Bootstrapping Science?

The Impact of a ‘Return Human Capital’ Programme on Chinese Research Productivity

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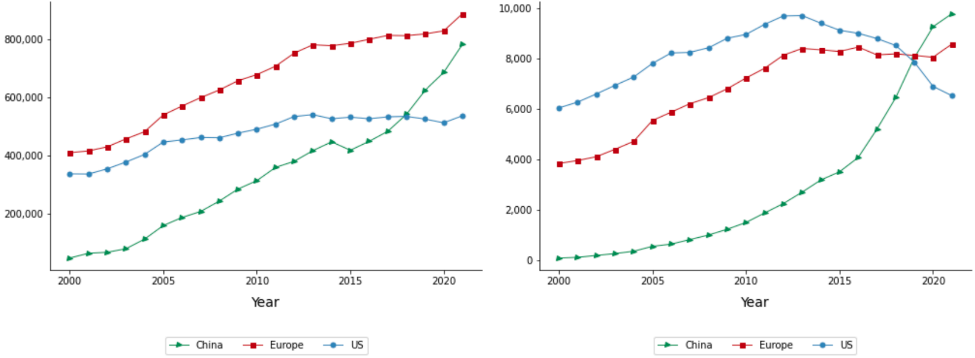
Global Scientific Competition

Figure 2: Number of total publications and top 1% cited publications by country or region of affiliation.

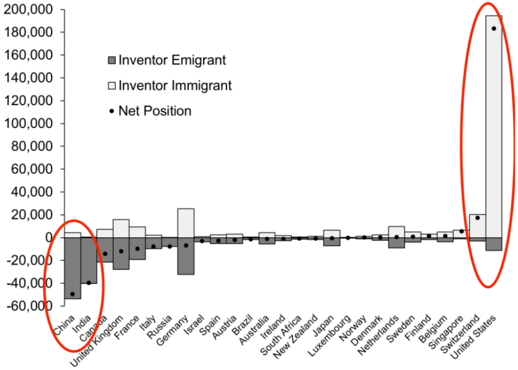


Source: Aghion et al (2023) - 7 authors! Based on Scopus database.

‘Return Human Capital’ Policies

Goal: Increase scientific competitiveness + address ‘brain drain’ by repatriating researchers.

Figure 1: Net global migration of inventors, 2000-2010



- India’s Visiting Advanced Joint Research Program
- Brazil’s Special Visiting Researcher and Young Talent Attraction
- Australia’s Federation Fellows

Policy Rationale

- These policies are designed to (re-)acquire talent and also build up the domestic research base via collaboration and peer effects.
- But alongside this, there is the potential for negative effects via mechanisms related to displacement and crowding out.

We look at a specific major talent programme...

China's 'Thousand Talents' program

- Jointly initiated by Central Committee of CCP and State Council in 2010.
- $750 million, 7,600 scientists, Expenditure $\approx$ 7-8% of US NSF Budget.
- We focus on the **Junior Thousand Talents Program** which targets:
  1) young scientists around age 35 & younger than 40;
  2) graduated or had 3+ years of research experience in top overseas universities;
  3) research in natural sciences or engineering
  4) lump-sum transfer of $75,000 bonus; opportunity for $154,000 - $460,000 research fund

What We Do

Provide an empirical analysis of the JTTP's impact using differences-in-differences:

- **Direct productivity effect** on JTTP scholars themselves: how beneficial is the move back to China for these scholars?

- **'Bootstrapping'**: Knowledge spillovers on incumbents + scholar agglomeration effects.

'Bootstrapping' - aka endogenously generated progress - will depend on the size, balance and persistence of these effects.

Identification is based on PS matching using a big comparison pool & covariates for trends.

Findings

- $\nearrow$ **Direct productivity effect on JTTP scholars:** drop of productivity in three years after move, but then an increase relative to controls.
- $\nearrow$ **Bootstrapping:** Positive knowledge spillovers and agglomeration.
- $\nearrow$ **Overall:** Impacts compatible with knowledge agglomeration in top departments. But not a 'trend shifter' relative to existing drivers of scientific productivity.

Data: Scopus & ORCID

Academic journal database maintained by Elsevier, covering all fields 1990 - 2019.

- Journal, Title, Abstract, Authors, Citations, Funding Sponsors.
- List of journal fields: 27 fields and 307 sub-fields
- Supplement with ORCID: provides unique identifiers for academic researchers with better biographical information (subsample).

But key data task is collecting JTTP information...

JTTP Scholar Records - Cohorts

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%

- Lists of selected scholars obtained from archived JTTP web site pages. Complement with personal website, CV, LinkedIn etc
- Names only disclosed for selected (don't observe applicant pool).
- Scale of programme increased over time from 150 to 1200. We focus on early cohorts by necessity (right censoring).

Summary Statistics on JTTP Scholars I

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*

As expected, the programme is focused on elite scholarship...

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%

Top Ten account for 16.9% of successful JTTPs.

Top Ten JTTP-Receiving Universities

Rank	University	Count	Pct
1	Chinese Academy of Sciences	493	13.74%
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%

Top 10 ‘receivers’ account for 54% of TTP (40.5% if CAS excluded).

Direct Productivity Effects

- **Goal**: Estimate within-scholar causal effect of joining JTTP program.
- **Problem 1**: Potential positive selection of scholars as joining the program.
- **Problem 2**: Endogenous timing of treatment among scholars. (Anticipation effects).
- **Problem 3**: Scarcity of information on potential counterfactual scholars. No precisely defined 'just missed out' scholars.

Approach = Matched Diff-in-Diff

Follow the literature that has matched on large numbers of static & dynamic characteristics.

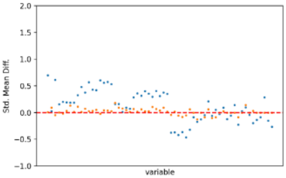
- e.g. Conti and Guzman (2021) (Israeli start-ups); Becker and Hvide (2021) (Entrepreneur deaths); Guadalupe et al (2012) (MNE acquisitions).
- Identify matched controls based on observable pre-treatment characteristics using a control donor pool that includes dynamic (career) information (35 out of 60).
- Most implementations consider 'static' averages of performance. This may not capture evolving unobservable trends well.

Matched Diff-in-Diff

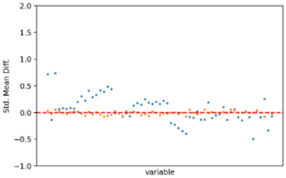
- Start with a pool of Chinese-name control scholars with overseas experience, recent Phd graduation & working in the JTTP fields (N = 4,558).
- Then estimate a logistic model to predict attendance D using 60 covariates covering university rank, career length, and (time-varying) publication productivity.
- For each JTTP scholar i choose a 'matched' non-treated neighbour (N = 2,787). Standardized mean difference illustrates that the difference in means has been closed...

Propensity Score Matching: Standardized Mean Difference

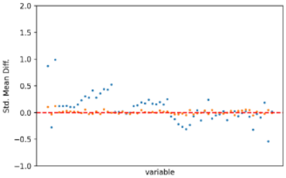
(a) 2011



(b) 2012

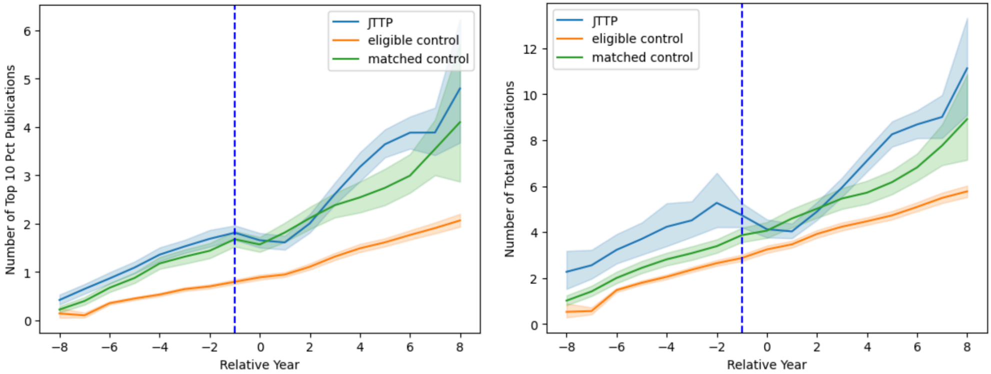


(c) 2013



Notes: The figures depict the standardized mean differences for each matching variable 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 for each covariate.

Raw publication trend of JTTPs and control scholars



Notes: The figures depict the trends for the number of publications, and number of top 10 percentile pulications for 934 unique JTTP scholars, eligible but not selected scholars and matched control scholars before and after the selection year ($t = 0$).

Matching on Static versus Dynamic Characteristics

Two-panel figure crappy versus good on pre-trends.

Figure: LHS(CiteScore): Match by static covariates $t \in [-5, -1]$

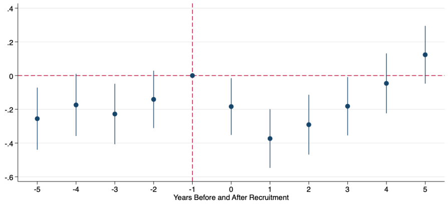
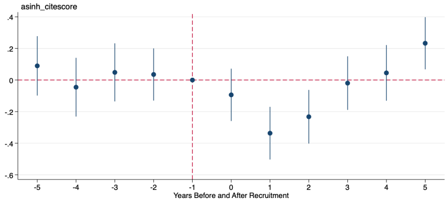


Figure: LHS(CiteScore):Match by dynamic covariates $t \in [-5, -1]$



Regression Specification: Direct Productivity Effects

Difference-in-Differences (scholar i, year t level panel):

$$Y_{ijct} = \beta(Treated_i \times Post_t) + \tau_t + \tau_{jt} + \tau_{Lt} + \mu_i + \epsilon_{ijct} \tag{1}$$

- Y_{ict} = number of publications, or cites to publications, etc;
- μ_i = scholar fixed effects, τ_{jt} = year-field effects, τ_{Lt} = time-career length effects
- Stacked DiD using balanced time interval $t \in [-10, 6]$ for each cohort as baseline
- Standard errors clustered by matched scholar pair.

Results #1 - Direct Effects

QUANTITY

- A dip then increase in total publications and funded publications.
- An increase in seniority, as proxied by first and last author status.

The initial dip means that productivity is effectively flat when measured over a 6-year period.

Direct Effect: Event Study

Figure 1: LHS(Number of Publications)

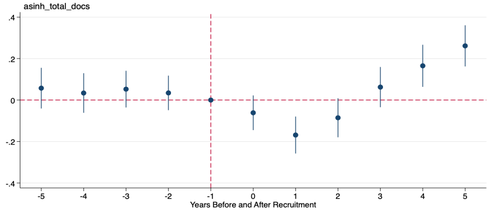


Figure 2: LHS(Funded Publications)

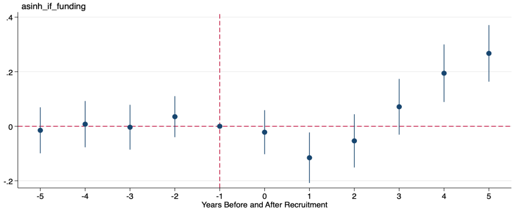


Figure 3: Fraction of Last Authored Publications

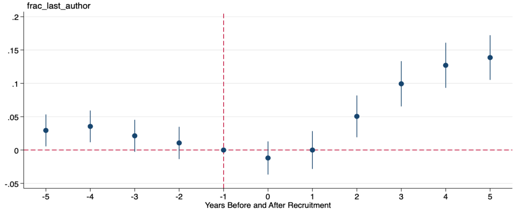
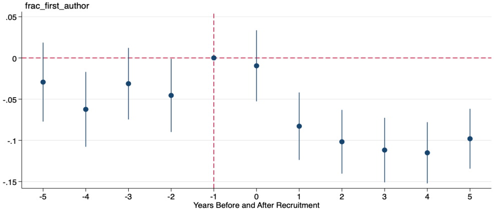


Figure 4: Fraction of First Authored Publications



Results #2 - Direct Effects

QUALITY

- Citation scores: Similar dip and recovery cycle as publication effects.
- Indication of a boost for very high quality journals (top 10%).

Direct Effect: Event Study

Figure 1: LHS(Cites)

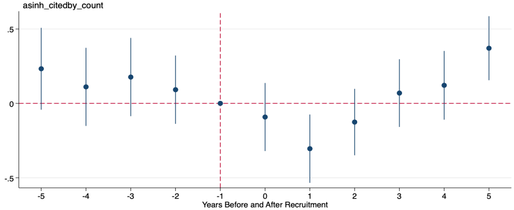


Figure 2: LHS(CiteScore)

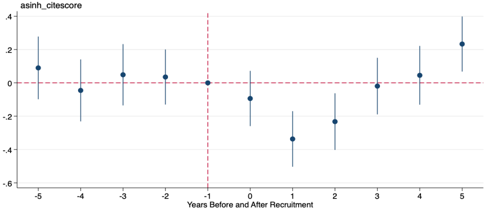


Figure 3: LHS(Top 10 Pct Publication)

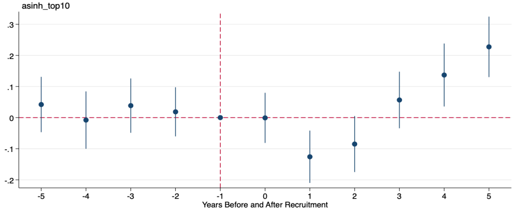
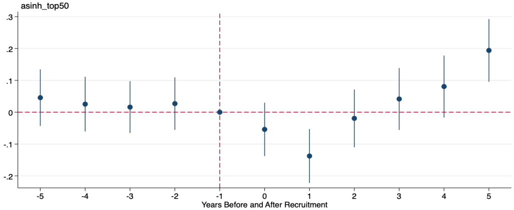


Figure 4: LHS(Top 50 Pct Publication)



Results #3 - Direct Effects

COLLABORATION

- More collaboration with same-institution co-authors.
- But these are systematically junior: shorter career length & more in their first year of research experience.

Effect of Joining JTTP on Collaboration Patterns

Figure 1: Number of Coauthors

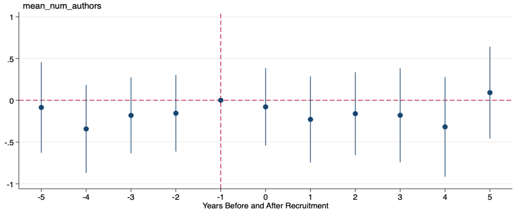


Figure 2: Average of Coauthors' Number of past Publications

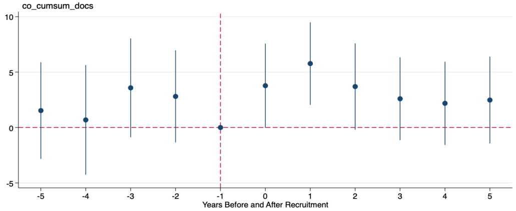
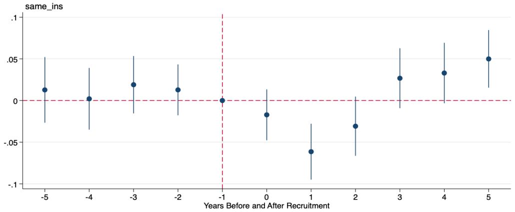


Figure 3: Fraction of Same-institution Coauthors



Effect of Joining JTTP on Collaboration Patterns

Figure 1: Average of Coauthors' Career Length

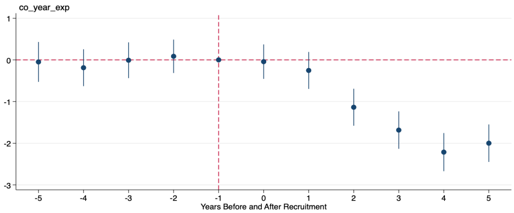
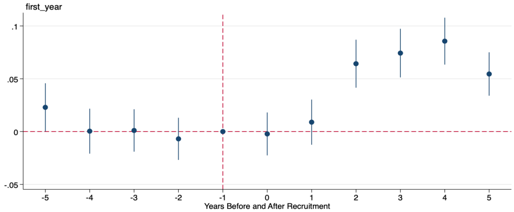


Figure 2: Fraction of First Year Coauthors



Knowledge Spillovers on Incumbents

- **Goal**: estimate effect on receiving department when JTTP scholar joins. To what extent are there direct knowledge transfer or passive knowledge spillover effects?
- **Problem**: Endogenous selection of scholars to departments with different productivity trends. Use a comprehensive set of scholar, field and dept trends to control for this.
- **Comparison**: Thought experiment is Scholar A, 5 years since first paper, in Computer Science in receiving university **I** is compared to Scholar B, also 5 years since first paper, in Computer Science in non-receiving university **II**.

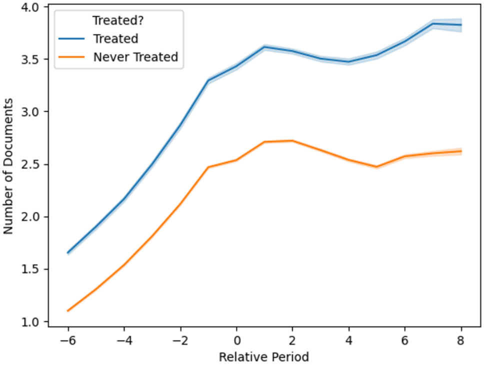
Constructing Spillover Sets

- We assign each scholar to a field and subfield by taking the most frequent in their publication record. JTTP's published in 24 (of 27) fields and 231 (of 307) subfields.
- Sample Frame: any field or university that receives at least one JTTP. De facto selects on natural science fields and 'high quality' universities.
- Individual Sample Restrictions: at least 3 year publication span + 5 papers.

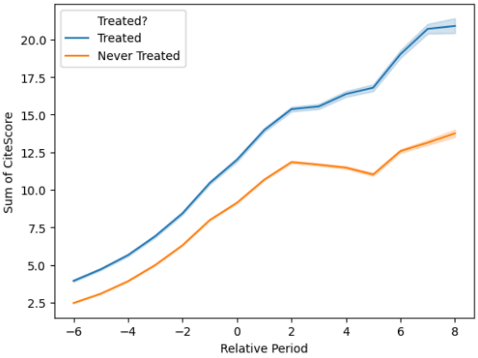
This (surprisingly!) delivers respectable raw trends...

Raw Differences - Spillover versus Non-Spillover Departments

(a) Publication Count



(b) Cite Scores



Notes: The above figures show the average number of publications and total CiteScores for treated and control scholars. For each scholar, we complete the publication records between 6 years before their treatment year and the end of our data in 2019 by imputing zeros for years where we don't observe any publication. There are 197,301 treated scholars and 169,426 never-treated scholars.

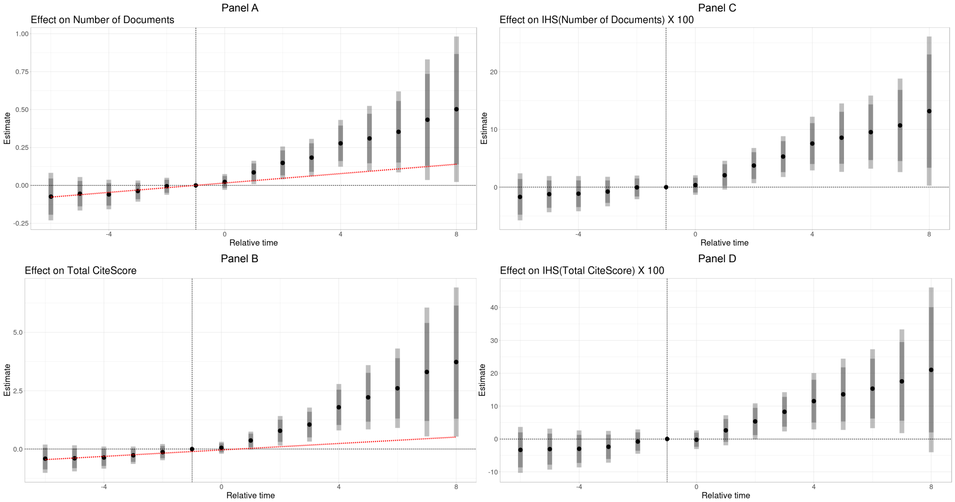
Regression Specification: Peer Effects

Differences-in-difference model in this case:

$$Y_{ijkct} = \gamma(JTTP_{jk} \times Post_t) + \tau_t + \tau_{jt} + \tau_{kt} + \tau_{Lt} + \mu_i + \varepsilon_{ijct} \tag{2}$$

- Treatment: Arrival of JTTP scholar in the same (university $\times$ 2-digit sub-field), defined at *jk* level.
- Field / department time effects, career-start year time effects, individual f.e's.
- As per the raw plots, this shows clearer effects on CiteScore....

Knowledge Spillovers from Receiving a JTTP Scholar: Event Study Estimates



Scale of Knowledge Spillovers

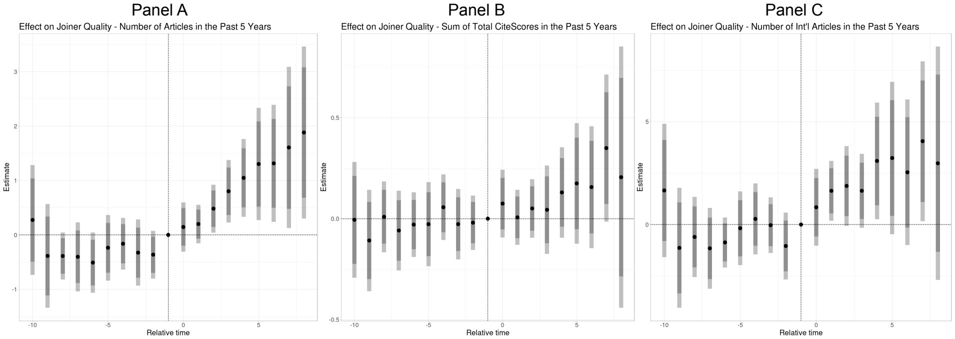
- Modest in scale. Point estimates represent about a 5-10% boost to publication count.
- But this is spread out across approx 40 scholars in each dept.
- So results are compatible with the collaboration results, that is, a narrow spillover focused on collaborators and linked to increases in quality.

Agglomeration

'Dept building' effects of scholar recruitment.

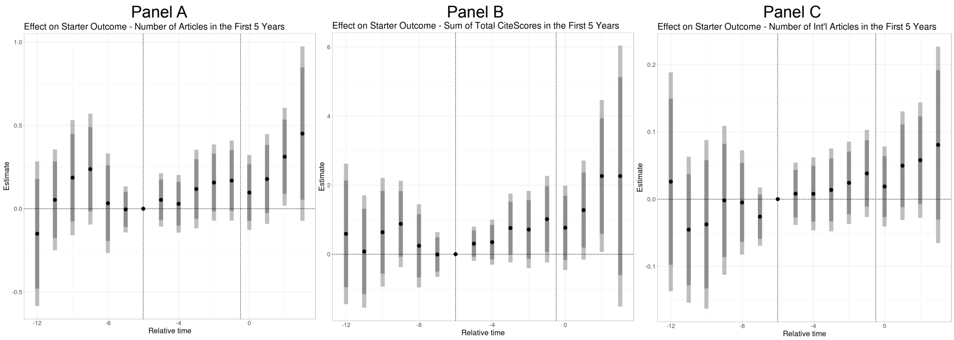
- **'Joiners'**: New recruits at all levels, reflecting mobility and reallocation.
- **'New Scholars'**: First-time publishers who emerge after the JTTPs arrival.
- Run this as repeated cross-sectional cohorts. Individual-level specs to in order to control for characteristics.

Joiner Analysis - Event Study



Performance measures for 5 years before joining.

New Authors Analysis - Event Study



Reference Cohort = Treatment Year - 6; If the year of first publications is first year of a PhD and PhD leaves after 5 years, then the reference cohort is the last one without any JTT exposure.

Articles in first 5-years (exposure increases)

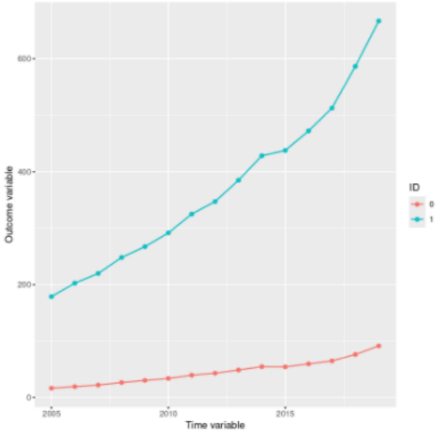
Agglomeration?

- Again, modest effects of 5-15% higher productivity scholars.
- But extra increment is tilted towards quality.
- How does this look with regard to the Chinese university system?

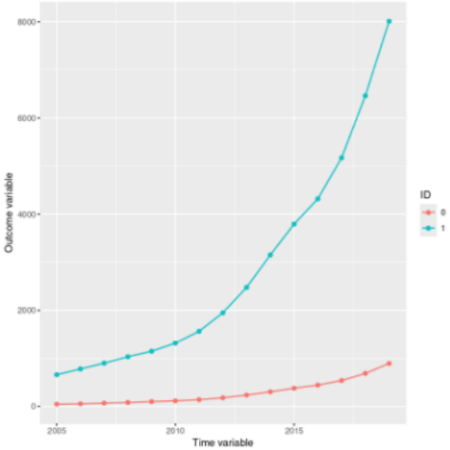
Total Summed Outcomes...

JTTP Versus Non-JTTP Departments

(a) Total Publications

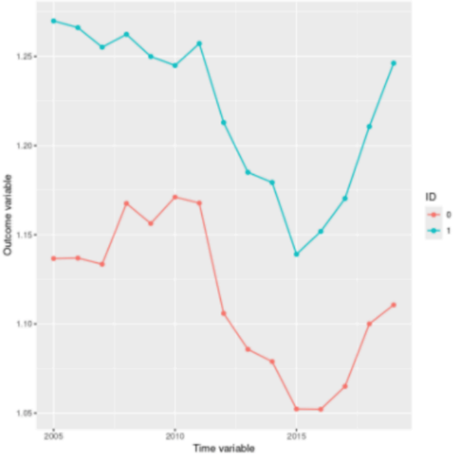


(b) Citescore weighted

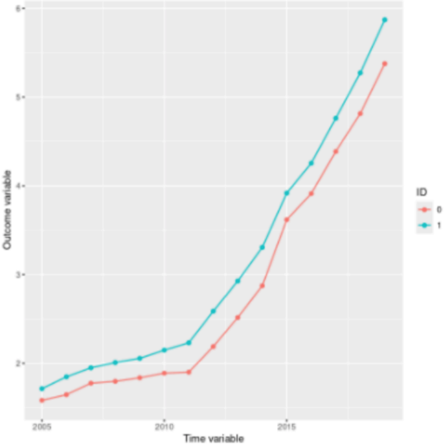


But disappears when normalised...

(a) #Publications / #Authors.



(b) Citescore / #Publications



Conclusions

- Overall, fits with earlier literature which finds mixed effects of scholar mobility (Waldinger 2010,2012; Borjas and Doran 2015 Agrawal et al 2017)
- Rather than ‘quality divergence’ there is agglomeration of scholars in the JTTP departments. Good depts are getting bigger.
- This is consistent with UK experience of the REF. In short, reallocation of human capital. Could lead to a ‘lift’ in relative quality over time.

Frametitle

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Conclusion

- Main effect of JTTP seems to be collaboration with the domestic Chinese research base.
- Need to examine the concentration of the knowledge spillover effect, especially as it relates to knowledge agglomeration.
- Identification: formalise the advantages of 'dynamic' matching, use 'just ineligible' cohorts based on age 40.

Stacked Difference in Difference: Robustness

We offer 12 robustness checks for our main result.

1. Dropping CAS - Measurement Error
2. Drop All Imputed Observations - Artificial Zeros
3. Time-Varying Slopes for Pretreatment Productivity
4. Same Relative Time Window across Cohorts - Weighting
5. Same Absolute Time Window across Cohorts - Weighting
6. Drop All Observations from Small Affiliations - Small Cell Size
7. Only Not-Yet-Treated as Control Group - Selection on Affiliations X 2-digit Trend
8. Only Never-Treated as Control Group
9. Only Non-treated Scholars in a Treated School as Control Group - Selection
10. Split Publications among Coauthors
11. Poisson Model
12. Separate Estimates by Cohort

Stacked Difference in Difference: 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
Drop Observations 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)
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)
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)
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)
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)
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)
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)
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)
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)

Stacked Difference in Difference: Robustness X

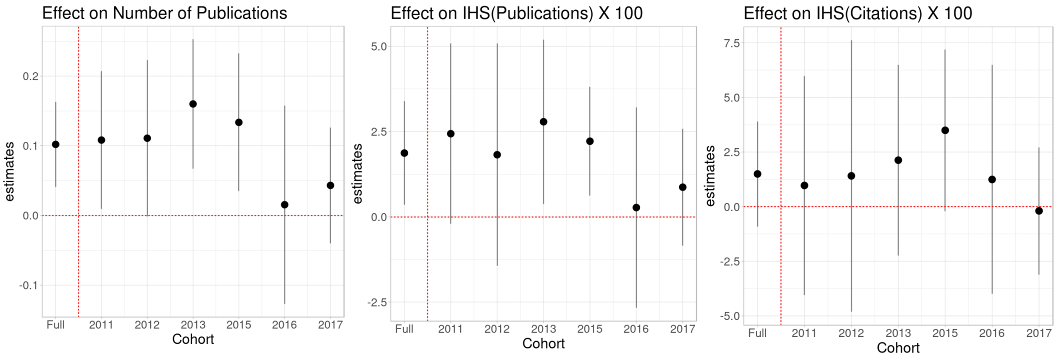
	(1)	(2)	(3)	(4)
	Publications Divide by # Coauthors	IHS(Publications Divide by # Coauthors) X 100	Citations Divide by # Coauthors	IHS(Citations Divide by # Coauthors) X 100
Treated X Post	0.0213***	1.074***	0.0494	0.8777
	(0.0063)	(0.3487)	(0.1141)	(0.7636)

Main Specification
N = 41,787,795

Stacked Difference in Difference: 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

Stacked Difference in Difference: Robustness XII



Peer Effect Results Overview

- $\nearrow$ Direct productivity effect on Peer Scholars:
  - $+.1$ publication each year (or 2% each year)
  - no effect when weighted by citations
  - no effect on average quality
  - effect larger when multiple JTTP arrive at once
- **Mechanism:**
  - **Evidence for Idea-based Spillover**
    1. Effect Larger then Closer in Knowledge Space
    2. More Collaboration then Closer in Knowledge Space
    3. No Heterogeneity by Seniority
  - Ruling out Direct Resource Effect

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

If the peer effect is driven by knowledge sharing, we expect those who are close to the incoming JTTP to benefit more.
(Note: we can also see the 2-digit v 4-digit as a triple difference, which would the using within university X 2-digit variation in treatment - addressing potential selection on department trends. Although the estimates would not be significant, but the fact that there's trend break after treatment buttresses the causal interpretation of our result.)

	(1)	(2)	(3)	(4)	(5)
	# Publications	IHS(# Publications) X 100	IHS(# Citations) X 100	% of Publications in Top 10% Journals	Average CiteScore
1[Post Treatment]	0.0833***	1.917***	2.330*	-0.2320	0.0223
	(0.0265)	(0.6699)	(1.178)	(0.1544)	(0.0194)
1[Post Treatment] X	0.0539	-0.1349	-2.403	-0.2716**	-0.0151
1[Same 4-digit]	(0.0361)	(0.7959)	(1.456)	(0.1121)	(0.0162)
Author X Affiliation X Cohort FE					
Differential Trends by: Subfield X Career Start+Affiliation X Career Start					

When a JTTP scholar arrives in the same four sub-field, we see an additional interaction effect on the number of publications. The interaction is sizeable although not significant.

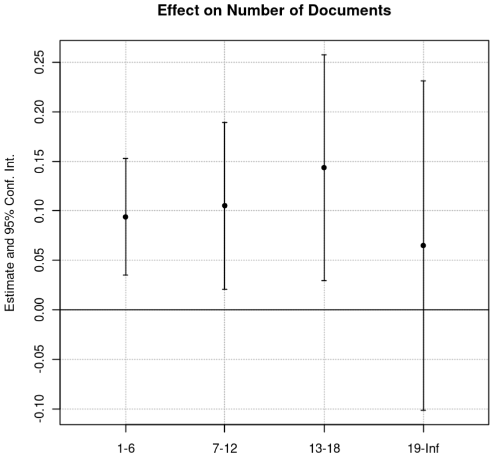
Distance in Knowledge Space: 2-digit v.s. 4-digit - Collaboration Pattern

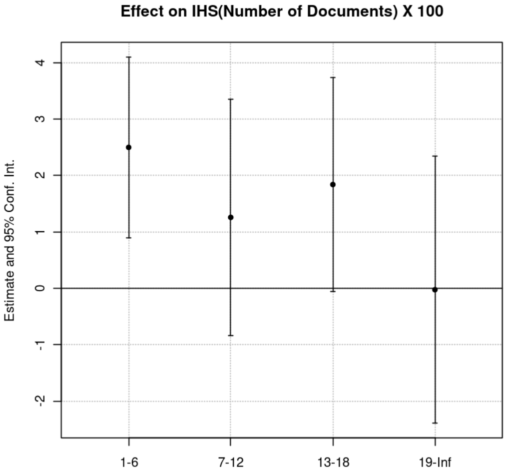
- If knowledge spillover is the mechanism, we expect to see that incumbent scholars will start to increase collaborate with the joiner.
- Collaboration intensity would vary by their distance in knowledge space.

We test this implication in a event study regression.

- Challenge: for never-treated scholars there are no incoming scholars - no reasonable counterfactuals
- Solution:
  - for treated scholars, create placebo coauthorship outcomes with the incoming JTTP with the statistical equivalent from the propensity score match
  - the fake dataset serves as the control group
  - use individual-specific time-trends

Heterogeneity by Seniority - Time Since First Paper





Similar effect size across seniority $\implies$
Consistent with a general, rather than top-down, knowledge spillover story

Peer Effect Results Overview

- $\nearrow$ Direct productivity effect on Peer Scholars:
  - $+.1$ publication each year (or 2% each year)
  - no effect when weighted by citations
  - no effect on average quality
  - effect larger when multiple JTTP arrive at once
- **Mechanism:**
  - Evidence for Idea-based Spillover
    1. Effect Larger then Closer in Knowledge Space
    2. More Collaboration then Closer in Knowledge Space
    3. No Heterogeneity by Seniority
  - **Ruling out Direct Resource Effect**
    1. No Effect on Fraction Funded
    2. No Dilution in Larger Departments
    3. No Effect if PhD Degree from China

No Effect on Fraction Funded

No evidence that incumbents received more funding after a JTTP shock.

	(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
Scholar X Affiliation X Year X Cohort Observations: 41,787,795			
Author X Affiliation X Cohort FE			
Differential Trends by: Subfield X Career Start+Affiliation X Career Start			

No Dilution in Larger Departments

Suppose the effect came from either (1) a fixed inflow of resources with the JTTP scholar and/or (2) a reduction of average administrative load due to the joiner. We would expect the effect to become diluted in larger incumbent groups.

	(1)	(2)	(3)	(4)	(5)
	# Publications	IHS(# Publications) X 100	IHS(# Citations) X 100	% of Publications in Top 10% Journals	Average CiteScore
1[Post Treatment]	-0.2362	-8.929**	-20.76**	0.0867	-0.1904*
	(0.1718)	(4.061)	(8.280)	(0.6830)	(0.1035)
1[Post Treatment] X IHS(Incumbents)	0.0005*	0.0161**	0.0332**	-0.0006	0.0003*
	(0.0003)	(0.0061)	(0.0122)	(0.0010)	(0.0002)
Author X Affiliation X Cohort FE					
Differential Trends by: Subfield X Career Start+Affiliation X Career Start					

The peer effects are larger when the receiving department is larger.

No Effect if PhD Degree from China

Suppose the effect came from an inflow of resources and/or general prestige associated with attracting a JTTP.
We would expect the domestic PhD to have the same effect as a foreign PhD.

	(1)	(2)	(3)	(4)	(5)
	# Publications	IHS(# Publications) X 100	IHS(# Citations) X 100	% of Publications in Top 10% Journals	Average CiteScore
1[Post Treatment]	0.1537***	3.051***	3.605***	-0.4227**	0.0326
	(0.0309)	(0.7483)	(1.271)	(0.1663)	(0.0231)
1[Post Treatment] X PhD from China	-0.1447***	-3.301***	-5.892**	0.2680	-0.0434*
	(0.0297)	(0.8228)	(1.578)	(0.2057)	(0.0234)
Author X Affiliation X Cohort FE					
Differential Trends by: Subfield X Career Start+Affiliation X Career Start					

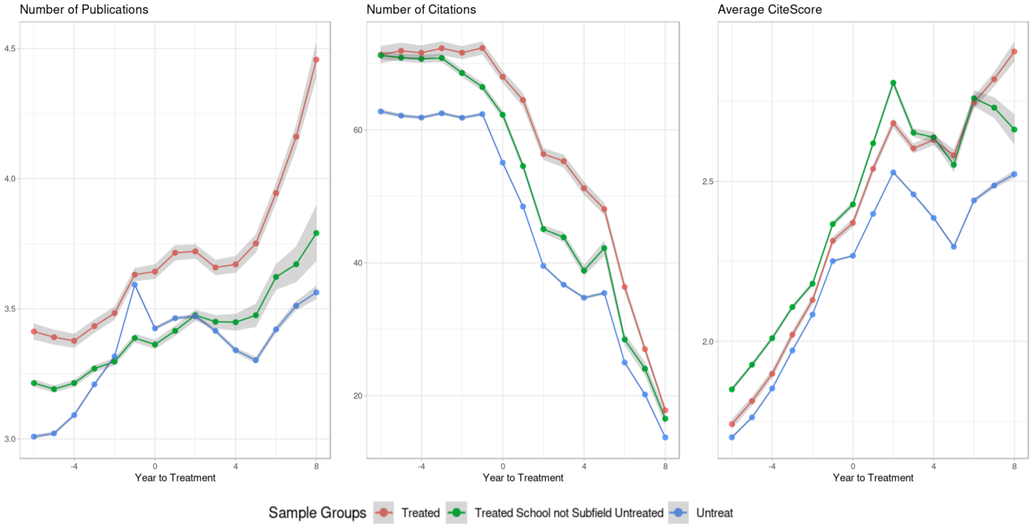
No effect when the joiner received his/her PhD from China.

JTTP Top Fields of Publication

Top Fields		*Top 20 Subfields*	
Field	*Pct*	Subfield	*Pct*
Physics	18.82%	General Chemistry	5.42%
Chemistry	12.67%	General Materials Science	5.18%
Material Engineering	12.55%	General Physics & Astronomy	4.32%
Engineering	12.17%	Electrical & Electronic Engineering	3.33%
Biochemistry	8.71%	Condensed Matter Physics	3.09%
Medicine	6.42%	Nuclear & High Energy Physics	2.55%
Chemical Engineering	4.94%	Electronic, Optical & Magnetic Materials	2.35%
Computer Science	4.58%	Atomic, Molecular Physics & Optics	2.13%
Earth and Planetary Sciences	4.44%	Mechanical Engineering	2.11%
Environmental Science	3.08%	Physics & Astronomy (miscellaneous)	2.06%
Mathematics	2.72%	General Medicine	1.87%
Energy	2.43%	Physical & Theoretical Chemistry	1.76%
Agriculture	2.09%	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%

Back to Peer Effects

Peer Effects of Receiving a JTTP Scholar: Raw Trends



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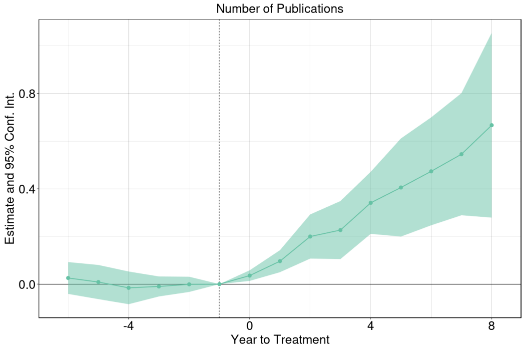
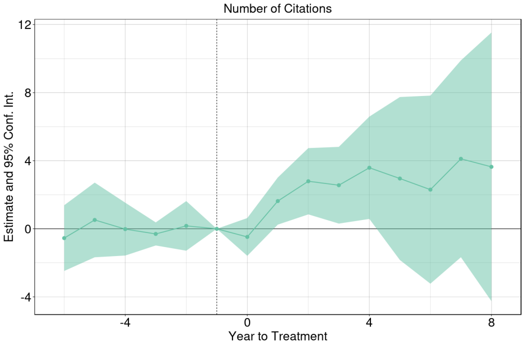
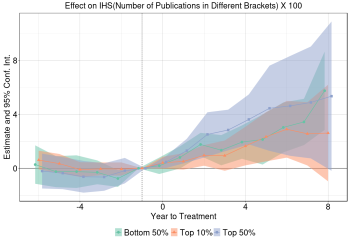
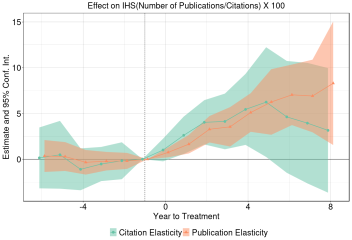
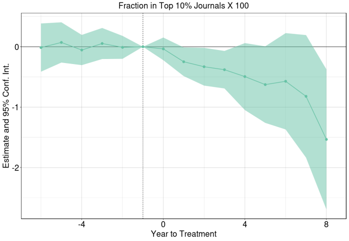
Peer Effects of Receiving a JTTP Scholar: Event Study Estimates











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Top Ten JTTP PhD Universities

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%

Top 10 PhD universities = 33.7% of JTTP scholars. Main path is China Phd then overseas Postdoc

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%

Top 10 ‘senders’ account for 16.9% of JTTP scholars

Top Ten JTTP-Receiving Universities

Rank	University	Count	Pct
1	Chinese Academy of Sciences	493	13.74%
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%

Top 10 ‘receivers’ account for 54% of TTP (40.5% if CAS excluded).

Additional Direct Effect Results

- Callaway and Sant'Anna estimator including all Cohorts Results
- include only JTTP scholars with ORCID in analysis Results
- DiD results using renegers as control group Reneger as controls
- Heterogeneity analysis

Appendix: Direct Productivity Effects

Table: Baseline Estimates: Number of Publications by Cohort 2011-2017

	2011	2012	2013	2015	2016	2017
$\textit{Treated} \times \textit{Post}[0,3]$	-0.069	-0.152	-0.141	0.000	0.058	-0.010
	(0.095)	(0.068)	(0.054)	(0.049)	(0.056)	(0.046)
$\textit{Treated} \times \textit{Post}[4,)$	0.209	0.034	0.133	0.160	0.000	0.000
	(0.126)	(0.079)	(0.066)	(0.066)	(.)	(.)
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.

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Appendix: Direct Productivity Effects

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

	Num Pubs	Num Cites	CiteScore	Top 10 Pct	Top 50 Pct	Last Authored	First Authored	Funded
$Treated \times Post[0,3]$	-0.136	-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)
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.

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Appendix: Renegers as Control Group

Table: 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)
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.

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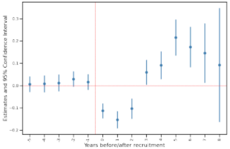
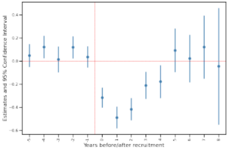
Appendix: Callaway and Sant'Anna DiD

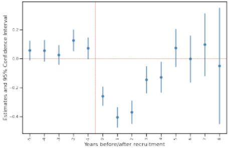
(a) number of publications



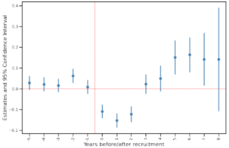
(b) cites



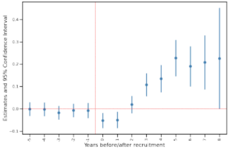
(c) citesscore



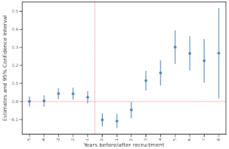
(d) top 10 percentile publications



(e) top 50 percentile publications



(f) funding



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Appendix: Including only Selected Scholars with ORCID

Table: Effect on JTTP Scholars: Estimates with ORCIDStacked 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. Back to Additional Analysis