#Science: How Twitter Shapes Economic Research*
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Abstract

We investigate the impact of Twitter usage on the production of economics research. Our analysis focuses on a sample of 17,000 economists, for whom we compile detailed data on publications, citations, co-authorship networks, and research topics using RePEc. We enrich this dataset by linking economists to their personal Twitter accounts and PhD cohorts, drawing on publicly available curricula vitae. To identify causal effects, we develop a novel instrumental variable strategy that leverages indirect peer influences across PhD cohorts and research fields. Our findings show that Twitter usage increases research productivity by approximately one additional paper every 2.2 years for the average user. While individual papers tend to receive slightly fewer citations, the overall rise in output results in an estimated 8.7 additional citations per year. These effects are most pronounced among intensive Twitter users, male economists, and those with more professional experience. We identify two main channels driving these outcomes: the expansion of co-authorship networks and a shift toward research topics that are more salient on Twitter—such as Covid-19, cryptocurrency, and issues related to Donald Trump. This topical reorientation is further associated with increased visibility of economists' work in mainstream media and among the general public.

Keywords: Science, Economic Research, Social Media, Information Aquisition
JEL Codes: D83, D91, L82, L86, O31

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1 Introduction

Scientists require a deep knowledge of existing and ongoing research to make critical decisions about which research questions to pursue. Such choices, in turn, shape careers and influence the direction of the discipline overall. Social networks play a crucial role in this knowledge acquisition process. Researchers learn about research from their academic peers at conferences and seminars. Moreover, academic peers influence where research is published and how widely it is cited as editors and referees. In the past decade, online social media have reshaped academic networks by providing new platforms for scholars to share their work and engage in academic discourse. In economics, the social media platform Twitter has emerged as particularly influential, with the hashtag *#EconTwitter* serving as an important channel through which economists learn what others in the field are working on, and what they are interested in.

Despite Twitter's growing prominence in the profession, little is known about how it affects scientific networks and the production of knowledge. The influence of social media likely operates through several, potentially opposing, mechanisms. On one hand, Twitter may raise visibility, expand professional networks, and help researchers identify which topics are perceived as important. On the other hand, it may distract researchers, amplify incentives to follow short-term trends, or contribute to inefficient herding behavior. As the first global, accessible, real-time platform to host a substantial share of academic debate, Twitter represents a novel development in the organization of scholarly communication. Understanding its impact is thus essential to assess how digital platforms shape the direction of scientific research.

In this paper, we explore these questions by examining research in the field of economics over the past two decades. Our analysis is based on an extensive data collection effort to link 17,000 economists to their personal Twitter profiles and collect publicly available curricula vitae from personal websites. Based on these new data, we are able to estimate the causal effect of Twitter using a novel instrumental variable strategy that allows us to overcome the endogeneity of Twitter adoption. This enables us to provide the first causal estimate of the impact of Twitter usage on economists' academic output, scientific networks, topics of research, and the visibility of their work both inside and outside academia.

For our analysis, we construct a comprehensive dataset linking economists to their academic output, Twitter activity, and early-career peer networks. Our sample consists of researchers with profiles on RePEc, a database of scholars and research papers in economics that provides detailed information on publications, citations, co-authors, and research topics. We identify personal Twitter accounts through a combination of sources, including personal websites, targeted Google and Twitter searches, and external datasets, hand-validating all matches with the assistance of research assistants. This procedure allows us to recover the date of Twitter sign-up as well as the usage intensity of the platform. To capture early career networks, we collect researchers' publicly available curricula vitae from RePEc, personal websites, and external datasets to infer PhD institutions and graduation years of researchers. Finally, we use Altmetric data to measure attention to researchers' work in the broader public.

The key empirical challenge when trying to estimate the effect of Twitter usage on research is the endogeneity of the decision to join Twitter. As a result, any naive comparison between Twitter users and non-Twitter users would almost certainly be biased. To overcome this endogeneity issue, we develop a novel instrumental variables strategy that exploits plausibly exogenous variation in indirect peer pressure to sign up for Twitter based on variation in research field composition of PhD cohorts. More specifically, we instrument each researcher's Twitter usage with the indirect Twitter pressure their PhD peers are exposed to through their respective research fields.

Put differently, we leverage the fact that PhD cohorts with more peers working on financial markets, as opposed to monetary policy, experience higher Twitter adoption rates, thereby generating plausibly exogenous variation in indirect Twitter pressure on their peers. In this way, our instrument does not rely on any individual's decision to sign up for Twitter, which is endogenous, but rather only exploits variation in the field composition across PhD cohorts. Importantly, our instrument accounts for any effect of the PhD institution itself and the research field of economists. We show that our instrument strongly predicts individual Twitter usage, which is robust to various choices of construction. Moreover, the timing of adoption confirms that indeed the composition of peers drives adoption.

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. We control for graduation year, cohort size, PhD institution, primary research field, and, in some specifications, pre-Twitter publication or citation counts. Our approach identifies the local average treatment effect of Twitter usage for researchers who joined the platform specifically due to Twitter usage among their PhD peers. The key identifying assumption is that, conditional on these controls, no omitted variable jointly affects researchers' outcomes and the Twitter pressure faced by their PhD colleagues.

Our analysis proceeds in three parts. In the first part, we show that Twitter usage increases the number of economists' publications and received citations. We estimate that Twitter users on average published one additional paper every 2.2 years. These increases are present both for journals with low and high impact factors, albeit of smaller absolute magnitude for more prestigious journals. To examine whether the productivity gains also lead to more academic recognition, we next turn to the effects on citations. We find that the average Twitter user receives an additional 8.7 citations per year. Interestingly, these *increases* in citation mask a slight *decrease* in citations per individual paper, which is being offset by economists' higher research output. Additionally, we establish that the increases in citations stem from a higher share of citations by other researchers on Twitter.

We additionally explore conduct heterogeneity analyses based on researchers' intensity of Twitter usage, gender, and career stage, to understand to what extent the benefits of Twitter usage differ by type. We find that economists with more followers, more following accounts, and more Tweets experience larger gains in publications and citations. Moreover, although the effects of Twitter usage are positive for both men and women, men benefit significantly more. Finally, economists who received their PhD before the year 2000 see larger increases in both publications and citations, while younger economists experience increases only in publications, but not in citations.

In the second part of the paper, we investigate whether the observed increase in research productivity can be explained by changes in co-authorship and referencing behavior. This allows us to shed more light on the effects of Twitter usage on research networks and the acquisition of knowledge about existing research. First, we show that economists using Twitter expand their network of co-authors, gaining on average 0.44 additional co-authors per year. Strikingly, most of these new collaborations involve economists who are also active on Twitter. We also observe modest effects on co-author quality with increases in the number of Top 5 and Top General Interest journal publications of co-authors. Second, we document that Twitter usage leads economists to reference more papers in their average publication. These increases again are driven by references to papers authored by other Twitter users, and are distributed equally across all levels of journal quality. This suggests that Twitter shapes the set of papers economists are aware of.

Motivated by the findings in the previous part, the third part of the paper studies how Twitter usage influences economists' choice of research topics. We find that Twitter usage increases the similarity of research to other Twitter users while decreasing the similarity to research of non-Twitter users. Note that this finding holds conditional on an economist's research field. We also show that Twitter usage increases the likelihood of economists working on trending or controversial themes such as Covid-19, cryptocurrencies, or Trump. Finally, we document that this shift in research topics coincides with increased attention in the broader media landscape, measured by mentions in mainstream media, blogs, and Twitter posts based on data from Altmetric.

Taken together, our results suggest that Twitter usage increases the recognition economists receive for their work, both within academia and in the broader public. This effect appears to operate primarily through two channels. First, Twitter seems to facilitate finding co-authors, leading to higher productivity. Second, economists choose research topics that resonate more with audiences on Twitter and beyond. However, the ability to realize these benefits likely depends on researchers' success in building a visible presence on the platform. In practice, this may advantage more experienced economists who are already established in the field and better positioned to attract a large follower base.

Related literature

Our findings contribute to the existing literature in at least three ways. First, our findings contribute to the literature on the economics of science. Previous studies have explored many important drivers of innovation, such as the relevance of patenting rights (Scotchmer, 1991; Moser and Voena, 2012; Galasso and Schankerman, 2015), the geography of knowledge spillovers (Jaffe et al., 1993; Peri, 2005), and productivity gains to collaboration (Wuchty et al., 2007; Jones et al., 2008). We contribute to this field by shedding light on how modern information technologies shape the direction of scientific progress, which has so far been overlooked.

Second, we relate to the literature on the effects of social media, that has been shown to impact voting, polarization, and protests (Bond et al., 2012; Tucker et al., 2018; Zhuravskaya et al., 2020; Fujiwara et al., 2021), hate crimes (Müller and Schwarz, 2021, 2022), as well as well-being and mental health (Allcott et al., 2020; Braghieri et al., 2022). However, evidence regarding the effects on academic research is limited. Tonia et al. (2016) randomizes social media exposure of 130 articles in the International Journal of Public Health published between 2012 and 2014 and finds no effects on downloads and citations. Instead, observational studies find a positive correlation between social media coverage and subsequent citations (Eysenbach et al., 2011; Haustein et al., 2014; Smith et al., 2019; Sathianathen et al., 2020; Özkent, 2022). We contribute to this literature by providing the first large-scale causal evidence for the effects of social media on scientific output, confirming the cross-sectional correlations found in other studies. Moreover, we are the first to explore how social media affects the *direction* of academic research.

Third, we relate to previous research on information acquisition and herd behavior. Theoretical papers have explored the origins of herd behavior (Banerjee, 1992; Bikhchandani et al., 1992) and the dynamics of information acquisition in networks (Acemoglu et al., 2010, 2011). Empirical studies have provided evidence for herd behavior in a wide range of contexts, for example in online product choice of private consumers (Huang and Chen, 2006; Babić Rosario et al., 2016) and investing decisions of professional financial investors (Scharfstein and Stein, 1990; Welch, 2000; Sias, 2004). We contribute to this literature by providing the first evidence on herd behavior among scientists.

2 Data

For our analysis, we built the largest existing database of economists, their Twitter usage, and their academic output. We identify personal Twitter accounts using a combination of information from personal websites, targeted web searches, and other existing datasets. We further augment this data with PhD institutions and graduation years by collecting CVs from personal webpages. We describe the data collection steps in the following.

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. A great 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 as shown Figure 1(a), and publicly available for download. By parsing these files, we obtain information on around 82,000 authors who produced more than 1.3 million published and working papers in more than 3,000 journals and working paper series. For each author, we observe current affiliation(s), and, if provided, links to their personal website and Twitter account. Moreover, we obtain their full history of published and working papers. In particular, the data record title, abstract, names of all co-authors, publishing journal or working paper series, and date of publication. For a subset of papers, we also have information on keywords and Journal of Economic Literature (JEL) topic codes chosen by the authors, as well as DOIs.[1] Finally, we observe the directed graph of citations between papers as of 2022.

We supplement the RePEc data using OpenAlex, a public database that tracks publications and citations of scholars across all disciplines. We link authors based on first and last name as well as paper titles. While OpenAlex is useful for validation, RePEc is better suited to our analysis as its exclusive focus on economics ensures higher data quality for this discipline.

[1] *Digital Object Identifier (DOI)*, a unique and persistent identifier that is widely used to link digital objects across different sources.

Figure 1: Example Data

(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) Twitter Data

Notes: Panel (a) presents an example RePEc database file. Panel (b) shows a screenshot of a Twitter profile.

2.2 Twitter profiles

As the second step of our data collection, we identify Twitter accounts of economists using a five-step procedure: 1) RePEc, 2) information from professional websites of economists, 3) Google searches, 4) Twitter profile search, and 5) information on Twitter profiles from Mongeon et al. (2023). Afterwards, all potentially matching Twitter accounts were hand-validated with the help of research assistants. The overall procedure is visualized in Appendix Figure A.2 and described in the following. Also note that the data collection in large part took place before Elon Musk's takeover of Twitter in October 2022, and we therefore also observe Twitter profiles of users who might have deleted their accounts afterwards.

First, we utilize all Twitter profiles registered by authors on their RePEc profiles. This provides us with Twitter profiles for 3,256 economists in the RePec data. The full list is available here: RePEc-registered economists on Twitter.

Second, we extract links to Twitter profiles from personal websites. In addition to websites linked on researchers' RePEc profiles, we retrieve additional websites using Google's Custom Search API. For each researcher, we run queries comprised of their first name, last name, and the keyword `economist`. We retain URLs from domains commonly used for personal pages (Google Sites, Wordpress, GitHub, etc.) or domains similar to the researcher's name. Research assistants manually validate that the identified website indeed belongs to the correct economists from the RePec data. Afterwards, we use a custom scraper to visit all pages and subpages on the identified sites and extract embedded links to Twitter user profiles.

Third, we run additional Google's Custom Search API queries of the form first name, last name, while restricting the search to Twitter.com, and retain all found Twitter user profiles.

This provides us with a large set of additional candidate accounts.

Fourth, we further augment the set of candidate accounts by using the Twitter Graph API, which was still active at the time of data collection, to directly search for profiles based on the first and last name of each economist. In the next step, we filter the set of candidate Twitter accounts we have obtained in steps three and four for name similarity between Repec and Twitter profiles, as well as keywords related to economics and academic positions in the biography (short description) of these Twitter profiles.

Fifth, we incorporate a recent dataset by Mongeon et al. (2023), which links OpenAlex authors to Twitter profiles. We match around 6,500 of these authors with Twitter profiles to our RePEc data. [2]

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 the matching between Twitter accounts and 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 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, we identify around 12,500 personal Twitter accounts among the economists in our sample. For each account, we collect the creation date, the total number of tweets, likes, and retweets, follower and following counts, and the full history of tweet content and timing. Figure 1 shows an example for the RePEc author file and the corresponding Twitter profile for Nobel Memorial Prize Winner Joshua Angrist.

2.3 PhD institution and graduation year

As the last 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 identification strategy. We collect information based on three different sources.

First, we use data from the RePEc Genealogy project, which records PhD institutions and graduation years for a subset of authors with RePEc profiles. The database currently includes around 24,000 economists, even though only around 15,000 entries contain both variables. For example, if someone indicated a RePec user as their advisor in the RePEc Genealogy Project,

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

the advisor's profile will be part of the Genealogy Project, but the advisor's graduation date is not available.

Second, we incorporate information on PhD institutions and graduation years of around 3,000 US-based economics faculty from J. R. Hasselback's Faculty Directories.[3] The information was hand-collected by James R. Hasselback in five cohorts 1999-2000, 2001-2002, 2003-2004, 2006-2007, 2020-2021, and contains information on economists in 130 U.S. Economics Departments, even though not all of them list PhD institutions and graduation years.

Third, we collect publicly available CVs from the personal websites identified either from the RePec data or our Google searches in our collection of Twitter profiles. Using a custom webscraper, we loop over all pages and subpages of economists' professional websites and identify links to CVs based on 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 avoid hallucinations by the large language model, we use a reverse string matching procedure to ensure that the extracted PhD information is indeed contained 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 CV for more than 9,000 economists, among them 7,700 in PDF format.

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 a single researcher. In total, we recover both the PhD institution and the graduation year for more than 17,000 economists. To the best of our knowledge, this provides us with the largest existing database of economists and their PhD institutions.[4]

2.4 Outcome measures

For the empirical analysis, we create outcome measures that capture economists' output, co-authorship, citation network, as well as research topics.

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

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

Scientific Output

The first set of outcome variables captures standard measures of scientific output. For each economist, we count the total number of publications and separately by journal quality. We distinguish between the commonly used "Top 5" (QJE, AER, JPE, ECMA, RESTUD) and "Top General Interest" journals[5], as well as the top 50 and top 100 journals based on RePEc's aggregate impact ranking. Moreover, we measure citations accrued by 2022 for papers published in each year. As above, we count both total citations and those coming from top-ranked journals. These measures aim to provide a differentiated account of the productivity and scientific impact of a researcher.

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

Further, we characterize the topics economists are working on in three ways. First, we use papers' JEL codes that jointly categorize the fields of each paper. We use the 20 one-character JEL codes (A-Z) as well as the 190 two-character JEL codes (A1-Z3). Second, we search for keywords related to "hot" topics in papers' abstracts, such as *Covid-19*, *Crypto*, or *Gender*. Third, we characterize the similarity of research topics by quantifying the similarity of abstracts using document embeddings. We construct document embeddings generated by Doc2Vec (Le and Mikolov, 2014) to represent each abstract as a 50-dimensional vector, and quantify the closeness between abstracts using cosine similarity. Then, we compute the average similarity of each abstract to the 100 most similar abstracts published in the same year, among papers published by authors who use Twitter and authors who do not, respectively. These measures reveal how similar the research by economists on Twitter is to other economists on Twitter, relative to research by economists outside the Twitter network.

[5] 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.

Attention Metrics

Finally, we capture the attention paid to economists' publications in the broader public based on data from Altmetric for roughly 130,000 papers for which we observe the DOI. Altmetric records the number of mentions across various platforms such as news media, blogs, and social media. Mentions on Twitter are classified by user type, including academics, journalists, and the general public, based on keywords in users' biographies. In addition to the number of individual mentions, Altmetric reports a composite attention score, with weights that reflect the relative importance of the source (e.g., mentions in the news receive a larger weight than social media posts).

2.5 Sample Construction and Descriptive Statistics

Our analysis is based on the economists in the RePec data with at least one journal publication between 2006 and 2022. We restrict our analysis to authors with at least one publication in this time frame to avoid using information from retired or dead economists. The time frame exactly covers the launch of Twitter in March 2006 until the takeover of the platform by Elon Musk in October 2022, which was followed by large platform changes and an exodus of many economists from the platform to BlueSky and other networks. Hence, we capture almost the entire life cycle of the social media platform and its use by economists.

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. This restriction also helps us to define a precise start year to include researchers in our data. Economists enter our sample in their graduation year, and leave it after their last observed paper.

Table 1 summarizes characteristics of the final sample. For comparison, Column (1) reports numbers for the full sample of RePEc economists, Column (2) includes only researchers active between 1995 and 2022, and Column (3) further restricts to researchers with information on PhD institution and year. The final sample contains 17,202 economists who graduated from more than 1,000 PhD institutions and produced almost 600,000 published and working papers that received close to 12 million citations. Among these researchers, we have found their personal website for 87.4 percent, and the full CV in PDF format for 34.5 percent. Moreover, at least 29.9 percent of these researchers have signed up for Twitter.[6]

[6] Successful researchers are more likely to join Twitter, as shown in Figure A.1, which plots the share of Twitter users over time by quartiles of the number of citations in the previous three years.

Table 1: Sample composition

	Sample		
	All RePEc	**1995-2022**	**Final**
	(1)	(2)	(3)
Panel A: Share of researchers linked to:			
Website	0.602	0.678	0.874
CV	0.093	0.112	0.345
RePEc Genealogy	0.214	0.258	0.773
OpenAlex	0.744	0.922	0.973
PhD Institution & Year	0.231	0.277	1.000
Twitter Account*	0.148	0.184	0.299
Panel B: Number of unique observations:			
Citations	22,273,206	18,266,839	11,870,391
Papers	1,331,566	1,153,468	573,869
Researchers	82,183	65,352	17,202
PhD Institutions	1,088	1,057	1,021

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. 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.

For our analysis, we create a cross-section of economists measuring their average outcomes over our observation period. Table 2 presents summary statistics. The average researcher publishes roughly one paper and receives around 33 citations per year. Less than 1 out of 2 papers are published in top 100 journals, and 1 in 25 are published in the Top 5. Around 1 in 6 citations originate from a paper published in a Top 100 journal, and less than 1 in 200 come from a Top 5 paper. Researchers reference around 39 papers in a typical year. Note that we include citations and references that involve researchers outside our sample, which is why the two numbers need not be equal. Over the entire sample period, only a small fraction of references point to papers authored by at least one Twitter user. We count around 1.5 unique co-authors per year, again with a small minority being Twitter users when considering all years. Altmetric records slightly less than one mention of researchers' work per year, most of them on Twitter. Four out of five of these mentions originate from members of the general public as opposed to scientists, according to Altmetric's estimate.

Table 2: Descriptive Statistics

	Mean	SD	Min	Max	N
General					
Year	2012.81	4.93	1995	2022	17,202
PhD graduation year	2004.09	11.93	1942	2022	17,202
Twitter sign-up year	2014.27	4.00	2006	2023	5,149
Years on Twitter	1.86	3.56	0	16	17,202
Female	0.22	0.42	0	1	14,026
Publications					
All	1.00	1.03	0	29	17,202
Top 100	0.38	0.44	0	7	17,202
Top General Interest	0.07	0.16	0	4	17,202
Top 5	0.04	0.12	0	3	17,202
With JEL code	0.31	0.46	0	15	17,202
With DOI	0.13	0.31	0	6	17,202
Citations					
All	32.71	81.50	0	2117	17,202
Top 100	5.44	13.91	0	438	17,202
Top General Interest	0.23	0.74	0	17	17,202
Top 5	0.14	0.48	0	12	17,202
Network					
References	39.00	49.90	0	921	17,202
Sh. Twitter users among references	0.10	0.11	0	1	16,711
Unique co-authors	1.56	1.71	0	34	17,202
Sh. Twitter users among co-authors	0.17	0.24	0	1	15,831
Altmetric					
All	0.88	7.97	0	426	17,202
News media	0.05	0.80	0	62	17,202
Social media	0.63	6.15	0	423	17,202
Twitter	0.62	6.01	0	423	17,202
Twitter, by general public	0.47	5.19	0	421	17,202
Twitter, by scientist	0.12	1.06	0	87	17,202
Aggregate Attention Score	1.03	9.77	0	610	17,202

Notes: Summary statistics at the scientist level, representing the average value across all years observed in the sample.

3 Empirical Strategy

The key challenge in estimating the causal effect of Twitter usage on the research of economists lies in the endogenous nature of the decision to sign up for Twitter. In other words, researchers may adopt Twitter for reasons that are correlated with outcomes but nearly impossible to control for. Due to this endogeneity, any naive regression estimates of research outcomes on Twitter usage would almost certainly be biased. On the one hand, the estimates could be biased upward if more productive researchers signed up for Twitter. On the other hand, the estimates could be biased downwards if researchers signed up for Twitter at points in time when they move away from research to a more policy-focused career.

Due to this endogeneity, the effect of Twitter usage has proven challenging to investigate empirically. We propose to estimate the causal impact of Twitter usage based on a novel instrumental variables strategy exploiting plausibly exogenous variation in *indirect* Twitter pressure through economists' peer network from their doctoral studies. We describe the construction and plausibility of our instrument in the following section and present the first stage evidence.

3.1 Instrument for Twitter Usage based on PhD Network and Academic Field

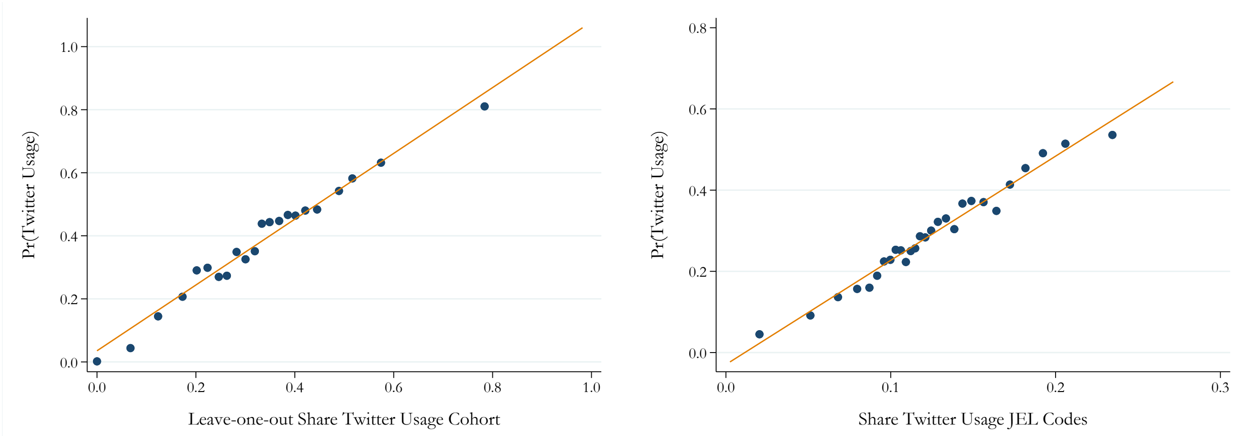
Our strategy is based on the idea that the utility from using social media platforms increases if more peers join the same platform. Indeed, existing research shows that individuals' decisions to join social media platforms strongly correlate with their peers' usage (e.g., Aridor et al., 2024). In the context of academic research, two particularly relevant networks are 1) classmates from the same PhD cohorts 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 instrument exploits a combination of two variations in these two key 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 Twitter for identification using the indirect effect of "peers of peers" (e.g., Bramoullé et al., 2009; Lin, 2010; De Giorgi et al., 2010). In combination, these sources of variation allow us to instrument for economists' own Twitter usage with the field-specific pressure to use Twitter faced by their PhD colleagues.

Using our data, we provide motivational evidence for the fact that both the Twitter usage in one's PhD cohort as well as one's research field are good predictors of an economist's own 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 field. In both cases, we find a strong and positive correlation between an economist's own decision to join Twitter and the 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)).

Building on this motivational evidence, we propose an empirical strategy in the spirit of Bramoullé et al. (2020), and instrument each researcher's Twitter usage with the Twitter usage of "peers of peers," defined as researchers who are two network links away. This strategy has several key advantages. First, by constructing the instrument without relying on the direct Twitter adoption decisions of either the researcher or their immediate colleagues, we avoid issues related to the mutual influence of peers on each other that is at the heart of the reflection problem (Manski, 1993). Second, as we use economists' early-career networks formed during doctoral studies – which is not subject to the direct choice of a research and remains fixed throughout their career – we preclude any endogenous changes in network links and the composition of PhD colleagues' fields. Third, as we only use variation in Twitter usage in fields in which economists do not themselves work in, we overcome concerns about correlated shocks that could drive Twitter adoption as well as output.

The construction of our instrument proceeds in three steps. As a first step, we determine PhD peers using information on researchers' doctoral institutions and graduation years. In our baseline measure, we construct a PhD cohort includes all scholars who graduated from the same institution within five years before or after the researcher's own graduation. This choice is motivated by the average 6-year length of economic PhD programs and therefore should cover all other PhDs economists potentially interact with during their PhDs. As we show in robustness tests, later this choice is not material to any of our findings.

As a second step, we identify the research fields of all economists and their PhD peers based on the JEL codes indicated in their research papers. In our baseline approach, we classify each economist's main fields based on the three most frequently used two-character JEL codes (i.e., A1–Z3, 190 distinct codes) among their research papers in their entire career. By doing so, we assume that economists' main fields are stable over time and thus unaffected by career stage or Twitter adoption. We consider this assumption justified for two reasons. First, economists typically specialize in one or two core fields and work on them throughout their careers. Second, by drawing on authors' work over all available years, we capture long-run field affiliations rather than transient research interests. In robustness checks, we again confirm that our instrument is robust to various alternative ways of defining the research fields of economists, employing among others the more aggregated one-letter JEL codes (A–Z, 20 codes).

As a third step, we construct our instrument, capturing each researcher's indirect Twitter Pressure as the average share of Twitter usage in the fields of their PhD colleagues (excluding the researcher's own fields). To facilitate exposition, we present the formal construction of the instrument for the simplified case in which each researcher contributes to exactly one field. The general version, which accounts for researchers contributing to multiple fields with varying intensity, is detailed in Appendix B.1. In the simplified case, indirect Twitter Pressure for researcher i in year t is defined as:

$$Twitter\ Pressure_{i,t} = \frac{1}{|Cohort_i| - 1} \sum_{\substack{c \in Cohort_i, \\ c \neq i}} \sum_{\substack{f \in Fields, \\ f \neq Field_i}} I(Field_c = f) \times Sh.\ Twitter\ Users\ in\ Field_t^f \tag{1}$$

The summation runs over the set of peers in economists i's cohort ($\sum_{\substack{c \in Cohort_i, \\ c \neq i}}$) and over the set of research fields excluding i's own one ($\sum_{\substack{f \in Fields, \\ f \neq Field_i}}$). The indicator $I(Field_c = f)$ equals one if colleague c is active in field f, and zero otherwise. $Sh.\ Twitter\ Users\ in\ Field_t^f$ denotes the share of researchers in field f who have a Twitter account in year t.[7] In other words, the resulting instrument captures the average share of Twitter usage in fields represented among economists' PhD peers, excluding their own area of specialization.

[7]We compute the share of Twitter users in each field as a leave-one-out measure, excluding colleague c from the calculation.

3.2 Estimation

To estimate the causal effect of Twitter usage, we make use of our measure of indirect Twitter pressure in a two-stage least squares (2SLS) specification, in which we instrument for the number of years that a researcher has been on Twitter. More specifically, we estimate the following cross-sectional regression:

$$y_i = \alpha + \beta \widehat{Years\ on\ Twitter}_i + \mathbf{X}'\theta + \varepsilon_i \ . \tag{2}$$

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 $Years\ on\ Twitter_i$ and captures the number of years an economist spent on Twitter until 2022.[8] In our regression, we additionally account for a large set of observable controls $\mathbf{X}'$. In particular, we control for PhD year fixed effects to absorb career stage and cohort-level productivity shocks, the number of peers in one's PhD cohort, PhD institution fixed effects to account for institutional characteristics, and field fixed effects to capture differences across research areas.

In the first stage, we instrument $Years\ on\ Twitter\ _i$ using average Twitter Pressure individual i faced between 2006 and 2022. This gives rise to the following first-stage equation:

$$Years\ on\ Twitter_i = \omega + \lambda Twitter\ Pressure_i + \mathbf{X}'\gamma + \eta_i \tag{3}$$

where $Twitter\ Pressure_i$ is the average of researcher i's Twitter Pressure aggregated over all years and $\mathbf{X}'$ is the above described set of control variables. In both specifications, we cluster standard errors at the PhD institution $\times$ PhD year level, which is the relevant level of variation of our instrument.

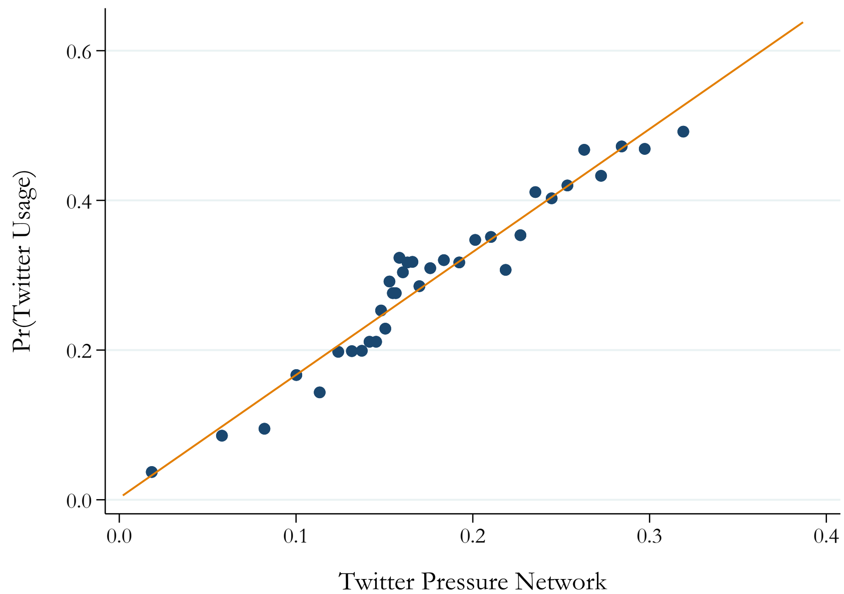
We estimate our regressions using a cross-sectional data structure as it circumvents at least two econometric issues that would arise in a panel setting. First and most importantly, our instrumental variable is both continuous and staggered, with repeated treatments, and to the best of our knowledge, no estimators exist for a staggered-IV-difference-in-differences design. Second, in a panel data structure, we would need to account for the autocorrelation of outcomes as well as the dynamic dependencies of treatment exposure explicitly, using lags of treatment and outcome variables. The cross-sectional data structure allows us to overcome both issues simultaneously, providing a transparent research design. By using the $Years\ on\ Twitter_i$ as our main treatment variable, we preserve variation in adoption timing. In addition, we will provide evidence for the timing of our treatment effects using a reduced-form staggered difference-in-differences regression.

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

3.3 First Stage Estimates

We start by confirming the relevance of our instrumental variable strategy using a binned scatter plot in Figure 3. We find a strong positive association between the amount of Higher Twitter Pressure (x-axis) and the likelihood of an economist joining Twitter (y-axis). The Figure also confirms an approximate linear relationship between the amount of Twitter pressure and the likelihood of Twitter usage.

Figure 3: First Stage: Network Twitter Pressare and Twitter Adoption



Notes: Binned scatter plot on researcher level correlating an indicator for ever using Twitter with Twitter Pressure. PhD cohorts include researchers graduating from the same institution within 5 years, and fields for each researcher are defined by the three most frequent two-character JEL codes indicated on their papers.

Next, we more formally investigate the strength of the relationship between the years of Twitter usage and our instrument in Table 3. To ease interpretation, we standardize the Twitter Pressure instrument to have a mean of 0 and a standard deviation of 1. The estimates confirm a strong and positive relationship between our instrument and the years of Twitter usage. We find that, on average, a one standard deviation increase in the amount of Twitter Pressure is associated with a 0.8-year increase in Twitter usage. This increase is substantial given that the average years of Twitter usage, including non-users, is around 1.9.

The first stage coefficient is also remarkably stable to the inclusion of additional control variables. In Column (1), we only control for the number of years since the completion of the PhD in our data using fixed effects. In Column (2), we additionally include indicators for the number of students in the same PhD cohort. In Column (3), we include over 1,000 fixed effects for each PhD institution. These fixed effects account for any difference in Twitter usage that can be explained by students from a particular university being more likely to join Twitter in general. Lastly, in Column (4), we include controls for the JEL codes economists are working in. These controls will account for any effect on Twitter usage that is driven by higher Twitter pressure in a particular research field. None of these controls makes any difference for the magnitude or the significance of our first-stage estimates. If anything, the estimates increase slightly in size in comparison to Column (1).

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

	Dep. Var.: Years of Twitter Usage			
	(1)	(2)	(3)	(4)
Twitter Pressure (std.)	0.784***	0.936***	0.903***	0.890***
	(0.028)	(0.028)	(0.031)	(0.031)
Observations	15,417	15,417	15,417	15,417
Mean of DV	1.94	1.94	1.94	1.94
R^2	0.03	0.03	0.03	0.03
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

Notes: Regressions of the number of years of Twitter usage on standardized Twitter Pressure, including fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Intensive vs. Extensive Margin

We also investigate if our instrument predicts both the extensive and the intensive margin of Twitter usage. Regarding the former, we replace the dependent variable in the first-stage regressions with an indicator that is equal to 1 if an economist uses Twitter. Similar to our baseline estimates, we find a strong and highly robust positive association between our instrumental variable and the decision to join Twitter (see Table 4). On average, a one standard deviation increase in Twitter pressure increases the probability that an economist joins Twitter by between 11.7 and 14.1 percentage points. Even the lower bound represents around a 40% increase relative to the mean.

To study the intensive margin, we restrict our estimation sample to the economists who have joined Twitter and, among these, investigate the relationship between Twitter pressure and the years of Twitter usage (see Table 5). We find that even among Twitter users, higher Twitter pressure is associated with a higher number of years on Twitter. In other words,

Table 4: Robustness First Stage: Extensive Margin

	Dep. Var.: I[Twitter Usage]			
	(1)	(2)	(3)	(4)
Twitter Pressure (std.)	0.117***	0.141***	0.133***	0.131***
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	15,417	15,417	15,417	15,417
Mean of DV	0.29	0.29	0.29	0.29
R^2	0.04	0.04	0.04	0.04
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

Notes: Regressions of an indicator for ever using Twitter on standardized Twitter Pressure, including fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

individuals who face higher Twitter pressure join Twitter earlier. A one-standard-deviation increase in Twitter pressure is associated with approximately one additional year of Twitter usage.

Table 5: Robustness First Stage: Intensive Margin

	Dep. Var.: Years Twitter Usage			
	(1)	(2)	(3)	(4)
Twitter Pressure (std.)	0.585***	0.930***	1.133***	1.157***
	(0.070)	(0.092)	(0.106)	(0.106)
Observations	4,462	4,459	4,308	4,308
Mean of DV	6.69	6.69	6.70	6.70
R^2	0.01	0.02	0.02	0.03
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

Notes: Regressions of the number of years of Twitter usage on standardized Twitter Pressure within the subsample of economists who have ever used Twitter. The specifications include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Robustness

We probe the robustness of our first-stage results with regard to several different margins. First, in Appendix Table A.1 we show that our instrument is robust to different definitions of PhD cohorts. In particular, we vary the size of the cohort window we consider for the instrument construction from ± 6 to ± 1 years around the researcher's graduation. This perturbation has no impact on any of our findings. Second, in Appendix Table A.2, we confirm the robustness of our findings to alternative definitions of researchers' fields. The relationship remains positive and significant for both one- and two-character JEL codes, and independent of the number of fields we consider per researcher. Third, Appendix Table A.3 shows that the results are robust to clustering standard errors by PhD cohort, institution, or graduation year. Fourth, Appendix Table A.4 shows that the instrument is robust to using alternative functional forms, including using the percentiles, inverse hyperbolic sine-transformed, and discretized variants split at the 50^{th}, 75^{th}, or 90^{th} percentile. Fifth, we show that our instrument holds in the sample of economists who completed their PhD before 2006 (see Appendix Table A.5) and who are therefore consistently observed in all years of our sample period.

3.4 Exclusion Restriction

As with any instrumental variable strategy, we require the exclusion restriction. In our particular case, the indirect Twitter pressure through the PhD cohort can only affect academic outcomes via its impact on Twitter usage. While this assumption is inherently untestable, it strikes us as highly plausible in our context for at least three main reasons.

First, given that we are using the indirect effect of Twitter pressure in other research fields, we do not use information on the extent of Twitter usage in economists' own PhD cohort or in the research field. Hence, it is highly unlikely that economists can directly influence their exposure to the instrument. This assumption is particularly credible for economist who completed their PhD before 2006 and for whom the Twitter pressure therefore only materializes after they had already begun their work at a different institution. As we have shown previously, our instrumental variable also holds for this subsample. Further, due to the large number of controls, it appears unlikely that an omitted variable jointly affects researchers' outcomes and the Twitter pressure. For example, our most restrictive specification includes fixed effects for both the PhD institution and the research field of each economist. Our instrument, therefore, only relies on residual variation due to the differential composition of PhD cohorts within the same PhD institution and research field.

Second, we can conduct a placebo test for our instrument by shifting the year of PhD graduation forward or backward by ten years. This allows us to construct two placebo instruments that capture the indirect Twitter Pressure economists would be exposed to if they had graduated from the same university at a different point in time and therefore would have interacted with a different peer group. For example, the Placebo Twitter Pressure for the pre-period captures the amount of Twitter pressure economists would have been exposed to if they graduated from Harvard in 2000 instead of 2010. The estimates using these placebo instruments are shown in Table 6. We find that the placebo estimates are, in all cases, significantly smaller than our instrument and, in nearly all cases, statistically indistinguishable from zero. If our instrument were an omitted variable that affects both our instruments and the probability of using Twitter, any such omitted variable should also affect the placebo Twitter pressure measures.

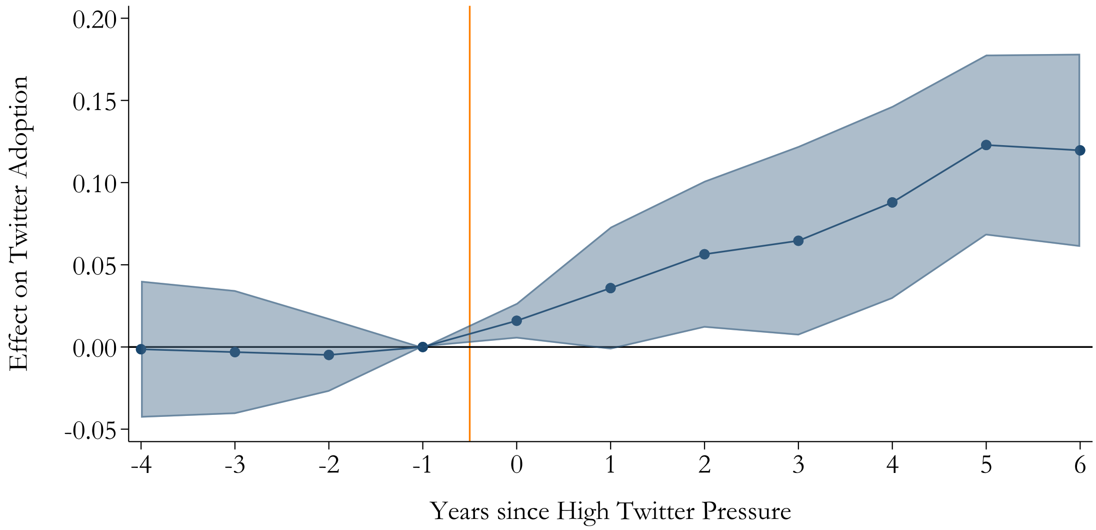
Table 6: First Stage: Placebo Network Twitter Pressure and Twitter Adoption

	Dep. Var.: Years of Twitter Usage			
	(1)	(2)	(3)	(4)
Twitter Pressure (std.)	0.548***	0.684***	0.651***	0.639***
	(0.029)	(0.031)	(0.035)	(0.035)
Placebo Twitter Pressure Pre. (std.)	0.046	0.003	0.002	0.009
	(0.030)	(0.036)	(0.041)	(0.041)
Placebo Twitter Pressure Post. (std.)	0.053*	0.054	0.051	0.057
	(0.031)	(0.036)	(0.035)	(0.035)
Observations	14,867	14,867	14,867	14,867
Mean of DV	1.62	1.62	1.62	1.62
R^2	0.02	0.02	0.02	0.02
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

Notes: Regressions of the number of years of Twitter usage on standardized Twitter Pressure, including fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code 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 can investigate the timing of the impact of our instrument relative to the decision of an individual to adopt Twitter. To do so, we estimate a staggered difference-in-difference specification in which researchers are treated once Twitter Pressure exceeds the 25^{th} percentile. The estimates, obtained using the robust estimator by De Chaisemartin and D'Haultfoeuille (2022), are shown in Figure 4. We find no evidence for the differential adoption of Twitter in the pre-period, but significant increases in the likelihood of joining Twitter once Twitter pressure rises beyond the 25th percentile. This provides strong evidence for the idea that individuals would not have joined Twitter in the absence of Twitter pressure.

Figure 4: Dynamic Effect of Twitter Pressure on Twitter Adoption



Notes: Point estimates and 95 percent confidence intervals for yearly effect of high Twitter Pressure on indicator for using Twitter in year, estimated using the heterogeneity-robust estimator by De Chaisemartin and d'Haultfoeuille (2020) in author-year panel. High Twitter Pressure is an indicator switching to one once Twitter Pressure ($\pm$5-year cohort, Top 3 JEL2 codes) exceeds the 25^{th} percentile.

Based on these multiple pieces of evidence, we believe 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 the research of economists.

4 Effect of Twitter on Scientific Output

In the first part, we start by investigating the effect of Twitter usage on the number of publications of economists, both in low- and high-ranked journals. We further study the impact on the number of citations received by economists. Additionally, we analyze heterogeneity conditional on gender, age, and the intensity of Twitter usage.

4.1 Publications

We start by estimating Equation (2), where the dependent variable is the average number of publications of an economist in all journals covered by the RePEc data. Table 7 presents the effect of Twitter usage on the number of yearly publications, using Twitter Pressure as an instrument for the number of years on Twitter. As for the first stage estimates, Column (1) includes fixed effects for years since the completion of the PhD, Column (2) adds fixed effects for the the number of students in the $\pm$5-year PhD cohorts used to construct the instrument, Column (3) further includes fixed effects for the PhD institutions, and Column (4) finally controls for each researcher's JEL code shares.

We find that Twitter usage substantially increases economists' publication output. The estimates are positive and significant across all specifications, and the magnitude increases slightly with the inclusion of additional control variables. Given that the average number of years of Twitter usage (including non-users) is 1.9, the estimate of 0.239 in the most restrictive specification suggests that Twitter users on average published one additional paper every 2.2 years.

Table 7: Effect of Twitter Usage on Number of Publications

	Dep. Var.: Nr. of Publications per Year			
	(1)	(2)	(3)	(4)
Years of Twitter Usage	0.147***	0.214***	0.236***	0.239***
	(0.016)	(0.013)	(0.015)	(0.015)
Observations	15,417	15,417	15,417	15,417
Mean of DV	1.07	1.07	1.07	1.07
F-Stat (KP)	775.82	1082.18	857.43	824.05
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				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 specifications cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

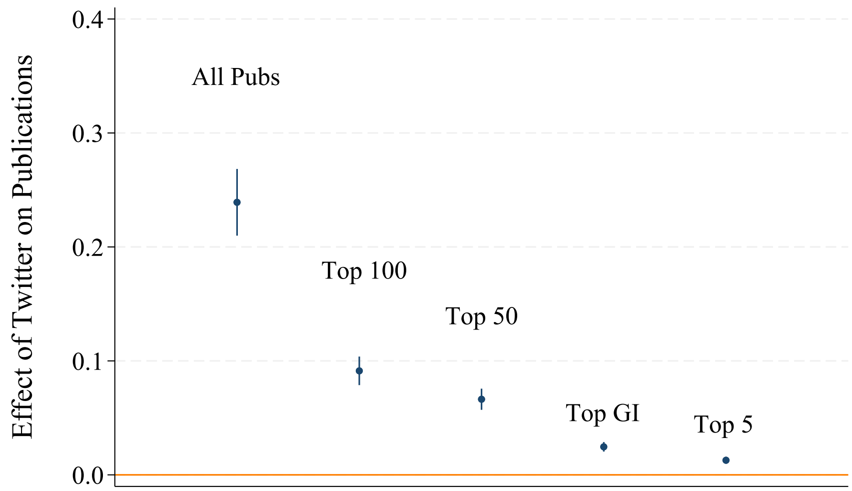
While the increase in publications is very stable across specifications, an obvious question regards the quality of these publications, as the publication of Twitter users could either appear in high-quality journals with low acceptance rates or lower-ranked journals with high acceptance rates. We investigate this question by replacing the dependent variable with the number of publications in journals of varying quality. More specifically, we consider publication in the Top 100, Top 50, Top General Interest, and Top 5 journals.[9]

We visualize the estimates from these regressions in Figure 5 and report the precise regression estimates in Appendix Table A.6. Interestingly, we find that Twitter usage is associated with an increase in the number of publications across all journal categories. The coefficients are decreasing with increasing journal quality: 0.239 (all publications), 0.091 (Top 100), 0.066 (Top 50), 0.02 (Top General interest and 0.013 (Top 5). In other words, the

[9]We discuss the precise definition of these categories in Section 2.4.

average Twitter usage is associated with around one additional Top 5 publication over the course of a 40-year career.

Figure 5: Heterogeneity by Publication Quality



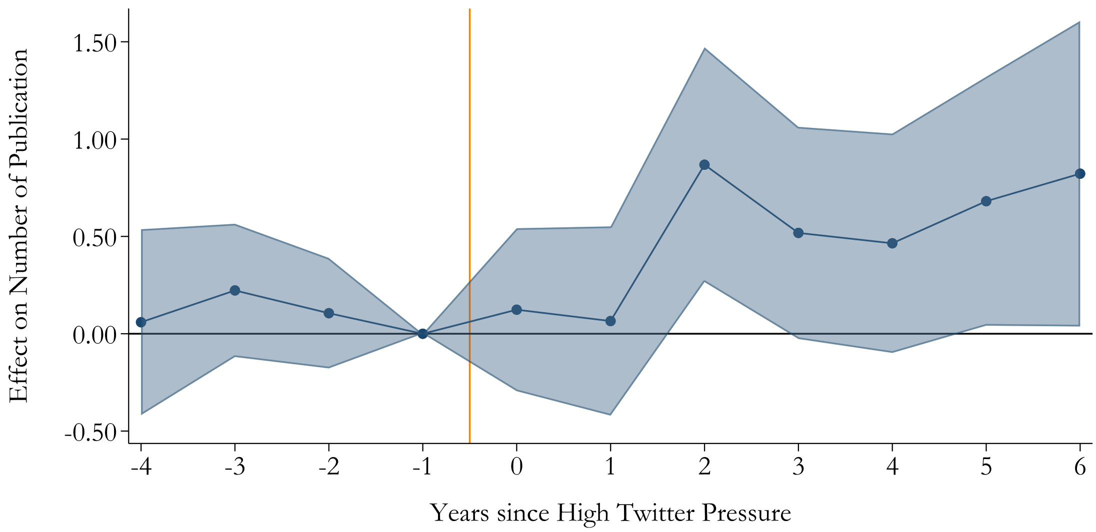
Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the number of yearly publications in different brackets of journal impact factor. The specifications include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code across all years. Standard errors are clustered by PhD institution-by-year.

One concern with the previously presented estimates could be that our instrument is correlated with the pre-existing quality of economists. To address this concern, we can control for the average number of publications of economists in the period before the launch of Twitter. More specifically, we control non-parametrically for pre-period publication levels by including an indicator variable for each value of the average number of publications. Note that this approach cuts our sample by more than half, as we can only estimate the specification for people who finished their PhD before 2006.

The results are reported in Appendix Table A.7. We find that the inclusion of this flexible control for pre-period productivity has hardly any bearing on our results. The estimate in Column (4) of 0.193 is very close to our original estimate of 0.239, and across all specifications, the estimates continue to be large, positive, and statistically significant. This finding suggests that our instrument captures variation in Twitter usage that is unrelated to the inherent productivity of economists.

We can also investigate the timing of the impact of our instrument on the number of publications. To do so, we again estimate a staggered difference-in-difference specification in which researchers are treated once Twitter Pressure exceeds the 25$^{\text{th}}$ percentile using the number of publications as the dependent variable. The estimates, obtained using the robust estimator by De Chaisemartin and D'Haultfoeuille (2022), are shown in Figure 6. We find no differential trend in the number of publications in the pre-period, but significant increases in the number of publications two years after Twitter pressure rises beyond the 25th percentile. The timing of this effect aligns with the typical publication lag in economics, such that the papers published in the third year after treatment are likely those economists wrote after joining Twitter.

Figure 6: Dynamic Effect of Twitter Pressure on Number of Publications



Notes: Point estimates and 95 percent confidence intervals for yearly effect of high Twitter Pressure on indicator for using Twitter in year, estimated using the heterogeneity-robust estimator by De Chaisemartin and d'Haultfoeuille (2020) in author-year panel. High Twitter Pressure is an indicator switching to one once Twitter Pressure (±5-year cohort, Top 3 JEL2 codes) exceeds the 25^{th} percentile.

Taken together, these results suggest that Twitter usage significantly increased economists' research output, both in terms of the total number of publications and in the ability to place their work in high-quality journals.

4.2 Citations

We next turn our attention to the number of citations economists receive to understand the impact of published papers and their recognition in the academic community. We find that Twitter usage is also associated with an increase in the average number of citations of economists (see Table 8). The estimates are again remarkably stable, independent of the included control variables. The magnitude in Column (4) implies that the average Twitter user receives an additional 8.7 ($4.615 \cdot 1.9$) citations per year.

To rule out that this result is driven by pre-existing citation differences, we again repeat this analysis while non-parametrically controlling for the number of pre-Twitter citations

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

	Dep. Var.: Nr. of Citations per Year			
	(1)	(2)	(3)	(4)
Years of Twitter Usage	7.443***	5.454***	4.879***	4.616***
	(0.640)	(0.623)	(0.683)	(0.689)
Observations	15,417	15,417	15,417	15,417
Mean of DV	29.95	29.95	29.95	29.95
F-Stat (KP)	775.82	1082.18	857.43	824.05
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

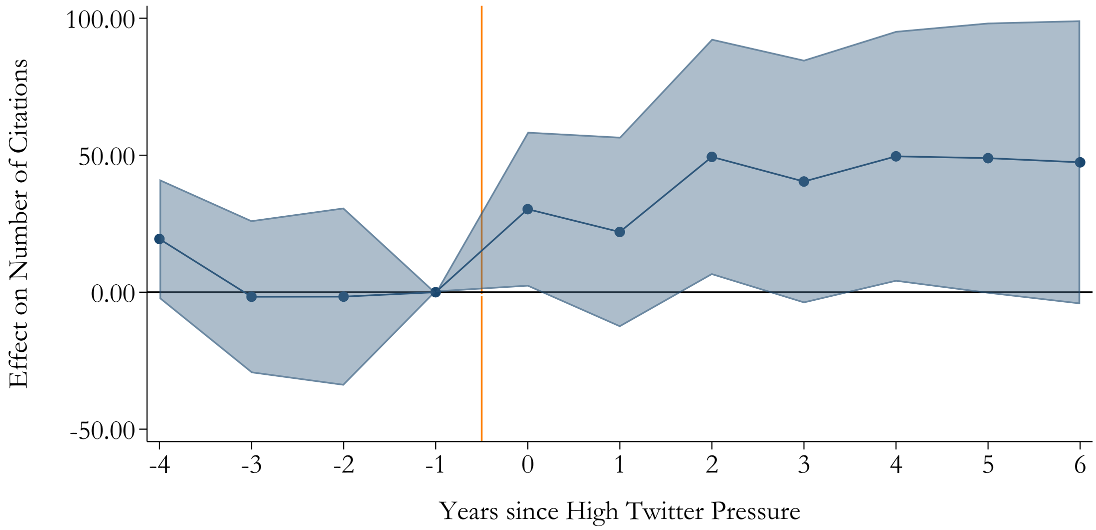
Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of citations received per year. The specifications cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

among researchers that were active before 2006 (see Table A.8). Our findings are again robust to the inclusion of these highly flexible controls, and the results are broadly similar, suggesting on average 5.4 ($2.855 \cdot 1.9$) additional citations per year for Twitter users.

We again analyze the timing of the Twitter effect using reduced form taggered difference-in-difference regressions. The estimates, obtained using the robust estimator by De Chaisemartin and D'Haultfoeuille (2022), are shown in Figure 7. We find no differential trend in the number of citations in the pre-period, but significant and immediate increases in the number of publications. The difference in the timing of the effect relative to the impact on publications suggests that Twitter helps economists immediately to advertise their papers on the social media platform.

The 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 9). We find that the higher number of citations for Twitter users appears to stem exclusively from the higher number of publications, and not from additional citations for each publication. Except for the least restrictive specification, the estimates for the number of citations per publication are negative and become more significant when including more control variables. The estimates suggest that the average publication of Twitter users receives 2.9 fewer citations per publication than non-Twitter users. Taken together, although individual papers become less impactful on average, the increase in publications offsets this

Figure 7: Dynamic Effect of Twitter Pressure on Number of Citations



Notes: Point estimates and 95 percent confidence intervals for yearly effect of high Twitter Pressure on indicator for using Twitter in year, estimated using the heterogeneity-robust estimator by De Chaisemartin and d'Haultfoeuille (2020) in author-year panel. High Twitter Pressure is an indicator switching to one once Twitter Pressure ($\pm$5-year cohort, Top 3 JEL2 codes) exceeds the 25$^{\text{th}}$ percentile.

reduction, resulting in a net increase in citations.

Table 9: 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	2.340***	-0.617	-1.138*	-1.520**
	(0.578)	(0.581)	(0.624)	(0.632)
Observations	14,588	14,588	14,562	14,562
Mean of DV	27.97	27.97	28.01	28.01
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				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. The specifications cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

An often suggested advantage of Twitter usage is that it allows researchers to advertise their research to their peers online. We investigate this hypothesis by analyzing who is citing Twitter users. For this, we calculate the share of citations that stem from papers that are written by Twitter users.[10] The results from this analysis are presented in Table 10. The estimates are consistently positive, independent of the included control variables. The coefficient in Column (4) implies that, on average, Twitter users receive 15% more citations from papers authored by economists who are also on Twitter.

Table 10: Effect of Twitter Usage on Share of Citations from Twitter

	Dep. Var.: Share of Citations from Twitter			
	(1)	(2)	(3)	(4)
Years of Twitter Usage	0.086***	0.084***	0.082***	0.081***
	(0.004)	(0.003)	(0.003)	(0.004)
Observations	14,665	14,665	14,635	14,635
Mean of DV	0.33	0.33	0.33	0.33
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average yearly share of citations originating from papers with at least one Twitter-using author. The specifications cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This result may reflect two mechanisms. First, researchers joining Twitter may promote their work to a broader audience, increasing visibility among other Twitter users. Second, Twitter usage may shift research topics toward those that are of greater interest to other economists active on the platform. We return to the latter mechanism in the last part of the paper.

4.3 Effect Heterogeneity

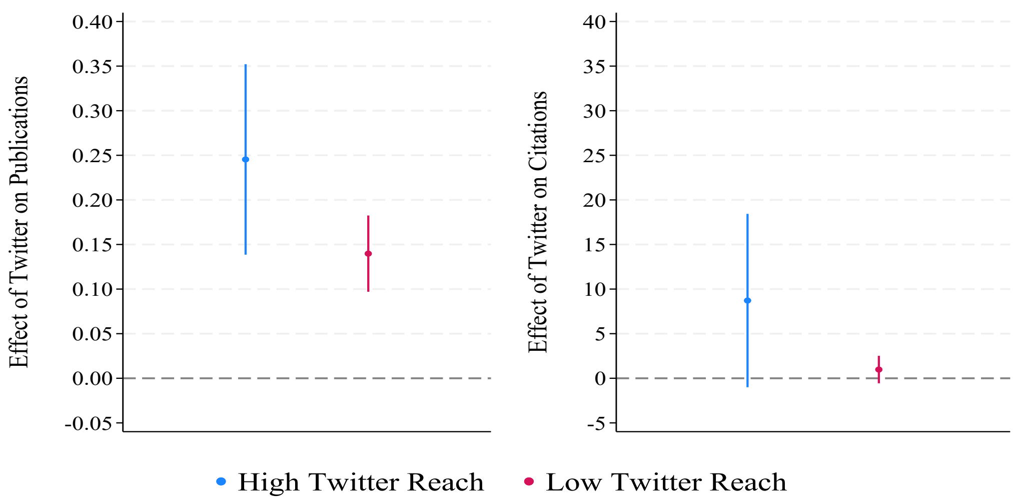
We next study the heterogeneity of the effects of Twitter usage across three dimensions: 1) the intensity of Twitter usage, 2) gender, and 3) the career age of an economist. The first is motivated by the fact that we would expect the effect of Twitter usage to be larger for users who use the platform more frequently. The second stems from the hypothesis that Twitter might allow minorities to reach greater visibility. Lastly, we hypothesize that the effects of Twitter usage could differ by career stage.

First, we investigate heterogeneity by the degree of Twitter usage. A key reason why certain economists benefit more from Twitter may be their differential ability to achieve

[10] A paper is considered to be authored by a Twitter user if at least one of the authors uses Twitter at the time of publication.

prominence on the platform. To study this, we estimate effects separately for Twitter users with high and low follower counts, defining high Twitter reach as having more followers than the 75$^{\text{th}}$ percentile (around 1,500 followers). Since this analysis includes only Twitter users, the variation exploited here represents the intensive margin of Twitter usage driven by our instrument. Figure 8 shows that among economists with high Twitter reach, more years on Twitter translate into more publications and citations than among economists with fewer followers.

Figure 8: Heterogeneity by Twitter Usage Intensity (Follower)



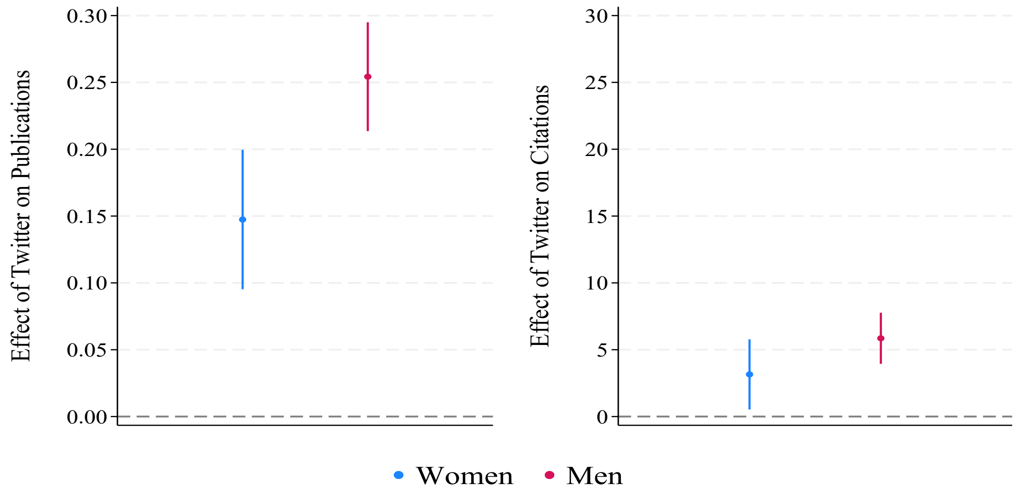
Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the number of yearly publications and citations among Twitter users. Blue and red represent results from separate regressions in the subgroups of users with high and low Twitter reach respectively, defined by whether the number of followers exceeds the 75$^{\text{th}}$ percentile ($\sim 1,500$). The specifications include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code across all years. Standard errors are clustered by PhD institution-by-year.

In Appendix Figures A.3 and A.4, we confirm that similar patterns emerge if we instead use an alternative measure of Twitter usage intensity based on the total number of tweets or the number of *followed* accounts. We broadly find stronger effects for the individuals who appear to use Twitter more intensively.

Second, we split our sample by gender and investigate whether men or women benefit more from Twitter usage (see Figure 9). The results suggest that the average effect of Twitter usage is larger among men, both for the number of publications and the number of citations. This suggests that, in contrast to popular narratives, social media usage is unlikely to narrow the gender gap in economics.

Third, we test whether more experienced economists benefit more from using Twitter. Figure 10 presents effects on publications and citations separately for economists who received

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. Blue and red represent results from separate regressions among women and men, respectively. The specifications include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code across all years. Standard errors are clustered by PhD institution-by-year.

their PhD before and after the year 2000. For publications, the effect of Twitter usage is larger for experienced economists. Among citations, the positive impact is driven entirely by experienced economists, while for younger economists, the estimated effect is statistically indistinguishable from zero.

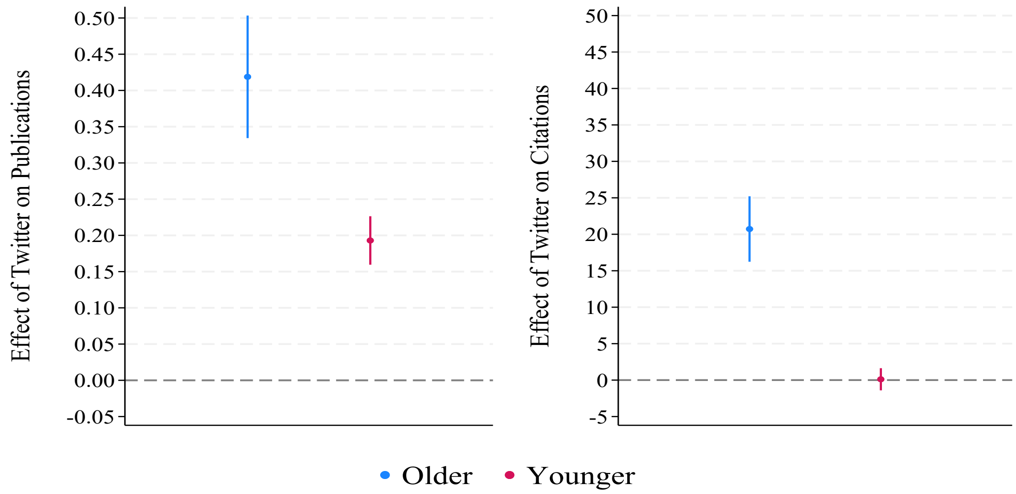
5 Effect of Twitter on Scientific Network

In the second part of the paper, we examine the extent to which Twitter influences the production of papers, as measured by the number of unique co-authors and references in papers. These results thereby shed light on the mechanism underlying the increased research productivity of Twitter users, which we documented in the previous part.

5.1 Co-authorship

One of the key factors that shape the production of papers are co-authorship opportunities. Hence, we investigate whether Twitter affects the number of co-authors economists are working with. For this analysis, we replace the dependent variable in Equation (2) with the average number of unique co-authors each economist in our data worked with per year between 2006 and 2022. The results in Table 11 show that Twitter usage increases in the number of

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. Blue and red represent results from separate regressions within the subgroups of economists who received their PhD before and after the year 2000, respectively. The specifications include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code across all years. Standard errors are clustered by PhD institution-by-year.

co-authors economists are working with. The estimates are positive and significant at the 1% level across all specifications, and the coefficients are remarkably stable, independent of the used control variables. On average, an additional year of Twitter usage leads to 0.23 more co-authors (see Column (4)). Given the observed average of 1.9 years of Twitter usage (including non-users), this estimate implies approximately 0.44 additional co-authors per year. These results suggest that the usage of Twitter facilitates the search for suitable co-authors, which explains some of the previously observed higher publication output.

As further evidence for the effect of Twitter on co-authorship patterns, we investigate whether the documented rise in co-authors is driven by economists who also use Twitter. In Table 12, we estimate regressions with the share of co-authors who also use Twitter as the dependent variable. In line with this hypothesis, we observe that the share of co-authors who use Twitter increases by 20 percentage points $(0.108 \cdot 1.9)$ – nearly doubling the baseline rate. This provides further evidence that Twitter facilitates connections among economists with shared research interests, ultimately increasing productivity.

As a last piece of evidence for the effect of Twitter on co-authorship, we study the impact of Twitter on the quality of co-authors. More specifically, we analyze whether Twitter changes the average number of Top 100, Top 50, Top General Interest, or Top 5 publications per co-author. The estimates from this exercise are reported in Figure 11. While we find

Table 11: Effect of Twitter Usage on Number of Co-authors

	Dep. Var.: Number of Co-authors			
	(1)	(2)	(3)	(4)
Years of Twitter Usage	0.300***	0.252***	0.237***	0.229***
	(0.024)	(0.022)	(0.022)	(0.023)
Observations	15,289	15,289	15,286	15,286
Mean of DV	1.72	1.72	1.72	1.72
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average yearly number of distinct co-authors. The specifications cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

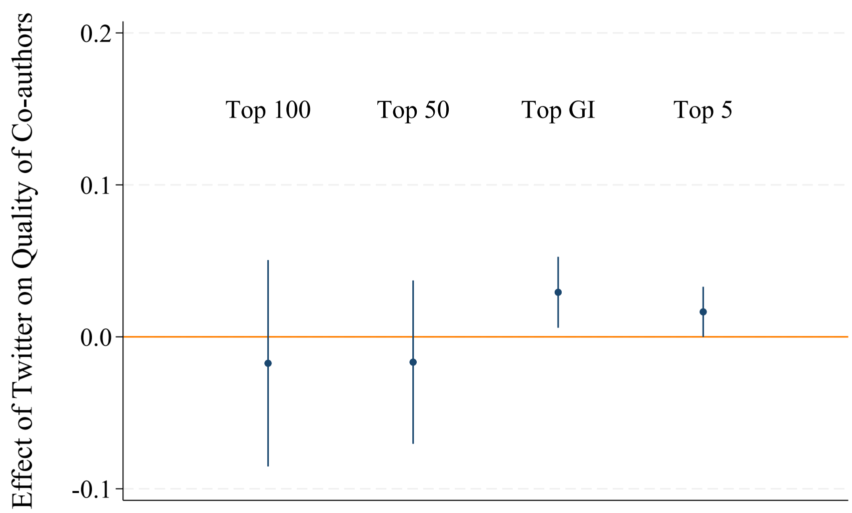
Table 12: Effect of Twitter Usage on Share of Co-authors from Twitter

	Dep. Var.: Share of Co-authors Twitter			
	(1)	(2)	(3)	(4)
Years of Twitter Usage	0.108***	0.107***	0.108***	0.108***
	(0.006)	(0.005)	(0.006)	(0.006)
Observations	14,292	14,292	14,253	14,253
Mean of DV	0.19	0.19	0.19	0.19
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average yearly share of Twitter-using co-authors. The specifications cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

insignificant and negative estimates for the number of Top 100 and Top 50 publications, we observe positive and statistically significant effects on the number of Top General Interest and Top 5 publications. Given the particular importance of publication in high-quality journals in economics, the results provide evidence for the fact that Twitter users, on average, are able to write papers with higher-quality co-authors.

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 number of yearly publications in different brackets of journal impact factor of researchers' average co-author. The specifications include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code across all years. Standard errors are clustered by PhD institution-by-year.

We report the precise estimates from this exercise in Appendix Table A.9. While the estimates appear small, the coefficient for the number of Top 5 publications implies that the average co-author of Twitter users has additional 0.03 Top 5 publications, an increase of around 6% relative to the mean (see Column (4)). Similarly, the estimate for publications in Top General Interest journals implies an increase of around 7% (see Column (3)).

Together, these results indicate that Twitter enhances the productivity of economists by expanding the number of co-authors, as well as improving the quality of co-authorship. We next turn our attention to the acquisition of new knowledge about papers through Twitter.

5.2 Referencing

Another important channel through which Twitter could impact research productivity is by helping economists to learn about new papers they otherwise would have missed. We study this question in Table 13, which analyzes the average number of references economists provide in their papers. Note that for this analysis, we exclude self-citations and control non-parametrically for the number of publications of each author. As a result, the estimates will only pick up if, conditional on the number of papers, Twitter increases the number of references to other people's research. We find that Twitter significantly increases the average number of references authors cite in their work across all specifications. This is in line with the hypothesis that Twitter usage helps economists learn about new and relevant research for their own work.

Table 13: Effect of Twitter Usage on Number of References

	Dep. Var.: Number of References			
	(1)	(2)	(3)	(4)
Years of Twitter Usage	11.032***	10.430***	10.351***	10.157***
	(0.676)	(0.586)	(0.648)	(0.649)
Observations	15,289	15,289	15,286	15,286
Mean of DV	43.40	43.40	43.40	43.40
Number of Publications FE	Yes	Yes	Yes	Yes
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average number of references provided per year (excluding references to own papers). All specifications include fixed effects for the average number of publications per year, and cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code 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 further evidence for this idea, we investigate the share of references that cite work by authors who are also on Twitter (see Table 14).[11] Similar to the results for co-authors, we find that Twitter usage significantly increases the share of references to work by other Twitter users. The estimates are large, positive, and significant, suggesting a more than doubling of the share of references to work by Twitter users.

As a last piece of evidence on the impact of Twitter on citation behaviors, we study the impact of Twitter on the number of references by quality. In Figure 12, we visualize the estimates for the number of references to papers published in the Top 100, Top 50, Top General Interest, and Top 5 journals. Detailed estimates are reported in Appendix Table A.10. Note that all of these specifications include fixed effects for the total number of publications. We find that Twitter usage increases the number of references across the quality distribution of journals. In other words, Twitter usage does *not* disproportionately concentrate citations

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

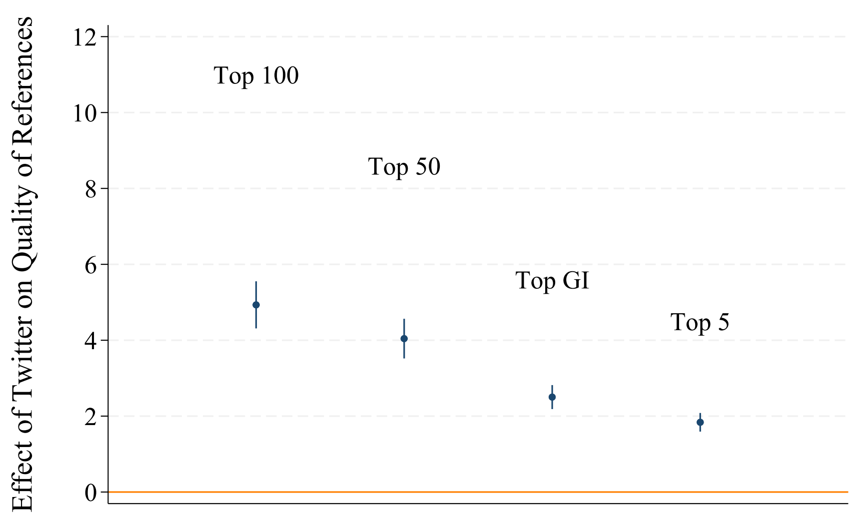
Table 14: Effect of Twitter Usage on Share of References to Twitter Users

	Dep. Var.: Share of References Twitter			
	(1)	(2)	(3)	(4)
Years of Twitter Usage	0.081***	0.086***	0.090***	0.090***
	(0.004)	(0.003)	(0.004)	(0.004)
Observations	15,029	15,029	15,015	15,015
Mean of DV	0.12	0.12	0.12	0.12
Number of Publications FE	Yes	Yes	Yes	Yes
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average yearly share of references to papers with at least one Twitter-using author (excluding references to own papers). All specifications include fixed effects for the average number of publications per year, and cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

in higher- or lower-ranked journals. Overall, this finding also suggests that Twitter helps economists discover papers relevant to their research.

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 specifications include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code across all years. Standard errors are clustered by PhD institution-by-year.

6 Effect of Twitter on Research Topics

Given the significant impact of Twitter on the co-authorship and citation networks we have documented in the previous part, it is only natural to ask to what extent Twitter also impacts the direction of research. In the last part of the paper, we therefore analyze to what extent Twitter influences the topics that researchers work on. First, we study the similarity of research done by other economists on and off Twitter. Second, we analyze whether Twitter increases the probability that economists work on "hot" topics such as Covid-19, cryptocurrencies, or Trump. Third, we investigate whether Twitter usage enhances the visibility and impact of economists beyond academia, as measured by Altmetric scores.

6.1 Topic Similarity to Twitter

We start by analyzing whether Twitter usage increases the similarity of one's own research to work done by other Twitter users. More specifically, we create embeddings for each paper in our data based on the words used in the abstract and calculate the cosine similarity to the 100 most similar papers published in the same year (excluding one's own papers). We repeat this similarity calculation separately for other papers that were authored by Twitter users and non-Twitter users. In Panel A in Table 15, we then report the estimates for the similarity to work done by Twitter users, while Panel B reports the estimates for the similarity to work done by non-Twitter users. To ease interpretation, we standardize the dependent variable to have a mean of 0 and a standard deviation of 1.

We find that Twitter usage indeed seems to lead economists to work on topics that are more similar to the work done by other economists on Twitter. On average, Twitter usage increases the cosine similarity to work done by other Twitter users by more than 1 standard deviation (see Column (4) Panel A). In stark contrast, Twitter usage appears to shift research away from the topics of economists who are not on Twitter, as we find significant decreases in the cosine similarity to the work of economists who are not using Twitter of around 0.2 standard deviations (see Panel B). These results indicate that Twitter adoption shifts economists' research away from more traditional topics in economics, toward topics that are more prominent among Twitter users. Further, they also suggest a divergence of research topics between economists who use and do not use Twitter.

6.2 Hot Topics

Motivated by the previous results, we investigate some of the topics that might underlie the shifts in similarity of research. More specifically, we analyze whether the increasing similarity

Table 15: **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	0.668***	0.765***	0.852***	0.864***
	(0.037)	(0.037)	(0.045)	(0.047)
Observations	14,089	14,089	14,054	14,054
Mean of DV	0.01	0.01	0.01	0.01
Panel B: Research of Economists off Twitter				
Years of Twitter Usage	-0.132***	-0.125***	-0.102***	-0.108***
	(0.020)	(0.020)	(0.021)	(0.021)
Observations	14,215	14,215	14,180	14,180
Mean of DV	0.01	0.01	0.01	0.01
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average textual similarity of research to that of Twitter users and non-users, respectively. The specifications cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

of economists' research to that of other Twitter users is reflected by a shared focus on trending ("hot") topics. To do so, we select a set of keywords that represent prominent hot topics and flag papers on these topics if they use one of the keywords in their abstract. Note that the aim of this analysis is not to cover all hot topics, but rather investigate some topics with a high salience on Twitter.

The results from this analysis are presented in Table 16, in which we report the effect of Twitter usage on the number of papers covering the topics: 1) Covid-19, 2) Climate Change, 3) Cryptocurrencies, 4) Gender, and 5) Donald Trump. Except for climate change, we find that Twitter usage significantly increases the likelihood of writing a paper on one of these hot topics. Most notably, an additional year of Twitter raises the number of abstracts mentioning Covid-19 by 3.8 percentage points, on average, from a baseline of 5 percent. Thus, roughly one out of every 14 economists on Twitter publishes a paper related to Covid-19 specifically due to joining the platform. We find similar, though smaller, increases in the number of papers on Cryptocurrencies, Gender, and Trump. The results are overall consistent with Twitter shifting economists' research towards topics that they see trending on Twitter.

Table 16: Effect of Twitter Usage on Research on Hot Topics

	Dep. Var.: Number of Abstracts with Keyword				
	Covid	Climate	Crypto	Gender	Trump
	(1)	(2)	(3)	(4)	(5)
Years of Twitter Usage	0.038***	0.002	0.002***	0.006*	0.002***
	(0.004)	(0.004)	(0.000)	(0.003)	(0.001)
Observations	15,011	15,011	15,011	15,011	15,011
Mean of DV	0.05	0.04	0.00	0.07	0.00
Years Since PhD FE	Yes	Yes	Yes	Yes	Yes
PhD Cohort Size FE	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes
JEL Code Control	Yes	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 papers mentioning specific keywords in abstract. All specification include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code across all years. Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.3 Attention outside of Academia

As a final piece of evidence, we study the attention that is paid to the work of economists outside of academia. For this analysis, we investigate whether Twitter usage impacts the Altmetric scores of researchers, as a proxy for the broader attention research receives. To start, we analyze the overall Altmetric Attention Score – standardized to mean 0 and standard deviation 1 – of research published by Twitter and non-Twitter users. The results in Table 17 show a substantial increase in the Attention Score for Twitter users. Each additional year on Twitter leads to a 0.08 standard deviation increase in attention, translating into a 0.15 standard deviation increase for the average Twitter user relative to non-Twitter users in our data.

To get a better understanding of what underlies these increases in the Altmetric Attention Score, we study its individual components. The results in Table 18 indicate that the increase in the Attention Score is primarily driven by mentions in mainstream news media and, to a lesser extent, by mentions in Twitter posts. In addition, we also find significant increases in the mentions of research in blogs, policy documents, and on Wikipedia. The magnitudes imply that the average Twitter user receives approximately 0.084 more mentions from mainstream media and 0.013 more mentions from blogs. These increases are sizable given the low baseline rate of such mentions, representing more than 100 percent growth. Moreover, each individual mention in the news typically receives relatively high attention, which is reflected by their large weight in the Altmetric Attention Score.

Overall, these results confirm that Twitter usage significantly increases the attention paid

Table 17: Effect of Twitter Usage on Impact of Research

	Dep. Var.: Average Altmetric Score (std.)			
	(1)	(2)	(3)	(4)
Years of Twitter Usage	0.086***	0.078***	0.079***	0.077***
	(0.013)	(0.013)	(0.015)	(0.016)
Observations	15,289	15,289	15,286	15,286
Mean of DV	0.00	0.00	-0.00	-0.00
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average yearly Altmetric Attention Score. The specifications cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

to research, not only inside academia but also by the media and policymakers. Thus, Twitter usage enhances the visibility of economists' work beyond academic circles.

Table 18: Effect of Twitter Usage on Altmetric Attention Score Components

	Dep. Var.: Yearly Number of Altmetric Mentions by				
	Mainstream Media (1)	Blogs (2)	Policy Documents (3)	Wikipedia (4)	Twitter Posts (5)
Years of Twitter Usage	0.044***	0.007***	0.011***	0.002**	0.498***
	(0.015)	(0.001)	(0.002)	(0.001)	(0.077)
Observations	15,286	15,286	15,286	15,286	15,286
Mean of DV	0.06	0.01	0.03	0.01	0.67
Years Since PhD FE	Yes	Yes	Yes	Yes	Yes
PhD Cohort Size FE	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes
JEL Code Control	Yes	Yes	Yes	Yes	Yes
Attention Score weight	8	5	3	3	0.25

Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the number of mentions in different media, as recorded by Altmetric. The weight of each mention in the Altmetric Attention Score by type is indicated below. All specification include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code across all years. Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7 Conclusion

This paper provides the first evidence that Twitter has substantially influenced economic research productivity, collaboration networks, and topic selection among economists. Based on a novel database of economists, their PhD institutions, and their Twitter accounts, we construct an instrumental variables strategy exploiting peer effects in Twitter usage across PhD cohorts, which allows us to isolate the effect of Twitter usage. We find that Twitter usage increases economists' academic output and citations, leads to more co-authorships with other economists on Twitter, and a higher share of references to research of other Twitter users. Moreover, research focuses more on topics that are prominent on Twitter, leading to increased attention both on Twitter and from the broader public.

Overall, our research highlights that Twitter has transformed the research done by economists, shaping not only how research is conducted and disseminated but also what research is produced. The key open questions involve assessing whether the observed pivot toward socially engaging topics represents an overall beneficial evolution in economic research, enhancing its relevance and societal impact, or whether it signifies a movement toward short-term interests and potentially superficial engagement. These considerations remain vital for shaping policy and institutional practices around the adoption and use of social media within academia.

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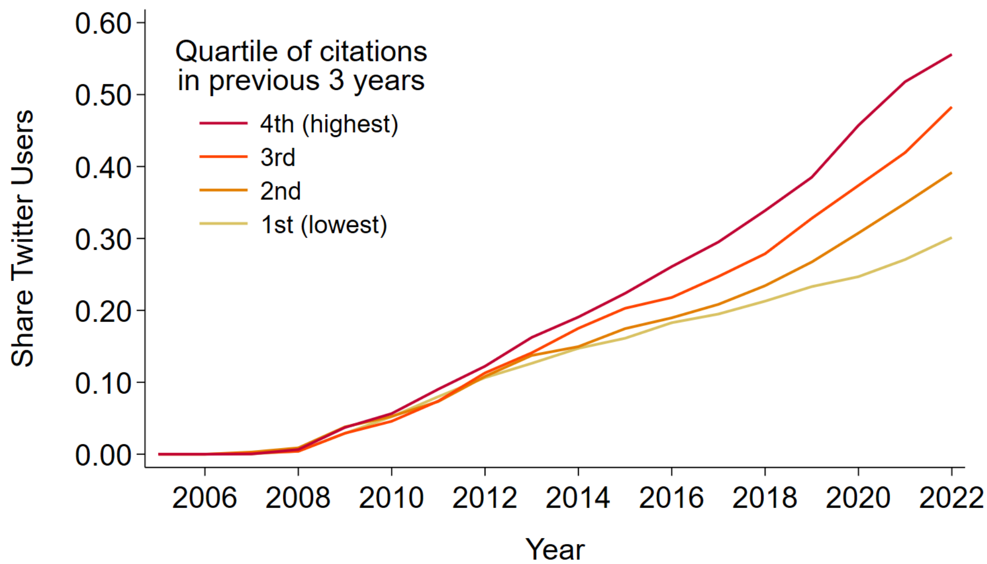
Appendix

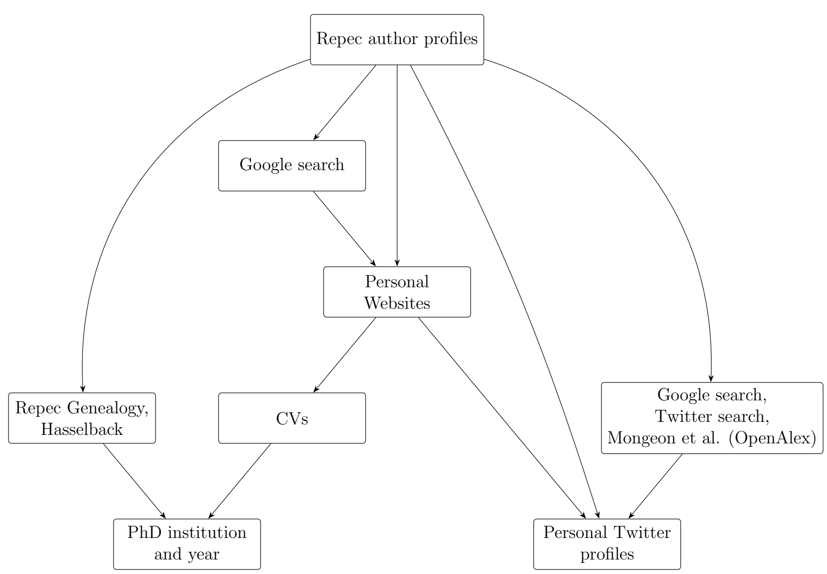
A Additional Details on Data

Figure A.1: Twitter share of active researchers over time, by quartiles of citations



Notes: Share of researchers with Twitter accounts among active researchers by year, split by quartiles of number of citations in past three years.

Figure A.2: 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.

B Additional Details on Instrument

B.1. General Definition

We define each researcher's Twitter Pressure as the average share of Twitter users in the fields of their PhD colleagues (excluding the researcher's own fields). Formally,

$$Twitter\ Pressure\ _{i,t} = \frac{1}{|Cohort_i| - 1} \sum_{\substack{c \in Cohort_i,\\ c \neq i}} \sum_{\substack{f \in Fields_c,\\ f \notin Fields_i}} Field\ Intensity\ _c^f \times Sh.\ Twitter\ in\ Field\ _t^f\ . \quad \text{(A.1)}$$

Twitter Pressure for researcher i in year t is a weighted average of Twitter adoption in fields f of PhD colleagues c. The summation runs over all colleagues in researcher i's cohort and over all fields except i's own ones. The weights $Field\ Intensity\ _c^f$ measure the relative focus of colleague c on field f. If colleague c is active in only one field, then $Field\ Intensity\ _c^f$ is an indicator equal to one for that field, and zero otherwise. Instead, if c is active in more than one field, then each field is weighted according to c's relative focus on that field. In particular,

$$Field\ Intensity\ _c^f = \frac{1}{N\ Papers\ _c} \sum_{p_c \in Papers\ _c} \frac{N\ Field\ f\ in\ p_c}{N\ Fields\ in\ p_c}\ , \quad \text{(A.2)}$$

where $N\ Papers\ _c$ is the number of c's papers that include a JEL code, and $N\ Field\ f\ in\ p_c$ counts how often field f appears in a given paper p_c. If, for example, a paper mentions JEL codes A10, A11, and B10, then the two-character JEL code A1 would receive weight two-third, and B1 would receive one-third. Moreover, in papers that mention fewer JEL codes, each individual JEL code receives more weight.

Similarly, the share of twitter users in each field is the sum of Twitter users in that field, weighted by the importance of that field for each researcher:

$$Sh.\ Twitter\ in\ Field\ _t^f = \sum_{\ell \in \substack{Researchers\\ in\ Field\ ^f}} \frac{Field\ Intensity\ _\ell^f}{\sum_m Field\ Intensity\ _m^f} \times I(Twitter_{\ell,t})\ , \quad \text{(A.3)}$$

where $I(Twitter_{\ell,t})$ is an indicator for whether we observe a Twitter account for researcher ℓ by year t. This weighting scheme ensures that researchers whose work is more exclusively focused on field f contribute more strongly to that field's Twitter share compared to researchers active across multiple fields. When computing the instrument, we apply a leave-one-out measure by excluding the researcher in question from all calculations.

C Additional Results: First Stage

Table A.1: Robustness First Stage: Cohort Lengths

	Dep. Var.: Years Twitter Usage					
	1-year (1)	2-year (2)	3-year (3)	4-year (4)	5-year (5)	6-year (6)
Twitter Pressure 1-year (std.)	0.613*** (0.035)					
Twitter Pressure 2-year (std.)		0.742*** (0.033)				
Twitter Pressure 3-year (std.)			0.825*** (0.031)			
Twitter Pressure 4-year (std.)				0.871*** (0.031)		
Twitter Pressure 5-year (std.)					0.890*** (0.031)	
Twitter Pressure 6-year (std.)						0.899*** (0.031)
Observations	15,417	15,417	15,417	15,417	15,417	15,400
Mean of DV	1.94	1.94	1.94	1.94	1.94	1.94
Years Since PhD FE	Yes	Yes	Yes	Yes	Yes	Yes
PhD Cohort Size FE	Yes	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes	Yes
JEL Code Control	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Regressions of the number of years of Twitter usage on standardized Twitter Pressure, 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 fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code 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.2: Robustness First Stage: Research fields

	Dep. Var.: Years Twitter Usage				
	JEL1	JEL 1 (Top 1)	JEL2	JEL2 (Top 3)	JEL2 (Top 5)
	(1)	(2)	(3)	(4)	(5)
Twitter Pressure JEL1 (std.)	0.205***				
	(0.033)				
Twitter Pressure JEL1 Top1 (std.)		0.856***			
		(0.031)			
Twitter Pressure JEL2 (std.)			0.655***		
			(0.032)		
Twitter Pressure JEL2 Top3 (std.)				0.890***	
				(0.031)	
Twitter Pressure JEL2 Top5 (std.)					0.892***
					(0.031)
Observations	15,417	15,417	15,408	15,417	15,411
Mean of DV	1.94	1.94	1.94	1.94	1.94
Years Since PhD FE	Yes	Yes	Yes	Yes	Yes
PhD Cohort Size FE	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes
JEL Code Control	Yes	Yes	Yes	Yes	Yes

Notes: Regressions of the number of years of Twitter usage on standardized Twitter Pressure, for different definitions of research fields based on JEL codes. Column (1) uses all one-character codes (A-Z), and Column (2) uses each researcher's most frequent one-character code. Similarly, Column (3) uses all two-character codes (A1-Z3), while Columns (4) and (5) use the Top 3 and Top 5, respectively. All specifications include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code 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.3: Robustness First Stage: Clustering

	Dep. Var.: Years Twitter Usage			
	(1)	(2)	(3)	(4)
	PhD Institution-by-Year	PhD Institution	PhD Year	Individual
Twitter Pressure JEL2 Top3 (std.)	0.890***	0.890***	0.890***	0.890***
	(0.031)	(0.039)	(0.052)	(0.030)
Observations	15,417	15,417	15,417	15,417
Mean of DV	1.94	1.94	1.94	1.94
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes
JEL Code Control	Yes	Yes	Yes	Yes

Notes: Regressions of the number of years of Twitter usage on standardized Twitter Pressure, 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 include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code 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.4: Robustness First Stage: Functional Form

	Dep. Var.: Years Twitter Usage					
	(1)	(2)	(3)	(4)	(5)	(6)
Twitter Pressure (std.)	0.890***					
	(0.031)					
Twitter Pressure (pct.)		0.031***				
		(0.001)				
Twitter Pressure (asinh)			1.155***			
			(0.040)			
I[Twitter Pressure≥50th pct]				1.151***		
				(0.080)		
I[Twitter Pressure≥75th pct]					1.226***	
					(0.090)	
I[Twitter Pressure≥90th pct]						0.714***
						(0.091)
Observations	15,417	15,417	15,417	15,417	15,417	15,417
Mean of DV	1.94	1.94	1.94	1.94	1.94	1.94
Years Since PhD FE	Yes	Yes	Yes	Yes	Yes	Yes
PhD Cohort Size FE	Yes	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes	Yes
JEL Code Control	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Regressions of the number of years of Twitter usage on different transformations of Twitter Pressure. Column (1) uses the z-standardized value. Column (2) transforms into percentiles, and Column (3) applies the inverse hyperbolic sine. Columns (4) to (6) use indicators for Twitter Pressure being above the 50^{th}, 75^{th}, and 90^{th} percentile. All specifications include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code 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: Restrict to pre-2006 PhD Graduates

	Dep. Var.: Years of Twitter Usage			
	(1)	(2)	(3)	(4)
Twitter Pressure (std.)	1.018***	1.409***	1.395***	1.391***
	(0.064)	(0.069)	(0.078)	(0.078)
Observations	7,088	7,088	6,963	6,963
Mean of DV	1.77	1.77	1.77	1.77
R^2	0.02	0.03	0.02	0.02
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				Yes

Notes: Regressions of the number of years of Twitter usage on standardized Twitter Pressure among researchers with at least one observed paper before 2006. The specifications include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D Additional Results: Output

D.1. Publications

Table A.6: 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	0.239***	0.091***	0.066***	0.025***	0.013***
	(0.015)	(0.006)	(0.005)	(0.002)	(0.002)
Observations	15417	15417	15417	15417	15417
Mean of DV	1.07	0.41	0.27	0.07	0.04
F-Stat (KP)	824.55	824.55	824.55	824.55	824.55
Years Since PhD FE	Yes	Yes	Yes	Yes	Yes
PhD Cohort Size FE	Yes	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes	Yes
JEL Code Control	Yes	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 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 include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code 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.7: Effect of Twitter Usage on Number of Publications (Controlling for Pre-Period)

	Dep. Var.: Nr. of Publications per Year			
	(1)	(2)	(3)	(4)
Years of Twitter Usage	0.098***	0.196***	0.194***	0.193***
	(0.023)	(0.019)	(0.020)	(0.021)
Observations	7,045	7,045	6,918	6,918
Mean of DV	1.26	1.26	1.26	1.26
Pre-Twitter Publication FE	Yes	Yes	Yes	Yes
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				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, among researchers with at least one observed paper before 2006. All specifications include fixed effects for the number of publications before 2006, and cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D.2. Citations

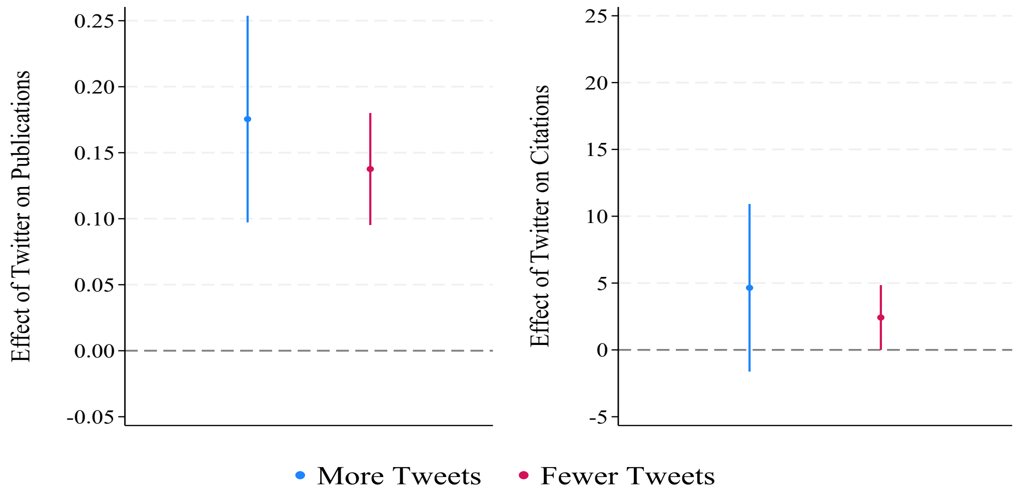
Table A.8: Effect of Twitter Usage on Number of Citations (Controlling for Pre-Period)

	Dep. Var.: Nr. of Citations per Year			
	(1)	(2)	(3)	(4)
Years of Twitter Usage	2.751***	2.878***	3.346***	2.855***
	(0.907)	(0.745)	(1.002)	(0.996)
Observations	5,491	5,490	5,356	5,356
Mean of DV	25.84	25.84	26.01	26.01
Pre-Period Citation FE	Yes	Yes	Yes	Yes
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE		Yes	Yes	Yes
PhD Institution FE			Yes	Yes
JEL Code Control				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, among researchers with at least one observed paper before 2006. All specifications include fixed effects for the number of citations before 2006, and cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

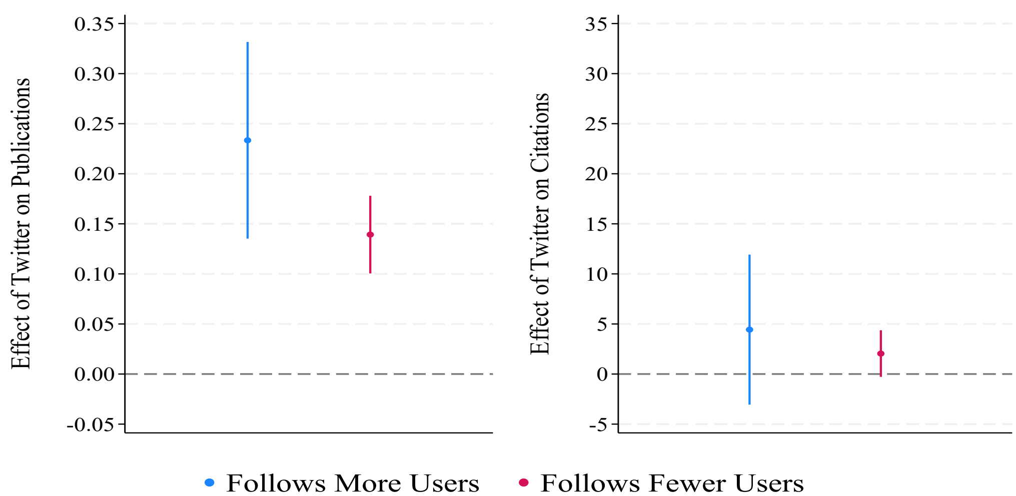
D.3. Effect Heterogeneity

Figure A.3: Heterogeneity by Twitter Usage Intensity (Tweets)



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 among Twitter users. Blue and red represent results from separate regressions in the subgroups of users with high and low intensity of Twitter usage, respectively, defined by whether the number of tweets exceeds the 75^{th} percentile ($\sim 1,600$). The specifications include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code across all years. Standard errors are clustered by PhD institution-by-year.

Figure A.4: Heterogeneity by Twitter Usage Intensity (Following)



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 among Twitter users. Blue and red represent results from separate regressions in the subgroups of users with high and low intensity of Twitter usage, respectively, defined by whether the number of followed accounts exceeds the 75^{th} percentile (~ 800). The specifications include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code across all years. Standard errors are clustered by PhD institution-by-year.

E Additional Results: Production of Papers

E.1. Co-authorship

Table A.9: 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	-0.017	-0.017	0.029**	0.016*
	(0.035)	(0.027)	(0.012)	(0.008)
Observations	15216	15216	15216	15216
Mean of DV	1.98	1.34	0.40	0.22
F-Stat (KP)	453.95	453.95	453.95	453.95
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes
JEL Code Control	Yes	Yes	Yes	Yes

Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average co-author's number of publications in journals of different quality brackets. 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. All specifications include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code across all years. Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

E.2. Referencing

Table A.10: Effect of Twitter Usage on Quality of References

	Dep. Var.: Nr. of References to Publication in:			
	Top 100 (2)	Top 50 (3)	Top GI (4)	Top 5 (5)
Years of Twitter Usage	4.932***	4.043***	2.502***	1.838***
	(0.317)	(0.267)	(0.161)	(0.125)
Observations	15286	15286	15286	15286
Mean of DV	21.24	17.64	9.05	7.17
F-Stat (KP)	504.79	504.79	504.79	504.79
Number of Publications FE	Yes	Yes	Yes	Yes
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes
JEL Code Control	Yes	Yes	Yes	Yes

Notes: 2SLS estimates for the effect of years of Twitter usage, instrumented by cohort-specific Twitter Pressure, on the average yearly number of references provided to publications in journals of different quality brackets. 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. All specifications include fixed effects for the average number of publications per year, and cumulatively include fixed effects for the number of years since PhD graduation (Column 1), size of the PhD cohort (2), PhD-granting institution (3), and the most frequent one-character JEL code across all years (4). Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

F Additional Results: Research Topics

F.1. Attention outside Academia

Table A.11: Effect of Twitter Usage on Twitter mentions

	Dep. Var.: Yearly Altmetric Twitter Mentions by			
	Public	Scientist	Clinician	Communicator
	(1)	(2)	(3)	(4)
Years of Twitter Usage	0.363***	0.120***	0.010***	0.005***
	(0.061)	(0.017)	(0.002)	(0.002)
Observations	15,286	15,286	15,286	15,286
Mean of DV	0.50	0.14	0.02	0.01
Years Since PhD FE	Yes	Yes	Yes	Yes
PhD Cohort Size FE	Yes	Yes	Yes	Yes
PhD Institution FE	Yes	Yes	Yes	Yes
JEL Code Control	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 Twitter mentions by different user types, as recorded by Altmetric. Column (1) refers to member of the public, while Columns (2) to (4) indicate mentions by users who indicate connections to academic research through their biography or tweets, separately classified as scientist, clinical scientist, or science communicator. All specification include fixed effects for the number of years since PhD graduation, size of the PhD cohort, PhD-granting institution, and the most frequent one-character JEL code across all years. Standard errors (in parentheses) are clustered by PhD institution-by-year. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.