increased the number of publications by economists and their ability to publish in high-quality journals.

**Figure 5: Heterogeneity by Publication Quality**




*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by Twitter Pressure in PhD cohort, on the number of yearly publications in different brackets of journal impact factor. The first three estimates refer to the Top 200, Top 100, and Top 50 ranked journals, while the last three estimates refer to the 12 Top General Interest and Top 5 journals, respectively. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of the average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Vertical bars denote 95-percent confidence intervals. Standard errors are clustered by PhD-institution-by-year.

### Placebo Test

One concern with the previously presented estimates is that our instrument may be correlated with university-level factors that independently drive research productivity, rather than capturing genuine peer-induced variation in Twitter adoption. To address this concern, we repeat the placebo test from the first stage using the number of publications as the outcome variable, assigning to each economist the Twitter Pressure they would have faced had they graduated from the same institution fifteen years earlier. The results are reported in Table 5. Mirroring the first-stage placebo results, the placebo Twitter Pressure estimates are small and statistically indistinguishable from zero. In contrast, the baseline Twitter Pressure estimates

remain positive and significant at the 1% level across all specifications, with coefficients ranging from approximately 0.014 to 0.019. The sharp contrast between the significant baseline estimates and the near-zero placebo estimates provides strong evidence that our instrument captures genuine peer-induced variation in Twitter adoption rather than spurious institutional or cohort-level confounders that could independently affect research productivity.

**Table 5: Placebo: Effect of Twitter Usage on Number of Publications**

| | Dep. Var.: Nr. of Publications per Year | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Twitter Pressure (std.) | 0.016*** | 0.015*** | 0.015*** | 0.014*** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Placebo Twitter Pressure Pre. (std.) | -0.001 | -0.009* | -0.009* | -0.008* |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Observations | 10,162 | 10,162 | 10,162 | 10,162 |
| Mean of DV | 0.28 | 0.28 | 0.28 | 0.28 |
| $R^2$ | 0.00 | 0.02 | 0.02 | 0.02 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* Reduced-form estimates for the effect of Twitter Pressure in PhD cohort and a placebo instrument, in which each researcher's graduation year is individually shifted back 15 years, on the average number of publications per year, for researchers graduating after 2010. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of the average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

### Pre-Period Balance Test

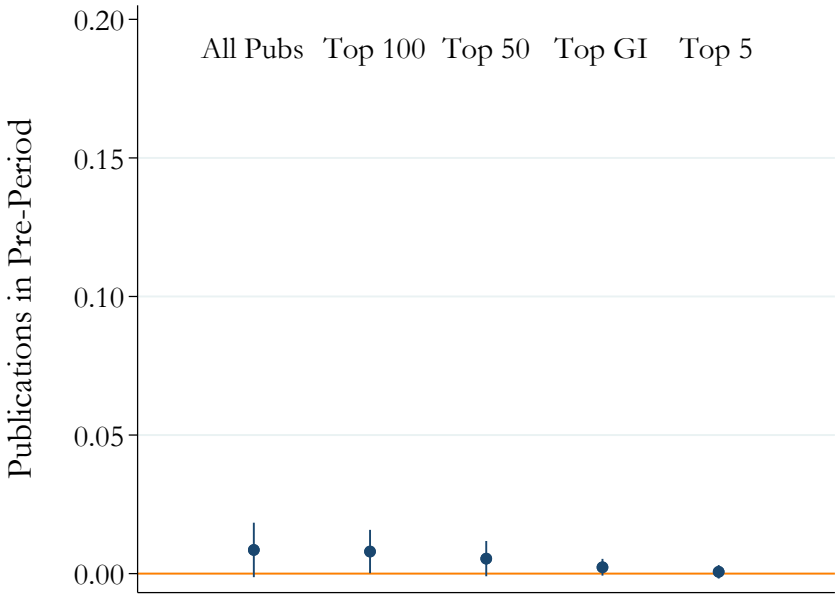
Another concern with our findings could be that our instrument captures pre-existing differences in research productivity rather than the genuine effect of Twitter adoption. To address this concern, we examine the correlation between our instrument and economists' publication output during the pre-Twitter period, 1996 through 2005.[16] The estimates from this exercise are reported in Figure 6. The figure plots the reduced-form coefficients from regressing pre-period publication counts on our standardized Twitter Pressure measure, separately for all publications and each journal quality tier.[17] If our instrument were capturing pre-existing

[16]Note that since we need to observe publications in the pre-period for this test, the sample is restricted to individuals who finished their PhD before 2005. As we show in Appendix Table A.9, we also observe a positive impact of our instrument on publication outcomes in this sample.

[17]We use a reduced form specification as mechanically nobody was a Twitter user in this time period. Note that this, if anything, would allow us to detect smaller pre-period differences than the IV specification.

differences in research productivity, we would expect to find a positive and significant relationship between Twitter Pressure and publication counts in this period. Across all five quality categories, the coefficients are economically small and statistically indistinguishable from zero. This balance test provides strong reassurance that our instrument is orthogonal to economists' pre-existing productivity, and that the publication gains we document in the post-Twitter period reflect a genuine causal effect of platform adoption rather than a spurious correlation with unobserved researcher quality.

**Figure 6: Correlation of Instrument with Publication in Pre-Period**



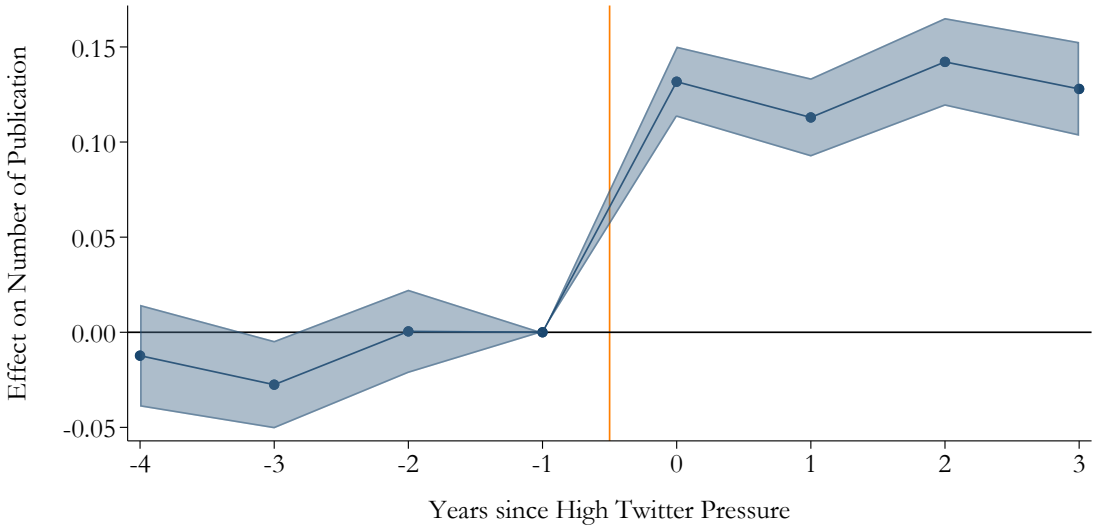

*Notes:* Reduced form estimates for the effect of Twitter Pressure on the number of yearly publications in different brackets of journal impact factor, for researchers graduating between 1990 and 2005. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of the average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Vertical bars denote 95-percent confidence intervals. Standard errors are clustered by PhD-institution-by-year.

### Timing of Effect

As an additional validity test of our instrumental variable strategy, we examine the timing of the effect of Twitter adoption on publication output by estimating a staggered difference-in-differences specification in which researchers are treated once their Twitter Pressure turns positive, using the heterogeneity-robust estimator of De Chaisemartin and D'Haultfoeuille (2022). The resulting event-study estimates are shown in Figure 7. We again find that pre-treatment coefficients are small and close to zero, confirming the absence of differential pre-trends in publication output. Only after the increase in Twitter pressure, we observe an increase in the number of publications, with the effect stabilizing at around 0.11 to 0.14

additional publications per year in the post-treatment periods. Notably, the increase occurs immediately upon treatment rather than with a delay, which is consistent with Twitter facilitating the dissemination and visibility of papers already in the pipeline at the time of adoption.

**Figure 7: Dynamic Effect of Twitter Pressure on Number of Publications**




*Notes:* Point estimates and 95 percent confidence intervals for the yearly effect of high Twitter Pressure on the indicator for using Twitter in the year, estimated using the heterogeneity-robust estimator by De Chaisemartin and d'Haultfoeuille (2020) in the author-year panel. High Twitter Pressure is an indicator that switches to 1 once Twitter Pressure exceeds 0.

## 4.2 Citations

We next study the effect of Twitter usage on received citations to understand the impact of published papers and their visibility in the academic community. Table 6 shows that Twitter usage also increases the average number of citations that economists receive.[18] Across all specifications, the estimates are positive and significant at the 5% level. The magnitude in Column (4) implies that the average Twitter user receives an additional 4.04 ($1.872 \cdot 2.16$) citations per year.

The documented increase in citations could stem from two different margins. First, as we have shown in the previous part, Twitter users publish more papers than non-Twitter users. Second, each individual publication of Twitter users could receive more citations. To differentiate between these two margins, we additionally investigate the average number of citations per publication (see Table A.11). We find that Twitter usage also increases the

[18]To avoid our findings being driven by outliers, we winsorize citations counts at the 99th percentile. The findings are very similar without this modification (see Table A.10)

**Table 6: Effect of Twitter Usage on Number of Citations**

| | Dep. Var.: Nr. of Citations | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Years of Twitter Usage | 2.063*** | 1.476** | 1.279** | 1.872** |
| | (0.638) | (0.668) | (0.650) | (0.921) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 6.53 | 6.53 | 6.53 | 6.53 |
| F-Stat (KP) | 42.78 | 33.58 | 33.38 | 18.61 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of citations received per year (winsorized at $99^{th}$ percentile). The specifications control for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of the average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

number of citations per publication. The estimates suggest that the average Twitter user's publication receives around 5 additional citations.

The previous results are consistent with the commonly suggested notion that Twitter enables economists to advertise their research directly to peers on the platform. We investigate this mechanism more directly by decomposing the citation effect into citations from other Twitter users and from non-Twitter users, respectively.[19] The results are presented in Table 7, with Panel A reporting estimates for citations from Twitter users and Panel B reporting estimates for citations from non-Twitter users. The decomposition reveals a striking asymmetry: the overall increase in citations documented above stems entirely from additional citations by other Twitter users, while citations from economists outside the platform remain unchanged across all specifications.[20] This pattern is difficult to reconcile with a productivity effect; if Twitter merely made economists more productive, one would expect citations to increase across both groups. Instead, the concentration of citation gains among Twitter users strongly points to a visibility mechanism: by joining the platform, economists gain exposure to a community of peers who are more likely to encounter, engage with, and ultimately cite their work.

[19]A paper is considered authored by a Twitter user if at least one of its authors was active on the platform at the time of publication.

[20]In Appendix Table A.12, we confirm that higher Twitter usage also leads to a significantly larger share of citations from Twitter users.

**Table 7: Effect of Twitter Usage on Number of Citations from Twitter**

| | Dep. Var.: Number of Citations | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: Citations from Twitter Users* | | | | |
| Years of Twitter Usage | 2.776*** | 2.389*** | 2.252*** | 2.208*** |
| | (0.550) | (0.572) | (0.554) | (0.743) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 5.26 | 5.26 | 5.26 | 5.26 |
| *Panel B: Citations from non-Twitter Users* | | | | |
| Years of Twitter Usage | 1.423* | 0.231 | -0.103 | 0.202 |
| | (0.783) | (0.831) | (0.818) | (1.095) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 10.39 | 10.39 | 10.39 | 10.39 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of citations received per year from papers with/without at least one Twitter-using author (winsorized at $99^{th}$ percentile). The specifications control for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of the average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

### Placebo Test

As with publications, we provide evidence for the validity of our instrumental variable strategy by repeating the placebo test using the number of citations as the outcome variable. The results are reported in Table 8. The pattern closely mirrors that observed for publications and the first stage. The placebo estimates are small and statistically indistinguishable from zero. By contrast, the baseline Twitter Pressure estimates remain positive and highly significant throughout, ranging from 0.311 to 0.345 across specifications. In this way, the placebo test again provides reassurance that the citation gains we document reflect genuine variation in Twitter adoption rather than confounding institutional characteristics.

**Table 8: Placebo: Effect of Twitter Usage on Number of Citations**

| | Dep. Var.: Nr. of Citations | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Twitter Pressure (std.) | 0.345*** | 0.335*** | 0.320*** | 0.311*** |
| | (0.086) | (0.082) | (0.082) | (0.083) |
| Placebo Twitter Pressure Pre. (std.) | 0.108 | -0.024 | -0.013 | -0.038 |
| | (0.100) | (0.100) | (0.099) | (0.099) |
| Observations | 10,162 | 10,162 | 10,162 | 10,162 |
| Mean of DV | 2.85 | 2.85 | 2.85 | 2.85 |
| $R^2$ | 0.04 | 0.05 | 0.05 | 0.04 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* Reduced-form estimates for the effect of Twitter Pressure in PhD cohort and a placebo instrument, in which each researcher's graduation year is individually shifted back 15 years, on the average number of citations received per year (winsorized at $99^{th}$ percentile), for researchers graduating after 2010. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of the average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

### Pre-Period Balance Test

Table 9 complements the placebo test by directly examining the correlation between our instrument and citation counts in the pre-Twitter period from 1996 to 2005.[21] If Twitter Pressure were proxying for unobserved researcher quality rather than capturing genuine variation in Twitter adoption, we would expect to find a positive and significant relationship

[21]This test is again necessarily restricted to economists who completed their PhD before 2005, as pre-period outcome data must be observed for all individuals in the sample. Reassuringly, as shown in Appendix Table A.9, our instrument retains a positive and significant effect on publication outcomes within this restricted sample.

between our instrument and pre-period citation counts. We again find no statistically significant correlation between our instrument and the number of citations in the pre-period. The fact that our instrument is uncorrelated with pre-period citation counts provides strong evidence that Twitter Pressure captures genuine variation in adoption pressure rather than pre-existing differences in economist quality, and that the citation gains we document in the post-Twitter period reflect a true causal effect of platform adoption.

**Table 9: Balance Test: Citations in Pre-Period**

| | Dep. Var.: Nr. of Citations (1996 - 2005) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Twitter Pressure (std.) | 0.711 | 0.389 | 0.325 | 0.343 |
| | (0.435) | (0.429) | (0.429) | (0.436) |
| Observations | 11,692 | 11,687 | 11,685 | 11,679 |
| Mean of DV | 13.45 | 13.46 | 13.46 | 13.47 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

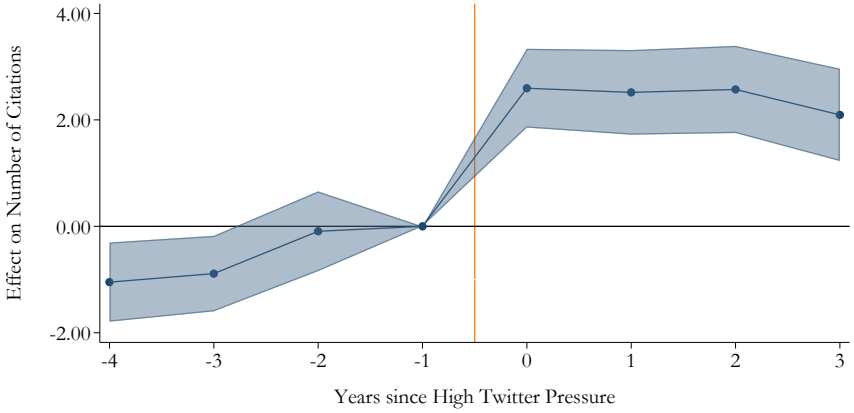
*Notes:* Reduced form estimates for the effect of Twitter Pressure on the average number of citations per year before 2005 (winsorized at $99^{th}$ percentile), for researchers graduating between 1990 and 2005. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of the average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

### Timing of Effect

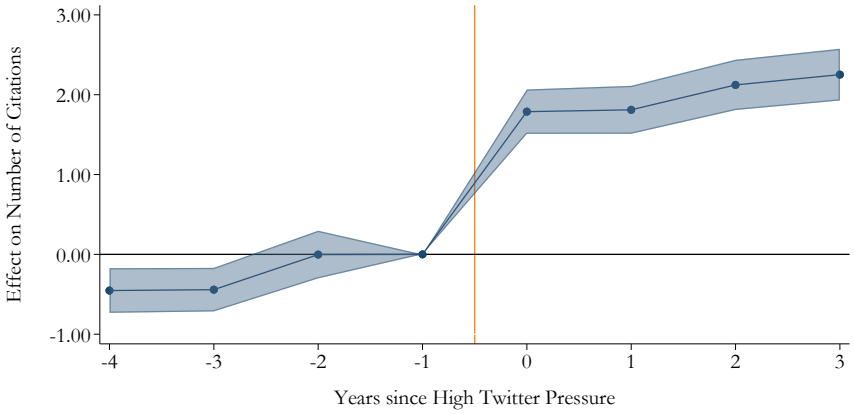
As a further validity check of our identification strategy, we again estimate staggered difference-in-differences estimates using citation counts as the dependent variable. Figure 8 presents the event-study estimates separately for all citations (Panel a) and citations originating exclusively from other Twitter users (Panel b). In both cases, the pre-treatment coefficients hover close to zero. Citation counts then rise sharply and immediately following the increase in Twitter pressure, with the effect on total citations stabilizing at approximately 2 to 2.5 additional citations per year and persisting over the following years. The immediate onset of the citation effect is consistent with Twitter serving as a rapid dissemination channel through which economists advertise their existing work to an audience of platform peers, thereby generating citations.

## Figure 8: Dynamic Effect of Twitter Pressure on Number of Citations

### (a) All Citations




### (b) Citations from Twitter Users




*Notes:* Point estimates and 95 percent confidence intervals for yearly effect of high Twitter Pressure on number of citations received per year (winsorized at $99^{th}$ percentile). Panel (a) counts all citations, while Panel (b) counts citations from papers with at least one Twitter user among the authors at the time of publication. Estimated using the heterogeneity-robust estimator by De Chaisemartin and d'Haultfoeuille (2020) in the author-year panel. High Twitter Pressure is an indicator switching to one once Twitter Pressure exceeds zero.

## 4.3 Robustness

We subject our publication estimates to the same battery of robustness checks as the first stage. Appendix Table A.14 confirms that the results are insensitive to the choice of cohort window, with estimates remaining stable across bandwidth definitions ranging from $\pm 3$ to $\pm 6$ years around the researcher's graduation year. Appendix Table A.15 shows that the findings are virtually unchanged when replacing the XGBoost prediction function with Ridge regression, demonstrating that our conclusions do not depend on the choice of prediction model used to construct the instrument. Appendix Table A.16 establishes that the estimates are robust to alternative clustering schemes, including clustering by PhD institution, graduation year, or PhD cohort, with standard errors remaining of comparable magnitude throughout. Finally, Appendix Figure A.3 presents a leave-one-institution-out analysis in which we sequentially exclude each PhD institution from the estimation sample, confirming that the publication effects are not driven by any single institution and hold uniformly across the distribution of PhD-granting universities.

We repeat all four robustness checks using citation counts as the dependent variable, with results reported in Appendix Table A.17, Table A.18, Table A.19, and Figure A.4, respectively. The citation estimates are equally robust across all dimensions, and the conclusions drawn from the robustness analysis for publication carry over without qualification.

## 4.4 Effect Heterogeneity

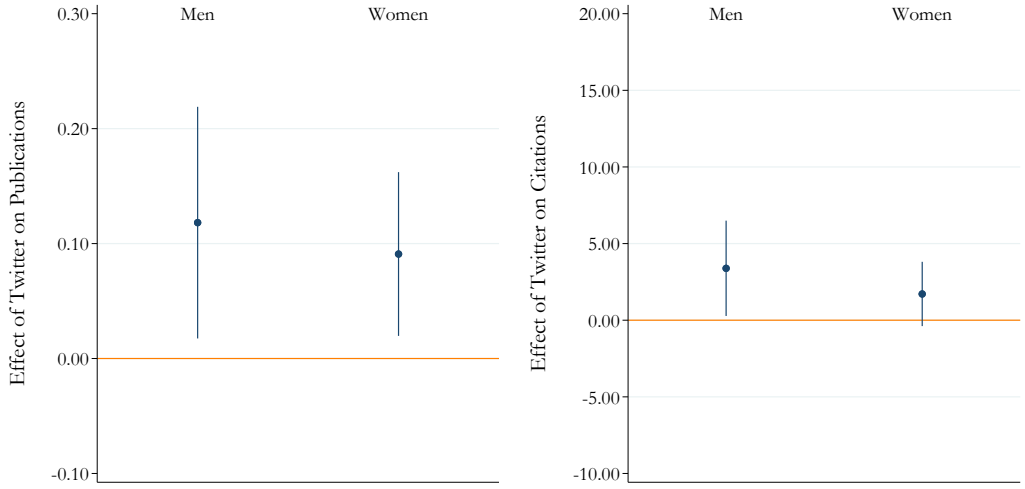
We next examine heterogeneity in the effects of Twitter usage along two dimensions. The first is gender, motivated by the hypothesis that social media platforms may disproportionately benefit economists from underrepresented groups by providing an alternative channel for visibility that bypasses traditional gatekeepers in the publication and citation process (e.g., Qiu et al., 2024). The second is career stage, motivated by the idea that the returns to Twitter engagement may differ systematically between junior and senior economists, either because established researchers command larger audiences on the platform or because younger economists have more to gain from expanding their professional networks.

### Heterogeneity by Gender

We examine gender heterogeneity by augmenting our baseline specification with interaction terms between years of Twitter usage and indicator variables for economists' gender, instrumenting these interactions with the corresponding interactions between Twitter Pressure and gender indicators. The results are presented in Figure 9, which plots the estimated effects on publications (left panel) and citations (right panel) separately for male and female economists.

Across both outcomes, the effect of Twitter usage is larger for men than for women. While there is no statistically significant difference for publications (p-value = 0.27), male Twitter users appear to receive more citations (p-value = 0.03). The larger gains accruing to male economists suggest that, contrary to popular narratives about social media as a leveling force, Twitter usage is unlikely to narrow the gender gap in economics. If anything, the platform appears to amplify existing disparities by conferring disproportionate benefits on those already better positioned to build large, influential followings.

**Figure 9: Heterogeneity by Gender**



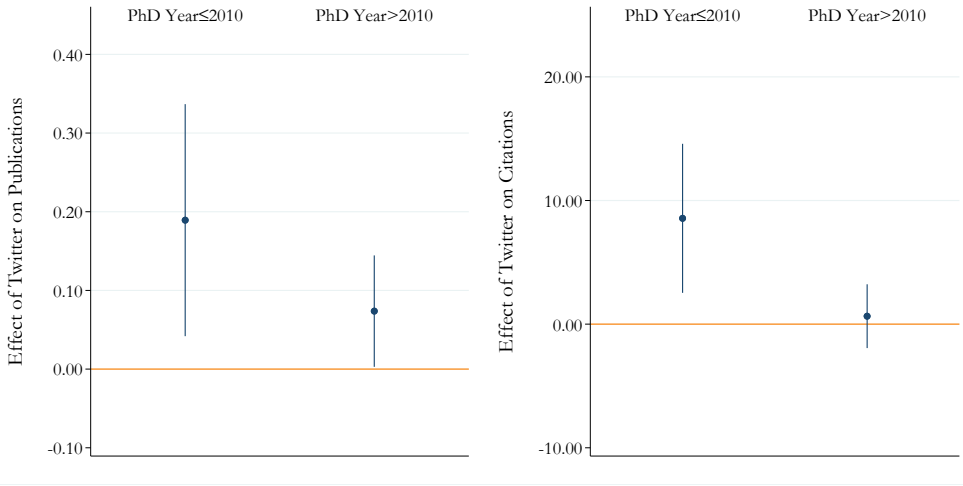

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the number of yearly publications and citations, separately for men and women. Estimates are obtained by instrumenting for interactions of years on Twitter and gender indicators with the corresponding interactions of Twitter Pressure and gender indicators. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of the average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Vertical bars denote 95-percent confidence intervals. Standard errors are clustered by PhD-institution-by-year.

### Heterogeneity by Career Age

Second, analogous to above, we investigate heterogeneity by career stage based on an indicator for whether economists completed their PhD before or after 2010. The results are presented in Figure 10, with effects on publications in the left panel and citations in the right panel. We find that returns to Twitter usage appear larger for more experienced economists. For publications, the effect is approximately 0.19 for economists who graduated before 2010, compared to 0.08 for those who graduated after (p-value = 0.013). The divergence is even more pronounced for citations, where the effect for pre-2010 graduates is approximately 9 citations per year and highly significant, whereas the corresponding estimate for post-2010 graduates is close to zero and statistically insignificant. Also, these two estimates are statistically significantly

different (p-value = 0.000). This pattern is consistent with the notion that the returns to Twitter engagement increase with professional standing. Established economists appear better positioned to attract large followings, convert platform visibility into citations, and leverage their networks for new collaborations, whereas junior economists may lack the reputation capital needed to fully benefit from the platform's reach.

**Figure 10: Heterogeneity by Age**




*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the number of yearly publications and citations, separately for researchers graduating before and after 2010, respectively. Estimates are obtained by instrumenting for interactions of years on Twitter and graduation year indicators with the corresponding interactions of Twitter Pressure and graduation year indicators. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of the average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Vertical bars denote 95-percent confidence intervals. Standard errors are clustered by PhD-institution-by-year.

# 5 Mechanisms: Collaboration and Knowledge Acquisition

Having established that Twitter usage increases both publication output and citation impact, we now turn to the mechanisms through which these effects might operate. In particular, we focus on two mechanisms that directly affect research production. First, we analyze whether Twitter usage leads to an expansion of the co-authorship networks. Second, given the importance of pre-existing knowledge for the creation of new ideas (e.g., Iaria et al., 2018), we analyse the impact of Twitter on the acquisition of knowledge about existing work, as proxied by the number of references. Together, these two mechanisms allow us to assess whether Twitter raises productivity by connecting economists with new co-authors, by broadening their awareness of relevant research, or through some combination of both.

## 5.1 Co-authorship

First, we investigate whether Twitter affects the number of collaborators economists work with by replacing the dependent variable in Equation (3) with the number of co-authors from 2006 to 2022. The results are reported in Panel A Table 10. The estimates are positive across all four specifications, declining gradually from 0.249 in Column (1) to 0.110 in Column (4). While statistically significant in the first, the estimate loses conventional statistical significance in the most demanding specification; even so, the estimate remains sizable. Overall, the estimates suggest a slight increase in the number of co-authors among Twitter users.

**Table 10: Effect of Twitter Usage on Number of Co-authors**

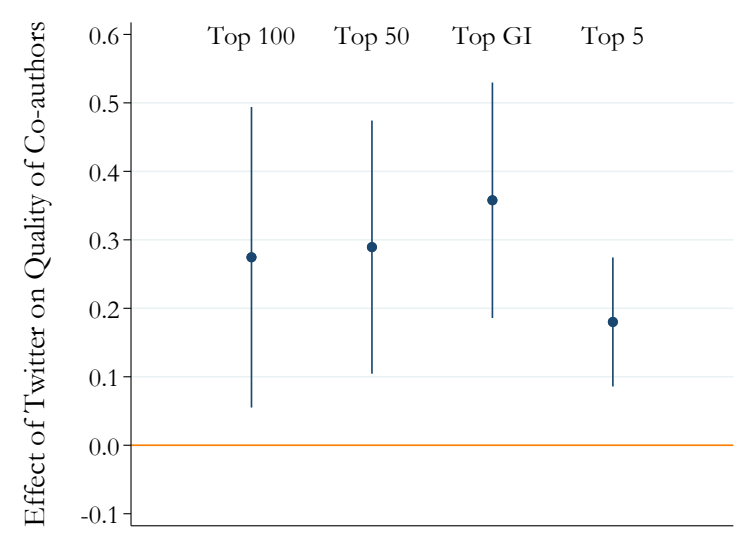
| | Dep. Var.: Number of Co-authors | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: All Co-authors* | | | | |
| Years of Twitter Usage | 0.249*** | 0.132** | 0.109* | 0.110 |
| | (0.067) | (0.067) | (0.064) | (0.085) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 1.23 | 1.23 | 1.23 | 1.23 |
| *Panel B: Co-authors who are Twitter Users* | | | | |
| Years of Twitter Usage | 0.150*** | 0.135*** | 0.131*** | 0.135*** |
| | (0.025) | (0.027) | (0.026) | (0.035) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 0.23 | 0.23 | 0.23 | 0.23 |
| *Panel C: Co-authors who are not Twitter Users* | | | | |
| Years of Twitter Usage | 0.099** | -0.003 | -0.022 | -0.025 |
| | (0.049) | (0.052) | (0.052) | (0.068) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 0.99 | 0.99 | 0.99 | 0.99 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of distinct co-authors per year. Panel A includes all co-authors, while Panels B and C count only co-authors who are/are not on Twitter at time of publication, respectively. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of the average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As the next step, we examine whether new collaborations are systematically concentrated among other Twitter users by decomposing the total effect on co-authors into the effects of

collaborations with other Twitter users and with non-Twitter users. Table 10 Panel B shows the estimates for co-authors who are themselves on Twitter at the time of publication, and Panel C shows the estimates for co-authors who are not. Similar to the citation results, the decomposition reveals a strong asymmetry. The increase in co-authorships is driven entirely by new collaborations with other Twitter users: the coefficient in Panel B is positive, stable, and significant across all four specifications. The magnitude suggests a doubling in the number of co-authors from Twitter relative to the sample mean. In contrast, the estimates in Panel C are close to zero, statistically indistinguishable from zero, and, if anything, negative in most specifications. This pattern suggests that Twitter facilitates the formation of new research partnerships among economists with a Twitter presence, rather than broadly expanding collaboration across the profession.

**Figure 11: Effect on Quality of Co-Authors**




*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of yearly publications in different brackets of journal impact factor of researchers' co-authors. The first three estimates refer to the Top 200, Top 100, and Top 50 ranked journals, while the last three estimates refer to the 12 Top General Interest and Top 5 journals, respectively. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of the average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Vertical bars denote 95-percent confidence intervals. Standard errors are clustered by PhD-institution-by-year.

Finally, we examine whether Twitter usage affects not only the quantity but also the quality of co-authors. Specifically, we analyze whether Twitter adoption affects the average number of co-authors' publications across journal-quality tiers. The estimates are visualized in Figure 11.[22] The point estimates are positive across all four quality tiers, ranging from approximately 0.28 for Top 100 and Top 50 journals to 0.36 for Top General Interest and 0.19 for Top 5 journals. These estimates indicate that Twitter users can attract higher-

[22]We report detailed estimates in Appendix Table A.20.

quality collaborators, as measured by their publication records across all journal tiers. This finding complements our findings on research production and suggests that Twitter facilitates collaborations with more accomplished co-authors who are likely better positioned to place their work in selective outlets.

## 5.2 References

A second channel through which Twitter may raise research productivity is by broadening economists' awareness of relevant work they might otherwise have missed. We examine this hypothesis in Table 11, which reports estimates for the average number of references economists provide in their papers, excluding self-citations. Panel A reports the effect on the total number of references per paper. The estimates are positive across all specifications but lose statistical significance once institution controls are introduced in Column (2), with the coefficient declining from 4.803 to 0.527 in our most demanding specification against a sample mean of 30.44 references per year. This suggests that Twitter usage does not increase the overall number of references economists include in their papers.

While the total number of references appears to be unaffected, we again provide a decomposition of references to works by Twitter users and non-Twitter Users (see Panels B and C).[23] Panel B shows a large increase in references to work authored by other Twitter users. The coefficient of 1.639 in Column (4) again implies a near doubling of references to papers by other Twitter users relative to the mean. In contrast, Panel C shows that references to work by non-Twitter users are unaffected once institution controls are included, with negative but statistically insignificant estimates in Columns (2) through (4). Taken together, these findings suggest that Twitter shapes economists' information sets selectively, expanding knowledge of papers circulating within the Twitter community but not broadening awareness of the discipline as a whole.

Analogous to our analysis of co-author quality, we examine whether the increase in references to Twitter users' work is concentrated within specific journal-quality tiers. Figure 12 plots the estimated effects on references to papers published in the Top 100, Top 50, Top General Interest, and Top 5 journals.[24] The point estimates are positive across all four quality tiers. Notably, the effects are, if anything, somewhat larger for the most selective outlets, suggesting that Twitter, in particular, appears to expose economists to high-quality work. Given the importance of frontier knowledge for the creation of new ideas (Iaria et al., 2018), these

[23] As before, a paper is considered to be authored by a Twitter user if at least one of the authors uses Twitter.

[24] Detailed estimates are reported in Appendix Table A.21.

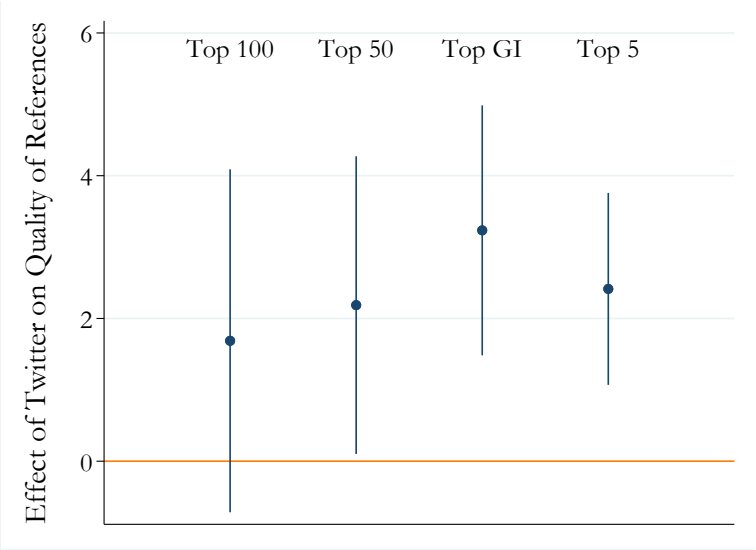
**Table 11: Effect of Twitter Usage on Number of References**

| | Dep. Var.: Number of References per Paper | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: All References* | | | | |
| Years of Twitter Usage | 4.803*** | 1.685 | 1.047 | 0.527 |
| | (1.840) | (1.928) | (1.893) | (2.475) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 30.44 | 30.44 | 30.44 | 30.45 |
| *Panel B: Refernces to Works by Twitter Users* | | | | |
| Years of Twitter Usage | 2.099*** | 1.792*** | 1.725*** | 1.639*** |
| | (0.419) | (0.444) | (0.435) | (0.566) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 3.99 | 3.99 | 3.99 | 3.99 |
| *Panel C: Refernces to Works by Non-Twitter Users* | | | | |
| Years of Twitter Usage | 2.705* | -0.108 | -0.678 | -1.112 |
| | (1.516) | (1.631) | (1.614) | (2.126) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 26.45 | 26.45 | 26.45 | 26.45 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, one the average number of references provided per year (excluding references to own papers). Panel A includes references, while Panels B and C count only references to papers with at least one / no Twitter-using author at time of publication, respectively. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of the average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

findings could also contribute to the previously documented increases in scientific output by Twitter users.

**Figure 12: Effect on Quality of References**




*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the number of yearly references to publications in different brackets of journal impact factor. The first three estimates refer to the Top 200, Top 100, and Top 50 ranked journals, while the last three estimates refer to the 12 Top General Interest and Top 5 journals, respectively. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of the average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Vertical bars denote 95-percent confidence intervals. Standard errors are clustered by PhD-institution-by-year.

Taken together, the co-authorship and referencing results point to consequential shifts in how economists engage with their discipline. Twitter does not merely provide a convenient channel for disseminating finished work; it appears to reshape the professional community that economists inhabit, drawing them into a self-contained network of platform users whose collaborative and intellectual influences are disproportionately concentrated among themselves. As economists on Twitter co-author more with other Twitter users, cite more of their work, and become more aware of the research circulating within the platform community, a natural question is whether this realignment also impacts the *topics* economists choose to work on. We investigate this possibility in the next section.

# 6 Effect of Twitter on Research Topics

In this section, we investigate whether Twitter also affects research content. Specifically, we examine whether Twitter adoption causes economists to work on topics that are more similar to those pursued by other Twitter users and less similar to those pursued by economists outside the platform.

## 6.1 Topic Similarity to Twitter

To measure the effect of Twitter on research topics, we construct sentence embeddings for each paper's abstract and compute the cosine similarity to the 100 most topically similar papers published in the same year, calculated separately for papers authored by Twitter users and non-Twitter users, respectively, and excluding the economist's own papers. We then estimate regressions replacing the dependent variable in Equation (3) with the newly constructed similarity measures. Panel A of Table 12 reports the effect of Twitter usage on similarity to the work of other Twitter users, and Panel B reports the corresponding effect on similarity to the work of economists outside the platform. To facilitate interpretation, we standardize the dependent variable to have a mean of zero and a unit standard deviation.

**Table 12: Effect of Twitter Usage on Similarity of Research to Twitter**

| | Dep. Var.: Similarity of Research (std.) to: | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: Research of Economists on Twitter* | | | | |
| Years of Twitter Usage | 0.144*** | 0.160*** | 0.162*** | 0.111** |
| | (0.038) | (0.045) | (0.045) | (0.052) |
| Observations | 23,392 | 23,380 | 23,378 | 23,376 |
| Mean of DV | 0.02 | 0.02 | 0.02 | 0.02 |
| *Panel B: Research of Economists off Twitter* | | | | |
| Years of Twitter Usage | -0.374*** | -0.401*** | -0.403*** | -0.504*** |
| | (0.067) | (0.079) | (0.080) | (0.126) |
| Observations | 23,633 | 23,621 | 23,619 | 23,615 |
| Mean of DV | 0.01 | 0.01 | 0.01 | 0.01 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average cosine similarity of research to the 100 most similar papers of Twitter users and non-users, respectively, published in the same year. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of the average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A shows that Twitter adoption increases the cosine similarity of an economist's research to that of other platform users by approximately 0.11 standard deviations in our most demanding specification, with the estimate positive, stable, and significant at least at the five percent level across all four columns. Panel B tells the mirror image of this story: Twitter adoption simultaneously *reduces* similarity to the work of non-Twitter economists by

approximately 0.50 standard deviations in Column (4), an effect that is large, negative, and significant throughout. These estimates suggest that Twitter adoption does not merely shift economists toward a different but equally broad set of topics; rather, it draws them into a more concentrated and self-referential research agenda centered on the topics discussed in the Twitter community. Taken together, these findings indicate that Twitter is reshaping the intellectual landscape of economics, driving a wedge between the research agendas of those inside and outside the platform.

# 7 Conclusion

This paper provides the first causal evidence that Twitter has substantially reshaped economic research. Drawing on a novel database linking over 25,000 economists to their Twitter accounts, PhD cohorts, and academic output, and exploiting plausibly exogenous variation in peer-induced Twitter adoption through PhD cohorts' field compositions, we document four main findings. Twitter use increases research productivity, with the average user publishing approximately one additional paper every few years and receiving significantly more citations, driven entirely by citations from other users on the platform. These productivity gains are accompanied by a systematic reorganization of professional networks: Twitter users co-author more with other platform users, cite their work more frequently, and become increasingly exposed to the research circulating within the Twitter community. Most strikingly, Twitter adoption shifts the content of economists' research, driving a growing divergence between the research agendas of economists inside and outside the platform.

These findings carry important implications for the role of social media in shaping scientific progress. On one hand, Twitter appears to be a genuinely productivity-enhancing technology, facilitating the formation of high-quality research partnerships, accelerating the diffusion of ideas, and increasing the visibility of economists' work. On the other hand, the platform's influence on research topics potentially raises concerns. If economists increasingly select research questions based on their salience to a self-selected online community rather than their scientific merit or social importance, the long-run consequences for the discipline could be significant, potentially amplifying herd behavior, shortening research horizons, and crowding out work on important but less "Twitter-friendly" questions. Whether the net effect of Twitter on economic research is ultimately beneficial depends on the extent to which topics that resonate on the platform overlap with those most valuable to society.

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# Appendix

## A Additional Details on Data

**Table A.1: List of Top 200 Journals from IDEAS/RePEc**

| Rank | Journal |
|---|---|
| 1 | Econometrica, Econometric Society |
| 2 | American Economic Review, American Economic Association |
| 3 | The Quarterly Journal of Economics, President and Fellows of Harvard College |
| 4 | Journal of Economic Literature, American Economic Association |
| 5 | Journal of Financial Economics, Elsevier |
| 6 | Journal of Political Economy, University of Chicago Press |
| 7 | Journal of Economic Growth, Springer |
| 8 | Journal of Economic Perspectives, American Economic Association |
| 9 | The Review of Financial Studies, Society for Financial Studies |
| 10 | Journal of Finance, American Finance Association |
| 11 | American Economic Journal: Macroeconomics, American Economic Association |
| 12 | The Review of Economic Studies, Review of Economic Studies Ltd |
| 13 | American Economic Journal: Applied Economics, American Economic Association |
| 14 | Journal of Monetary Economics, Elsevier |
| 15 | Journal of Econometrics, Elsevier |
| 16 | Annual Review of Economics, Annual Reviews |
| 17 | The Review of Economics and Statistics, MIT Press |
| 18 | Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution |
| 19 | Journal of the European Economic Association, European Economic Association |
| 20 | The Economic Journal, Royal Economic Society |
| 21 | RAND Journal of Economics, RAND Corporation |
| 22 | Journal of International Economics, Elsevier |
| 23 | Journal of Labor Economics, University of Chicago Press |
| 24 | Journal of Accounting and Economics, Elsevier |
| 25 | American Economic Journal: Economic Policy, American Economic Association |
| 26 | Journal of Public Economics, Elsevier |
| 27 | Journal of Business & Economic Statistics, Taylor & Francis Journals |
| 28 | Journal of Applied Econometrics, John Wiley & Sons, Ltd. |
| 29 | Strategic Management Journal, Wiley Blackwell |
| 30 | Economic Policy, CEPR, CESifo, Sciences Po; CES; MSH |
| 31 | Journal of Development Economics, Elsevier |
| 32 | Journal of Money, Credit and Banking, Blackwell Publishing |
| 33 | Review of Economic Dynamics, Elsevier for the Society for Economic Dynamics |
| 34 | Journal of Economic Theory, Elsevier |
| 35 | Journal of Financial Intermediation, Elsevier |
| 36 | International Economic Review, Department of Economics, University of Pennsylvania and Osaka University Institute of Social and Economic Research Association |
| 37 | Experimental Economics, Springer; Economic Science Association |
| 38 | European Economic Review, Elsevier |
| 39 | Journal of Business Venturing, Elsevier |
| 40 | Research Policy, Elsevier |
| 41 | Journal of Banking & Finance, Elsevier |
| 42 | Journal of International Business Studies, Palgrave Macmillan; Academy of International Business |
| 43 | Journal of Human Resources, University of Wisconsin Press |
| 44 | American Economic Review: Insights, American Economic Association |

45 Management Science, INFORMS
46 Proceedings, Federal Reserve Bank of Cleveland
47 Organization Science, INFORMS
48 Journal of Law and Economics, University of Chicago Press
49 Journal of Economic Dynamics and Control, Elsevier
50 Journal of Financial and Quantitative Analysis, Cambridge University Press
51 Journal of Accounting Research, John Wiley & Sons, Ltd.
52 Journal of Environmental Economics and Management, Elsevier
53 Journal of Economic Surveys, Wiley Blackwell
54 Oxford Bulletin of Economics and Statistics, Department of Economics, University of Oxford
55 The World Bank Economic Review, World Bank
56 International Journal of Central Banking, International Journal of Central Banking
57 Annual Review of Financial Economics, Annual Reviews
58 Journal of Urban Economics, Elsevier
59 Quantitative Economics, Econometric Society
60 Quarterly Review, Federal Reserve Bank of Minneapolis
61 IMF Economic Review, Palgrave Macmillan; International Monetary Fund
62 Energy Economics, Elsevier
63 The Journal of Business, University of Chicago Press
64 Proceedings, Board of Governors of the Federal Reserve System (U.S.)
65 Journal of Risk and Uncertainty, Springer
66 The World Bank Research Observer, World Bank
67 Econometric Theory, Cambridge University Press
68 Journal of Health Economics, Elsevier
69 Journal of International Money and Finance, Elsevier
70 Review of Finance, European Finance Association
71 The Journal of Law, Economics, and Organization, Oxford University Press
72 The Econometrics Journal, Royal Economic Society
73 Labour Economics, Elsevier
74 Journal of Corporate Finance, Elsevier
75 Review of Environmental Economics and Policy, University of Chicago Press
76 Journal of Consumer Research, Journal of Consumer Research Inc.
77 Proceedings, Federal Reserve Bank of San Francisco
78 BIS Quarterly Review, Bank for International Settlements
79 World Development, Elsevier
80 Energy Policy, Elsevier
81 American Economic Journal: Microeconomics, American Economic Association
82 Scandinavian Journal of Economics, Wiley Blackwell
83 Games and Economic Behavior, Elsevier
84 Journal of Financial Markets, Elsevier
85 Journal of Economic Behavior & Organization, Elsevier
86 Economics Letters, Elsevier
87 Journal of Economic Geography, Oxford University Press
88 Mathematical Finance, Wiley Blackwell
89 Journal of Industrial Economics, Wiley Blackwell
90 Marketing Science, INFORMS
91 Journal of Financial Stability, Elsevier
92 Ecological Economics, Elsevier
93 Journal of Political Economy Macroeconomics, University of Chicago Press
94 European Journal of Operational Research, Elsevier
95 Stata Journal, StataCorp LLC
96 Journal of Economics & Management Strategy, Wiley Blackwell
97 Journal of Empirical Finance, Elsevier
98 Journal of Population Economics, Springer; European Society for Population Economics
99 Journal of the Royal Statistical Society Series B, Royal Statistical Society

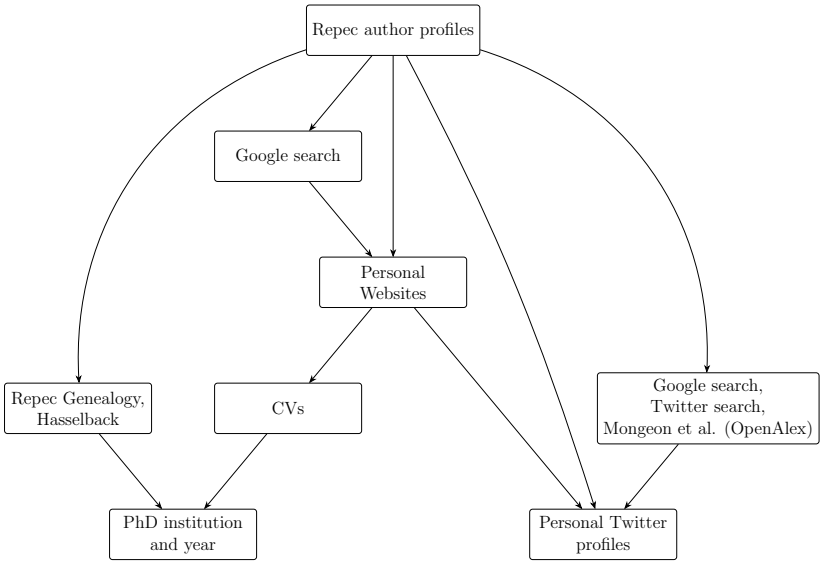
100 Entrepreneurship Theory and Practice
101 Oxford Economic Papers, Oxford University Press
102 Economic Policy Review, Federal Reserve Bank of New York
103 Economía Journal, The Latin American and Caribbean Economic Association – LACEA
104 International Journal of Industrial Organization, Elsevier
105 Foundations and Trends(R) in Microeconomics, now publishers
106 Journal of the American Statistical Association, Taylor & Francis Journals
107 Financial Management, Financial Management Association International
108 Oxford Review of Economic Policy, Oxford University Press and Oxford Review of Economic Policy Limited
109 The Review of Corporate Finance Studies, Society for Financial Studies
110 Canadian Journal of Economics/Revue canadienne d'économique, John Wiley & Sons
111 Small Business Economics, Springer
112 Theoretical Economics, Econometric Society
113 Journal of the Association of Environmental and Resource Economists, University of Chicago Press
114 Economic Inquiry, Western Economic Association International
115 Proceedings, Federal Reserve Bank of Dallas
116 Econometric Reviews, Taylor & Francis Journals
117 Journal of Financial Econometrics, Oxford University Press
118 Annual Review of Resource Economics, Annual Reviews
119 American Journal of Agricultural Economics, John Wiley & Sons
120 Political Analysis, Cambridge University Press
121 Journal of the Economic Science Association, Springer; Economic Science Association
122 Journal of Management Studies, Wiley Blackwell
123 European Journal of Political Economy, Elsevier
124 Economics and Politics, Wiley Blackwell
125 Economica, London School of Economics and Political Science
126 Industrial and Corporate Change, Oxford University Press and the Associazione ICC
127 Regional Science and Urban Economics, Elsevier
128 Journal of Human Capital, University of Chicago Press
129 IZA Journal of Labor Economics, Sciendo & Forschungsinstitut zur Zukunft der Arbeit GmbH (IZA)
130 Proceedings – Economic Policy Symposium – Jackson Hole, Federal Reserve Bank of Kansas City
131 Economic Development and Cultural Change, University of Chicago Press
132 Economic Theory, Springer; Society for the Advancement of Economic Theory (SAET)
133 National Tax Journal, University of Chicago Press
134 Critical Finance Review, now publishers
135 Journal of World Business, Elsevier
136 American Journal of Political Science, John Wiley & Sons
137 Journal of Business Ethics, Springer
138 International Journal of Forecasting, Elsevier
139 Journal of Comparative Economics, Elsevier
140 Journal of Global Economic Analysis, Center for Global Trade Analysis, Department of Agricultural Economics, Purdue University
141 European Financial Management, European Financial Management Association
142 Accounting, Organizations and Society, Elsevier
143 The Energy Journal
144 Public Choice, Springer
145 International Tax and Public Finance, Springer; International Institute of Public Finance
146 Contemporary Accounting Research, John Wiley & Sons
147 Demography, Springer; Population Association of America (PAA)
148 Organizational Behavior and Human Decision Processes, Elsevier
149 Renewable and Sustainable Energy Reviews, Elsevier
150 Regional Studies, Taylor & Francis Journals
151 Environmental & Resource Economics, Springer; European Association of Environmental and Resource Economists
152 The Journal of Economic Inequality, Springer; Society for the Study of Economic Inequality
153 Journal of Interactive Marketing, Elsevier

| | |
|---|---|
| 154 | Journal of Productivity Analysis, Springer |
| 155 | Quantitative Marketing and Economics (QME), Springer |
| 156 | Journal of Mathematical Economics, Elsevier |
| 157 | Journal of Statistical Software, Foundation for Open Access Statistics |
| 158 | Empirical Economics, Springer |
| 159 | American Political Science Review, Cambridge University Press |
| 160 | Resource and Energy Economics, Elsevier |
| 161 | Nature, Nature |
| 162 | International Finance, Wiley Blackwell |
| 163 | Journal of Financial Services Research, Springer; Western Finance Association |
| 164 | Economics of Education Review, Elsevier |
| 165 | OECD Journal: Economic Studies, OECD Publishing |
| 166 | Annals of Economics and Finance, Society for AEF |
| 167 | Journal of Business Research, Elsevier |
| 168 | Conference Series; [Proceedings], Federal Reserve Bank of Boston |
| 169 | Journal of Economic Psychology, Elsevier |
| 170 | The B.E. Journal of Macroeconomics, De Gruyter |
| 171 | Review of International Economics, Wiley Blackwell |
| 172 | Journal of International Financial Markets, Institutions and Money, Elsevier |
| 173 | Journal of Development Studies, Taylor & Francis Journals |
| 174 | Economic Modelling, Elsevier |
| 175 | China Economic Review, Elsevier |
| 176 | ILR Review, Cornell University, ILR School |
| 177 | The Review of Asset Pricing Studies, Society for Financial Studies |
| 178 | Journal of the Japanese and International Economies, Elsevier |
| 179 | Finance and Stochastics, Springer |
| 180 | Information Systems Research, INFORMS |
| 181 | Journal of Retailing, Elsevier |
| 182 | The B.E. Journal of Economic Analysis & Policy, De Gruyter |
| 183 | Applied Energy, Elsevier |
| 184 | Review of Income and Wealth, International Association for Research in Income and Wealth |
| 185 | Current Issues in Economics and Finance, Federal Reserve Bank of New York |
| 186 | IZA Journal of Labor Policy, Sciendo & Forschungsinstitut zur Zukunft der Arbeit GmbH (IZA) |
| 187 | The Economics of Transition, The European Bank for Reconstruction and Development |
| 188 | Economic Quarterly, Federal Reserve Bank of Richmond |
| 189 | Health Economics, John Wiley & Sons, Ltd. |
| 190 | Agricultural Economics, International Association of Agricultural Economists |
| 191 | The Journal of Legal Studies, University of Chicago Press |
| 192 | Economics of Innovation and New Technology, Taylor & Francis Journals |
| 193 | The World Economy, Wiley Blackwell |
| 194 | International Review of Financial Analysis, Elsevier |
| 195 | Cambridge Journal of Economics, Cambridge Political Economy Society |
| 196 | Journal of Accounting and Public Policy, Elsevier |
| 197 | Operations Research, INFORMS |
| 198 | Tourism Management, Elsevier |
| 199 | Journal of Applied Economics, Universidad del CEMA |
| 200 | Applied Economics, Taylor & Francis Journals |

*Notes:* 200 highest-ranked journals on IDEAS/RePEc, based on the aggregate impact score computed over all available years. This score is computed as the harmonic mean of several standard impact factors, such as the number of citations, impact-factor-weighted number of citations, or h-index. For more information, visit IDEAS/RePEc Aggregate Rankings for Journals.

## A.1. Additional Details on Collection of Twitter Account

**Figure A.1: Data collection process for Twitter profiles and PhD information**




*Notes:* Schematic visualization of data collection process for identifying researchers' PhD information and personal Twitter profiles. Nodes represent datasets, and edges indicate usage or combination of data.

## A.2. Additional Details on Sample Composition

**Table A.2: Sample composition**

| | Sample | | |
|---|---|---|---|
| | **All RePEc** | **1996-2022** | **Final** |
| | (1) | (2) | (3) |
| *Panel A: Share of researchers linked to:* | | | |
| **Website** | 0.602 | 0.678 | 0.801 |
| **CV** | 0.093 | 0.112 | 0.213 |
| **RePEc Genealogy** | 0.214 | 0.258 | 0.430 |
| **OpenAlex** | 0.744 | 0.922 | 0.956 |
| **PhD Institution & Year** | 0.448 | 0.551 | 1.000 |
| **Twitter Account**$^{*}$ | 0.148 | 0.184 | 0.258 |
| *Panel B: Number of unique observations:* | | | |
| **Citations** | 22,273,198 | 18,266,834 | 10,226,802 |
| **Papers** | 1,331,566 | 1,153,468 | 676,214 |
| **Researchers** | 82,183 | 65,352 | 28,285 |
| **PhD Institutions** | 1,705 | 1,690 | 619 |

*Notes:* This Table summarizes how we construct our final estimation sample. Column (1) includes all economists with a profile on RePEc. Column (2) restricts to economists with at least one observed paper between 1995 and 2022. Column (3) further restricts to economists for which we observe both PhD institution and graduation year, who graduated between 1990 and 2022, in cohorts with at least five members. The share of users linked to their Twitter accounts is representative only in Column (3) because some data collection steps conditioned on having full PhD information.

# B Additional Results: First Stage

**Table A.3: First Stage: Extensive Margin**

| | Dep. Var.: I[Twitter User] | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Twitter Pressure (std.) | 0.025*** | 0.022*** | 0.022*** | 0.016*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 0.27 | 0.27 | 0.27 | 0.27 |
| $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* Regressions of a dummy for Twitter usage on standardized Twitter Pressure in PhD cohort (excluding self), controlling for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.4: First Stage: Intensive Margin**

| | Dep. Var.: I[Years of Twitter Usage] | | | |
|---|---|---|---|---|
| | ≥2 years | ≥5 years | ≥7 years | ≥10 years |
| | (1) | (2) | (3) | (4) |
| Twitter Pressure (std.) | 0.015*** | 0.013*** | 0.010*** | 0.007*** |
| | (0.003) | (0.003) | (0.003) | (0.002) |
| Observations | 25,251 | 25,251 | 25,251 | 25,251 |
| Mean of DV | 0.26 | 0.21 | 0.17 | 0.11 |
| $R^2$ | 0.01 | 0.01 | 0.01 | 0.00 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | Yes | Yes | Yes | Yes |
| PhD Cohort Quality | Yes | Yes | Yes | Yes |
| JEL Code | Yes | Yes | Yes | Yes |

*Notes:* Regressions of dummies for at least X years of Twitter usage on standardized Twitter Pressure in PhD cohort (excluding self), controlling for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Table A.5: Robustness First Stage: Cohort Lengths

| | Dep. Var.: Years Twitter Usage | | | |
|---|---|---|---|---|
| | 3-year (1) | 4-year (2) | 5-year (3) | 6-year (4) |
| Twitter Pressure 3-year (std.) | 0.112*** | | | |
| | (0.030) | | | |
| Twitter Pressure 4-year (std.) | | 0.090*** | | |
| | | (0.030) | | |
| Twitter Pressure 5-year (std.) | | | 0.134*** | |
| | | | (0.031) | |
| Twitter Pressure 6-year (std.) | | | | 0.156*** |
| | | | | (0.031) |
| Observations | 24,050 | 24,834 | 25,251 | 25,345 |
| Mean of DV | 2.19 | 2.18 | 2.16 | 2.16 |
| $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | Yes | Yes | Yes | Yes |
| PhD Cohort Quality | Yes | Yes | Yes | Yes |
| JEL Code | Yes | Yes | Yes | Yes |

*Notes:* Regressions of the number of years of Twitter usage on standardized Twitter Pressure in PhD cohort (excluding self), for different definitions of cohort lengths. Years represent the maximum difference between graduation years to be considered part of the same cohort. All specifications include controls for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.6: First Stage: Network Twitter Pressure and Twitter Adoption (Ridge)**

| | Dep. Var.: Years of Twitter Usage | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Twitter Pressure (std.) | 0.177*** | 0.154*** | 0.154*** | 0.111*** |
| | (0.027) | (0.027) | (0.027) | (0.027) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 2.16 | 2.16 | 2.16 | 2.16 |
| $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

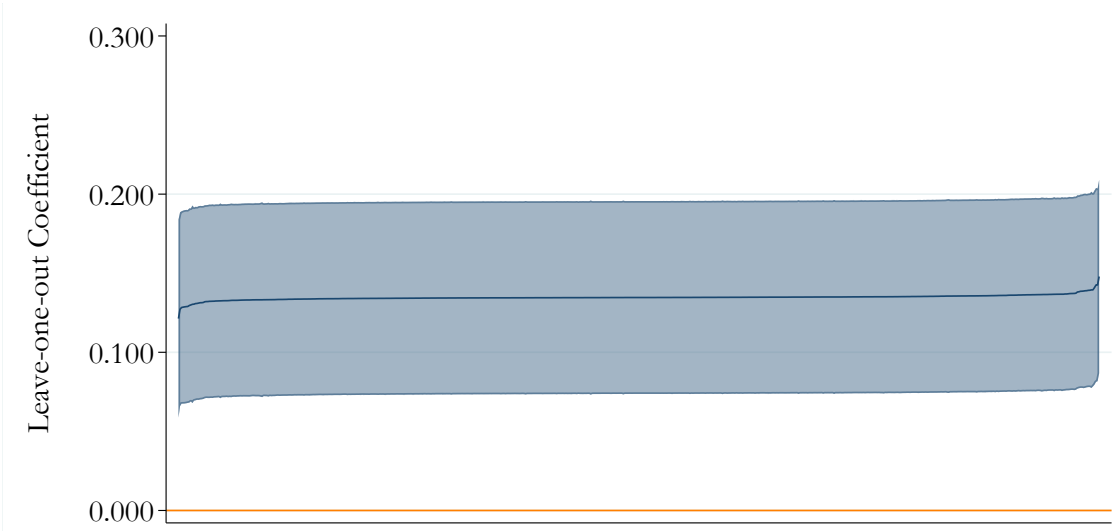
*Notes:* Regressions of a dummy for Twitter usage on standardized Twitter Pressure in PhD cohort (excluding self), the latter obtained from a cross-fitted Ridge regression of cohort (leave-one-out) Twitter share on field composition and their interactions. Controls include the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.7: Robustness First Stage: Clustering**

| | Dep. Var.: Years Twitter Usage | | | |
|---|---|---|---|---|
| | (1) PhD Institution-by-Year | (2) PhD Institution | (3) PhD Year | (4) Individual |
| Twitter Pressure (std.) | 0.134*** | 0.134*** | 0.134*** | 0.134*** |
| | (0.031) | (0.038) | (0.031) | (0.031) |
| Observations | 25,251 | 25,251 | 25,251 | 25,251 |
| Mean of DV | 2.16 | 2.16 | 2.16 | 2.16 |
| $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | Yes | Yes | Yes | Yes |
| PhD Cohort Quality | Yes | Yes | Yes | Yes |
| JEL Code | Yes | Yes | Yes | Yes |

*Notes:* Regressions of the number of years of Twitter usage on standardized Twitter Pressure in PhD cohort (excluding self), clustering standard errors at different levels. Years represent the maximum difference between graduation years to be considered part of the same cohort. All specifications include controls for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Figure A.2: First Stage: Leave-one-PhD Institution-out Estimates**




*Notes:* Regressions of the number of years of Twitter usage on standardized Twitter Pressure in PhD cohort (excluding self), leaving out one PhD institution at a time. All specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, and the most frequent JEL code letter across all years. Shaded region denotes 95-percent confidence intervals. Standard errors are clustered by PhD-institution-by-year.

# C Additional Results: Output

## C.1. Publications

### Table A.8: Effect of Twitter Usage on Number of Publications by Journal Quality

| | Dep. Var.: Nr. of Publications per Year | | | | |
|---|---|---|---|---|---|
| | All | Top 100 | Top 50 | Top GI | Top 5 |
| | (1) | (2) | (3) | (4) | (5) |
| Years of Twitter Usage | 0.092*** | 0.112*** | 0.092*** | 0.052*** | 0.024*** |
| | (0.032) | (0.032) | (0.025) | (0.014) | (0.008) |
| Observations | 25251 | 25251 | 25251 | 25251 | 25251 |
| Mean of DV | 0.38 | 0.26 | 0.17 | 0.04 | 0.02 |
| F-Stat | 18.73 | 18.73 | 18.73 | 18.73 | 18.73 |
| PhD Year FE | Yes | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes | Yes |
| PhD Institution Quality | Yes | Yes | Yes | Yes | Yes |
| PhD Cohort Quality | Yes | Yes | Yes | Yes | Yes |
| JEL Code | Yes | Yes | Yes | Yes | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by Twitter Pressure in PhD cohort, on the average number of publications per year in journals of different quality brackets. Column (1) includes all publications, while Columns (2) and (3) count publications in the Top 100 and Top 50 journals by impact factor, respectively, while Columns (4) and (5) refer to the 12 Top General Interest and Top 5 journals, respectively. All specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of the average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Table A.9: Post Period for People in Pre-Period

| | Dep. Var.: Nr. of Publications per Year | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: Top 100 Publications* | | | | |
| Twitter Pressure (std.) | 0.024*** | 0.016*** | 0.015*** | 0.018*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Observations | 11,692 | 11,687 | 11,685 | 11,679 |
| Mean of DV | 0.32 | 0.32 | 0.32 | 0.32 |
| *Panel B: Top 50 Publications* | | | | |
| Twitter Pressure (std.) | 0.018*** | 0.012*** | 0.011*** | 0.015*** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Observations | 11,692 | 11,687 | 11,685 | 11,679 |
| Mean of DV | 0.21 | 0.21 | 0.21 | 0.21 |
| *Panel C: Top General Interest Publications* | | | | |
| Twitter Pressure (std.) | 0.010*** | 0.009*** | 0.008*** | 0.007*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Observations | 11,692 | 11,687 | 11,685 | 11,679 |
| Mean of DV | 0.05 | 0.05 | 0.05 | 0.05 |
| *Panel D: Top 5 Publications* | | | | |
| Twitter Pressure (std.) | 0.004*** | 0.004*** | 0.004*** | 0.003** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 11,692 | 11,687 | 11,685 | 11,679 |
| Mean of DV | 0.03 | 0.03 | 0.03 | 0.03 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* Reduced-form estimates for the effect cohort-level Twitter Pressure on the average number of publications per year after 2005 in journals of different quality brackets, for researchers graduating between 1990 and 2005. Panels A and B count publications in the Top 100 and Top 50 journals by impact factor, while Panels C and D refer to the 12 Top General Interest and Top 5 journals, respectively. The specifications include controls for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## C.2. Citations

**Table A.10: Effect of Twitter Usage on Number of Citations (No Winsorization)**

| | Dep. Var.: Nr. of Citations per Year | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Years of Twitter Usage | 2.469*** | 1.799* | 1.531 | 2.307* |
| | (0.942) | (1.016) | (0.991) | (1.394) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 7.31 | 7.31 | 7.31 | 7.31 |
| F-Stat (KP) | 42.78 | 33.58 | 33.38 | 18.43 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of citations received per year. The specifications include controls for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.11: Effect of Twitter Usage on Number of Citations per Publication**

| | Dep. Var.: Nr. of Citations per Publication | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Years of Twitter Usage | 4.376*** | 3.857*** | 3.676*** | 4.997** |
| | (1.234) | (1.259) | (1.250) | (2.007) |
| Observations | 20,246 | 20,238 | 20,236 | 20,235 |
| Mean of DV | 14.95 | 14.95 | 14.95 | 14.95 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of citations per publication per year (winsorized at $99^{th}$ percentile). The specifications include controls for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Table A.12: Effect of Twitter Usage on Share of Citations from Twitter Users

| | Dep. Var.: Share of Citations from Twitter Users | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Years of Twitter Usage | 0.130*** | 0.136*** | 0.136*** | 0.138*** |
| | (0.021) | (0.024) | (0.024) | (0.033) |
| Observations | 23,815 | 23,804 | 23,802 | 23,797 |
| Mean of DV | 0.31 | 0.31 | 0.31 | 0.31 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the share of citations per publication originating from papers with at least one Twitter-using author per year (winsorized at $99^{th}$ percentile). The specifications include controls for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Table A.13: Effect on Citations for People in pre-Period

| | Dep. Var.: Nr. of Citations per Year | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Twitter Pressure (std.) | 1.096*** | 0.803*** | 0.738*** | 0.763*** |
| | (0.243) | (0.231) | (0.231) | (0.233) |
| Observations | 11,692 | 11,687 | 11,685 | 11,679 |
| Mean of DV | 10.21 | 10.21 | 10.22 | 10.22 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

*Notes:* Reduced-form estimates for the effect of cohort-specific Twitter Pressure on the average number of citations per publication per year after 2005 (winsorized at $99^{th}$ percentile), for researchers graduating between 1990 and 2005. The specifications include controls for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## C.3. Robustness

**Table A.14: Robustness Second Stage Publications: Cohort Lengths**

| | Dep. Var.: Nr. of Publication per Year | | | |
|---|---|---|---|---|
| | 3-year | 4-year | 5-year | 6-year |
| | (1) | (2) | (3) | (4) |
| Years of Twitter Usage | 0.133*** | 0.148** | 0.091*** | 0.089*** |
| | (0.044) | (0.059) | (0.033) | (0.028) |
| Observations | 24,050 | 24,834 | 25,251 | 25,345 |
| Mean of DV | 0.38 | 0.38 | 0.38 | 0.38 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | Yes | Yes | Yes | Yes |
| PhD Cohort Quality | Yes | Yes | Yes | Yes |
| JEL Code | Yes | Yes | Yes | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of publications per year, for different definitions of cohort lengths. Years represent the maximum difference between graduation years to be considered part of the same cohort. All specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of the average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A.15: Second Stage: Network Twitter Pressure and Publications (Ridge)**

| | Dep. Var.: Nr. of Publication per Year | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Years of Twitter Usage | 0.110*** | 0.081*** | 0.078*** | 0.125*** |
| | (0.023) | (0.024) | (0.024) | (0.040) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 0.38 | 0.38 | 0.38 | 0.38 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

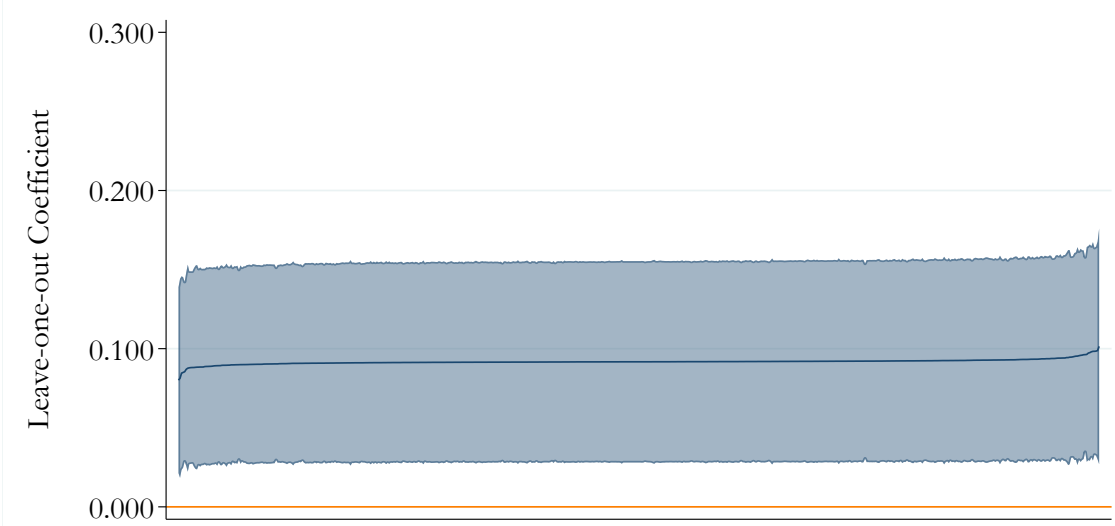
*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of publications per year. The instrument is obtained from a cross-fitted Ridge regression of cohort (leave-one-out) Twitter share on field composition and their interactions. The specifications include controls for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Table A.16: Robustness Second Stage Publication: Clustering

| | Dep. Var.: Nr. of Publication per Year | | | |
|---|---|---|---|---|
| | (1) PhD Institution-by-Year | (2) PhD Institution | (3) PhD Year | (4) Individual |
| Years of Twitter Usage | 0.091*** | 0.091** | 0.091** | 0.091*** |
| | (0.033) | (0.038) | (0.035) | (0.031) |
| Observations | 25,251 | 25,251 | 25,251 | 25,251 |
| Mean of DV | 0.38 | 0.38 | 0.38 | 0.38 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | Yes | Yes | Yes | Yes |
| PhD Cohort Quality | Yes | Yes | Yes | Yes |
| JEL Code | Yes | Yes | Yes | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of publications per year, clustering standard errors at different levels. Column (1) clusters by unique combinations of PhD institution and graduation year, while Columns (2) and (3) cluster separately by institution and graduation year, respectively. Column (4) does not cluster standard errors, computing simple heterogeneity-robust standard errors. All specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of the average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Figure A.3: Second Stage: Leave-one-PhD-Institution-out Estimates for Publications




*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of publications per year, leaving out one PhD institution at a time. All specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, and the most frequent JEL code letter across all years. Shaded region denotes 95-percent confidence intervals. Standard errors are clustered by PhD-institution-by-year.

## Table A.17: Robustness Second Stage Citations: Cohort Lengths

| | Dep. Var.: Nr. of Citations per Year | | | |
|---|---|---|---|---|
| | 3-year | 4-year | 5-year | 6-year |
| | (1) | (2) | (3) | (4) |
| Years of Twitter Usage | 2.592** | 1.826 | 1.866** | 2.518*** |
| | (1.054) | (1.173) | (0.925) | (0.835) |
| Observations | 24,050 | 24,834 | 25,251 | 25,345 |
| Mean of DV | 6.68 | 6.57 | 6.53 | 6.51 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | Yes | Yes | Yes | Yes |
| PhD Cohort Quality | Yes | Yes | Yes | Yes |
| JEL Code | Yes | Yes | Yes | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of citations received per year (winsorized at $99^{th}$ percentile). The instrument is obtained from a cross-fitted Ridge regression of cohort (leave-one-out) Twitter share on field composition and their interactions. The specifications include controls for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Table A.18: Second Stage: Network Twitter Pressure and Citations (Ridge)

| | Dep. Var.: Nr. of Citations per Year | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Years of Twitter Usage | 2.921*** | 2.357*** | 2.237*** | 3.204*** |
| | (0.617) | (0.644) | (0.627) | (1.025) |
| Observations | 25,271 | 25,259 | 25,257 | 25,251 |
| Mean of DV | 6.53 | 6.53 | 6.53 | 6.53 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | | Yes | Yes | Yes |
| PhD Cohort Quality | | | Yes | Yes |
| JEL Code | | | | Yes |

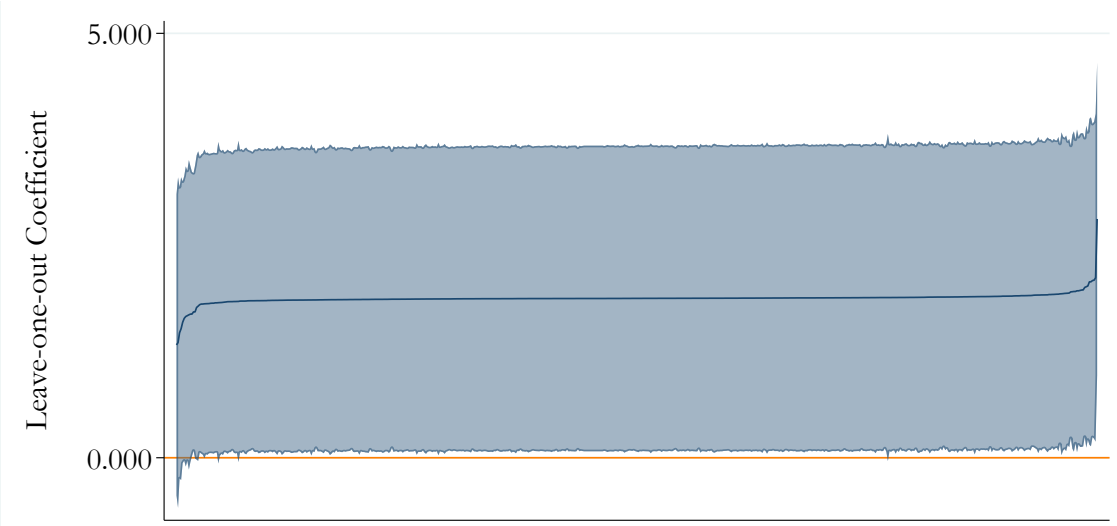
*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of citations received per year (winsorized at $99^{th}$ percentile). The instrument is obtained from a cross-fitted Ridge regression of cohort (leave-one-out) Twitter share on field composition and their interactions. The specifications include controls for the number of PhD cohort members and PhD graduation year fixed effects (1), the first principal components of average number of publications and citations among peers in the PhD institution (2) and peers in the PhD cohort (3), and the most frequent JEL code letter across all years (4). Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Table A.19: Robustness Second Stage Citations: Clustering

| | Dep. Var.: Nr. of Citations per Year | | | |
|---|---|---|---|---|
| | (1) PhD Institution-by-Year | (2) PhD Institution | (3) PhD Year | (4) Individual |
| Years of Twitter Usage | 1.866** | 1.866 | 1.866* | 1.866** |
| | (0.925) | (1.562) | (1.090) | (0.782) |
| Observations | 25,251 | 25,251 | 25,251 | 25,251 |
| Mean of DV | 6.53 | 6.53 | 6.53 | 6.53 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | Yes | Yes | Yes | Yes |
| PhD Cohort Quality | Yes | Yes | Yes | Yes |
| JEL Code | Yes | Yes | Yes | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of citations received per year (winsorized at $99^{th}$ percentile), clustering standard errors at different levels. Column (1) clusters by unique combinations of PhD institution and graduation year, while Columns (2) and (3) cluster separately by institution and graduation year, respectively. Column (4) does not cluster standard errors, computing simple heterogeneity-robust standard errors. All specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of the average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Standard errors (in parentheses) are clustered by PhD-institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Figure A.4: Second Stage: Leave-one-PhD Institution-out Estimates for Citations




*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of citations received per year (winsorized at $99^{th}$ percentile), leaving out one PhD institution at a time. All specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, and the most frequent JEL code letter across all years. Shaded region denotes 95-percent confidence intervals. Standard errors are clustered by PhD-institution-by-year.

# D Additional Results: Production of Papers

## D.1. Co-authorship

**Table A.20: Effect of Twitter Usage on Quality of Co-authors**

| | Dep. Var.: Nr. of Publications of Co-authors | | | |
|---|---|---|---|---|
| | Top 100 (1) | Top 50 (2) | Top GI (3) | Top 5 (4) |
| Years of Twitter Usage | 0.275** | 0.289*** | 0.358*** | 0.180*** |
| | (0.112) | (0.094) | (0.088) | (0.048) |
| Observations | 25251 | 25251 | 25251 | 25251 |
| Mean of DV | 1.39 | 0.92 | 0.25 | 0.13 |
| F-stat | 18.61 | 18.61 | 18.61 | 18.61 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | Yes | Yes | Yes | Yes |
| PhD Cohort Quality | Yes | Yes | Yes | Yes |
| JEL Code | Yes | Yes | Yes | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of yearly publications in different brackets of journal impact factor of researchers' co-authors. Columns (1) and (2) count publications in the Top 100 and Top 50 journals by impact factor, respectively, while Columns (3) and (4) refer to the 12 Top General Interest and Top 5 journals, respectively. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of the average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## D.2. References

**Table A.21: Effect of Twitter Usage on Quality of References**

| | Dep. Var.: Nr. of References to Pub. in: | | | |
|---|---|---|---|---|
| | Top 100 (2) | Top 50 (3) | Top GI (4) | Top 5 (5) |
| Years of Twitter Usage | 1.687 | 2.187** | 3.234*** | 2.414*** |
| | (1.226) | (1.064) | (0.893) | (0.686) |
| Observations | 25251 | 25251 | 25251 | 25251 |
| Mean of DV | 14.71 | 12.13 | 6.01 | 4.72 |
| F-stat | 18.61 | 18.61 | 18.61 | 18.61 |
| PhD Year FE | Yes | Yes | Yes | Yes |
| PhD Cohort Size | Yes | Yes | Yes | Yes |
| PhD Institution Quality | Yes | Yes | Yes | Yes |
| PhD Cohort Quality | Yes | Yes | Yes | Yes |
| JEL Code | Yes | Yes | Yes | Yes |

*Notes:* 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the number of yearly references to publications in different brackets of journal impact factor. Columns (1) and (2) count publications in the Top 100 and Top 50 journals by impact factor, respectively, while Columns (3) and (4) refer to the 12 Top General Interest and Top 5 journals, respectively. The specifications control for the number of PhD cohort members and PhD graduation year fixed effects, the first principal components of the average number of publications and citations among peers in the PhD institution and peers in the PhD cohort, respectively, and the most frequent JEL code letter across all years. Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.