Bootstrapping Science? The Impact of a "Return Human Capital" Programme on Chinese Research Productivity

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Preliminary Draft – Comments Welcome

Abstract

We study the impact of a large-scale scientist recruitment program – China's Junior Thousand Talents Plan (青年千人计划) – on the productivity of recruited scholars and their local peers in Chinese host universities. Using a comprehensive dataset of published scientific articles, we estimate effects on quantity and quality in a matched difference-in-differences framework. We observe neutral direct productivity effects for participants over a 6-year post-period: an initial drop is followed by a fully offsetting recovery. However, the program participants collaborate at higher rates with more junior China-based co-authors at their host institutions. Looking to peers in the hosting department, we observe positive and rising productivity impacts for peer scholars, equivalent to approximately 0.6 of a publication per peer scholar in the long-run. Heterogeneity analysis and the absence of correlated resource effects point to the peer effect being rooted in a knowledge spillover mechanism.

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1 Introduction

Can government-led talent programs aiming to recruit overseas scientists improve domestic research productivity? On the one hand, scientists trained at world-class research institutes could benefit from an infusion of resources and add directly to productivity, while potentially generating positive knowledge spillovers and long-term benefits through ideas and innovation. On the other hand, these programs could reallocate personnel without increasing overall productivity, and there could even be negative spillovers on incumbent local scientists who may subsequently have to compete with recruits for scarce resources in hosting departments. Accordingly, existing empirical studies on scientists migration or recruitment show mixed evidence on the productivity impacts (Moser, Voena and Waldinger 2014; Waldinger 2012; Borjas and Doran 2015; Borjas, Doran and Shen 2018; Agrawal, McHale and Oettl 2017).

This paper seeks to understand the effect of a recent and large-scale effort to recruit overseas experts to boost domestic scientific research and innovation – the Thousand Talents Plan. According to one of the earliest advocates for this program, renowned scientist Shi Yigong, the goal was to "counter decades of brain drain of scientists from China" and "to recruit scientists and support them to carry out basic science which will be of benefit to mankind".[1] Since its launch in 2010, it has brought over 7,600 overseas scientists to Chinese research institutions, including 3,589 young scientists in the Junior Thousand Talents Plan (青年千人计划, henceforth JTTP), who subsequently held full-time positions in Chinese universities after being recruited. According to the official guidelines, the central government would offer each selected candidate a signing bonus and salaries comparable with those in the United States.[2]

Despite the scope and associated media coverage, there has been limited quantitative evidence on the effectiveness of the JTTP or similar government development programs that aim to attract overseas talents. Taking JTTP attendance as a natural experiment, we examine the impact of participating in the program both on the awardees' research productivity and the productivity of 'peer' scholars in Chinese host institutions. The second set of peer effects is crucial for understanding the potential 'bootstrap' effects of the programme, whereby JTTP scholars could have boosted the domestic Chinese research base via either additional

[1]For media coverage of the Thousand Talents Plan, see Fighting Trend, China Is Luring Scientists Home, New York Times, 2010.

[2]The signing bonuses total is estimated to be $550 million to $1.1 billion.
https://foreignpolicy.com/2020/09/17/china-thousand-talents-plan-invest-us-xenophobia/

resources, direct collaboration, or knowledge spillovers.

To measure scholar productivity, we produce a rich set of outcomes based on the Scopus academic publication database. From the article metadata, we can produce measures on number of publications and citations, academic fields, journal quality, grant funding, and co-authorship patterns. We link these outcomes to JTTP scholars, their affiliations, and newly hand-collected information about their professional backgrounds.

Starting with the direct effect on JTTP awardees, the core of the research design is matched difference-in-difference model (e.g. Guadalupe, Kuzmina and Thomas, 2012; Becker and Hvide, 2021). Starting with a donor pool of non-JTTP-awardees that otherwise satisfy program criteria, we use a regularized propensity score matching model to identify matched control scholars based on observable pre-treatment characteristics that predict attendance in a given cohort. The matching process produces matched controls that are much closer to JTTP's on observables (both in levels and trends) than a standard diff-in-diff using all non-attenders. Our event study regressions indicate flat pre-trends using the matched diff-in-diff model.

The event study estimates show a non-monotonic effect on the trend in productivity. JTTP scholar productivity drops in the immediate 3 years after entry, before reversing itself and turning positive. Hence, there is an initial disruption period in productivity, but there is an overall increase in long-term output. Further, we observe notable increases amongst JTTP scholars in the fraction of co-authors at Chinese institutions, including at the receiving institutions where the scholars 'landed'. Furthermore, we show that there is more co-authorship as last author with junior co-authors, reflecting a change in role to primary investigator and lab leader.

Moving to the peer effects analysis, our research design is also differences-in-differences, where the treated group is peer scholars in the receiving department. The control group includes other scholars in the same university in other departments, and in the same field but other universities. Again, we can show flat pre-trends with this specification.

The empirical estimates indicate positive productivity impacts for peer group scholars. Decomposing this effect, we find that it comes from publications in journals that are in the top-half but not top 10% of the journal quality distribution. Three elements of effect heterogeneity point to the operation of a knowledge spillover effect rather than a resource effect. Firstly, we find no evidence that the treated incumbents receive more grant funding as indicated in article acknowledgements. Further, the JTTP effect is larger in large departments, which points to spillovers rather than resource effects (which would be diluted in larger departments). Finally, we find that the peer effect is driven by joiners who obtained their PhD outside of China, again consistent with more agglomeration due to higher knowledge differentiation.

These results add to the literature on human capital and the production of scientific knowledge. The previous work has focused on historical migration of scientists due to arguably exogenous shocks, such as the collapse of Soviet Union or the expulsion of scientists by Nazi Germany. A series of papers studying the emigration of Soviet mathematicians into the U.S. show that an inflow of scientific talent can have mixed effects on overall knowledge production (Borjas and Doran 2012, Borjas and Doran 2015,Borjas, Doran and Shen 2018). Ganguli (2015) shows that the inflow of Soviet scientists increased the exposure of American scientists to knowledge accumulated in the Soviet era. Waldinger (2010, 2012) analyze the expulsion of Jewish scientists from German universities and show that this loss of scientific talent had long-term negative effects on originating departments while bringing wide-spread positive spillover effects in patent creation in the United States. Agrawal, McHale and Oettl (2017) find that a star-focused recruitment program in evolutionary biology did not affect overall incumbent productivity but did lead to higher quality of subsequent recruits.

An adjacent related literature is that on global talent flows. Previous work has focused on increases in high-skilled migration from developing countries to developed countries, highlighting the associated "brain gain" in developed countries (Kerr et al. 2017) and "brain drain" in developing countries (Agrawal, Goldfarb and Teodoridis 2016; Docquier, Ozden and Peri 2014). A notable recent exception is Fry (2022), who looks at the other direction of talent flow from a developed country (U.S.) to developing countries (in Africa). Fry shows that the returning African scientists generated positive spillovers on publication outcomes for non-immigrant peers. Two contemporaneous papers have analyzed the effects of the JTTP with a different focus, finding that returnee scholars increase output via establishing their own research teams (Shi, Liu and Wang 2022), and that mathematics departments joined by a JTTP scholar are subsequently able to attract higher-caliber hires (Jia and Fleisher 2020).[3]

The rest of the paper is organized as follows. Section 2 provides an overview of the institutional background of the Junior Thousand Talents Plan, including its recruitment criteria and benefits to awardees. In section 3, we introduce the main datasets and report descriptive statistics. Section 4 outlines the empirical strategy and estimating models, while

[3]Relative to Shi, Liu and Wang 2022, we extend the analysis to peer effects on the incumbents. Relative to Jia and Fleisher 2020, we expand the scope of our analysis to all disciplines covered by the JTTP, allowing us to rule out confounding factors at the university level.

Section 5 reports the empirical results. Section 6 concludes.

2 The Thousand Talents Plan

The Thousand Talents Plan was issued jointly by the Central Committee of the Chinese Community Party and the State Council in 2010. The Plan targets high-level overseas scholars who conduct research in natural sciences or engineering with a focus on the national strategic goals. Thousand Talents Plan includes three categories: the Senior Thousand Talents Plan, the Foreign Thousand Talents Plan, and the Junior Thousand Talents Plan. So far, this program has a total spending equivalent to \$750 million to bring over 7,600 overseas scientists, mostly Chinese nationals to China.

We focus on the Junior Thousand Talents Plan for several reasons. First, it is the only program of the three that the full list of participants is publicly available. In addition, after being recruited, almost all Junior Thousand Talents Plan participants moved to China and began to hold full-time academic positions in Chinese institutions. In contrast, for the senior program, the list of participants has not been made public, and the senior scholars usually held part-time positions in Chinese universities, which makes it hard to assess the intensity of treatment. Finally, the Junior Thousand Talents Plan recruits the largest number of individuals of the three programs, and thus we expect its impact to be the most significant.

The Junior Thousand Talents Plan held ten rounds of recruitment from 2011 to 2017.[4] According to official documents, the program recruiters target applicants who "engaged in scientific researches and below the age of 40, shall possess a Ph.D. degree granted by prestigious overseas universities, with formal teaching and researching positions in overseas prestigious universities, institutions or enterprises, who will be able to work full time in China. " Successful applicants can expect a lump sum 500,000 yuan (\$75,000 in U.S. dollars) starting bonus, and the opportunity to apply for a research subsidy of 1–3 million yuan (\$154,000 - \$460,000) [5]. The screening process takes the following steps. First, after screening potential candidates, the candidate's future employer (university or research institute in China) submits an application to the recruiting platform. Then experts in the platform reviewed applications and interviewed potential candidates to make a preliminary list of successful candidates. The Thousand Talent's Special Office, in conjunction with the Overseas

[4] In 2019, the Thousand Talents Plan switched its name to National High-end Foreign Experts Recruitment Plan, and the lists of successful applicants are not made public.

[5] The Recruitment Program for Young Professionals, Accessed on Feb 25, 2021. https://web.archive.org/web/20200204105420/http://www.1000plan.org.cn/en/young.html

Table 1: Junior Thousand Talent Scholars: Recruitment by Round and Year

Round	Year	# Applicants	# Interviewed	# Selected	Selection Rate	#Joined
1	2011	1035	218	152	14.69%	134
2	2012	1609	485	399	24.80%	315
3	2013	2376	670	581	24.45%	498
4	2015	2241	708	664	29.63%	558
5	2016	2325	654	565	24.30%	496
6	2017	6604	NA	1228	18.59%	1083
	All	16190		3589	22.17%	3083

Notes: The information on number of applicants, number of interviewed, and number of selected scholars are from the Office for the Recruitment of Overseas High-level Talents. We hand check JTTP scholars personal websites, LinkedIn and CVs to identify renegers. We consider a scholar to be a reneger if she holds part or full time academic or non-academic positions in institutions other than the institution as shown in the Thousand Talents Plan website. The last column number of joined is the number of non renegers.

High-Level Talent Introduction Small Group, then make final decisions on the recruitment.[6]

Table 1 provides statistics on the number of applicants, interviews, and selected scholars. The JTTP program increased its recruitment over time, from 152 scholars in 2011 to 1,228 scholars in 2017. The number of applicants also increased, and there is large variation of selectivity across years. The first round in year 2011 is the most selective with only 14.69% acceptance rate while the 4th round in year 2015 has the highest acceptance rate of 29.63%.

3 Data

3.1 Data Sources

3.1.1 Junior Thousand Talent Program Scholars

We obtained the name lists of ten rounds of Junior Thousand Talents Plan between 2011 and 2017 from the Thousand Talents Plan official website using the Wayback Machine. In total, there are 3,589 recruited scholars.[7] For each individual that appears in the list, we know her full Chinese name, the program starting year, and the name of the Chinese

[6]The Recruitment Program of Global Experts, Accessed on Feb 25, 2021. https://web.archive.org/web/20200313080106/http://www.1000plan.org.cn/qrjh/section/2?m=rcrd.

[7]The 10 rounds have 3,745 scholar names in total. We dropped duplicate names: persons with same name, birth date and recruiting universities. We also dropped names from round 10, which appeared to be a subset of names from round 5.

institution where she obtains employment. We do not observe the names of applicants who were not selected.

Starting with the official list of scholars, a team of research assistants manually searched for the professional web sites for each JTTP, plus LinkedIn and curriculum vitaes. From these web sources, we obtain affiliation history information and other metadata. We collected data on postdoctoral affiliation for 98.4% of JTTP scholars, Ph.D. alma maters for 99.2% of scholars, and Ph.D. graduation year for 95.4% of scholars.

What are the academic background of the JTTP scholars? Appendix Tables A2 and A3 report the top 10 universities for JTTP scholars' PhDs and Postdoc affiliations. On average, each scholar has 1.3 postdoctoral appointment, and 1.02 Ph.Ds. We find that 39.4% individuals finished their Ph.D. in China. 34.0% of individuals finished their Ph.D. in the United States. For their postdoctoral experience, we find that almost all scholars have research experience in a developed country, with the United States by far the most common country (60% of JTTP's). The other popular countries are Germany (6.7%), United Kingdom (5.4%), and Singapore (3.9%). Looking to specific universities, we see that many JTTP Scholars conducted postdoctoral research at prestigious universities, including Harvard (3.3%), Stanford (2.2%), MIT (2.1%), and Berkeley (1.6%).

Appendix Table A4 list the top Chinese universities that recruit JTTP scholars. The largest number of scholars (503 persons) are recruited by 82 branch institutes under Chinese Academy of Sciences, the leading national academy for natural sciences in China. Other top recruiting universities such as Peking University, Tsinghua University, and Zhejiang University, are also prestigious universities either in China's C9 League or the 985 Project. Figure A1 shows a map of geographical distribution of top Chinese universities that recruit the scholars.

3.1.2 Scopus Academic Articles Database

Our measures of research productivity come from Scopus, a large database of journal articles maintained by Elsevier. Scopus includes a rich information on publications, including title, authors, journal, academic field, funding sponsors, number of forward and backward citations, and the abstract text. An advantage of Scopus relative to other academic databases is that it is designed to identify and match individual authors across documents. It assigns each author a unique id and uses a partly algorithmic process to disambiguate authors with the same name, using information such as publishing history, author affiliation, and co-citation behavior to determine if a paper belongs to an existing author or not. Scopus also allows authors to verify the information and provide corrections when needed. These methods largely alleviate the same-name issue that researchers usually encounter when using academic publication databases.

While it is better than other data sources, the Scopus database still has errors in author-article assignment. Given that there are many common names, there are cases where two authors have the same name, the same affiliation, and similar fields. In such cases, Scopus can mistakenly pool these two authors' profiles into one. To address this concern, we dropped scholars whose publication records look spurious (over 200 publications), and those who published before 1990, which is very unlikely given the coverage of the database. The results are robust to including these observations.

3.1.3 ORCID Database of Academics

To augment information from Scopus on academics, we collect data from ORCID, the acronym of Open Researcher and Contributor Identifier. ORCID originally developed to resolve the author name ambiguity problem and made unique IDs for authors or contributors of academic publications. ORCID also provides information on an author's affiliation history, title and work. The most important information is the information on career academic titles and years of affiliation for the profile, including Ph.D. affiliation and graduation years. We download the late 2020 version of ORCID public data file [8]. From the raw data, we identified 2.6 million scholars with 7.2 million affiliation records on affiliation history. An affiliation record reports information including the scholar's institution name, department, start year, end year and academic title. The rich information on affiliation records allows us to credibly identify potential candidate pools for the program. We first limit to scholars with Chinese surnames [9] We then process the academic title strings and identify titles relevant to undergraduate, master, PhD and professorship, which allows us to construct career history of the scholars. Additionally, we observe scholar names, countries and institution names for each experience, which would allow us to identify potential applicant pools for the Junior Thousand Talents Plan based on their affiliation history. Lastly, we are able to impute the birth year of scholars using their undergraduate or Ph.D. graduation year [10].

[8] Accessed on May 1, 2022. ORCID 2020 Public Data

[9] We use a dictionary of Chinese last names from here.

[10] We assume a person is 18 at the start year for undergraduate and 22 at the graduation year for undergraduate. For records that we only observe PhD graduation year, we impute the birth year using the average age of JTTP scholars when they obtain Ph.D.

Table 2: Junior Thousand Talent Scholars: Match Statistics

Year	# Selected	# Matched Scopus	% Matched Scopus	# Matched ORCID	% Matched ORCID
2011	152	152	100.00%	38	25.00%
2012	399	397	99.50%	118	29.72%
2013	581	578	99.50%	157	27.16%
2015	664	664	100.00%	186	28.01%
2016	565	563	99.60%	142	25.22%
2017	1228	1210	99.30%	364	30.08%
Total	3589	3564	99.30%	1005	28.20%

3.2 Measuring Scholar Productivity

3.2.1 Linking Authors to Publications

The first data linking step is to find matches of Thousand Talents scholars in the potential matches pool from Scopus. We match Scopus author profiles and JTTP profiles using their past career affiliations and full names. The stringent criteria result in relatively high precision but low recall – that is, we can be quite confident of any included match, yet we might miss potential matches. For example, a scholar who recently returned to China may not yet have published in the hiring university. In this case, we do not observe this university in the Scopus database, and such scholar may not have a perfect match with our hand-collected affiliation history. To improve recall, we followed up with manual searching of Scopus to distinguish scholars whose affiliations in Scopus and websites partially overlapped and shared the same research fields. Using the above methods, we are able to identify and match 3,541 unique Scopus authors profiles to the JTTP scholars.

With this match, we are also able to identify 506 selected JTTP scholars who did not end up taking the grant. These renegers are dropped in robustness checks below. They are also used as an alternative control group in a further robustness check.

To match JTTP scholars to their ORCID profiles, we match using the name string of the JTTP scholars to the name string in the ORCID database. For duplicated matches (one JTTP scholar's name matched to multiple ORCID profiles), we impose the criteria that the affiliation history in ORCID profiles must overlap with the JTTP scholar's affiliation history by mapping affiliation names to unique affiliation IDs provided by Scopus. In the end, we obtain 1,005 uniquely matched ORCID profiles to the JTTP scholars. Table 2 reports statistics on the the match rate for JTTP scholars in Scopus and ORCID by year. The match rate are rather similar across recruitment cohorts.

To match scholars in ORCID database to their Scopus publication record, we impose the criteria that person name strings must be matched. However, matching only using names provide large number of duplicated matches for common names. Because of this caveat, we additionally use any available unique identifiers (DOI, PMID, PII and others) in ORCID publication record and that in Scopus to screen the matched pool with duplicated profiles. The idea is, if a scholar in ORCID shares the same name and overlaps at least in one publication with a candidate Scopus profile, then we are confident that they are the same person.

3.2.2 Creating Scholar Career Trajectory

For each scholar in our dataset, we create academic careers based on their publication records. In Step 1, for each observed scholar-affiliation combination s, a, we assume that scholar s is at affiliation a between the first and last year when we observe a publication by s at a. In Step 2, for all the years between the first and last publication for s when we do not observe or impute an affiliation from Step 1, we assume scholar s is at the last known affiliation. If the scholar did not publish a paper in a year, that will be imputed as a zero for number of publications and other corresponding outcomes.

3.2.3 Field Assignment

We have granular data on field and sub-field, defined by the Scopus All Science Journal Classification Codes (ASJC) specified for each journal.[11] There are 307 sub-fields across 27 broad fields. For example, the chemistry related sub-fields include: Chemical Health and Safety, Colloid and Surface Chemistry, Filtration and Separation, Analytical Chemistry, Electrochemistry, Physical and Theoretical Chemistry, etc.

We assign scholars to subfields using the distribution of their publications across subfields. To begin, we take all scientific articles published in the first five years of a scholar's observed career. We assign a scholar to the modal subfield in these first five years.

3.2.4 Descriptive Statistics

Table 3 reports summary statistics on JTTP scholars. We find that the JTTP scholars are relatively young and productive. The average scholar has an age of 34.6, career length of 8 years (number of years since first publication showing up in Scopus) and 5.5 years since she

[11] All Science Journal Classification Codes. A journal can have multiple sub-field assignments and we exclude general sub-fields. If one journal has multiple Subject Area Categories, we weight it by its fraction.

Table 3: Summary Statistics on JTTP Scholars

Panel A: Education Background

Variable	Mean	SD	Count	Source
Years since PhD Graduation	5.52	2.4	3493	*Website*
Age at Recruitment	34.6	2.9	3589	*Website*

Variable	Pct		Count	
PhD in US	34.00%		1238	*Website*
PhD in China	39.40%		1433	*Website*
PhD in RoW	26.60%		969	*Website*
Postdoc in US	60.40%		2742	*Website*
Postdoc in DE	6.70%		303	*Website*
Postdoc in RoW	39.60%		1492	*Website*

Panel B: Publication Record

Variable	Mean	SD	Count	Source
Years since First Publication	8	4.24	3541	*Scopus*
Top 10 Percentile Pubs. (-5,-1)	8.24	11.13	3541	*Scopus*
Top 50 Percentile Pubs. (-5,-1)	6.54	25.67	3541	*Scopus*
Num. Publications (-5,-1)	21.61	78.94	3541	*Scopus*
Num. Publications (Total)	64.59	147.55	3541	*Scopus*

Variable	Pct		Count	
Physics	13.06%		27016.62	*Scopus*
Material Science	10.45%		21600.20	*Scopus*
Chemistry	10.50%		21717.53	*Scopus*
Engineering	10.73%		22194.38	*Scopus*
Biochemistry	7.17%		14818.46	*Scopus*
Other Field	48.09%		99443.81	*Scopus*
Total	100.00%		206791.00	*Scopus*

Notes: The source *Website* refers to information from Thousand Talents Plan or JTTP scholar personal website data. The source *Scopus* are computed using all of the matched JTTP scholars' publication records in Scopus. (-5,-1) means during the time interval of five years before the recruitment year and one year before the recruitment year.

obtained her Ph.D. degree at the year of recruitment. During the 5 years time period before joining the program, JTTP scholars published 21.6 articles on average, roughly 4.3 article per year, of which 1.6 articles are in the top 10th percentile journals in their respective field by CiteScore.[12] Based on their Scopus record, the JTTP's together published over 200,000 articles in total through their career until 2019.

Table 3 Panel B reports some summary statistics on JTTP fields. Over half of their publications concentrate on the following five fields: physics, material sciences, chemistry, engineering and biochemistry. These statistics are consistent with the official objective of the program to recruit young talents in natural sciences and engineering. Appendix Table A1 reports more detailed summary statistics on JTTP publications by field and subfield.

4 Empirical Methods

This section outlines the empirical methods for producing our regression estimates. First, Section 4.1 outlines the method for analyzing direct effects on the JTTP joiners. Section 4.2 describes our method for the peer effects analysis on host department scholars.

4.1 Direct Effect on JTTP Scholars

The first part of our empirical analysis is designed to estimate a causal effect of JTTP attendance on the productivity of joined scholars. This is a challenge because JTTP's are not selected randomly, so they could differ from other scholars in levels and trends due to other factors that will confound regression estimates. More specifically, a first-order issue is potential positive selection into the program due to the competitive application process (with only 22% applicant success rate). The JTTP program likely targets more productive junior scholars who have a higher prospect for subsequent research productivity. Further, prospective applicants may endogeneously adjust publication and research fields in anticipation of being selected by the program. This anticipation effect may exacerbate pre-trends and endogenous timing.

Our empirical approach to address these issues is matched differences-in-differences. An appropriate control group is identified using a machine-learning-powered matching approach

[12]CiteScore is constructed by Elsevier to reflect the citation impact of a journal's research-based contributions, similar to the Impact Factor index calculated by Clarivate. A journal's CiteScore in year t is defined as the number of citations received by articles in a journal during the year interval $[t, t-3]$, divided by the total number of publications during that interval.

applied to observables that predict attendance. We then use that control group to estimate the dynamic treatment effect on JTTP joiners. We discuss the details of those steps in the following sections.

4.1.1 Donor pool for potential matched controls

The first step of matched differences-in-differences is to find an appropriate donor pool for matched controls. We use information in ORCID to identify never-treated scholars that meet JTTP recruitment criteria.[13] Starting with all researchers with a Chinese last name, we restrict the sample further based on the JTTP requirements that applicants have a PhD, have three or more years of overseas research experience, and are at most age 40. Beyond having a PhD, we require the comparison group to have overseas experience and at least two years post-PhD. We limit their imputed age to be between 23 and 43, thus excluding scholars with minimal propensity to join the program. Further we exclude research fields that do not participate in JTTP: psychology, health, nursing, and veterinary science. These criteria are applied separately for each JTTP cohort, so the donor pool where vary slightly based on the time-varying requirements (years of experience and age). This procedure gives us a baseline donor pool of potential control scholars for each JTTP recruitment year cohort. Table **??** provides summary statistics on this control donor pool.

4.1.2 Propensity Score Matching

The next step is to use a propensity score matching approach to match treated scholars with similar control scholars from the donor pool (**?**, **?**). To match on the time trends in covariates, we select control observations that are similar to treated units based on matching time-varying covariate histories. These matched pairs will then be used in the regression analysis.

Formally, we index scholars by i, including all JTTP cohort treated at time $t \in$ [2011, 2012, 2013, 2015, 2016, 2017], along with the full control donor pool associated with each cohort. For each i, we observe a vector of time-invariant pre-treatment covariates $\mathbf{X}_i$, which include career length (number of years since the author's first publication), years since obtaining PhD, and research field (based on modal publication field before the recruitment year). Further, we observe a vector of time-varying covariates $\{\mathbf{Z}_{i,t-\ell}\}_{\ell=1}^{L}$ with $L = 5$, which

[13] One potential problem with this approach is that scholars in ORCID are selected, and in particular may not be comparable to JTTP scholars who do not have ORCIDs. In a robustness check, we show that our results are robust to dropping all JTTP scholars who do not have an ORCID.

include (by year) the number of publications, publication CiteScore, publication citations, number of publications in top 10 percentile, number of publications in top 50 percentile, and university ranking [14].

For each cohort t, we build a dataset with each JTTP entrant at t along with the donor pool associated with t. Define $J_{it} = 1$ for the JTTP entrants at t and $J_{it} = 0$ for the donor pool. We then train a logistic regression model to predict J_{it} based on the covariates $\{\mathbf{Z}_{i,t-\ell}\}_{\ell=1}^{L}$ and $\mathbf{X}_i$. The trained machine learning model provides a predicted probability $\hat{J}_{it} = \Pr(J_{it} = 1)$. Using these probabilities, we take each JTTP scholar i in cohort t and match them to the scholar j in the donor pool with the closest $\hat{J}_{jt}$. We use this 1 nearest-neighbor matching algorithm without replacement to select the nearest control scholar based on their propensity score distances. Lastly, we impose the requirement that the treated and control unit must be on common support.

Propensity score matching greatly improves sample balance based on observables. As shown in Appendix Figure A4, the statistical difference between treatment and control groups on the matching covariates is greatly reduced across the board.[15] Appendix Table A7 reports the percentage reduction in standardized mean difference, variance ratio, and empirical CDF statistics. In general, we find a large percentage reduction of these statistics after matching, meaning increased comparability between treated and control groups.[16] However, the match is much better in the earlier cohorts than the later ones, so in our baseline results we focus on the effects in the first three cohorts (2011-2013).

4.1.3 Matched Difference-In-Difference Model

We are interested in the effect of JTTP attendance on a set of publication outcomes Y_{ict} (publications, citations, journal quality, etc.) for a scholar i in cohort c in year t. Using the datasets of treated units by cohort along with the matched controls, we estimate the

[14] We construct university ranking by using the 2011 World University Ranking provided by Times Higher Education. We map universities with ranking 1-10 to rank group 1, 11-20 to rank group 2, 21-50 to rank group 3, 51-100 to rank group 4 and others to group 5

[15] The figure reports the standardized mean difference (SMD), which gives the difference in the means of each covariate between treatment groups standardized by a standardization factor so that it is on the same scale for all covariates. Empirical studies in general have found a high correlation between the mean or maximum absolute SMD and the degree of bias in the treatment effect (Belitser et al. 2011 and Stuart, Lee and Leacy 2013).

[16] See Appendix Table A6 for the number of control and treated units that we successfully matched for each cohort.

following stacked difference-in-difference model:

$$Y_{ict} = \beta(Treated_i \times Post_{ct}) + u_{ic} + v_{ct} + \gamma_{ict} + \epsilon_{ict} \tag{1}$$

In the equation above, $Treated_i$ is a dummy variable that equals to 1 if scholar i ever joins the JTTP program, and $Post_{ct}$ is a dummy variable that equals one for the years after cohort c joined the program. u_{ic} is a scholar-cohort fixed effect, v_t is cohort-year fixed effect, and γ_{ict} includes other time-varying controls. We cluster standard errors by matched scholar pair.

We use stacked differences-in-differences, rather than a standard panel data model, to address issues with negative weighting under staggered treatment timing (**?**, **?**). Similar to standard difference-in-difference estimators, cohort-time fixed effects control for any confounders that simultaneously affect all participants in a specific cohort. Scholar fixed effects control for all time-invariant potential confounders that differ between scholars. To account for other potential confounding trends at different career stage or fields, we include in γ_{ict} career length $\times$ year dummies and research field $\times$ year dummies.

In the descriptive trends for joiners (Appendix Figure A2), we observe an immediate drop in performance for 2-3 years after joining, followed by a longer-run increase. To better summarize the short-run and long-run effect, we also estimate:

$$Y_{ict} = \beta_1 Treated_i \times I(t \in [0,3]) + \beta_2 Treated_i \times I(t \in [4,6]) + u_{ic} + v_{ct} + \gamma_{ict} + \epsilon_{ict} \tag{2}$$

where β_1 summarizes the average treatment effect on participants in the first three years after joining, while β_2 summarizes the effect in the next three years. The other items are as in (1).

To get at the dynamics of the effect more directly, we also estimate an event study version of the following form: Event study specification:

$$Y_{ict} = \alpha + \sum_{\tau \geq -5, \tau \neq -1}^{\tau=5} \beta_\tau (Treated_i \times Year_t^\tau) + u_{ic} + v_{ct} + \gamma_{ict} + \varepsilon_{ict} \tag{3}$$

where all variables are defined as in equation (1). The difference is we interact the treatment dummy with each of the year fixed effects, relative to to year $\tau = -1$, which is omitted.

4.2 Peer Effects on Joined Departments

The second part of our analysis is to look for peer effects among researchers in the Chinese academic departments to which JTTP scholars join. This section describes how we build the cohorts of peer scholars and estimate associated treatment effects. On a high-level, we consider a scholar to be a JTTP scholar's peer if (a) she shares a research subfield with a JTTP scholar, and (b) she is affiliated with an institution that has ever received the JTTP scholar at the year before the arrival of the JTTP scholar. We then estimate the productivity effects on those scholars using stacked differences-in-differences.

4.2.1 Constructing Departments and Peer Groups

This section described how we define the peer group of a JTTP scholar. First, we apply three sample restrictions, requiring (i) a publication span of more than three years and (ii) more than 5 papers in total (Acemoglu, Yang and Zhou, 2021), and (iii) less than 250 papers in the 5 year period before treatment.[17]

Next, we make a number of simplifying assumptions required by our context. We define a "department" as all scholars in a specific affiliation (usually, a university) with the same 2-digit field (with 27 categories). This constructed department does not necessarily correspond to the administrative classification.

Given that we can potentially have multiple arrivals in each affiliation and school, we condense arrivals at the scholar level to department level. Hence we use the time of first arrival in each department as the treatment event. The idea is that estimating the effect of the first arrival captures the total effect of bringing in a JTTP scholar, including effects on attracting future JTTP scholars to join the same department. Out of the 3,589 different arriving JTTP scholars, we have 751 treated department. Within each department, we also label the scholars that share the same four digit sufield with the incoming scholar.

For each JTTP entry event, we identify all scholars working at the host department in the year before entry to be treated. Other scholars in the host university but in other untreated departments are included as controls. Further, other scholars in the treated field at untreated departments in other schools serve as controls.

[17] These restrictions filter out (A) Ph.D. or other graduate students who often leave academia with a few publications by restriction (i) and (ii) and (B) Scopus' algorithm's mistake in collapsing different authors with the same Pinyin name into a single profile by (iii), which gets rid of 0.1% of scholars.

Table 4: Descriptive Statistics for Peer Scholars

	(1)	(2)	(3)
	Treated Department Treated Group	Non-treated Department in Receving School Control Group (a)	Other Non-treated Department Control Group (b)
Unique Affiliations	159	159	82939
Unique Departments	751	2942	151421
Number of Unique Author IDs	255062	406780	742245
		# Author IDs in Departments	
[10%,50%,90%]	[21, 188, 870]	[3, 41, 393]	[1, 1, 10]
Max	3823	3741	3366
		Pre-treatment Career Length of Author IDs	
Mean	6.30	5.98	6.32
[10%,50%,90%]	[2, 6, 16]	[2, 7, 17]	[2, 6, 15]
		Total Publications of Author IDs 5-year Pre-treatment	
Mean	10.51	9.82	9.37
[10%,50%,90%]	[1, 6, 31]	[1, 7, 33]	[1, 5, 24]
		Total Citations to Author IDs 5-year Pre-treatment	
Mean	208.90	192.8	164.71
[10%,50%,90%]	[1, 55, 625]	[0, 62, 677]	[0, 39, 444]

Notes: This table describes the number of affiliations and affiliation X 2-digit groups in each treatment year in the estimation sample. For the affiliation X 2-digit group size statistics, we report 10%, 50%, 90%, and 100% quantiles. For the pre-treatment productivity statistics, we report 10%, 50%, and 90% quantiles.

4.2.2 Balance Checks for Peer Analysis

Table 4 summarize and compares the characteristics of treated and control group scholars for the peer effects analysis. Broadly, there is no major discrepancy in observables between these groups in terms of number of publications. Treated departments are larger than non-treated ones, presumably because JTTP's select into larger, more well-resourced departments.[18] Appendix Figure A8 shows raw productivity trends for the three groups and they appear to be on parallel trends before entry. Appendix Table A18 provides a breakdown by cohort.

Compared to incoming JTTP scholars (Table 3), the median incumbent scholar is slightly younger but much less well published. In the 5 years before a JTTP land, the median incumbent scholar published less than 10 articles while the JTTP scholar, on average, has 36 articles in that period.

[18]In a robustness exercise, we drop all observations from departments with less than 10 individuals, and our results are robust.

4.2.3 Estimation Approach

We examine the effect of the arrival of JTTP scholars in a difference-in-difference framework, where we compare productivity of scholars exposed the an arriving JTTP scholar to an otherwise similar scholar who was not. As done above in the direct effects section, we address issues with staggered treatment (?; ?; ?) by a differences-in-differences estimator following Cengiz et al. 2019.[19] Using the treated peer departments along with the non-peer control groups described above, we form cohort-specific datasets centered at the treatment year. We then stack the cohort-specific datasets to estimate aggregate treatment effects across cohorts.

The main empirical model is:

$$Y_{itc} = \beta * 1[\text{post treatment}] + \gamma_{tc} + u_{ic} + \mathbf{X}'_{itc}\Gamma + \varepsilon_{itc} \tag{4}$$

where Y_{itc} is an outcome variable of interest (e.g. publications or citations) for scholar i in year t associated with cohort c, u_{ic} is a scholar-cohort fixed effect, γ_{tc} is year-cohort fixed effect, and $\mathbf{X}'_{itc}\Gamma$ includes other controls and fixed effects to be described further below.[20] The parameter of interest is β, capturing the effect of being exposed to an arriving JTTP scholar. Next, we estimate the event-study specification

$$Y_{itc} = \sum_{\tau \neq -1, \tau = -6}^{\tau = 8} Z_t^{\tau}\beta_{\tau} + \gamma_{tc} + u_{ic} + \mathbf{X}'_{itc}\Gamma + \varepsilon_{itc} \tag{5}$$

which includes leads and lags of treatment timing to examine pretrends and dynamic effects For inference, we use two-way clustering of standard errors by university and broad field.

To account more flexibly for confounding trends, the term $\mathbf{X}_{itc}$ can include more subtle sets of fixed effects. First, we include an affiliation-year-experience-cohort fixed effect, where experience is years since PhD. This fixed effects allows for time-varying confounding factors that operate at the university level and by seniority. Second, we include subfield-year-experience-cohort FE, which allow for time-varying confounding factors at the 4-digit subfield level which can also interact with seniority.

[19] A detailed discussion on how to construct a stacked regression can be found in Baker, Larcker and Wang (2021). See also Clemens and Strain (2021).

[20] By a 'scholar i', we refer to a unique scholar X affiliation combination, meaning that when a scholar has multiple affiliations, they show up multiple times in the data. However, we down-weight them by the inverse number of affiliations so that scholar-years are weighted equally.

5 Results

This section reports the empirical results. First, we look at direct effects on joining JTTP scholars in Section 5.1. Second, we examine peer effects on scholars in the host department (Section 5.2).

5.1 Direct Effect on JTTP Scholars

5.1.1 Main Results

Now we report our main results for the direct effects of JTTP entry, following the method from Section 4.1. We report stacked matched differences-in-differences estimates based on the propensity score match. As mentioned, we focus on the first three JTTP cohorts (2011, 2012 and 2013), mainly because the match quality based on observable is much higher, but also due to censoring of our outcomes (which end in 2019). With the earlier cohorts, we have a longer time window after joining the program to help us understand the impact on productivity and collaboration patterns.

Figure 1 reports the baseline stacked event-study estimates for a rich range of outcomes: number of publication, number of cites, journal CiteScore of published articles, and number of publications with grant funding. The first thing to note is that there are limited pre-trends in these outcomes. Hence, the matched controls provide good counterfactuals based on both observable covariates and the outcome trends.

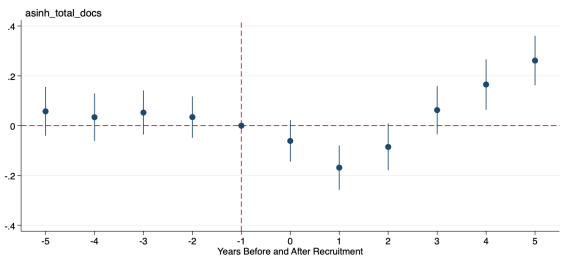
Consider first the number of publications and cites. We observe an immediate drop in productivity upon joining, consistent with disruption due to moving and setting up a new lab. That trend is reversed after the third year and becomes positive. We see a similar trend in the other measures of quality provided by the journal CiteScore and grant-funded publications.

Table A8 shows consistent results for differences-in-differences, rather than the event study. We can highlight a preferred productivity impact estimate here in column(1) for the 4th-6th years after becoming a JJTP. This shows an average $e^{0.127-1} = 13.5\%$ increase in the number of publications for the treated JTTPs. However, this is of course completely offset by the dip in the first 3 years. In Table A13 and Table A14 we report the estimates by cohort, and they are qualitatively similar to the results reported in baseline.

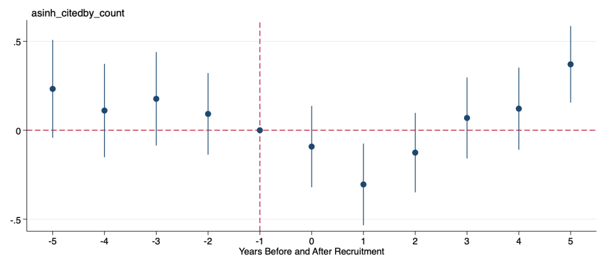
The appendix provides a number of heterogeneity analyses to better understand these results. First, we show that the JTTP program is more helpful for participants with a PhD

Figure 1: Event Study Baseline Estimates

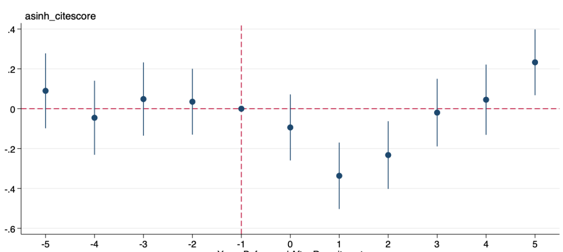
(a) Number of publications



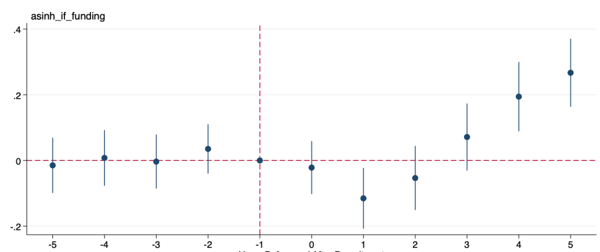
(b) Number of cites



(c) Journal CiteScore



(d) Funded Pubs



Notes: The figures depict the differences in dependent variables between treated and control scholars before and after joining the JTTP. The dependent variable is the inverse hyperbolic sine transformation of (a) number of publications; (b) cites; (c) citescore; (d) number of funded publications. The dashed vertical line represents 1 year before recruitment occurs. The regression includes scholar fixed effects, year fixed effects, pre-treatment career length $\times$ year fixed effects, and field $\times$ year fixed effects.

from outside of China (Appendix Table A15). Second, treatment effect of the program is much larger for younger scholars compared to older ones (Appendix Table A16).

5.1.2 Robustness Checks

The appendix reports a number of robustness checks. First, Appendix Table A9 reports similar results when using only those JTTP scholars who have ORCID. Second, we use the Callaway and Sant'Anna estimator (?) to estimate the overall effects of the program including all cohorts. This estimator allows for treatment effect heterogeneity and aggregates the cohort effects to produce measures of overall treatment effects. In the event-study plot in Appendix Figure A6, the results are consistent with the pattern we observe in the baseline. Third, we also report additional analysis using renegers as controls in Appendix Table A10, A11 and A12. Lastly, one may worry that later cohorts endogenously adjust their effort and publication dynamics in anticipation of joining the program. The earliest cohort arguably should not be affected by such anticipation effect much. We thus report the baseline estimates by cohort in Table A14.

5.1.3 Collaboration Patterns

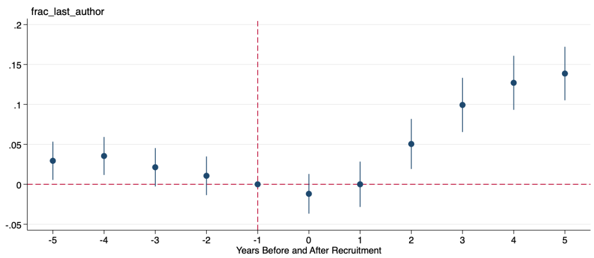
Next, we compare the collaboration patterns of JTTP scholars to the control group, using the same estimation strategy and reporting the results in Figure 2. First, we show that the fraction of last-authored publications increases while the fraction of first-authored publications declines, reflecting a shift in role to leading a team of individuals who are playing the main role in published papers. Next, we proxy for co-authorship with junior scholars by looking at the share of co-authors who are in their first year on Scopus. Again reflecting an increase in leadership and supervision, the number of first-year co-authors, presumably PhD advisees, goes up starting 2 years after joining. Turning to co-authorships with the current affiliation, we see that there is a large negative impact effect, reflecting publications from prior affiliation collaborations. But then co-authoring with the JTTP institution is positive starting 3 years later. Appendix Table A17 summarizes the overall post treatment effects on collaboration patterns.

5.1.4 Discussion

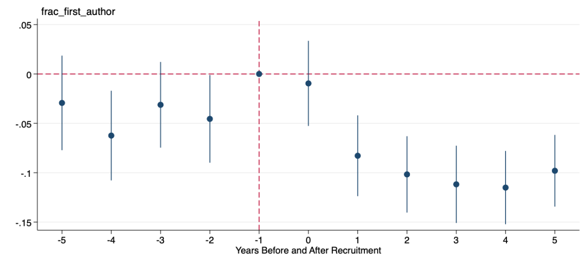
For the program effect on JTTP scholars, we acknowledge the limitations on disentangling channels that lead to the effect. The initial drop of productivity in the first two or

Figure 2: Event Study: Collaboration Patterns

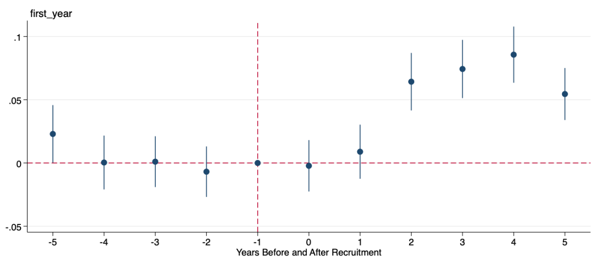
(a) Fraction last-authored publications



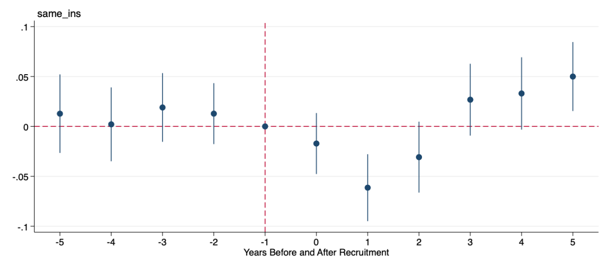
(b) Fraction first-authored publications



(c) Fraction of First Year Coauthors



(d) Fraction of Same-institution Coauthors



Notes: The figures depict the differences in dependent variables between treated and control scholars before and after joining the JTTP. The dashed vertical line represents 1 year before recruitment occurs. The regression includes scholar fixed effects, year fixed effects, pre-treatment career length × year fixed effects, and field × year fixed effects.

three years is most likely a temporary result from switching to new department and new research environment. This may include a adjustment cost and reallocation of effort in building network, creating research team and finding funding resources. One alternative hypothesis is that this effect is caused by publication lag. If the dip in publications after joining the program is caused by publication lag, then the JTTP scholars have to be relatively less productive before joining the program. This is less likely because JTTP scholars need to apply and compete for the positions and they would have no incentive to decrease their publications before joining the program at a junior stage of academic career. Another hypothesis is this is a reversion to mean after these scholars "swing for the fences" to achieve this reward. However, existing studies tend to find a persistent decline in productivity under such scenarios, which would be inconsistent with the sharp rise of productivity after the third year after joining the program.

The increase of productivity in the longer run could be a combination of multiple synergy forces. Getting into the Junior Thousand Talent Program leads to an immediate large sum of funding and greater prospect for additional funding in the future. Also, the JTTP title is considered as an important reward in early career, and could significantly affect chances of promotions in later career in many universities. It is possible that the increase of productivity in the longer run is a result from additional funding, and its effect on research productivity could take time to reap. Second, we note that the increase of productivity coincides with their change of roles in science production to professors, lab owners or principal investigators. The JTTP scholars could get promoted at a faster rate and as a result they may get access to additional lab equipment, resources and research assistants that can boost productivity. We could check this hypothesis with additional data on their position and titles. Third, their collaboration pattern start to change and they start working with a group of more junior coauthors who are becoming more productive over time. A combination of these factors may lead to the boost in publication productivity as an outcome.

5.2 Peer Effects on Host Departments

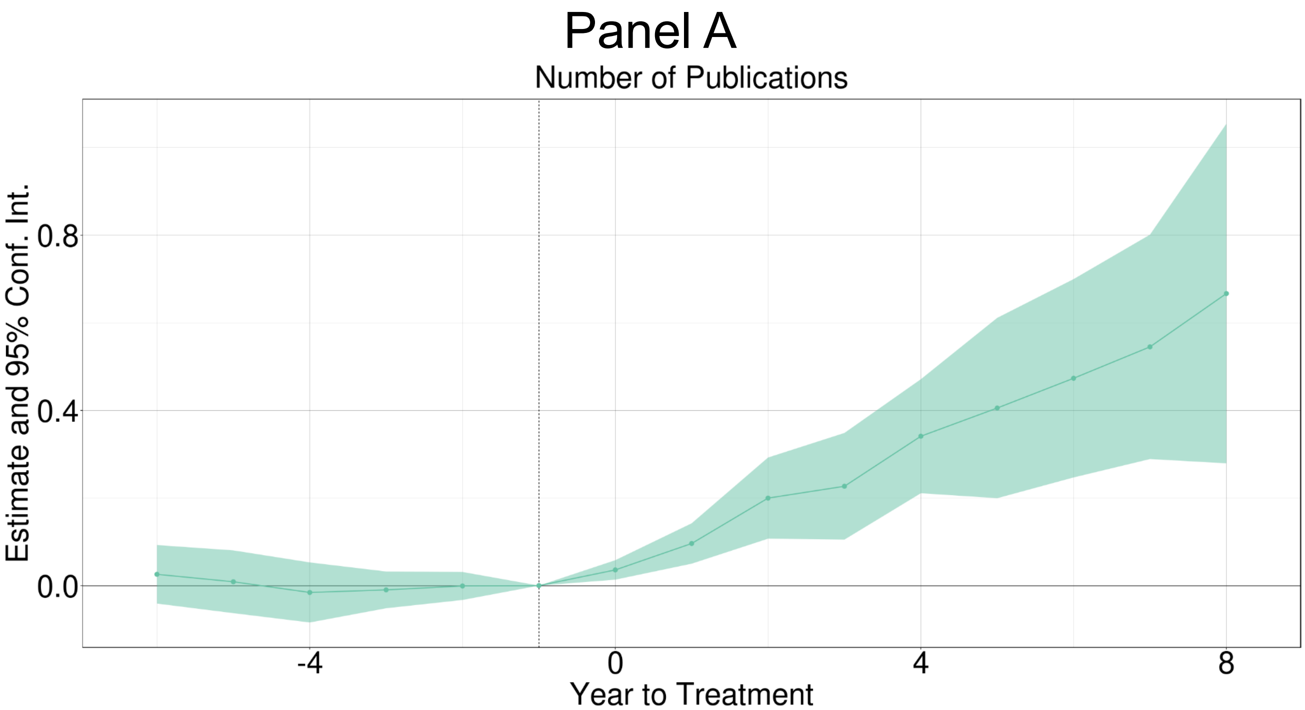
5.2.1 Main Results

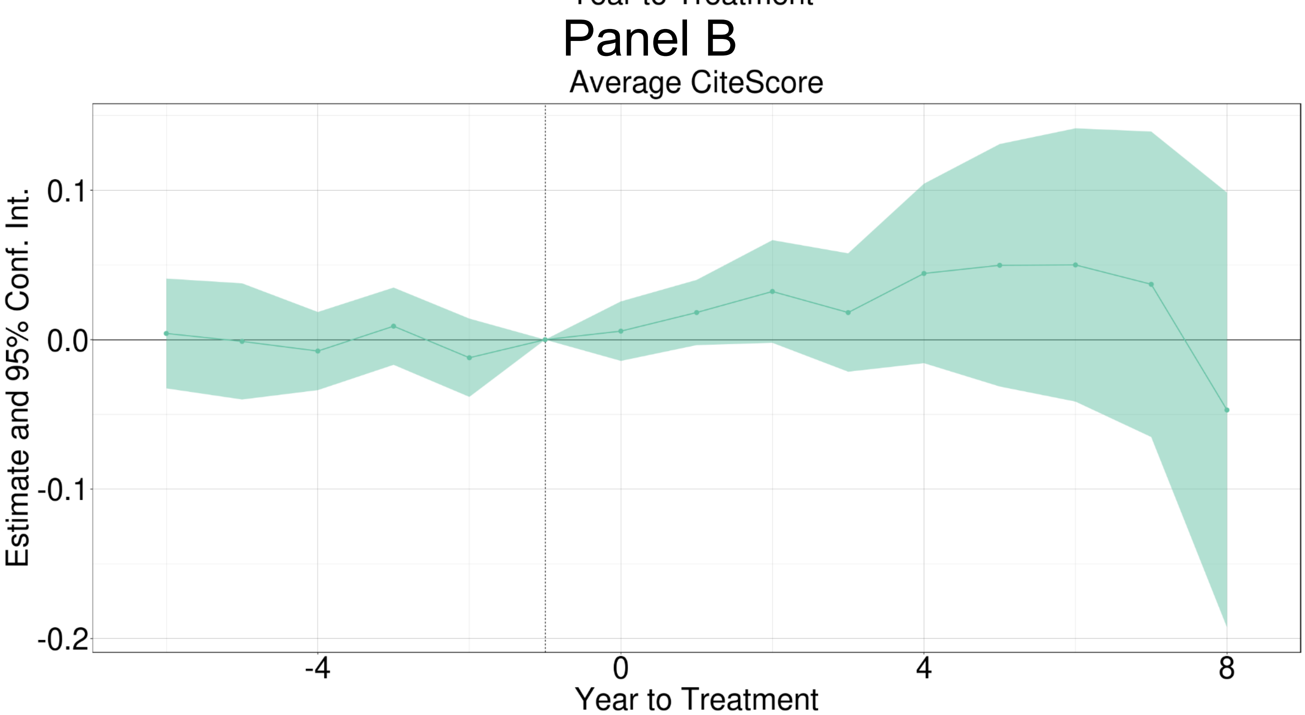
In our main results for peer effects, we use the event study model (5) to analyze the dynamics of the effects and assess pre-trends. Figure 3 shows the corresponding estimates, with number of publications in Panel A and CiteScore (journal quality) in Panel B. In both graphs, there is no sign of a pre-trend. For number of publications, we see a clear positive and increasing effect. For CiteScore, there is not much of a peer effect; perhaps a a small increase. Hence, there is a positive increase in quantity for peers, with no decrease in quality.

Table 5 reports the stacked difference-in-difference estimates. In Column (1), we present the basic specification including only scholar FE and a common time trend. In Column (2), we further allow affiliation and subfield specific time trends. In Column (3), we introduce experience specific time trends, as defined by the first year of publication, to account for life cycle effects. Column (4) is our preferred specification with affiliation specific trends and 4-digit subfield specific trends interacted with experience.

Consistently across specifications, we find an effect on the total number of publications of .1 paper per year. Using the inverse hyperbolic sine transformation, we convert this to an elasticity of roughly 1.9%. When looking at total citations, the effect is statistically insignificant. Decomposing the quantity effect across the distribution of journal qualities, we find that the effect comes from publications in journals in the top-half but not top 10% of the journal quality distribution. In fact, the top 10% journals takes a slightly smaller share of all outputs after treatment. We see no significant change in the average quality of outputs, as measured by the average CiteScore of the journals.

Figure 3: Peer Effect Event Study Estimates: Quantity and Quality





Notes: This figure reports the event study estimates β_τ for the quantity and quality effects of receiving a JTTP scholar in one's department. Standard errors clustered by affiliation level and 2-digit subfield level. The regression estimates are reported in Appendix Table A19.

Table 5: Difference-in-Difference Estimate of Peer Effects

	(1)	(2)	(3)	(4)
$\bar{Y} = 3.357$	*Number of Publications*			
Treated X Post	0.2167***	0.0942***	0.0956***	0.1020***
	(0.0546)	(0.0318)	(0.0327)	(0.0306)
	IHS(Number of Publications) X 100			
Treated X Post	2.727*	1.928**	1.855**	1.871**
	(1.573)	(0.8368)	(0.8229)	(0.7601)
$\bar{Y} = 53.05$	*Number of Citations*			
Treated X Post	-1.085	-0.9656	-0.2362	-0.2532
	(1.878)	(0.7715)	(0.7707)	(0.6939)
	IHS(Number of Citations) X 100			
Treated X Post	-3.145	2.616*	2.088	1.498
	(4.122)	(1.304)	(1.330)	(1.201)
	IHS(Number of Publications in Top 10% Journals) X 100			
Treated X Post	4.134***	0.4165	0.4150	0.3949
	(0.7264)	(0.4005)	(0.3939)	(0.3789)
	IHS(Number of Publications in Top 10%-50% Journals) X 100			
Treated X Post	1.451	1.480*	1.605**	1.515**
	(1.738)	(0.7511)	(0.7549)	(0.6988)
	IHS(Number of Publications in Bottom 50% Journals) X 100			
Treated X Post	-1.302*	0.5811**	0.6677	0.7667
	(0.7359)	(0.1387)	(0.5550)	(0.5199)
$\bar{Y} = 13$	*Fraction of Publications in Top 10% Journals X 100* *Observations = 27,308,939*			
Treated X Post	1.303***	-0.3156**	-0.3038**	-0.3277**
	(0.1987)	(0.1387)	(0.1410)	(0.1361)
$\bar{Y} = 2.2$	*Average CiteScore*			
Treated X Post	0.1325**	0.0276	0.0264	0.0170
	(0.0379)	(0.0193)	(0.0204)	(0.0193)
Observations	41,787,795			
Author X Affiliation X Cohort FE	Y	Y	Y	Y
Relative Year X Cohort FE	Y			
Affiliation Specific Trends		Y	Y	
4-digit Field Specific Trends		Y	Y	
Career Start Specific Trends			Y	
Affiliation X Career Age Specific Trends				Y
4-digit Field X Career Age Specific Trends				Y

Notes: This table documents the baseline stacked regression difference-in-difference estimates of the peer effects of Junior Thousand Talent scholars. Standard errors clustered by affiliation level and 2-digit subfield level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.2 Robustness

Event studies for more outcomes are reported in Appendix Figure A9. The flat pre-trend is not sensitive to functional form and holds across various specifications. More systematically, we perform a number of robustness checks, varying sample used, regression specification, and functional form assumptions to probe the validity of our results (Appendix Table A20). The results are robust to dropping observations from the university with the most JTTPs, the Chinese Academy of Science, or dropping all observations with zero publications. They are robust to interacting pre-treatment productivity measures with time FE's, by adjusting the number of pre and post periods, dropping departments with few scholars, perturbing the control group, down-weighting co-authored papers, or using a Poisson regression.

5.2.3 Heterogeneity and Mechanisms

We now explore some heterogeneity and probe the mechanisms behind the result. Table 6 collects some regression results in this direction. All regressions use the preferred specification i.e. Equation 4) with additional interactions on the treatment variable.

First, Panel (A) tests an interaction term for cases where more than one JTTP scholar joins a specific department. This occurs in roughly 20% of cases across the 751 unique groups affected by the JTTP programme. These multiple-treated groups have a strong additional effect on publication productivity. Panel (B) then looks at department size, specifying a continuous (IHS) interaction term and finding a strong relationship. As we show in A12, this group size effect is monotonic over the support of the size variable with minimal shifts in the slope.

As a first suggestion of potential knowledge spillovers, Panel (C) indicates that the JTTP effect is coming from non-Chinese Phd awardees.[21] Panel (D) shows that there is not much of a difference in the effect for the closest peers who share the same 4-digit subfield. However, in the event study for this analysis (Appendix Figure A13), there seems to be an additional positive effect on publications in relatively low-ranked journals for the closest peers (Appendix Figure A14). These heterogeneity results point towards a knowledge spillover channel, specifically one that could be related to the department-level knowledge agglomeration.

Another potential channel for peer effects is through an increase in available resources

[21] As per Table 3, 39.4% of JTTP scholars have Phds from within China.

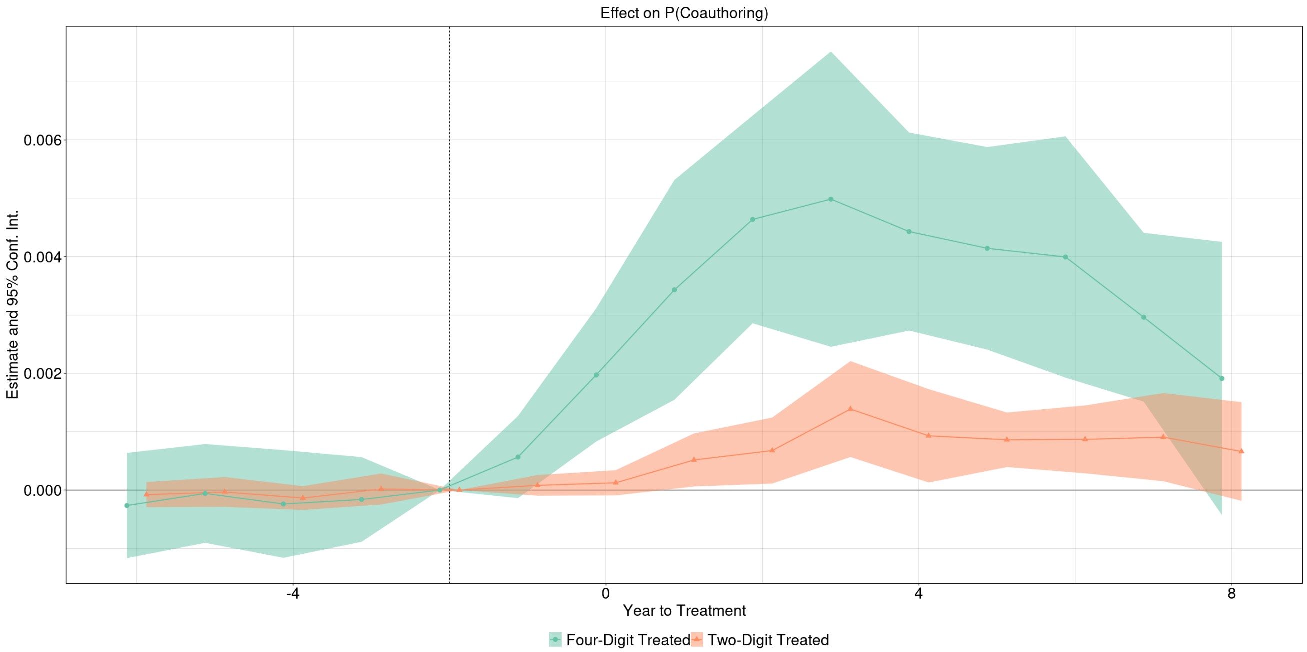
Table 6: Peer Effect DiD Estimates - Heterogeneity and Mechanism

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of Publications	IHS(Publications) X 100	Number of Citations	IHS(Citations) X 100	Fraction of Publications in Top 10% Journals X 100	Average CiteScore
			A: More than 1 Incoming JTT Scholar			
Treated X Post	0.0800***	1.326*	-0.7477	0.0604	-0.3409**	0.0010
	(0.0272)	(0.6872)	(0.6359)	(1.038)	(0.1416)	(0.0178)
Treated X Post X More than 1	0.1760***	3.703***	1.410	6.332***	-0.2827	0.0710*
	(0.0520)	(1.266)	(1.096)	(2.223)	(0.2474)	(0.0345)
			B: Number of Incumbent Scholars			
Treated X Post	-0.2362	-8.929**	-8.537***	-20.76**	0.0867	-0.1904*
	(0.1718)	(4.061)	(2.925)	(8.280)	(0.6830)	(0.1035)
Treated X Post X IHS(Incumbents)	.0005*	0.0161**	0.0123***	0.0332**	-0.0006	0.0003*
	(0.0003)	(0.0061)	(0.0042)	(0.0122)	(0.0010)	(0.0002)
			C: If Obtained PhD in China			
Treated X Post	0.1537***	3.051***	0.4342	3.605***	-0.4227**	0.0326
	(0.0309)	(0.7483)	(0.8396)	(1.271)	(0.1663)	(0.0231)
Treated X Post X PhD in China	-0.1447***	-3.301***	-1.922	-5.892***	0.2680	-0.0434*
	(0.0297)	(0.8228)	(1.299)	(1.578)	(0.2057)	(0.0234)
			D: If Same 4-digit subfield			
Treated X Post	0.0833***	1.917***	0.4827	2.330*	-0.2320	0.0223
	(0.0265)	(0.6699)	(0.7188)	(1.178)	(0.1544)	(0.0194)
Treated X Post X 4-digit	0.0539	-0.1349	-2.125*	-2.403	-0.2716**	-0.0151
	(0.0361)	(0.7959)	(1.124)	(1.456)	(0.1121)	(0.0162)

Main Specification
N = 41,787,795

Notes: This table reports heterogeneity results. Standard errors clustered by affiliation level and 2-digit subfield level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 4: Distance in Knowledge Space: 2-digit v.s. 4-digit - Coauthorship Pattern



Notes: This figure compares coauthorship patterns with the joiner for the treated incumbent who share a 4-digit subfield and those who don't. The estimates are mutually exclusive dummies for these two groups interacted with relative time. Standard errors clustered by affiliation level and 2-digit subfield level.

for resources. Appendix Table A24 shows that the number of funded publications among peers increases after treatment, but not the share. This result suggests that extra funding is not driving the peer effect on productivity.

To dig further into agglomerations through collaboration, we study the co-authorship patterns with the joiner. Figure 4 shows that there is a significant positive effect of JTTP entry on co-authorship with the new scholar by peers. That effect is much larger for the closest peers sharing the same microfield.[22] These collaboration patterns indicate an important channel for the transmission of knowledge spillovers.

6 Conclusion

This paper has provided empirical evidence that the Junior Thousand Talents Plan (JTTP) has had a significant impact on scientific productivity in China. There is a shift for the scholars selected, as well as spillovers on the departments they join. The overall shift is

[22]Figure A15 in the appendix additionally describes the raw trends of the probability of coauthoring and becoming a once-coauthor. In appendix A9 we describe the regression specification to generate this event study graph.

compatible with a knowledge-spillovers and team-building story. That is, the JTTP scholars experience a neutral productivity impact overall but shift the direction of their research effort towards China-based science. This is apparent both in our results relating to direct collaboration behaviour and also the peer effects estimates, which point to a knowledge spillovers mechanism.

A priority for further extensions of this paper is to gain a better understanding of the peer effect result. In particular, we will quantify how concentrated the peer effect is amongst incumbents and calculate the implied 'value for money' of the programme. Finally, a further important theme to our results is a potential role for knowledge agglomeration. A large segment of departments receive multiple JTTPs and our peer effect is increasing in department size. Hence, it is in these large departments where the program may be 'bootstrapping' the domestic Chinese academic research base.

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A Appendix

A.1 Descriptive Statistics Tables and Figures

Table A1: Top Fields and Subfields of Publication

Top Fields		*Top 20 Subfields*	
Field	*Pct*	Subfield	*Pct*
Physics	16.05%	General Chemistry	5.42%
Engineering	13.18%	General Materials Science	5.18%
Chemistry	12.90%	General Physics & Astronomy	4.32%
Material Engineering	12.83%	Electrical & Electronic Engineering	3.33%
Biochemistry	8.80%	Condensed Matter Physics	3.09%
Medicine	6.44%	Nuclear & High Energy Physics	2.55%
Computer Science	5.03%	Electronic, Optical & Magnetic Materials	2.35%
Chemical Engineering	5.01%	Atomic, Molecular Physics & Optics	2.13%
Earth and Planetary Sciences	4.72%	Mechanical Engineering	2.11%
Environmental Science	3.15%	Physics & Astronomy (miscellaneous)	2.06%
Mathematics	3.05%	General Medicine	1.87%
Agriculture	2.23%	Physical & Theoretical Chemistry	1.76%
Energy	2.14%	Catalysis	1.74%
Neuroscience	1.18%	Biochemistry	1.72%
Immunology and Microbiology	1.02%	Materials Chemistry	1.70%
Pharmacology, Toxicology & Pharmaceutics	0.97%	Mechanics of Materials	1.52%
Social Sciences	0.37%	Organic Chemistry	1.37%
Decision Sciences	0.19%	Molecular Biology	1.31%
Business, Management and Accounting	0.12%	General Engineering	1.24%
Psychology	0.12%	General Chemical Engineering	1.16%
Nursing	0.11%	*Bottom Five Subfields*	
Health Professions	0.10%	Assessment and Diagnosis	0.00%
Arts and Humanities	0.09%	Care Planning	0.00%
Economics	0.06%	Critical Care Nursing	0.00%
Veterinary	0.04%	Dentistry (miscellaneous)	0.00%
Dentistry	0.03%	Pharmacy	0.00%

Notes: This table shows the fraction of number of publications for all matched JTTP scholars (N = *3541*) in Scopus defined fields (N = *27*) and subfields (N = *307*)

Figure A1: Map of Chinese universities that recruit JTTP scholars

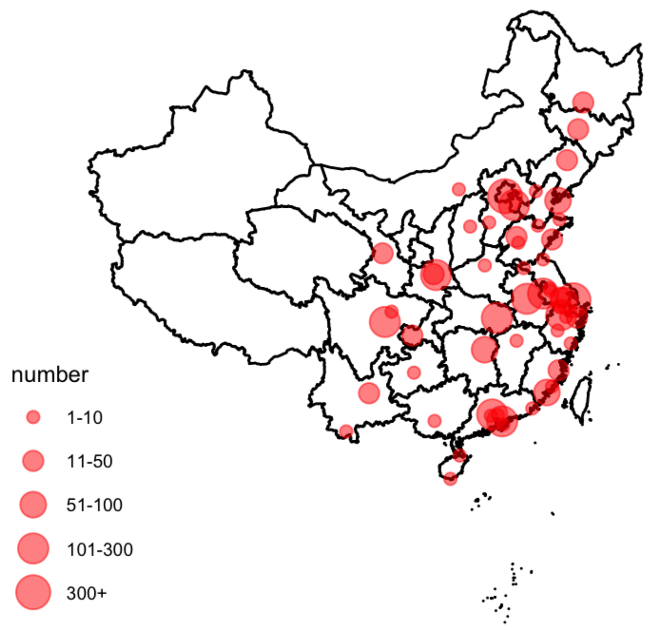


Table A2: Top 10 JTTP PhD universities account for 32.6% of JTTP scholars

Rank	University	Count	Pct
1	Chinese Academy of Sciences	546	14.99%
2	Peking University	140	3.84%
3	Tsinghua University	120	3.29%
4	University of Science and Technology of China	91	2.50%
5	National University of Singapore	72	1.98%
6	Nanyang Technological University	67	1.84%
7	Hong Kong University of Science and Technology	54	1.48%
8	Fudan University	53	1.46%
9	Zhejiang University	46	1.26%
10	Wuhan University	39	1.07%

Notes: Percentage is calculated relative to the sample with PhD information (N = 3642).

Table A3: Top Ten JTTP Source Universities (Postdoc)

	University	Count	Pct
1	Harvard University	151	3.28%
2	Stanford University	102	2.21%
3	Massachusetts Institute of Technology	97	2.10%
4	University of California Berkeley	73	1.58%
5	University of California Los Angeles	71	1.54%
6	Nanyang Technological University	66	1.43%
7	Yale University	58	1.26%
8	University of Michigan	55	1.19%
9	National University of Singapore	53	1.15%
10	University of California San Diego	52	1.13%

Notes: Top 10 'senders' account for 16.9% of JTTP scholars. Percentage is calculated relative to the sample with postdoc information (N = 4537).

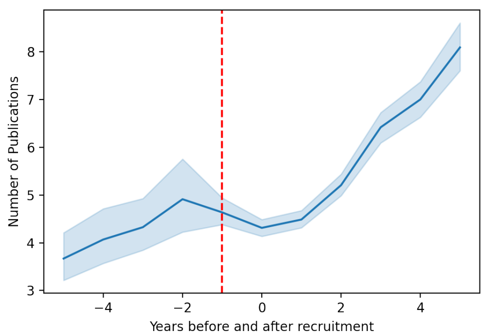
Table A4: Top Ten Chinese Universities that Recruit Junior Thousand Talents Scholars

Rank	University	Count	Pct
1	Chinese Academy of Sciences	503	14.02 %
2	Tsinghua University	223	6.21 %
3	Zhejiang University	201	5.60 %
4	Peking University	194	5.41 %
5	University of Science and Technology of China	183	5.10 %
6	Shanghai Jiao Tong University	158	4.40 %
7	Fudan University	137	3.82 %
8	Nanjing University	127	3.54 %
9	Sun Yat-Sen University	115	3.20 %
10	Huazhong University of Science and Technology	114	3.18 %

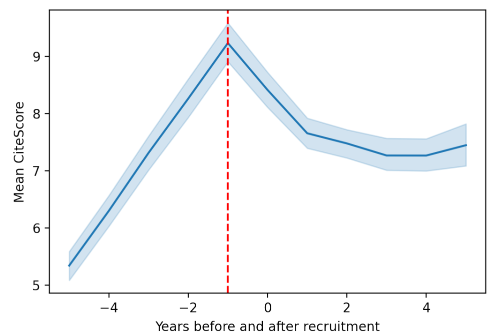
Percentage are calculated relative to the whole sample (N = 3589).

Figure A2: Productivity Trend for JTTP Scholars

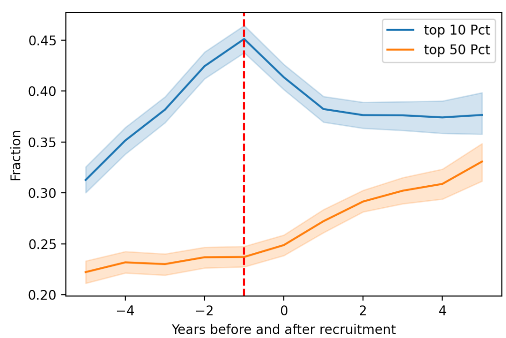
(a) number of publications



(b) citescore

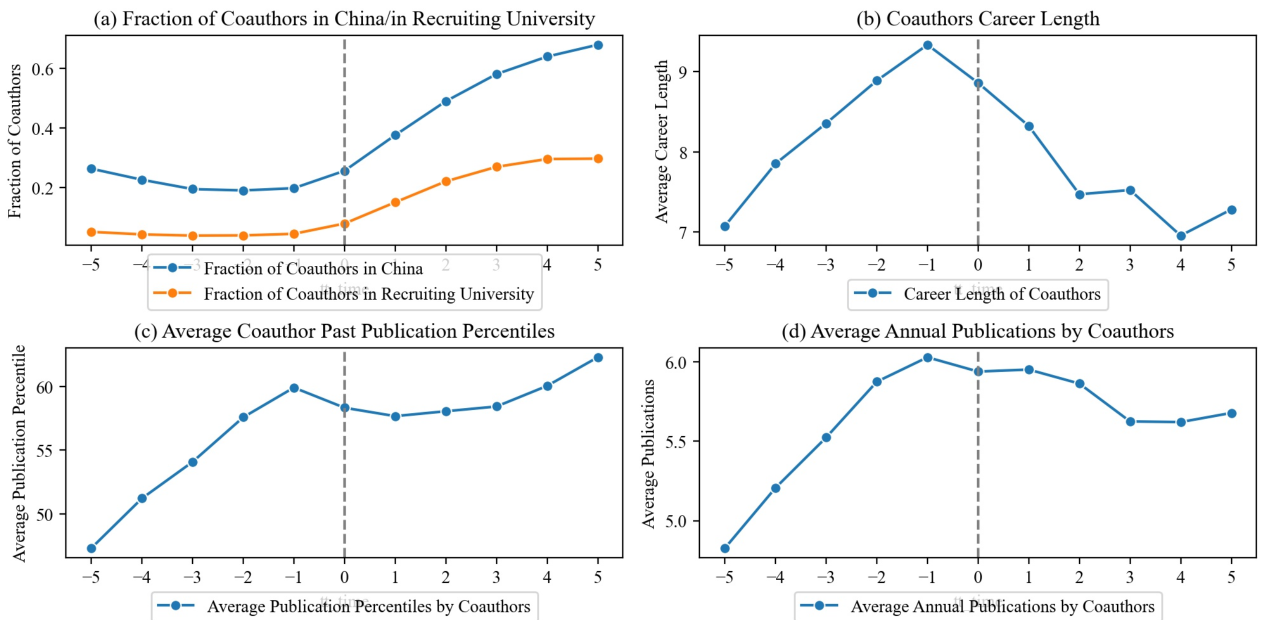


(c) share of top 10/50 pct publications



Notes: The figures depict the time trends for the number of publications, mean CiteScore and share of top 10 percentile pulications, share of top 50 percentile publications before and after recruitment year.

Figure A3: JTTP Coauthorship Trends



Notes: These Figures plot raw trend of coauthor outcomes over ten years surrounding JTTP recruitment year. Sub-figure (a) reports average fraction of coauthors in China / in recruiting university for a JTTP across years. Sub-figure (b) reports average coauthor career length, defined as number of years since year of first publication. Sub-figure (c) reports average publication percentile of coauthors' past publications. Sub-figure (d) shows the average annual number of publication by coauthors.

A.2 Propensity Score Matching

Table A5: Summary Statistics: Matched JTTP Scholars and Control Donor Pool Scholars

	matched treated			control pool		
	cohort 2011 (N = 131)			*cohort 2011 (N = 3253)*		
	mean	std	median	mean	std	median
Num Pubs	4.13	5.81	3	2.63	4.30	1
Num Cites	264.94	621.39	99	117.78	419.32	24
CiteScore	23.21	28.15	15	11.90	20.79	4.2
Top 10 Pct	1.55	2.03	1	0.70	1.41	0
Top 50 Pct	1.12	1.76	0	0.97	1.68	0
Year since First Pub	7.75	3.79	8	7.66	5.30	8
Year since PhD	5.44	2.77	5	7.11	3.51	6
	cohort 2012 (N = 306)			*cohort 2012 (N = 3409)*		
	mean	std	median	mean	std	median
Num Pubs	3.62	6.69	2	2.74	4.59	1
Num Cites	234.51	688.76	73	119.88	422.54	25
CiteScore	21.82	30.41	11.25	12.42	21.60	4.5
Top 10 Pct	1.32	1.81	1	0.74	1.48	0
Top 50 Pct	1.08	2.59	0	1.03	1.83	0
Year since First Pub	7.48	4.23	8	8.04	5.22	8
Year since PhD	5.55	2.42	5	7.31	3.48	6
	cohort 2013 (N=486)			*cohort 2013 (N=3467)*		
	mean	std	median	mean	std	median
Num Pubs	3.63	7.80	2	2.84	4.78	2
Num Cites	234.42	563.70	70	122.40	437.89	27
CiteScore	23.79	34.21	11.9	13.27	23.01	4.9
Top 10 Pct	1.42	2.05	1	0.77	1.51	0
Top 50 Pct	1.10	2.55	0	1.08	1.95	0
Year since First Pub	7.16	4.44	7	8.51	5.12	9
Year since PhD	5.15	2.41	5	7.55	3.40	7
	cohort 2015 (N=530)			*cohort 2015 (N=3248)*		
	mean	std	median	mean	std	median
Num Pubs	3.68	4.41	2	3.23	5.27	2
Num Cites	240.27	483.72	86	123.52	345.71	30
CiteScore	28.68	36.32	16.8	16.62	29.32	6.5
Top 10 Pct	1.59	1.98	1	0.93	1.80	0
Top 50 Pct	1.17	2.00	0	1.22	2.16	1
Year since First Pub	8.30	4.37	8	9.90	4.98	10
Year since PhD	5.68	2.16	6	8.60	3.17	8
	cohort 2016 (N=432)			*cohort 2016 (N=3063)*		
	mean	std	median	mean	std	median
Num Pubs	3.56	4.64	2	3.45	5.41	2
Num Cites	180.35	351.50	64	120.56	323.09	31
CiteScore	25.84	33.59	14.7	18.80	33.71	7.6
Top 10 Pct	1.51	2.01	1	1.04	2.06	0
Top 50 Pct	1.06	1.75	0	1.32	2.27	1
Year since First Pub	8.09	4.15	8	10.72	4.88	11
Year since PhD	5.98	2.13	6	9.27	3.00	9
	cohort 2017 (N=902)			*cohort 2017 (N=2877)*		
	mean	std	median	mean	std	median
Num Pubs	3.32	4.38	2	3.62	5.47	2
Num Cites	153.66	348.62	53	112.90	315.04	29
CiteScore	27.01	36.91	14.3	20.97	39.45	8.4
Top 10 Pct	1.48	2.01	1	1.15	2.34	0
Top 50 Pct	1.02	1.83	0	1.39	2.29	1
Year since First Pub	8.34	4.15	8	11.45	4.79	12
Year since PhD	5.68	2.20	5	9.90	2.85	10

Notes: This table shows summary statistics on publication and career information for the matched JTTP scholars and scholars in the control donor pool constructed using ORCID. *Num Pubs* is average number of publications in a year during five years to one year before the year of recruitment. Other publication variables are defined similarly as the mean over the five year interval.

Table A6: Propensity Score Matching: Number of Matched Units

	2011		2012		2013		2015		2016		2017	
	control	treated	control	treated	control	treated	control	treated	control	treated	control	treated
All	3253	133	3409	309	3467	492	3248	553	3063	478	2877	1014
Matched	131	131	306	306	486	486	530	530	432	432	902	902
Discarded	0	2	0	3	0	6	0	23	0	46	0	112

Notes: This table shows number of matched and discarded units in propensity score matching by cohort. We discard some units in the treated group because they are off common support.

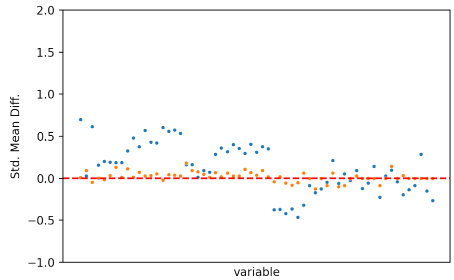
Table A7: Propensity Score Matching Quality

cohort	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max
2011	98.63	97.77	99.89	97.11
2012	95.57	89.66	99.74	90.84
2013	87.75	70.80	98.45	79.99
2015	80.35	60.70	95.31	66.99
2016	82.77	69.73	95.79	70.68
2017	48.24	26.58	71.28	32.17

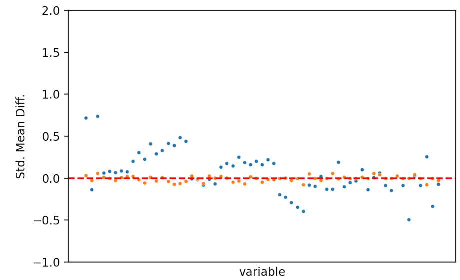
Notes: Propensity score matching, percent improvement of balance after matching. Values between 0 and 100 indicate that balance improved after matching as measured by the statistic.

Figure A4: Standardized Mean Difference for Matching Variables

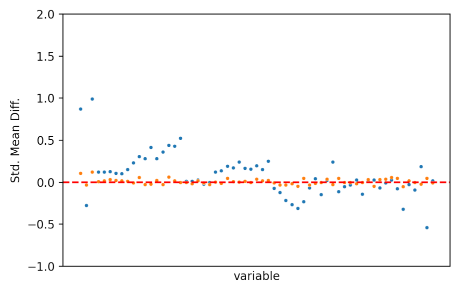
(a) 2011



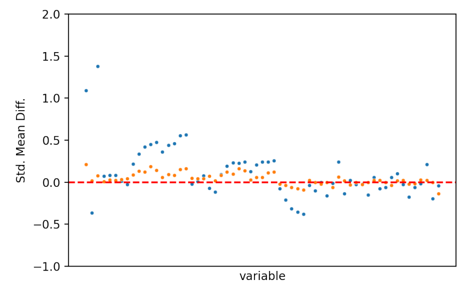
(b) 2012



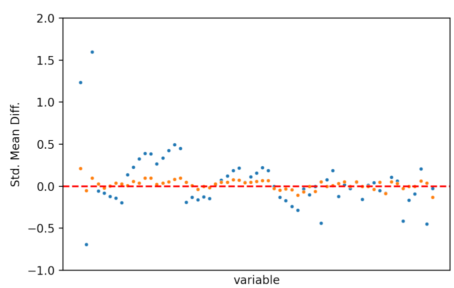
(c) 2013



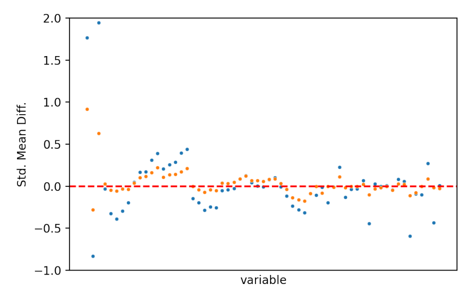
(d) 2015



(e) 2016



(f) 2017



Notes: The figures depict the standardized mean differences for matching variables between treated and control groups before and after matching. Blue dots depict the standardized mean differences before matching and yellow dots depict the standardized mean differences after matching. The matching variables include 26 time-invariant variables: career length since first publication, career length since PhD graduation, 23 publication fields. The 34 time varying variables include average author rank, total number of cites, total number of top 10 publications, total number of top 50 publications, number of publications, average publication percentile, average university rank for each year during five years before the recruitment year and one year before the recruitment year.

A.3 JTTP Direct Effect Estimates: Tables and Figures

Table A8: Effect on JTTP Scholars: Baseline Estimates
Stacked Cohorts 2011, 2012, 2013

	ihs(Num Pubs)	Num Cites	CiteScore	Top 10 Pct	Top 50 Pct	Last Authored	First Authored	Funded
$Treated \times Post[0,3]$	-0.136	-0.172	-0.253	-0.070	-0.093	-0.041	-0.070	-0.059
	(0.038)	(0.060)	(0.081)	(0.033)	(0.031)	(0.032)	(0.023)	(0.034)
$Treated \times Post[4,6]$	0.127	0.103	0.104	0.133	0.085	0.328	-0.072	0.177
	(0.046)	(0.072)	(0.084)	(0.043)	(0.039)	(0.044)	(0.024)	(0.046)
Constant	0.922	1.643	2.324	0.515	0.451	0.282	0.359	0.508
	(0.005)	(0.008)	(0.010)	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)
Scholar FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Career×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of the Dept. Variable	0.9193	1.6361	2.3115	0.5173	0.4488	0.2962	0.3502	0.5130
No. of Observations	47936	47936	47936	47936	47936	47936	47936	47936
Adjusted R^2	0.6689	0.6702	0.6378	0.5458	0.4620	0.5008	0.3958	0.5992

Notes: Standard errors in parentheses. For each cohort we keep scholar-year observations in the same window $t \in [-21, 6]$, where $t = 0$ is the time of junior thousand talents plan recruitment year. There are 856 JTTP scholars and 856 matched scholars. All dependent variable has transformed using inverse hyperbolic sine. We control for pre-treatment baseline covariates times cohort times year fixed effect. Career length is defined as number of years since graduating from Ph.D. program. Field is defined as the field with maximum number of publications before recruitment for a scholar. (1)= number of publications;(2)=CiteScore; (3)=Cites; (4)=number of top 10 percentile publications; (5)=number of top 50 percentile publications; (6)=number of last authored publications; (7) number of first authored publications (8) number of funded publications

Table A9: Effect on JTTP Scholars: Estimates with ORCID
Stacked Cohorts 2011, 2012, 2013

	Num Pubs	Num Cites	CiteScore	Top 10 Pct	Top 50 Pct	Last Authored	First Authored	Funded
$Treated \times Post[0,3]$	-0.194	-0.155	-0.206	-0.091	-0.127	-0.123	-0.080	-0.096
	(0.084)	(0.126)	(0.172)	(0.071)	(0.069)	(0.072)	(0.049)	(0.073)
$Treated \times Post[4,6]$	0.121	0.148	0.148	0.163	0.139	0.343	-0.126	0.183
	(0.098)	(0.150)	(0.179)	(0.091)	(0.080)	(0.093)	(0.048)	(0.094)
Constant	0.985	1.781	2.496	0.581	0.469	0.307	0.374	0.543
	(0.010)	(0.016)	(0.020)	(0.009)	(0.008)	(0.009)	(0.005)	(0.009)
Scholar FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Career×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of the Dept. Variable	0.9776	1.7781	2.4892	0.5831	0.4670	0.3167	0.3618	0.5459
No. of Observations	12852	12852	12852	12852	12852	12852	12852	12852
Adjusted R-squared	0.6814	0.6837	0.6548	0.5615	0.4650	0.5229	0.4148	0.6141

Notes: Standard errors in parentheses. For each cohort we keep scholar-year observations in the same window $t \in [-21, 6]$, where $t = 0$ is the time of junior thousand talents plan recruitment year. There are 236 JTTP scholars with ORCID and 236 matched scholars. All dependent variable has transformed using inverse hyperbolic sine. We control for pre-treatment baseline covariates times cohort times year fixed effect. Career length is defined as number of years since graduating from Ph.D. program. Field is defined as the field with maximum number of publications before recruitment for a scholar. (1)= number of publications;(2)=CiteScore; (3)=Cites; (4)=number of top 10 percentile publications; (5)=number of top 50 percentile publications; (6)=number of last authored publications; (7) number of first authored publications (8) number of funded publications

Table A10: Comparison between Joiners and all Renegers: Stacked Cohorts 2011-2017

	Num Pubs	Num Cites	CiteScore	Top 10 Pct	Top 50 Pct	Last Authored	First Authored	Funded
Treated × *Post*	0.095	0.162	0.139	0.066	0.013	0.014	0.071	0.076
	(0.053)	(0.083)	(0.097)	(0.041)	(0.041)	(0.039)	(0.025)	(0.048)
Constant	0.735	1.327	1.825	0.414	0.355	0.200	0.300	0.429
	(0.008)	(0.012)	(0.014)	(0.006)	(0.006)	(0.006)	(0.003)	(0.007)
Scholar FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Career×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of the Dept. Variable	0.7487	1.3501	1.8446	0.4233	0.3573	0.2022	0.3103	0.4402
No. of Observations	98640	98640	98640	98640	98640	98640	98640	98640
Adjusted R^2	0.6437	0.6587	0.6299	0.5415	0.4495	0.4630	0.4303	0.5932

Notes: Standard errors in parentheses. All dependent variable has transformed using inverse hyperbolic sine. We control for pre-treatment baseline covariates times cohort times year fixed effect. Career length is defined as number of years since graduating from Ph.D. program. Field is defined as the field with maximum number of publications before recruitment for a scholar.

Table A11: Comparison between Joiners and Return Renegers: Stacked Cohorts 2011-2017

	Num Pubs	Num Cites	CiteScore	Top 10 Pct	Top 50 Pct	Last Authored	First Authored	Funded
Treated × *Post*	0.009	0.027	-0.077	-0.004	-0.008	-0.002	0.025	-0.003
	(0.074)	(0.116)	(0.141)	(0.059)	(0.057)	(0.055)	(0.032)	(0.067)
Constant	0.739	1.345	1.845	0.426	0.353	0.196	0.303	0.440
	(0.011)	(0.018)	(0.022)	(0.009)	(0.009)	(0.008)	(0.005)	(0.010)
Scholar FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Career×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of the Dept. Variable	0.7409	1.3492	1.8332	0.4256	0.3519	0.1958	0.3065	0.4395
No. of Observations	89910	89910	89910	89910	89910	89910	89910	89910
Adjusted R^2	0.6452	0.6617	0.6307	0.5468	0.4487	0.4673	0.4296	0.5996

Notes: Standard errors in parentheses. All dependent variable has transformed using inverse hyperbolic sine. We control for pre-treatment baseline covariates times cohort times year fixed effect. In this table we include renegers who returned to China but to other institutions as control group.

Table A12: Comparison between Joiners and Overseas Renegers: Stacked Cohorts 2011-2017

	Num Pubs	Num Cites	CiteScore	Top 10 Pct	Top 50 Pct	Last Authored	First Authored	Funded
Treated × *Post*	0.141	0.241	0.267	0.110	0.020	0.015	0.098	0.122
	(0.070)	(0.108)	(0.124)	(0.053)	(0.053)	(0.052)	(0.033)	(0.062)
Constant	0.727	1.314	1.805	0.407	0.353	0.199	0.297	0.422
	(0.010)	(0.016)	(0.018)	(0.008)	(0.008)	(0.008)	(0.005)	(0.009)
Scholar FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Career×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of the Dept. Variable	0.7482	1.3499	1.8447	0.4235	0.3561	0.2017	0.3117	0.4400
No. of Observations	93420	93420	9342	93420	9342	93420	93420	93420
Adjusted R^2	0.6445	0.6594	0.6306	0.5411	0.4486	0.4622	0.4322	0.5943

Notes: Standard errors in parentheses. All dependent variable has transformed using inverse hyperbolic sine. We control for pre-treatment baseline covariates times cohort times year fixed effect. In this table we include renegers who stayed overseas as control group.

Table A13: Effect on JTTP Scholars: Baseline Estimates:
Number of Publications by Cohort 2011-2017

	2011	2012	2013	2015	2016	2017
$Treated \times Post[0,3]$	-0.069	-0.152	-0.141	0.000	0.058	-0.010
	(0.095)	(0.068)	(0.054)	(0.049)	(0.056)	(0.046)
$Treated \times Post[4,)$	0.209	0.034	0.133	0.160	0.000	0.000
	(0.126)	(0.079)	(0.066)	(0.066)	(.)	(.)
Constant	1.047	0.947	0.845	0.725	0.664	0.595
	(0.015)	(0.009)	(0.007)	(0.004)	(0.004)	(0.002)
Scholar FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Career×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Field×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of the Dept. Variable	1.0596	0.9395	0.8425	0.7275	0.6675	0.5946
No. of Observations	7410	17070	26880	30060	24540	51960
Adjusted R-squared	0.7109	0.6688	0.6687	0.6514	0.6489	0.6089

Notes: Standard errors in parentheses. Dependent variable is ihs transformation of number of publications. We control for pre-treatment baseline covariates times cohort times year fixed effect. (1)-(6) refers to specifications for year 2011, 2012, 2013, 2015, 2016, 2017 respectively.

Table A14: Effect on JTTP Scholars: Estimates with ORCID
Number of Publications by Cohort 2011-2017

	2011	2012	2013	2015	2016	2017
$Treated \times Post[0,3]$	0.045	-0.081	-0.325	0.034	0.018	-0.098
	(0.223)	(0.128)	(0.117)	(0.091)	(0.111)	(0.081)
$Treated \times Post[4,)$	0.402	0.200	-0.017	0.165	0.000	0.000
	(0.325)	(0.158)	(0.136)	(0.126)	(.)	(.)
Constant	1.040	1.018	0.910	0.753	0.706	0.639
	(0.036)	(0.017)	(0.014)	(0.008)	(0.007)	(0.004)
Scholar FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Career×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Field×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of the Dept. Variable	1.0737	1.0254	0.8876	0.7584	0.7070	0.6337
No. of Observations	1680	5280	6810	8400	6090	14130
Adjusted R-squared	0.6741	0.6856	0.6926	0.6830	0.6683	0.6348

Notes: Standard errors in parentheses. Dependent variable is ihs transformation of number of publications. We control for pre-treatment baseline covariates times cohort times year fixed effect. (1)-(6) refers to specifications for year 2011, 2012, 2013, 2015, 2016, 2017 respectively.

Table A15: Effect on JTTP Scholars: Heterogeneity by Overseas PhD
Stacked Cohorts 2011, 2012, 2013

	Num Pubs	CiteScore	Num Cites	Top 10 Pct	Top 50 Pct	Last Authored	First Authored	Funded
$Treated \times Post[0,3]$	-0.2074***	-0.1503	-0.2817**	0.0023	-0.2294***	0.0623	-0.1416***	-0.1250**
	(0.0598)	(0.0961)	(0.1282)	(0.0531)	(0.0509)	(0.0449)	(0.0363)	(0.0543)
$Treated \times Post[4,)$	0.0098	0.0141	-0.0837	0.1656**	-0.0364	0.4736***	-0.2498***	0.0788
	(0.0741)	(0.1129)	(0.1281)	(0.0694)	(0.0662)	(0.0762)	(0.0395)	(0.0755)
$Treated \times Post[0,3] \times Overseas$	0.1786**	0.0400	0.1499	-0.0706	0.2530***	-0.1010*	0.1152**	0.1491**
	(0.0770)	(0.1249)	(0.1653)	(0.0678)	(0.0623)	(0.0609)	(0.0473)	(0.0688)
$Overseas \times Post[0,3]$	-0.2059***	-0.3133***	-0.4738***	-0.1174**	-0.1792***	0.1451***	-0.1380***	-0.2152***
	(0.0513)	(0.0824)	(0.1094)	(0.0473)	(0.0441)	(0.0419)	(0.0317)	(0.0484)
$Treated \times Post[4,) \times Overseas$	0.2232**	0.2140	0.3658**	0.0158	0.2190***	-0.1931**	0.2699***	0.2121**
	(0.0955)	(0.1469)	(0.1663)	(0.0892)	(0.0819)	(0.0954)	(0.0495)	(0.0978)
$Overseas \times Post[4,)$	-0.2391***	-0.4095***	-0.5410***	-0.2219***	-0.1841***	0.0711	-0.1617***	-0.2973***
	(0.0587)	(0.0914)	(0.1060)	(0.0600)	(0.0518)	(0.0629)	(0.0349)	(0.0619)
Observations	51,688	51,688	51,688	51,688	51,688	51,688	51,688	51,688
R^2	0.65963	0.65566	0.62723	0.52962	0.47533	0.48012	0.38564	0.59533
Within R^2	0.00443	0.00373	0.00314	0.00694	0.00399	0.01380	0.00348	0.00847
Scholar FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Career×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. Dependent variable is ihs transformation of number of publications. In all specifications, we control for pre-treatment baseline covariates (career length and research field) times cohort times year fixed effect.

Table A16: Effect on JTTP Scholars: Heterogeneity by Career Length
Stacked Cohorts 2011, 2012, 2013

	Num Pubs	CiteScore	Num Cites	Top 10 Pct	Top 50 Pct	Last Authored	First Authored	Funded
$Treated \times Post[0,3]$	-0.2161***	-0.2768***	-0.3853***	-0.1365***	-0.1502***	-0.1431***	-0.0528*	-0.1571***
	(0.0468)	(0.0714)	(0.0953)	(0.0394)	(0.0375)	(0.0408)	(0.0286)	(0.0415)
$Treated \times Post[4,)$	0.0248	-0.0075	0.0040	0.0622	0.0044	0.2027***	-0.0633**	0.0856
	(0.0587)	(0.0904)	(0.1038)	(0.0537)	(0.0493)	(0.0559)	(0.0300)	(0.0603)
$Treated \times Post[0,3] \times Young$	0.2791***	0.3464***	0.4588***	0.2099***	0.1885***	0.3201***	-0.0359	0.2916***
	(0.0703)	(0.1106)	(0.1464)	(0.0611)	(0.0580)	(0.0577)	(0.0437)	(0.0626)
$Young \times Post[0,3]$	-0.2651***	-0.3308***	-0.4104***	-0.2211***	-0.1715***	-0.2903***	0.0211	-0.2641***
	(0.0624)	(0.1010)	(0.1348)	(0.0565)	(0.0498)	(0.0540)	(0.0377)	(0.0589)
$Treated \times Post[4,) \times Young$	0.2963***	0.3611***	0.3335**	0.2459***	0.2356***	0.3293***	-0.0177	0.2969***
	(0.0848)	(0.1308)	(0.1496)	(0.0814)	(0.0731)	(0.0844)	(0.0478)	(0.0877)
$Young\times$ Post[4,)	-0.2414***	-0.3439***	-0.3174**	-0.3135***	-0.1579***	-0.3412***	0.1042**	-0.2581***
	(0.0723)	(0.1150)	(0.1319)	(0.0711)	(0.0607)	(0.0753)	(0.0432)	(0.0758)
Observations	51,688	51,688	51,688	51,688	51,688	51,688	51,688	51,688
R^2	0.65978	0.65517	0.62664	0.52920	0.47505	0.48274	0.38440	0.59508
Within R^2	0.00488	0.00232	0.00159	0.00606	0.00346	0.01877	0.00146	0.00785
Scholar FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Career×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field×Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. Dependent variable is ihs transformation of number of publications. In all specifications, we control for pre-treatment baseline covariates (career length and research field) times cohort times year fixed effect.

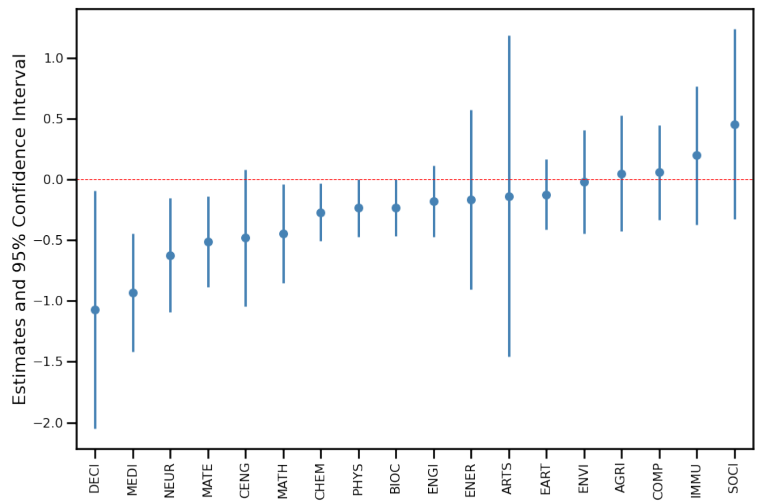
Table A17: Effect on JTTP Scholars Coauthorship: Stacked Cohorts 2011, 2012, 2013

	Frac First Year Coauthor	Same Univ Coauthor	Mean Cum Pub Coauthor	Mean Year Exp Coauthor
$Treated \times Post$	0.039	0.001	0.884	-1.075
	(0.005)	(0.010)	(1.143)	(0.128)
Constant	0.152	0.555	27.485	8.951
	(0.001)	(0.002)	(0.270)	(0.030)
Scholar FE	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes
Career×Cohort×Year FE	Yes	Yes	Yes	Yes
Field×Cohort×Year FE	Yes	Yes	Yes	Yes
Mean of the Dept. Variable	0.1612	0.5550	27.6940	8.6970
No. of Observations	21706	21706	21706	21706
Adjusted R-squared	0.1735	0.3766	0.2931	0.3777

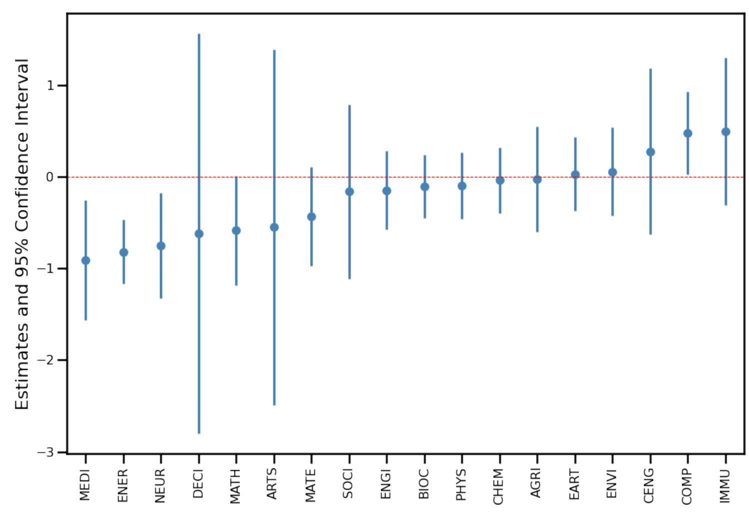
Notes: Standard errors in parentheses. Column (1) reports fraction of coauthors for a scholar in a year who publish their first paper in that year. Column (2) reports fraction of coauthors in the same institution in that year. Column (3) reports mean cumulative number of publications until a year by all coauthors. Column (4) reports the mean number of years of experience of coauthors.

Figure A5: Heterogeneity by Research Field

(a) Effect $t \in [0, 3]$ years



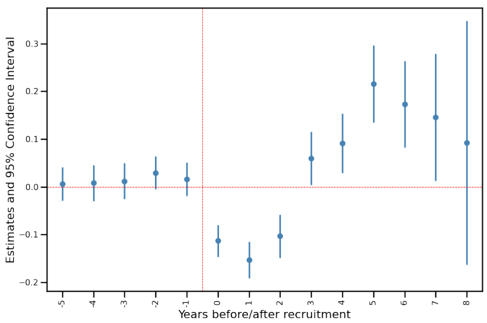
(b) Effect $t \in [4, 6]$ years



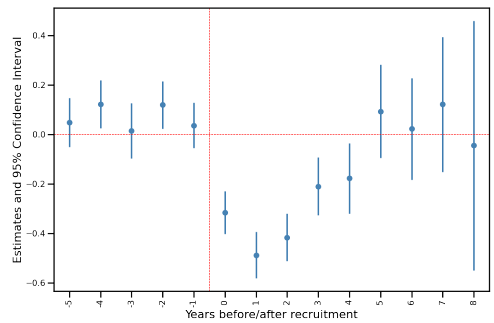
Notes: The regression includes scholar fixed effects, cohort-year fixed effects, pre-treatment career length × cohort-year fixed effects, and field × cohort-year fixed effects.

Figure A6: Event Study Callaway and Sant'Anna Estimates

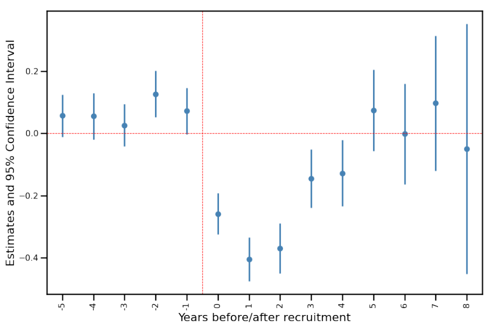
(a) number of publications



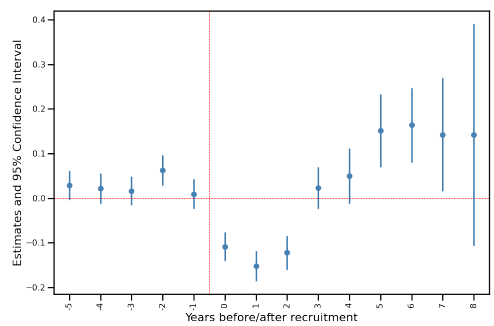
(b) cites



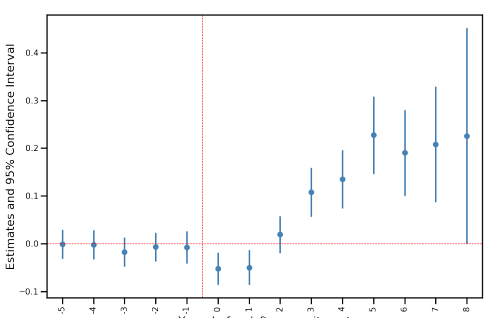
(c) citesscore



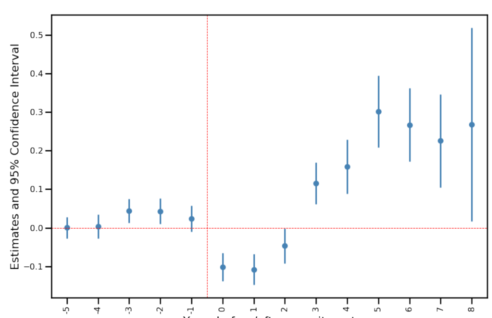
(d) top 10 percentile publications



(e) top 50 percentile publications



(f) funding



Notes: The figures depict the differences in dependent variables between treated and control scholars before and after joining the JTTP using the Callaway and Sant'Anna estimator including all cohorts. The dashed vertical line represents 1 year before recruitment occurs. The regression includes scholar fixed effects, year fixed effects, pre-treatment career length $\times$ year fixed effects.

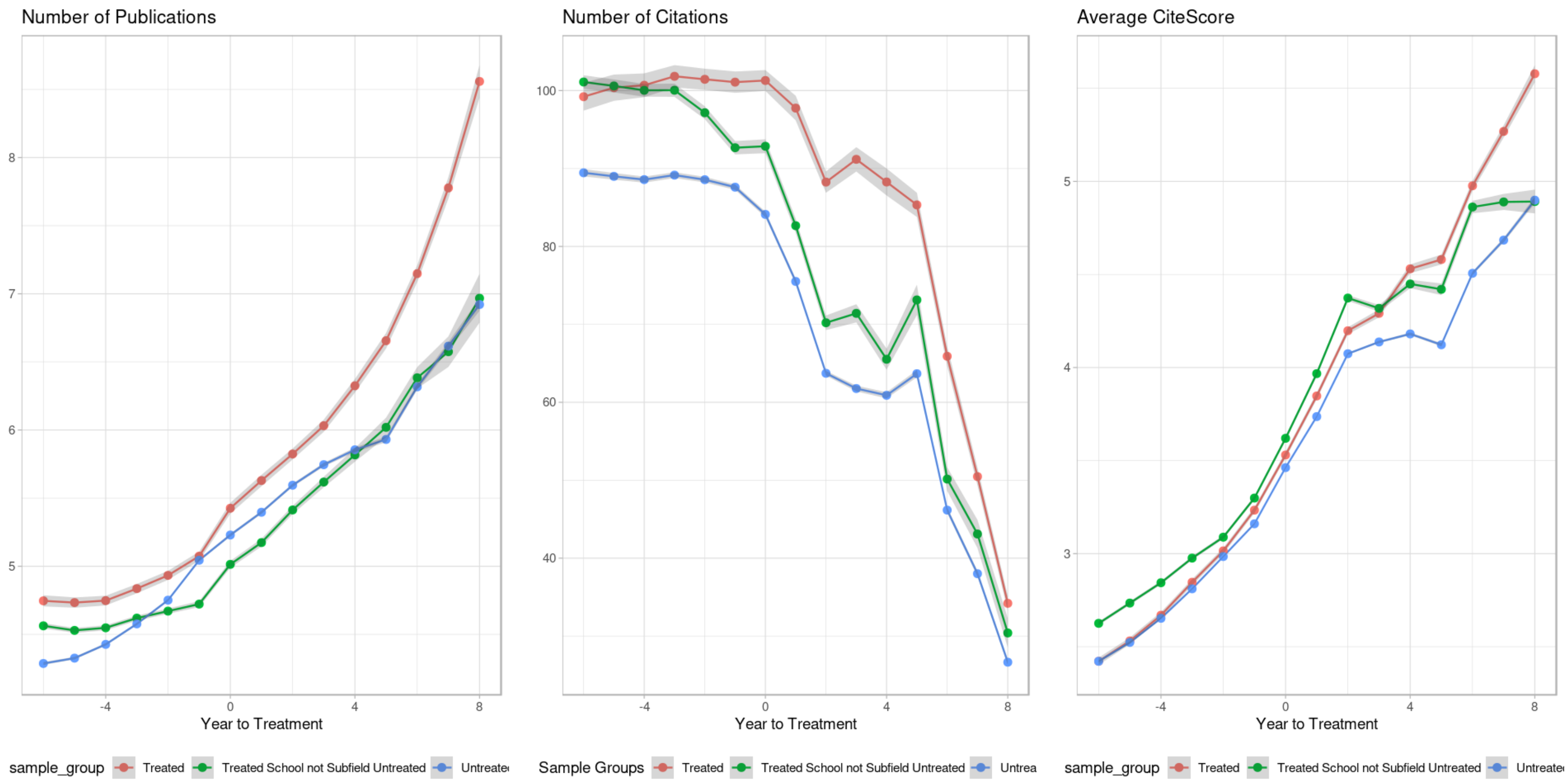
A.4 Descriptive Statistics - Peers by Cohort

Table A18: Descriptive Statistics for Peer Scholars

		2011	2012	2013	2015	2016	2017	Total
Unique Affiliations	Treated Dept.	47	59	70	78	67	95	159
	Non-treated Dept. in Receving School	47	59	70	78	67	95	159
	Other Non-treated Dept.	22537	26548	32845	41782	45093	48787	82939
Unique Departments	Treated Dept.	104	132	131	135	92	157	751
	Non-treated Dept. in Receving School	727	892	1101	1218	1112	1628	2942
	Other Non-treated Dept.	43951	48565	58349	73677	79632	86621	151421
Author IDs in Affiliations X Two-Digit Fields [10%,50%,90%,100%]	Treated Dept.	[47, 398, 1617, 3823]	[31, 275, 1156, 2865]	[20, 165, 706, 2969]	[11, 169, 583, 1632]	[32, 139, 659, 2058]	[18, 126, 577, 2463]	
	Non-treated Dept. in Receving School	[3, 40, 363, 2588]	[3, 40, 397, 3741]	[3, 40, 474, 3625]	[4, 48, 419, 3334]	[5, 56, 428, 3217]	[2, 33, 315, 2898]	
	Other Non-treated Dept.	[1, 1, 13, 2465]	[1, 1, 12, 2068]	[1, 1, 11, 3117]	[1, 1, 10, 2871]	[1, 1, 10, 3099]	[1, 1, 9, 3366]	
Number of Unique Author IDs	Treated Dept.	70719	60449	36800	34685	23553	41673	255062
	Non-treated Dept. in Receving School	98925	145156	196719	202769	191340	196312	406780
	Other Non-treated Dept.	448534	476394	526629	665912	743333	708288	742245
Pre-treatment Career Length of Author IDs [10%,50%,90%]	Treated Dept.	[1, 6, 16]	[1, 6, 15]	[1, 6, 14]	[1, 6, 15]	[2, 7, 16]	[2, 7, 17]	
	Non-treated Dept. in Receving School	[1, 5, 14]	[2, 6, 16]	[2, 7, 16]	[3, 8, 17]	[3, 9, 19]	[3, 8, 17]	
	Other Non-treated Dept.	[1, 5, 13]	[1, 5, 13]	[2, 6, 14]	[2, 7, 15]	[2, 7, 15]	[2, 8, 16]	
Total Publications of Author IDs 5-year Pre-treatment [10%,50%,90%]	Treated Dept.	[1, 6, 34]	[1, 6, 29]	[1, 6, 28]	[1, 6, 28]	[1, 6, 30]	[1, 7, 32]	
	Non-treated Dept. in Receving School	[1, 5, 28]	[1, 6, 31]	[1, 6, 32]	[1, 7, 33]	[0, 7, 36]	[1, 7, 35]	
	Other Non-treated Dept.	[1, 5, 22]	[1, 5, 22]	[1, 5, 22]	[1, 6, 25]	[1, 6, 26]	[1, 6, 26]	
Total Citations to Author IDs 5-year Pre-treatment [10%,50%,90%]	Treated Dept.	[0, 52, 730]	[1, 48, 588]	[1, 58, 639]	[2, 69, 625]	[1, 62, 594]	[1, 52, 534]	
	Non-treated Dept. in Receving School	[1, 43, 557]	[1, 58, 678]	[0, 62, 695]	[0, 64, 675]	[0, 69, 725]	[0, 70, 669]	
	Other Non-treated Dept.	[0, 32, 427]	[0, 34, 422]	[0, 34, 416]	[0, 42, 468]	[0, 44, 469]	[0, 44, 441]	

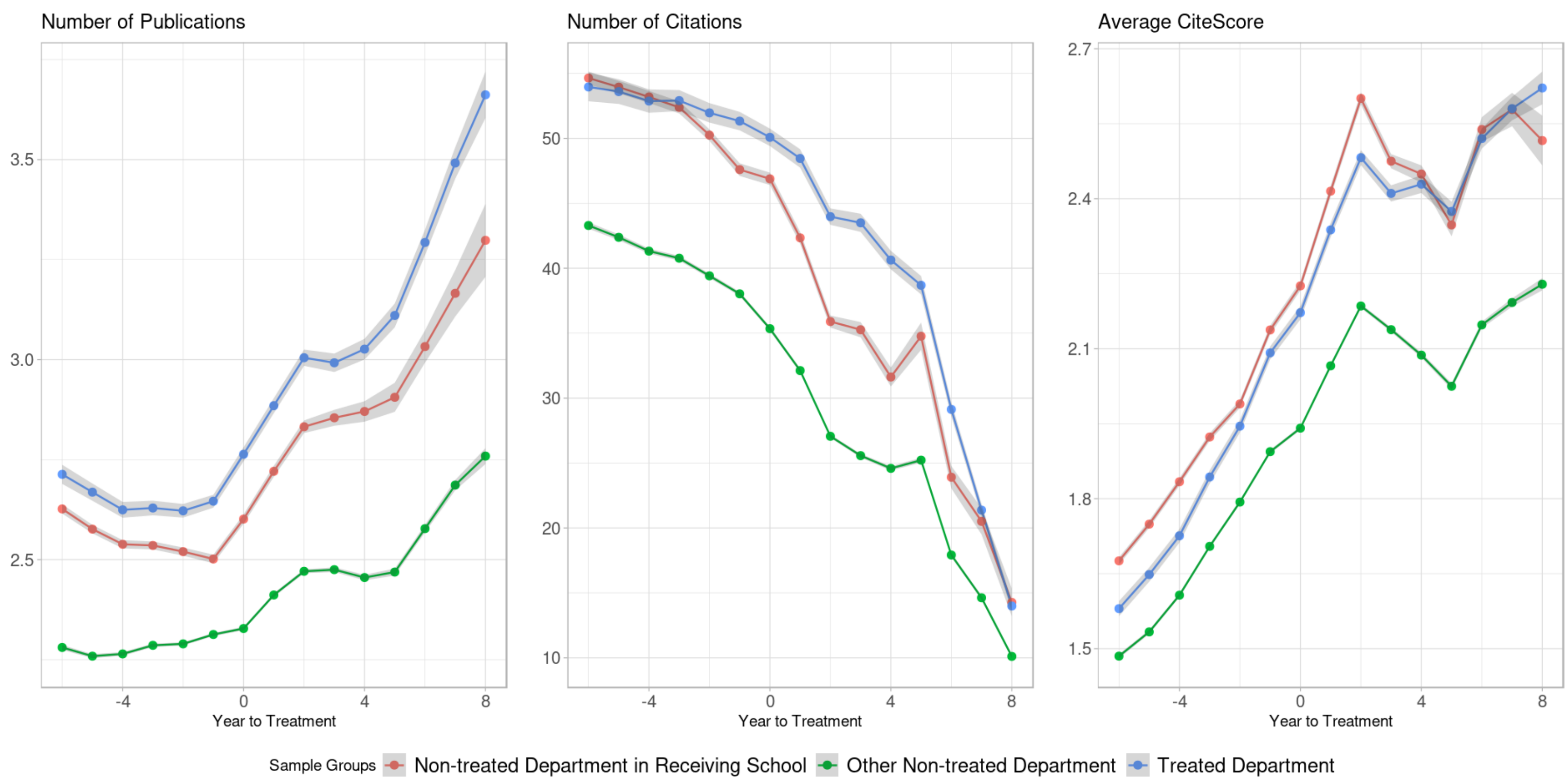
Notes: This table describes the number of affiliations and affiliation X 2-digit groups in each treatment year in the estimation sample. For the affiliation X 2-digit group size statistics, we report 10%, 50%, 90%, and 100& quantiles. For the pre-treatment productivity statistics, we report 10%, 50%, and 90% quantiles.

Figure A7: Raw Trends - By Sample Group - No Zeros



Notes: The figures depict the raw trends of productivity for the three groups in our figure: (1) Treated Scholars, (2) scholars in an affiliation that received a JTTP scholar but are in a his/her field, and (3) non-treated scholars. In each year, the dataset contains all scholars in all fields that received a JTTP scholar that year.

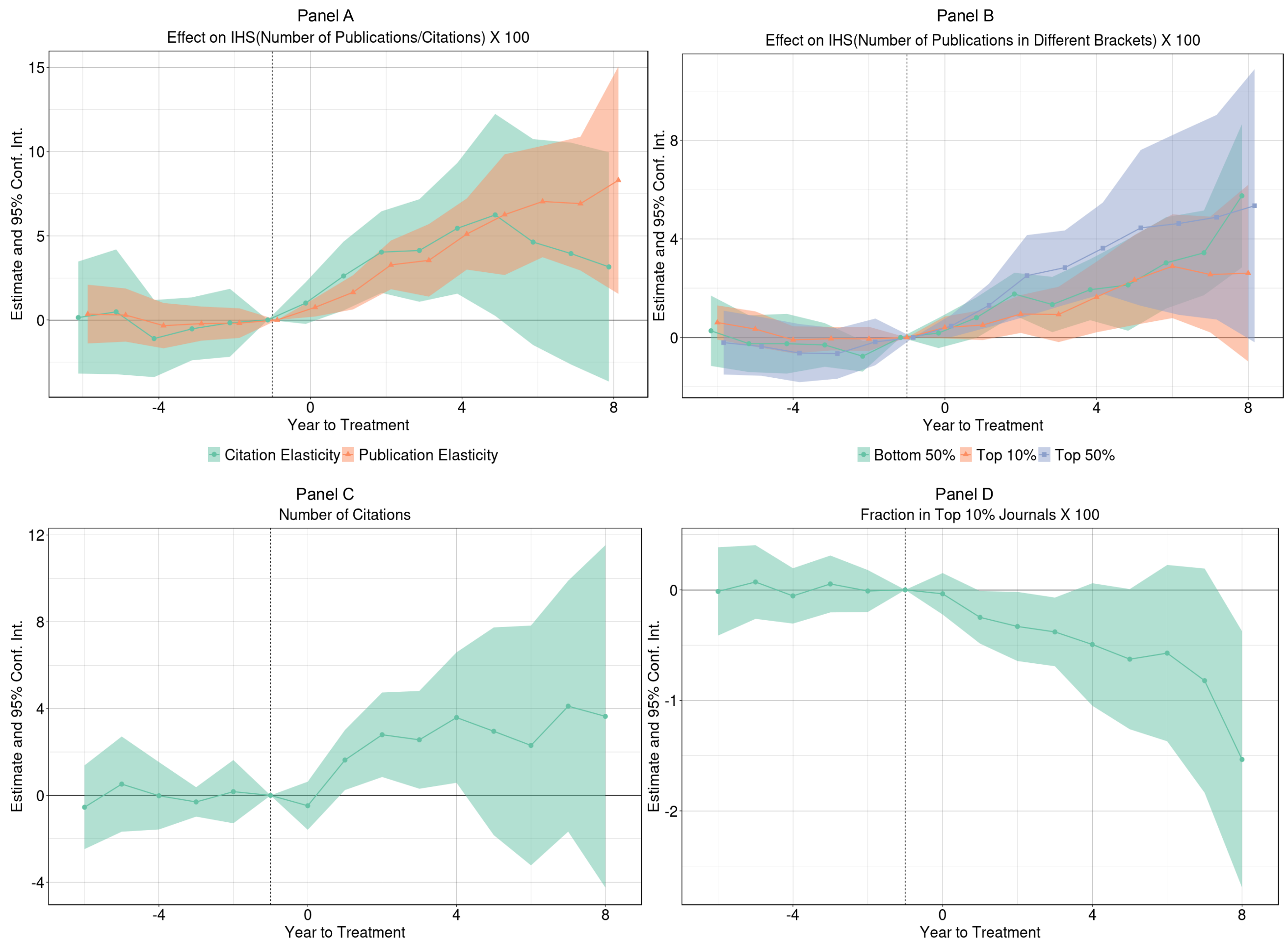
Figure A8: Raw Trends - By Sample Group - Weighted



Notes: The figures depict the raw trends of productivity for the three groups in our figure: (1) Treated Scholars, (2) scholars in an affiliation that received a JTTP scholar but are in a his/her field, and (3) non-treated scholars. In each year, the dataset contains all scholars in all fields that received a JTTP scholar that year.

A.5 Peer Effect Event Study - More Outcomes

Figure A9: Peer Effect Event Study Estimates - More Outcomes



Notes: This figure reports the event study estimates β_τ for the quantity and quality effects of receiving a JTTP scholar in one's affiliation X 2 digit group. Standard errors clustered by affiliation level and 2-digit subfield level.
The estimating equation is Equation 5: $Y_{itc} = \sum_{\tau \neq -1, \tau=-6}^{\tau=8} Z_t^\tau \beta_\tau + \Gamma' \mathbf{X}_{itc} + u_{ic} + \varepsilon_{itc}$

A.6 Peer Effects, Additional Results

Table A19: Peer Effect Event Study Coefficients

	(1)	(2)	(3)	(4)	(5)
	Number of Publications	IHS(Publications) X 100	Number of Citations	IHS(Citations) X 100	Average CiteScore
Treated X 1[T = -6]	0.0257 (0.0341)	0.3477 (0.8898)	-0.5455 (0.9841)	0.1422 (1.699)	0.0042 (0.0187)
Treated X 1[T = -5]	0.0087 (0.0365)	0.2897 (0.8057)	0.5209 (1.118)	0.4811 (1.893)	-0.0012 (0.0198)
Treated X 1[T = -4]	-0.0156 (0.0350)	-0.3401 (0.6860)	-0.0171 (0.7917)	-1.107 (1.169)	-0.0076 (0.0133)
Treated X 1[T = -3]	-0.0098 (0.0214)	-0.2181 (0.5168)	-0.3008 (0.3454)	-0.5284 (0.9532)	0.0090 (0.0132)
Treated X 1[T = -2]	-0.0009 (0.0163)	-0.1887 (0.4481)	0.1717 (0.7433)	-0.1696 (1.030)	-0.0121 (0.0134)
Treated X 1[T = -1]	-	-	-	-	-
Treated X 1[T = 0]	0.0358*** (0.0113)	0.7513** (0.2796)	-0.4767 (0.5658)	1.004 (0.6322)	0.0057 (0.0101)
Treated X 1[T = 1]	0.0962*** (0.0235)	1.643*** (0.5186)	1.630** (0.7058)	2.611** (1.043)	0.0182 (0.0111)
Treated X 1[T = 2]	0.1998*** (0.0473)	3.272*** (0.7380)	2.795*** (0.9929)	4.033*** (1.237)	0.0322* (0.0175)
Treated X 1[T = 3]	0.2268*** (0.0621)	3.541*** (1.099)	2.561** (1.149)	4.128** (1.554)	0.0182 (0.0202)
Treated X 1[T = 4]	0.3411*** (0.0664)	5.105*** (1.078)	3.587** (1.533)	5.446** (1.981)	0.0443 (0.0306)
Treated X 1[T = 5]	0.4055*** (0.1050)	6.258*** (1.830)	2.954 (2.442)	6.243* (3.061)	0.0498 (0.0414)
Treated X 1[T = 6]	0.4735*** (0.1155)	7.040*** (1.690)	2.301 (2.818)	4.627 (3.121)	0.0500 (0.0466)
Treated X 1[T = 7]	0.5452*** (0.1307)	6.913*** (2.027)	4.111 (2.949)	3.944 (3.363)	0.0371 (0.0521)
Treated X 1[T = 8]	0.6669*** (0.1978)	8.303** (3.446)	3.641 (4.025)	3.151 (3.476)	-0.0471 (0.0742)

Author X Affiliation X Cohort FE
4-digit Field X Career Start Specific Trends
Affiliation X Career Start Specific Trends
Sample Size: 41,787,795

Notes: This table reports the event study estimates β_τ for different outcomes of receiving a JTTP scholar in one's affiliation X 2 digit group. Standard errors clustered by affiliation level and 2-digit subfield level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The estimating equation is Equation 5: $Y_{itc} = \sum_{\tau \neq -1, \tau=-6}^{\tau=8} Z_t^\tau \beta_\tau + \Gamma' \mathbf{X}_{itc} + u_{ic} + \varepsilon_{itc}$

A.7 Difference-in-Difference Estimates - Robustness

The detailed regression outcomes for robustness checks I-IX are in Table A20 in the appendix.

Robustness I: Dropping All Observations associated with the Chinese Academy of Science.

One may worry that the Scopus algorithm does not do a good job in distinguishing the different branches of the CAS scatter across China and hence using CAS as an umbrella affiliation may lead to measurement error. We run the same regression, excluding all observations associated with the CAS and find the results to be insensitive to this concern.

Robustness II: Dropping All Observations with Zero Publications.

One may worry that our regression specification may not adequately address life-cycle concerns and the artificial zeros we impute can be driving the result. The trade-off, however, is that if the JTTP effect work through the extensive margin, dropping zeros may introduce another bias. In this robustness check we drop all observations with zero publications. We find the results to be quantitatively and qualitatively similar albeit slightly smaller but within the confidence interval of the original estimate.

Robustness III: Introducing Time Varying Slopes for Pre-treatment Productivity Measure

One may worry that scholars with different pre-treatment productivity levels could potentially be on different productivity trends. We address this by including time-invariant IHS transformed 5-year pre-treatment total publications and citations fully interacted with time FEs in our regression. We find our result to be insensitive.

Robustness IV: Treatment Cohort Weighting - Equal Relative Time Window

One may worry that the fact that earlier periods have more post periods and potential heterogeneous effects across cohorts to be driving the result. In this robustness check, we only keep post periods [0,1,2] which is present in all cohorts in our estimating sample. We find the result to be qualitatively similar but smaller in magnitude, although still within the CI of the original estimates. This is to be expected as we found the result to accumulate over time and we dropped the last period in this excercise.

Robustness V: Treatment Cohort Weighting - Equal Absolute Time Window

One may worry that the fact that earlier periods have more periods and and potential heterogeneous effects across cohorts to be driving the result. In this robustness check, we only keep observations after year 2009 which for each cohorts leaves at least 1 pre-period and 9 periods in total for each cohort (after dropping the last period for the 2011 cohort).

We find the results to be qualitatively and quantiatively similar and within the CI of the original estimates.

Robustness VI: Dropping Dropping All Obervations from an Affiliation X 2-digit Group with Less than 10 Members
One may worry that scholars affiliated with small affiliation X 2-digit code groups to be a fundamentally different group. They are more likely to affiliated with corporate research groups and therefore an inappropriate control group. In this robustness check we drop all observations associated with an affiliation X 2-digit group with Less than 10 members, roughly bottom 10% in the cell size distribution. We find our result to be insensitive.

Robustness VII: Only Pre-treatment Periods of Not-Yet-or-Previously Treated as Control Group
One may worry that the affiliation X 2-digit groups joined by JTTP scholars are on a different trend compared to untreated groups. In this robustness check we keep only the pre-treatment periods of previously or not-yet treated groups as the control group. We find the result to be qualitatively similar but smaller in magnitude, although still close to or within the CI of the original estimates. This could be driven by (a) there are less post-periods in the dataset as the last post-period control group are the 1 years before treatment observations of the cohort treated in 2017, i.e. 2016, this means we can have at most 5 post-periods in our data, among other things.

Robustness VIII: Only Non-treated Scholars in a Treated School as Control Group
One may worry that the affiliation joined by JTTP scholars are on a different trend compared to untreated affiliations. In this robustness check we keep only the non-treated scholars in a treated school as the control group. We find the results to be qualitatively and quantiatively similar and within the CI of the original estimates.

Robustness IX: Only Never-treated Scholars in a Treated School as Control Group
One may worry that the previously or not-yet treated groups to be an inappropriate control group, not for econometric reasons but for things like anticipation effects. In this robustness check we keep only scholars in never-treated affiliation X 2-digit groups as the control group. We find the result to be qualitatively similar but larger in magnitude, although still within the CI of the original estimates.

The regression outcomes for robustness check X are in Table A21 in the appendix.

Robustness X: Accounting for Coauthorship
To account for the fact that a publication with multiple coauthors requires less effort than a single authored one, we divide each publication by its number of coauthors before aggregating

at the scholar X year level. We find the result to be qualitatively similar but smaller in magnitude. We think this might mean that the treated affiliatin X 2-digit group acquired different research norms after a JTTP joins. However, the raw number of publication is still an outcome of independent interest.

The regression outcomes for robustness check XI are in Table A22 in the appendix.

Robustness XI: Poisson Regression - Functional Form
One may worry that our result is driven by the bias introduced by the Inverse Hyperbolic Sine approximation and that a more appropriate model is the Poisson model estimated via QMLE. We use the poisson regression in this robustness check and found that our elasticity estimate to be qualitatively similar and perhaps understated for raw document counts, but the difference is not large in absolute terms.

A graphical representation of this check is Figure A10 and the regression outcomes for robustness checks XII are in Table A23, both in the appendix.

Robustness XII: DiD Estimate by Cohort - Effect Heterogeneity
One may worry that our result is driven by specific cohorts or effect heterogeneity. In this robustness check we estimate the DiD coefficients seperately for each treatment cohort. We find that the last two cohorts report a null effect. This may be due to the fact that we only have 3 and 2 post periods for the later cohorts.

Table A20: Peer Effect DiD Estimates - Robustness - I - IX

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Number of Publications	IHS(Publications) X 100	Number of Citations	IHS(Citations) X 100	IHS(Publications in Top 10% Journals) X 100	IHS(Publications in Top 50% Journals) X 100	IHS(Publications in Bottom 50% Journals) X 100	Fraction of Publications in Top 10% Journals X 100	Average CiteScore
	I: Drop Obervations from the Chinese Academy of Science N = 41,609,160								
Treated X Post	0.1024***	1.909**	-0.2096	1.556	0.3960	1.527**	0.7864	-0.3328**	0.0173
	(0.0312)	(0.7670)	(0.7008)	(1.211)	(0.3840)	(0.7041)	(0.5282)	(0.1372)	(0.0196)
	II: Drop All Imputed Observations N = 27,308,939								
Treated X Post	0.0824**	1.305**	-1.187	0.0037	0.1376	1.174	0.2201	-0.3277**	2.46E-05
	(0.0345)	(0.4970)	(1.047)	(1.085)	(0.4736)	(0.6980)	(0.6050)	(0.1361)	(0.0191)
	III: Pre-treatment Publication and Citations - Time Varying Slopes - IHS N = 41,787,795								
Treated X Post	0.0963***	1.677**	-0.0005	2.225*	0.4467	1.601**	0.5600	-0.2894**	0.0256
	(0.0301)	(0.7705)	(0.7191)	(1.267)	(0.3553)	(0.6946)	(0.5146)	(0.1361)	(0.0188)
	IV: Keep Only Post Period = [0,1,2] for All Cohorts N = 31,867,230								
Treated X Post	0.0691***	1.323**	0.1710	1.689*	0.2967	1.190**	0.6138	-0.1978	0.0205
	(0.0219)	(0.5402)	(0.5951)	(0.8625)	(0.2721)	(0.4911)	(0.4275)	(0.1174)	(0.0140)
	V: Keep Only Post 2009 Obervations and Drop Post Period 8 N = 36,026,474								
Treated X Post	0.0811**	1.520**	-0.0894	1.243	0.3514	1.319*	0.3448	-0.2679**	0.0228
	(0.0292)	(0.7124)	(0.6965)	(1.011)	(0.3492)	(0.6639)	(0.5114)	(0.1275)	(0.0175)
	VI: Dropping All Obervations from an Affiliation X 2-digit Group with Less than 10 Members N = 34,669,890								
Treated X Post	0.1031***	2.099**	-0.1371	1.991	0.4608	1.661**	0.7818	-0.3241**	0.0212
	(0.0300)	(0.7529)	(0.6934)	(1.205)	(0.3755)	(0.6996)	(0.5165)	(0.1333)	(0.0193)
	VII: Only Pre-treatment Periods of Not-Yet-or-Previously Treated as Control Group N = 6,028,083								
Treated X Post	0.0387**	0.8753*	1.340	1.729	0.2617	1.280***	0.1053	-0.2987**	0.0241
	(0.0184)	(0.5043)	(1.044)	(1.296)	(0.2272)	(0.4186)	(0.6022)	(0.1414)	(0.0163)
	VIII: Only Non-treated Scholars in a Treated School as Control Group N = 7,426,038								
Treated X Post	0.0797***	1.609***	0.1493	1.701	0.5818*	1.582***	0.1676	-0.2479*	0.0164
	(0.0243)	(0.5423)	(0.6105)	(1.028)	(0.3294)	(0.5368)	(0.4410)	(0.1402)	(0.0182)
	IX: Only Never-treated as Control Group N = 38,760,942								
Treated X Post	0.1317***	2.407**	-0.8717	1.061	0.7282	1.640*	0.7532	-0.2900	0.0168
	(0.0403)	(0.8643)	(0.9667)	(1.611)	(0.5069)	(0.8905)	(0.6782)	(0.1743)	(0.0271)
	Main Specification N = 41,787,795								
Treated X Post	0.1020***	1.871**	-0.2532	1.498	0.3949	1.515**	0.7667	-0.3277**	0.0170
	(0.0306)	(0.7601)	(0.6939)	(1.201)	(0.3789)	(0.6988)	(0.5199)	(0.1361)	(0.0193)

Notes: This table reports the robustness of our DiD results with respect to a range of different regression specification and sample choices. Standard errors clustered by affiliation level and 2-digit subfield level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Unless otherwise specified, the estimating equation is Equation 4: $\mathrm{Y}_{itc} = \beta * 1[\text{post treatment}] + \Gamma' \mathbf{X}_{itc} + u_{ic} + \varepsilon_{itc}$

Table A21: Peer Effect DiD Estimates - Robustness - X

	(1)	(2)	(3)	(4)
	Publications Divide by # Coauthors	IHS(Publications Divide by # Coauthors) X 100	Citations Divide by # Coauthors	IHS(Citations Divide by # Coauthors) X 100
Treated X Post	0.0213***	1.074***	0.0494	0.8777
	(0.0063)	(0.3487)	(0.1141)	(0.7636)
	Main Specification N = 41,787,795			

Notes: This table reports the robustness of our DiD results with outcome variables normalized by the number of coauthors. Standard errors clustered by affiliation level and 2-digit subfield level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The estimating equation is Equation 4: $\mathrm{Y}_{itc} = \beta * 1[\text{post treatment}] + \Gamma'\mathbf{X}_{itc} + u_{ic} + \varepsilon_{itc}$

Table A22: Peer Effect DiD Estimates - Robustness - XI

	Linear Model - Main Specification N = 41,787,795	
	(1)	(2)
	IHS(Publications) X 100	IHS(Citations) X 100
Treated X Post	1.871**	1.498
	(0.7601)	(1.201)
	Poisson Model - Main Specification N = 41,787,795	
	Publications	Citations
Treated X Post	0.0304**	0.0068
	(0.0118)	(0.0118)
Percentage Effect - [e^(beta)-1]*100	3.0867	0.6823

Notes: This table reports the robustness of our DiD results under a poisson model. Standard errors clustered by affiliation level and 2-digit subfield level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The estimating equation for the Poisson regression is 4: $\mathrm{E}[\mathrm{Y}_{itc}|1[\text{post treatment}], X_{itc}, u_{ic}] = exp(\beta * 1[\text{post treatment}] + \Gamma'\mathbf{X}_{itc} + u_{ic})$

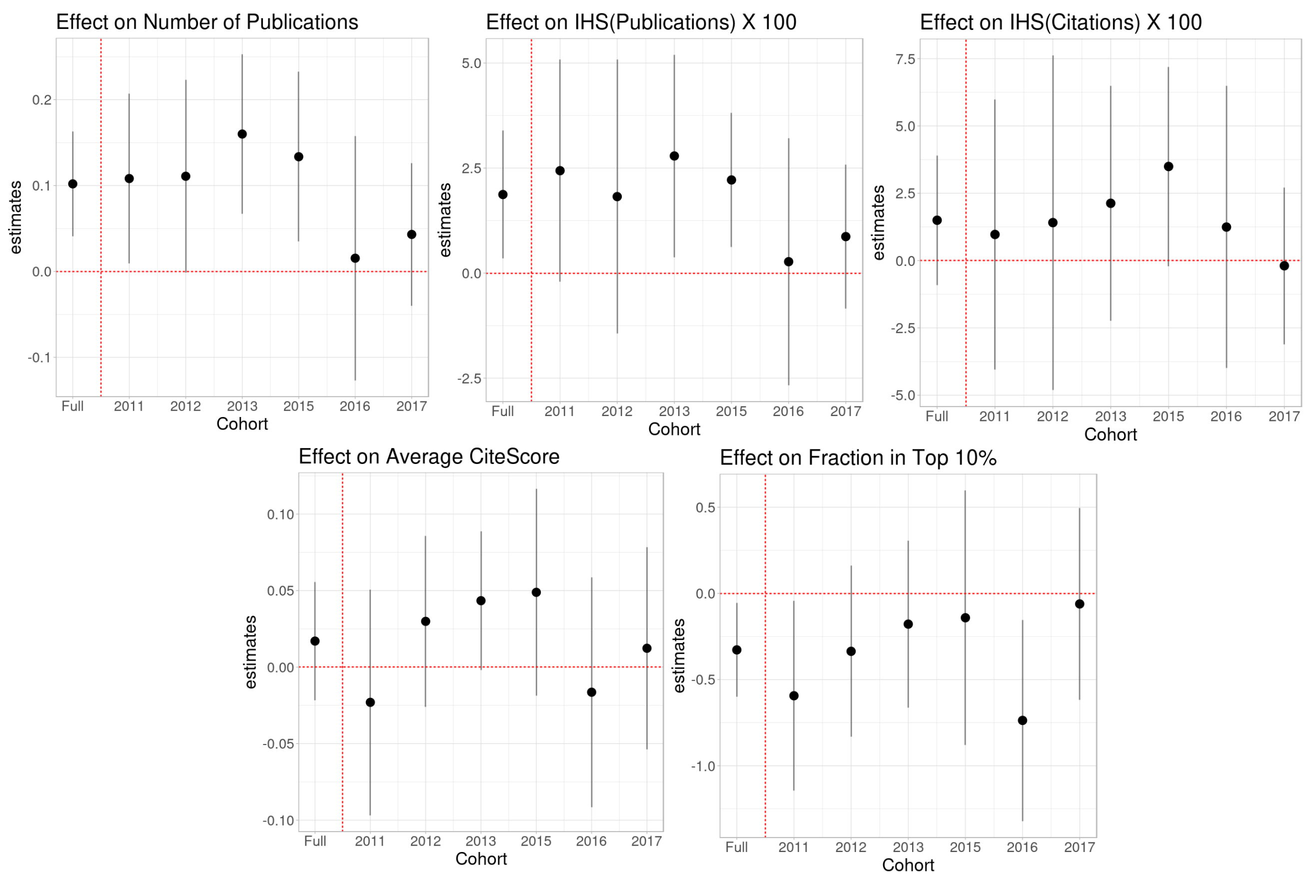
Table A23: Peer Effect DiD Estimates - Robustness - XII

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full Sample	2011	2012	2013	2015	2016	2017
				Number of Publications			
Treated X Post	0.1020***	0.1082**	0.1108*	0.1600***	0.1336**	0.0154	0.0431
	(0.0306)	(0.0495)	(0.0562)	(0.0464)	(0.0494)	(0.0711)	(0.0415)
				IHS(Publications) X 100			
Treated X Post	1.871**	2.438*	1.821	2.788**	2.217**	0.272	0.869
	(0.7601)	(1.323)	(1.630)	(1.204)	(0.7999)	(1.468)	(0.8558)
				Number of Citations			
Treated X Post	-0.2532	-1.098	1.205	-0.1270	-0.6502	-0.9606	-0.2988
	(0.6939)	(1.631)	(1.124)	(1.750)	(1.125)	(1.621)	(1.432)
				IHS(Citations) X 100			
Treated X Post	1.498	0.9699	1.410	2.127	3.494*	1.244	-0.1925
	(1.201)	(2.504)	(3.105)	(2.178)	(1.852)	(2.619)	(1.456)
Sample Size	41,787,795	7,385,531	7,131,431	7,005,590	7,066,657	6,568,569	6,456,357
				Author X Affiliation X Cohort FE			
				4-digit Field X Career Start Specific Trends			
				Affiliation X Career Start Specific Trends			

Notes: This table reports the robustness of our DiD results for each cohort. Standard errors clustered by affiliation level and 2-digit subfield level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The estimating equation is Equation 4: $\mathrm{Y}_{itc} = \beta * 1[\text{post treatment}] + \Gamma'\mathbf{X}_{itc} + u_{ic} + \varepsilon_{itg}$

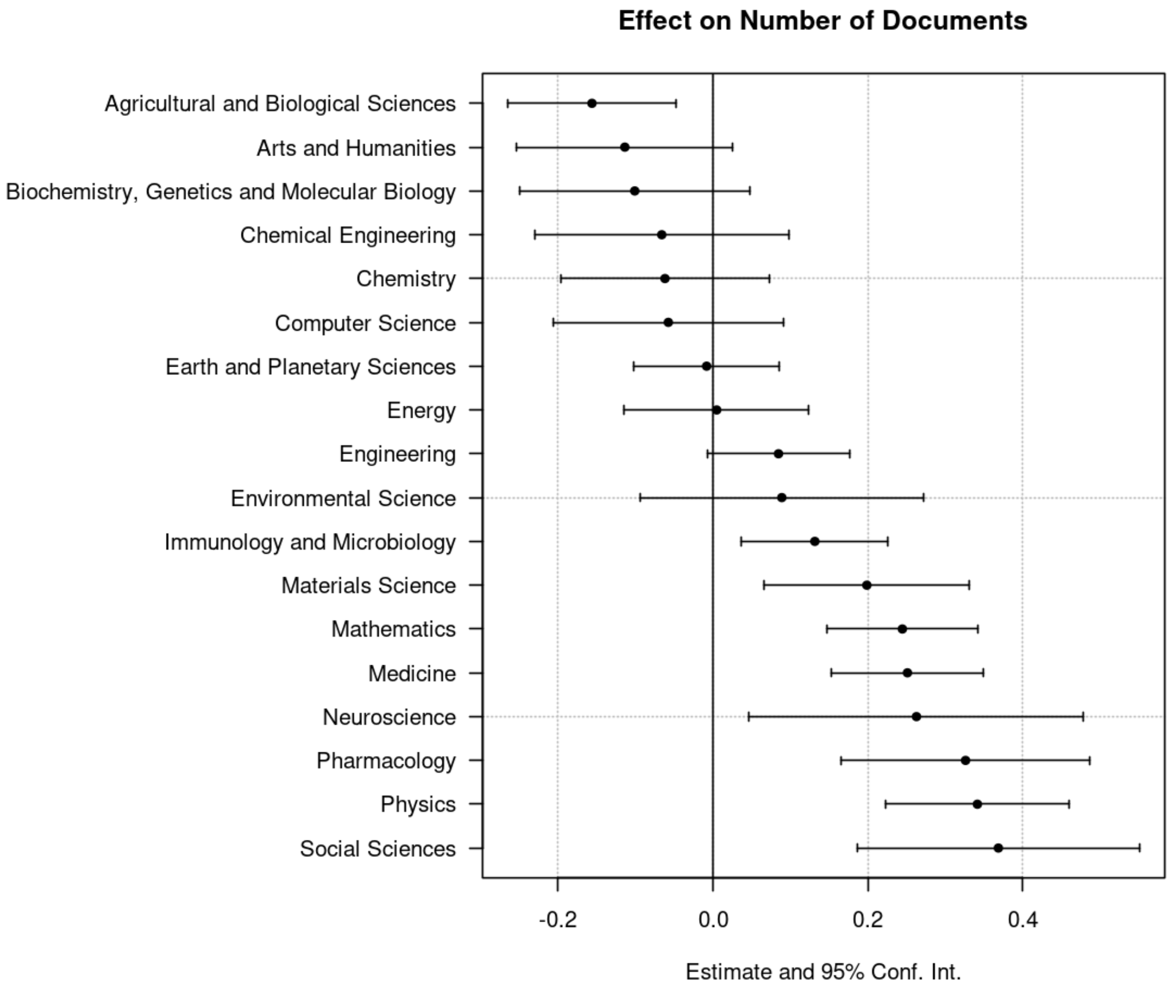
Figure A10: Peer Effect DiD Estimates - By Cohort



Notes: This figure compares DiD estimates across cohorts with the main estimate. Standard errors clustered by affiliation level and 2-digit subfield level. The estimating equation is Equation 4: $\text{Y}_{itc} = \beta * 1[\text{post treatment}] + \Gamma' \mathbf{X}_{itc} + u_{ic} + \varepsilon_{itc}$

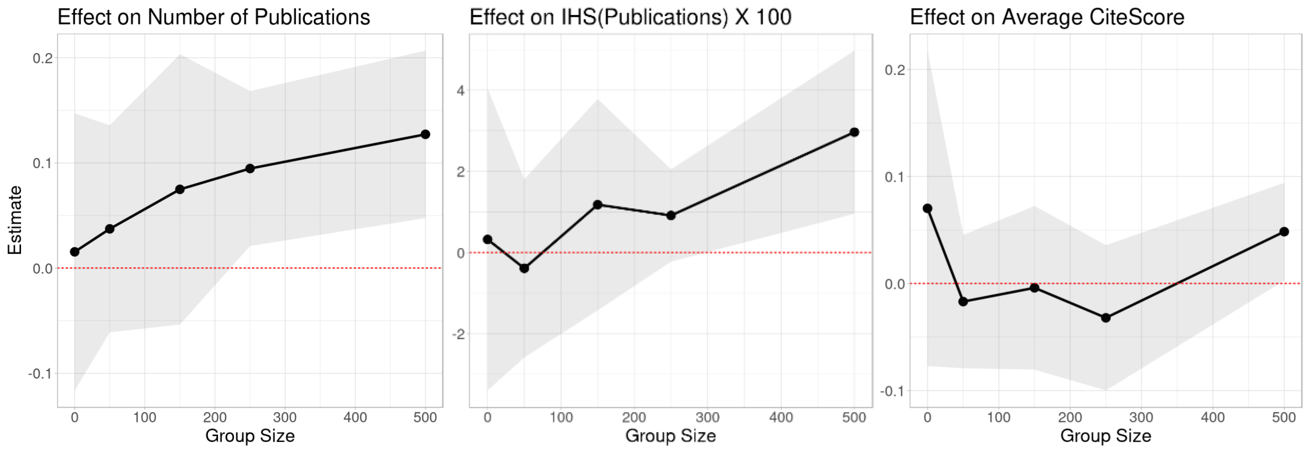
A.8 Additional Heterogeneity

Figure A11: Peer Effect DiD Estimates - 2-digit Code



Notes: This figure compares DiD estimates for each discipline, sorted by effect magnitude. 2-digit subfields with less than 5 treated schools (Business, Decision Sciences, Economics, Nursing, Dentistry, and Health Professions) have been dropped from the figure to reduce noise. Standard errors clustered by affiliation level and 2-digit subfield level.

Figure A12: Peer Effect DiD Estimates - Group Size



Notes: This figure compares DiD estimates for affiliation X 2-digit groups of different sizes. The coefficient estimates from interacting Treated × Pose with indicators of group size bins: (0,50], (50,150], (150,250], (250,500], and (500, Infinity] The cutoff sizes of the bin roughly corresponds to 20,40,60,80 percentiles in the size distribution among treated affiliation X 2-digit groups. Standard errors clustered by affiliation level and 2-digit subfield level.

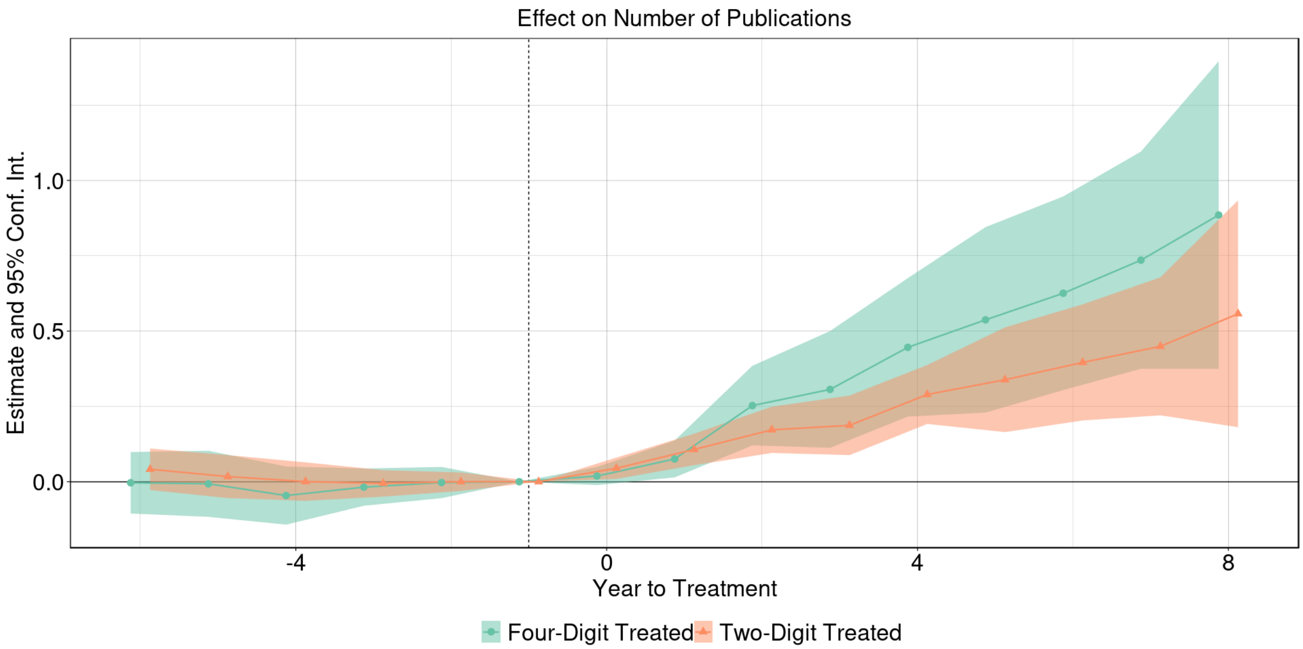
Table A24: Peer Effect DiD Estimates - Heterogeneity and Mechanism - Funding Outcome

	(1)	(2)	(3)
	Fraction Funded	# Funded	# Publications
1[Post Treatment]	0.0016	0.0563***	0.1020***
	(0.0022)	(0.0201)	(0.0306)
Sample Mean	0.2302	1.381	3.36
Observations: 41,787,795			
Author X Affiliation X Cohort FE			
Differential Trends by: Subfield X Career Start+Affiliation X Career Start			

Notes: This table reports difference in difference estimates on funding outcome. Standard errors clustered by affiliation level and 2-digit subfield level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

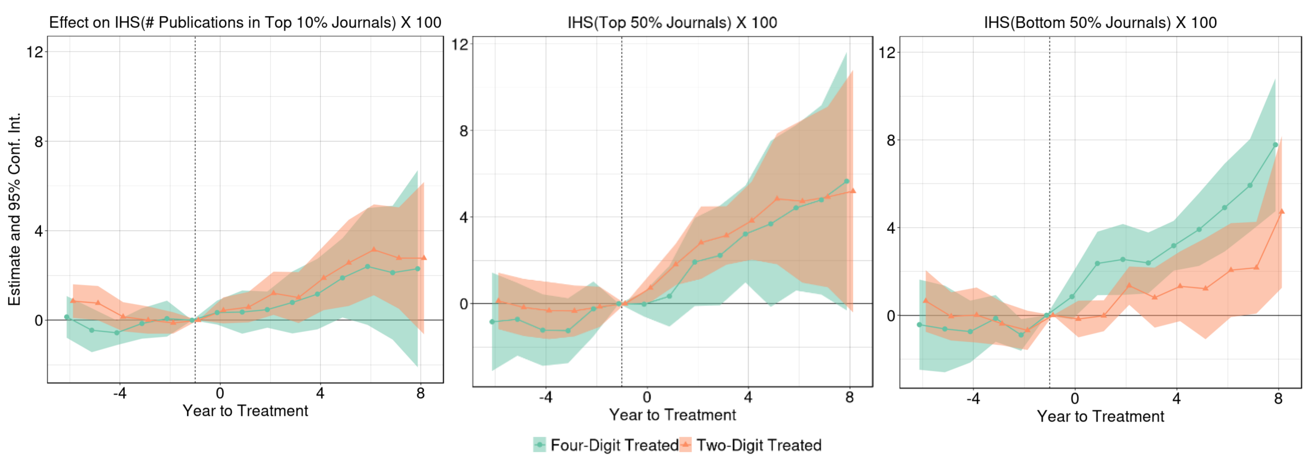
The estimating equation is Equation 4: $\mathrm{Y}_{itc} = \beta * 1[\text{post treatment}] + \Gamma' \mathbf{X}_{itc} + u_{ic} + \varepsilon_{itc}$

Figure A13: Distance in Knowledge Space: 2-digit v.s. 4-digit - Event Study



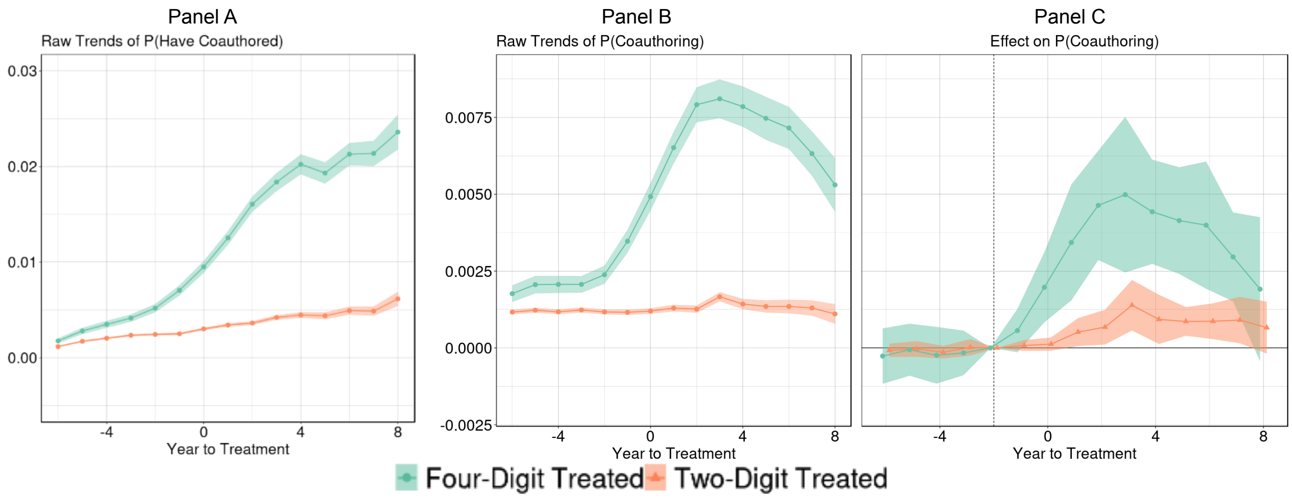
Notes: This figure compares event study estimates for the treated incumbent who share a 4-digit subfield and those who don't. The estimates are mutually exclusive dummies for these two groups interacted with relative time. Standard errors clustered by affiliation level and 2-digit subfield level.

Figure A14: Distance in Knowledge Space: 2-digit v.s. 4-digit - Event Study - Journal Distribution



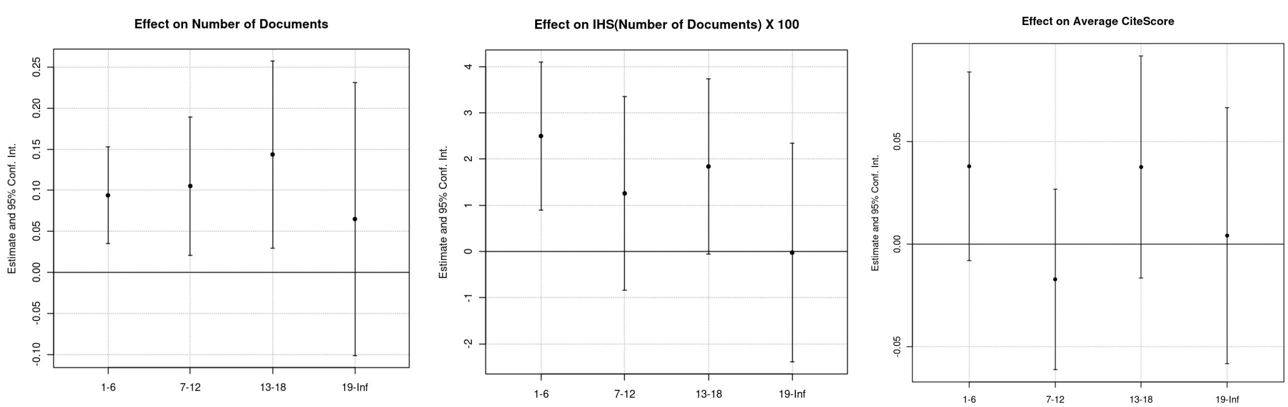
Notes: This figure compares event study estimates for treated incumbent who share a 4-digit subfield and those who don't across the journal quality distribution. The estimates are mutually exclusive dummies for these two groups interacted with relative time. Standard errors clustered by affiliation level and 2-digit subfield level.

Figure A15: Distance in Knowledge Space: 2-digit v.s. 4-digit - Coauthorship Pattern



Notes: This figure compares coauthorship patterns with the joiner for the treated incumbent who share a 4-digit subfield and those who don't. The estimates are mutually exclusive dummies for these two groups interacted with relative time. Standard errors clustered by affiliation level and 2-digit subfield level.

Figure A16: Peer Effect DiD Estimates - Career Age



Notes: This figure compares event study estimates for treated incumbent of different seniority. The estimates are mutually exclusive dummies for career age groups interacted Treated × Post. Standard errors clustered by affiliation level and 2-digit subfield level.

A.9 Coauthorship Regression

We face an empirical challenge here as we do not have a joiner for the never treated scholars - hence we do not have a natural counterfactual. We overcome this by creating a placebo dataset for all the treated scholars with coauthorship pattern generated with the statistical counterpart in the propensity score matching part of the paper and use that as the counter factual. The regression specification is as follows:

$$\begin{aligned} Y_{itcr} = & \sum_{\tau \geq -6, \tau \neq -2}^{\tau=8} \beta_\tau^2 (Treated_i \times 2digit_i \times real_{ir} \times Year_t^\tau) + \\ & \sum_{\tau \geq -6, \tau \neq -2}^{\tau=8} \beta_\tau^4 (Treated_i \times 4digit_i \times real_{ir} \times Year_t^\tau) + \\ & \alpha(1 - Treated_i \times 4digit_i \times real_{ir}) + \\ & \delta(1 - Treated_i \times real_{ir}) + \\ & \gamma_{itc} + \varepsilon_{itcr} \end{aligned}$$

- Treatment: arrival of JTTP scholar in the same university $\times$ 2-digit sub-field in the real dataset.
- γ_{itc} scholar X affiliation X cohort specific trend
- $2digit_i$ and $4digit_i$ are exclusive dummies; $2digit_i$ turns on when the scholar receives a JTTP scholar in her 2-digit field but does not share a 4-digit subfield with the joiner
- $real_{ir} = 1$ on the real dataset and 0 for the placebo
- $(1 - Treated_i \times 4digit_i \times real_{ir})$ and $(1 - Treated_i \times real_{ir})$ are included to saturate the regression within each scholar X affiliation X cohort
- Standard errors two-way clustered by university and two-digit subfield.

β_τ^2 and β_τ^4 thus captures the dynamic effects of the joiner on coauthoring.