The Impact of U.S.-China Tensions on U.S. Science*

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Abstract

While there has been much discussion about recent investigations of foreign influence in research, very little work has quantified how these investigations have affected the productivity of U.S. scientists. We uncover evidence of adverse effects on U.S. scientists with collaborators in China using publication data from PubMed and Dimensions during 2010–2020. By studying the publication records of over 102,000 scientists during 2015–2020, we find that the investigations coincide with a decline in the productivity of scientists with previous collaborations with scientists in China in comparison to scientists with international collaborators outside of China, especially when the quality of publications is considered. The decline is particularly salient for fields with more pre-investigation NIH funding and U.S.-China collaborations. Our findings suggest that scientific research may be very sensitive to political tensions, and we further explore these mechanisms with qualitative interviews with scientists.

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1. Introduction

Science is becoming more collaborative, and scientific collaboration is increasingly international (Wuchty, Jones and Uzzi, 2007; Hsiehchen, Espinoza and Hsieh, 2015; Wagner and Leydesdorff, 2005; Hoekman, Frenken and Tijssen, 2010). From 2008 to 2018, the percentage of science and engineering papers with authors from institutions in different countries has increased from 17% to 23% (White, 2019). International collaborations in science have resulted in great achievements, exemplified by the International Space Station and the completion of the Human Genome Project. A large literature has documented how international collaboration and talent flows can facilitate progress in science (e.g. Van Raan 1998; Barjak and Robinson 2008; Didegah and Thelwall 2013; Wagner, Whetsell and Leydesdorff 2017; Freeman and Huang 2015; Nomaler, Frenken and Heimeriks 2013).

However, science is never isolated from politics, and is often affected by national and international policies (Doria Arrieta, Pammolli and Petersen, 2017; Borjas and Doran, 2012; Moser, Voena and Waldinger, 2014; Moser and San, 2020; Waldinger, 2010, 2012; Cheung, 2009). In recent years, due to political tensions between the U.S. and China, scientific collaborations between U.S. and Chinese academic institutions have come under increasing scrutiny by U.S. policymakers. The U.S. Department of Justice started the China Initiative, which ran from 2018–2022, aimed at countering national security threats from China, with a particular focus on intellectual property and technology.[1] Also in 2018, the National Institutes of Health (NIH) began contacting institutions of higher education about investigations of hundreds of scientists, largely for failure to disclose receipt of foreign resources on federal research grants.[2] While the investigations were not specific to China, the vast majority of investigated cases involved receipt of resources from China. As of July 2021, these investiga-

[1]See: https://www.justice.gov/nsd/information-about-department-justice-s-china-initiative-and-compilation-china-related

[2]See Dear Colleague Letter from NIH Director Francis Collins: https://www.insidehighered.com/sites/default/server_files/media/NIH%20Foreign%20Influence%20Letter%20to%20Grantees%2008-20-18.pdf

tions involved 93 institutions of higher education and 214 scientists, 90% of which involved receipt of resources or activities in China.[3] Some cases resulted in suspension of funding, termination of employment, and in rare cases criminal investigations of scientists.

While the merits of the China Initiative and NIH investigations have been widely discussed (Lewis, 2021; Mervis, 2021; Thorp, 2022; Viswanatha and O'Keeffe, 2020; *The US crackdown on Chinese economic espionage is a mess. We have the data to show it.*, N.d.), much less is known about the impact of these policies on U.S. production of science. In this paper, we study the impact of the NIH investigations on U.S. production of science by examining the publications of U.S. scientists in the fields of life sciences. Because the focus of the scrutiny has been on researchers with academic collaborations in China, we closely examine scientists with a history of collaborating with institutions in China. Using large-scale publication databases, we investigate whether life scientists at U.S. institutions with a history of collaborating with scientists in China have been less productive since the onset of the NIH investigations, relative to their colleagues in the U.S. who have a history of collaborating with scientists from other countries.

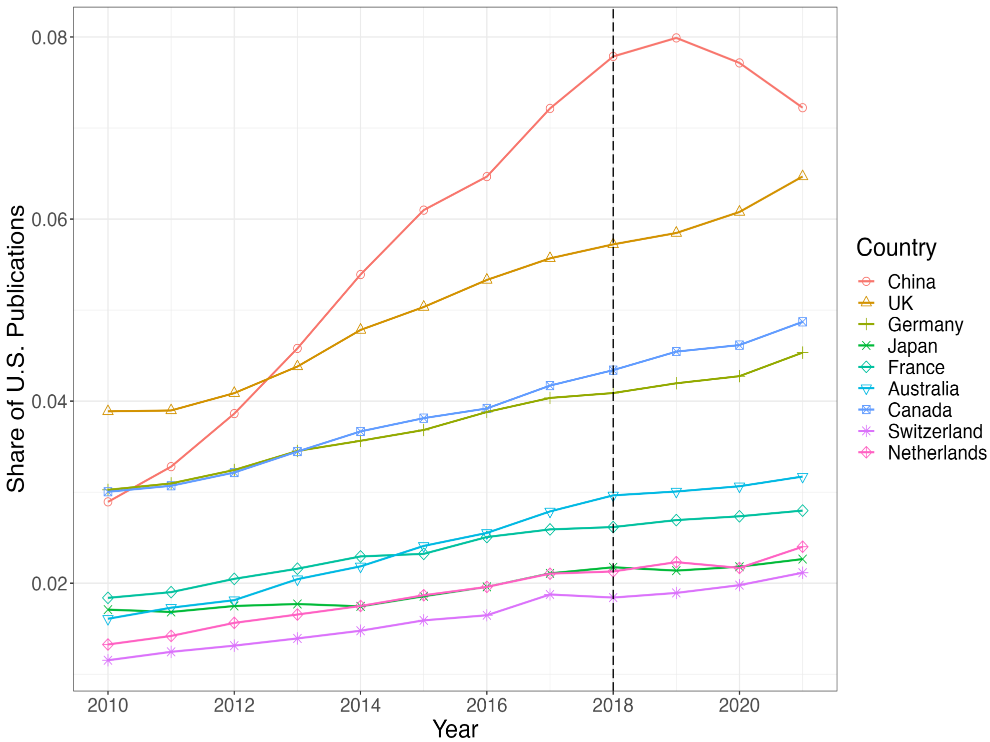
We focus on life sciences for both conceptual and empirical reasons. Conceptually, the NIH's focus is on funding scientists in life sciences.[4] Empirically, there exist multiple data sources on publications in these fields, making quantitative analysis of publication trends tractable. Specifically, we employ two data sources: the PubMed database (`https://pubmed.ncbi.nlm.nih.gov/`) that covers publications on life sciences and biomedical topics and is maintained by institutions located at the NIH and the Dimensions database (`https://www.dimensions.ai/`) that covers publications from all scientific fields. As shown in Figure 1, China has been the most important collaborator of the U.S. in life sciences since 2013. However, compared with U.S. collaborations with other countries, U.S.-China

[3]Lauer, Michael. "Foreign Interference in National Institutes of Health Funding and Grant Making Processes: A Summary of Findings From 2016 to 2021." July 30, 2021. `https://grants.nih.gov/grants/files/NIH-Foreign-Interference-Findings-2016-2018.pdf`

[4]While other federal research agencies also conducted investigations about foreign influence in research, the NIH was the first and to our knowledge most frequent federal agency to conduct them.

collaborations appear to slow down in 2019, which coincides with the NIH investigations, and have turned downward since then.

FIGURE 1. COLLABORATION AS SHARE OF TOTAL U.S. PUBMED PUBLICATIONS



Note: The data is based on publications indexed by PubMed from Dimensions. Each line represents U.S. collaboration with a given country in PubMed publications as its share of total U.S. PubMed publications. Note that the data include all scientists in the Dimensions database, not just those included in the data we describe below.

To estimate the causal effect of the investigations on scientists with previous collaborations with institutions in China, we employ a difference-in-differences approach. Specifically, we define the treated and control groups of Principal Investigators (PI) based on the publication records during 2010–2014. We assume that those who had collaborations with scholars in China during this period are "treated," in that they are particularly affected by the investigations, and use those who collaborated with scholars from other non-U.S. countries as the control group. In our data, 32,056 PIs belong to the treated group and 70,746 PIs to the control group. Then, using publication data during 2015–2020, we examine how the quantity and quality of publications differ between treated and control groups before and after the NIH investigations in 2018. To consider possible differences in individual characteristics and career paths, our analyses control for individual fixed effects, year fixed effects, and consider year-specific impacts of ethnicity and pre-treatment productivity. We complement our analyses with a reweighting strategy in which we ensure the covariates are comparable between the treated and control groups.

We find that the PubMed publications of scientists with a history of collaborating with scientists in China experienced a decline after 2018, compared with their counterparts without collaborators in China. While the magnitude of the decline in quantity is small (1.9%), the impact becomes sizable (7.1%) once we consider the quality of publications and employ citations of publications as the outcome. This finding suggests that the treated scientists were affected not only in terms of quantity but also quality of their research output. For non-PubMed publications, we find a minimal increase in quantity but a sizable decline in citations (5.4%). Together, in terms of total publications, the treated scientists experienced a decline of 7.2% in publication citations. When examining the pre-trends, we find that the productivity of the treated scientists was not on a clearly different trend but declined after the investigations.

Then, we take a closer look at publications by scientist characteristics, institutions, and research fields. We document three patterns. First, motivated by the discussion on racial profiling in the China Initiative (Mervis, 2021), we examine whether Asian scientists are more adversely affected. We find that among the treated, Asian scientists are more affected for both NIH-funded and China-funded publications. Second, the adverse effects appear to apply to most of the institutions, suggesting that this is a broad phenomenon and is not limited to the institutions reported by the media. Third, to investigate which fields are more affected, we calculate the importance of NIH funding and U.S.-China collaboration by fields and estimate the impact in each field. We find that the fields where NIH funding is more important and had more U.S.-China collaborations experienced a larger decline.

These patterns further support that our findings are driven by U.S.-China tensions rather than other shocks during this period that are orthogonal to NIH funding or U.S.-China collaboration.

Further, we provide suggestive evidence that our findings are relevant for science at the aggregate level for both the U.S. and China. Specifically, we correlate the changes in scientific output by field in China and the U.S. (relative to 48 other countries) with our estimated impact of the NIH investigations by field. We find that the fields that we identify to be more adversely affected by the NIH investigations experienced slower growth in scientific output than fields that are less affected. This association holds both for China and the U.S., though the U.S. appears to be more sensitive to the adverse impacts of these investigations.

Finally, to shed light on the underlying mechanisms, we complement our quantitative analyses with interviews of scientists. The interviews of 12 scientists suggest that the short-run impacts we document stem from three channels: a direct effect of NIH funding reduction, a decline in access to human capital, including students and collaborators, from China, and a chilling effect on collaborating with institutions in China. Multiple scientists emphasize that they are less willing to start new collaborations with scientists in China, which has forced them to reorient their work toward other topics, and has been costly in terms of productivity. These channels suggest that our findings above may underestimate the impacts in the long run, since it takes time for the reduction of new joint projects to appear in our data.

The NIH investigations have attracted much attention from scientists and the public. Yet, the consequences of these investigations have been little understood. Our study provides a step toward depicting how scientific production is affected. Admittedly, our characterization focuses on the outcomes in the short run and additional impacts are likely to unfold in the long run.

Our research is related to an extensive literature in economics, science and technology studies, and political science that investigates how constraints on information, collaboration and talent mobility impact scientific progress and innovation. Researchers have characterized the rapid growth of collaborations among scientists located in different countries, especially those between the U.S. and China. For example, Tang and Shapira (2011) document that an increasing number of papers in nanotechnology are co-authored by Chinese and American scientists. Indeed, Wagner, Bornmann and Leydesdorff (2015) find that the growth in U.S.-China scientific collaborations is unprecedented, in that the U.S. has not seen such exponential growth in collaboration with any other country. Others have noted that U.S.-China collaborations could be problematic for U.S. security, for example, Stoff and Tiffert (2021) examine a database of scientific publications and find collaborations between U.S. institutions and their counterparts in China affiliated with the military, some of which are on the entity list or involved in mass surveillance in China. With political tensions between the U.S. and China increasing, it is not clear how scientific collaboration between the two countries will evolve, and so far studies have focused only on narrow topics of collaboration, such as scientific collaboration on COVID-19 (Lee and Haupt, 2021). Our study provides evidence that scientific production and collaboration can be very sensitive to political pressure.

2. Data

We focus on publications in the biomedical fields and life sciences in the period 2010–2020. We start with publications indexed by PubMed, an online resource from the National Library of Medicine that archives literature in the biomedical and life sciences. To obtain the metadata associated with these publications, we make use of another database, Dimensions (`https://www.dimensions.ai/`), that provides metadata such as author affiliations, citation counts, and fields of study. As each author in the Dimensions database is indexed by a unique author identifier, we are able to track each author's publication record.

Data construction. In order to assess the impact of NIH investigations on the scientific output of U.S. scientists, we construct a dataset of U.S. scientists whose primary fields are in the medical and life sciences. To do so, we first query Dimensions to get the list of 1,450,806

PubMed publications in 2010–2014, for which at least one of the authors is based in the U.S. We impose two restrictions on the scientists in our dataset: (1) each scientist has to have at least two PubMed publications in 2010–2014 for which they are the Principal Investigator (PI);[5] and (2) at least one of their publications needs to have a U.S. affiliation. The criterion (1) selects authors whose primary fields are more likely to be in the medical and life sciences and (2) focuses our attention on scientists who are based in the U.S. Applying the restrictions results in a list of 197,799 scientists.

Based on the initial list of scientists, we query Dimensions to get all of the selected scientists' publications (including non-PubMed publications) from 2015–2020. To ensure the scientists we study were still in the U.S. immediately before treatment, we further restrict that each scientist's last publication prior to the beginning of the NIH investigations (August 20, 2018) shows they have a U.S. affiliation. This reduces the number of scientists to 161,429. Using affiliation data from Dimensions, we determine whether each paper included a U.S.-China collaboration, a U.S. collaboration with any country other than China, or included only authors from the U.S. We also use Dimensions-provided data to keep track of other metadata such as the funding information, citation count, and research field of each paper for our analysis.

Validating data quality. Because of the scale of the PubMed and Dimensions data and the algorithmic approach to coding authors, papers, and institutions that these databases use to produce them inevitably has errors. To check the extent to which Dimensions data aligns with other existing datasets, we validate our data from Dimensions with data from Google Scholar, which is thought to be the most complete in terms of counting publication citations, but does not have an API for researcher access (Martín-Martín et al., 2021). In particular, we check whether our main outcomes of interest we use in this paper—authors' publication record and citation counts—are comparable between the two sources.

[5] To determine the PI of each paper, we treat the last author of each paper as the PI for that paper, as per the convention in the life sciences. When information about corresponding authors is available in the data, we also include the corresponding authors as the PIs of the paper.

To do so, we draw a random sample of 100 authors from our data. For these 100 authors, we are able to identify 54 authors who have Google Scholar profiles.[6] For each matched author, we compare their number of publications in 2010–2020 based on Dimensions with that based on Google Scholar. We also compare citation counts for each author-year from the two data sources. We should note that Google Scholar includes information on working papers that have not been published.

Both measures are highly correlated between Dimensions and Google Scholar, with a correlation of 0.76 on publication records (Appendix Figure A.1.1) and a correlation of 0.82 on citation counts (Appendix Figure A.1.2). This gives us confidence that Dimensions data captures similar dynamics to other comparable data sources.

Defining treatment and control groups. We define the treated group as scientists in our sample who had at least one paper collaborated with some scholar from an institution in China in the period between 2010 and 2014. In our data, 32,056 PIs belong to the treated group.

The control group consists of those who both (1) had at least one paper collaborated with some scholar from a foreign country other than China from 2010–2014 and (2) had no collaboration with scholars in China in the pre-treatment period from 2010 to 2018.[7] We define the control group in this way to make it more comparable to the treated group because scientists who have international collaborators in our data to be more productive than those who do not.[8] In our data, 70,746 PIs belong to the control group.

We consider 2019 as the first year under treatment. On August 20, 2018, the Director of the NIH, Francis Collins, sent out an open letter to U.S. universities, calling for investigations

[6]Authors must create a Google Scholar profile themselves, which is why we cannot match 100% of authors.

[7]An alternative way to define the treatment and control groups is to consider scientists who had or did not have collaborations with Chinese scholars between 2015 and 2018. We employ the current definition to exclude the influence of new entrants (those who became PIs during this period) on our results, but our results are robust to this alternative definition.

[8]In our data, 142,347 U.S. scientists with international collaboration publish on average 6.17 papers per year, compared to 18,969 U.S. scientists without international collaboration, who publish on average 1.57 papers per year.

Table 1. Summary Statistics

	Control Group		Treated group	
	Mean	St Dev	Mean	St Dev
A. Pre-treatment (2015-2018)				
Total Citations	106.6	258.4	338.5	824.2
PubMed Citations	99.2	254.2	301.2	785.8
NIH Citations	47.7	173.7	169.8	611.7
PubMed Publications	3.3	4.2	6.2	7.7
B. Post-treatment (2019-2020)				
Total Citations	45.6	151.0	135.5	382.3
PubMed Citations	42.0	148.0	117.1	355.1
NIH Citations	20.9	108.4	65.0	268.5
PubMed Publications	3.3	4.9	6.0	8.4
C. $\triangle \ln(post) - \ln(pre)$				
Total Citations	-0.85		-0.92	
PubMed Citations	-0.86		-0.94	
NIH Citations	-0.83		-0.96	
PubMed Publications	0.00		-0.03	
Asian Researchers	7,745		9,073	
No. of obs.	70,746		32,056	

into foreign influence in research and undisclosed foreign funding.[9] This date marks the beginning of the treatment we are interested in and was also frequently cited in our interviews as the year that scientists began to feel pressure on their collaborations with scientists in China. Nevertheless, there is a time gap between research and publication, meaning that the impacts of the investigations may not be reflected immediately, which is why we select 2019 as the first year under treatment.[10]

Summary statistics. We present summary statistics by treated and control groups in Table 1. We use two measures of productivity: quantity and citations, the latter of which can be considered as a quality-weighted productivity measure and is our focus.

As shown in Panels A and B, treated scientists are on average more productive than

[9] https://www.insidehighered.com/sites/default/server_files/media/NIH%20Foreign%20Influence%20Letter%20to%20Grantees%2008-20-18.pdf

[10] In fact, we expect this time lag in some cases to be longer than one or two years, which might mean the effects we find are a lower bound on an effect that will reveal itself over the course of the next few years.

control scientists and are better cited. This partly reflects the prominence of collaborations with China among the more productive U.S. scientists. These data also reveal that PubMed citations account for the majority of total citations and NIH-supported citations account for about half of the PubMed citations among the scientists in our sample.

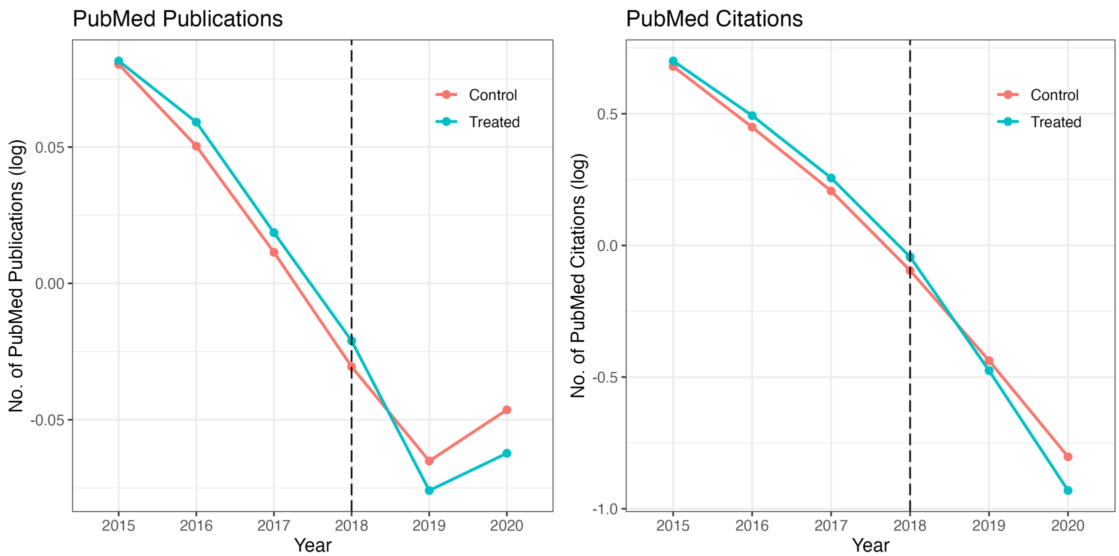
Panel C presents the change in citations and publications for the treated and control groups. As more recently publications have fewer citations, there exist a general decline in citations of publications over time. However, the decline appears systematically larger for the treated scientists than their counterparts. For instance, for the treated scientists, the relative decline is 7% more in terms of total citations, 8% more in terms of PubMed citations, and 13% more in terms of NIH citations. The difference in PubMed publications exhibits a similar pattern but the magnitude is smaller.

In addition, using the prediction method in Imai and Khanna (2016), we estimate whether a scientist is of Asian heritage by using his or her family names (see more details about the prediction method in Appendix A.2). In our sample, the shares of Asian scientists in the treatment and control groups are 28.3% and 10.9% respectively, reflecting that Asian scientists are more likely to collaborate with scientists in China.

3. Descriptive Evidence and Research Design

To check the trends in productivity of scientists in the treatment and control groups, we present the logged number of publications and the logged number of citations across the treatment and control groups by year in Figure 2. To take scientist heterogeneity into consideration, we demean these measures by the individual average and focus on the within-scientist comparison. As shown, the treated group was more productive before 2018 than the control group and there were no clear differences in the productivity trend. However, the difference reversed after 2018, which suggests some influence of the political tensions, which we examine systematically in the following sections.

Figure 2. Productivity Trends across the Treatment and Control Groups



Note: The figures present time trends for the logged number of PubMed publications and the logged number of PubMed citations across the treatment and control groups, after the individual average is subtracted from each observation.

Motivated by this evidence, we use a difference-in-differences (DID) design to investigate the causal impacts generated by the NIH investigations. Our specification is as follows:

$$Y_{i,t} = \mu + \beta \mathbf{1}\{TiesToChina_i\} * \mathbf{1}\{Post_t\} + \alpha_i + \xi_t + X_i * \xi_t + \varepsilon_{i,t}, \tag{1}$$

where $Y_{i,t}$ is the outcome of interest, such as the logged numbers of *PubMed* publications, total publications, and corresponding citations. $\mathbf{1}\{TiesToChina_i\}$ is a dummy indicating whether individual i belongs to the treated group; $\mathbf{1}\{Post_t\}$ is a dummy that equals to 1 in the post-treatment periods and 0 otherwise.

α_i and ξ_t stand for individual and year fixed effects, respectively. The individual fixed effects control for all time-invariant characteristics of a scientist such as gender and education background. The year fixed effects control for the factors that influence all scientists similarly such as the pandemic. Moreover, to further control for potentially different trends in productivity and personal background, we include four pre-investigation measures in X_i—one's number of publications, citations and NIH-supported publications during 2010 and 2014 and an indicator for being an Asian researcher—and allow for their impacts to vary over time by controlling for $(X_i * \xi_t)$. We cluster the standard errors at the individual level to account for inter-temporal correlation within each individual.

In addition to our main specification, we employ a reweighting approach, entropy balancing (Hainmueller, 2012), to balance all covariates before running the regression and compare the estimates from our standard DID analysis. To check whether the treated group was in a different trend before the investigations, we complement our DID design with an event-study design and examine the impacts of the investigations year by year.

4. Results

4.1. Main results: Quantity and Quality of Publications

We present the DID estimates for our main outcomes in Table 2. Panel A shows the results for the logged number of PubMed publications.[11] Column (1) uses the logged number and the vanilla two-way fixed effects model, without the controls. In Column (2), we control for the influences of each scientist's pre-investigation productivity measures and their ethnicity. In Column (3), we report the estimate after conducting entropy balancing so that the baseline covariates are comparable between treated and control groups. Columns (4)–(6) present the results for citations which capture both quantity and quality of the publications.

As shown in Columns (2)–(3) of Panel A, the number of PubMed publications of the treated scientists declined around 1.8–1.9%. However, the decline is more striking once the citations of the publications are considered: the decline becomes 6.6–7.1% compared with the control. These results reveal that the investigations may have affected not only the quantity but also the quality of publications of those who had collaboration histories with

[11] To facilitate interpretation, we present the results using log (1+number of publications or citations) as the dependent variable. Our results are similar if we use hyperbolic sine transformation to deal with observations of zeros, as reported in Appendix A.3.

China.

Panel B presents the estimates for non-PubMed publications. In terms of quantity, we observe a minimal increase using our DID design and after balancing the covariates. However, once the quality of publications is considered, non-PubMed citations of the treated scientists declined by 5.4–5.9%. We consider all publications in Panel C. Again, the impact on the number of publications of the treated scientists is minimal but that on quality-adjusted productivity is sizable, with a decline of 7.1–7.2%.

Our identification assumption is that the productivity of scientists in our treated and control groups would be comparable without the NIH investigations. To check the validity of our assumption, we plot the year-by-year estimates in Figure 3. Because our previous findings reveal that the citation of the publications is the main margin that gets affected, we focus on citations as the outcome. Panel A presents the estimates after only controlling for scholar fixed effects and yearly fixed effects whereas Panel B reports those after balancing the covariates. In either method, we find that the decline in productivity for the treated scientists occurred only after the investigations, suggesting that the pre-trends concern is not critical for our findings.

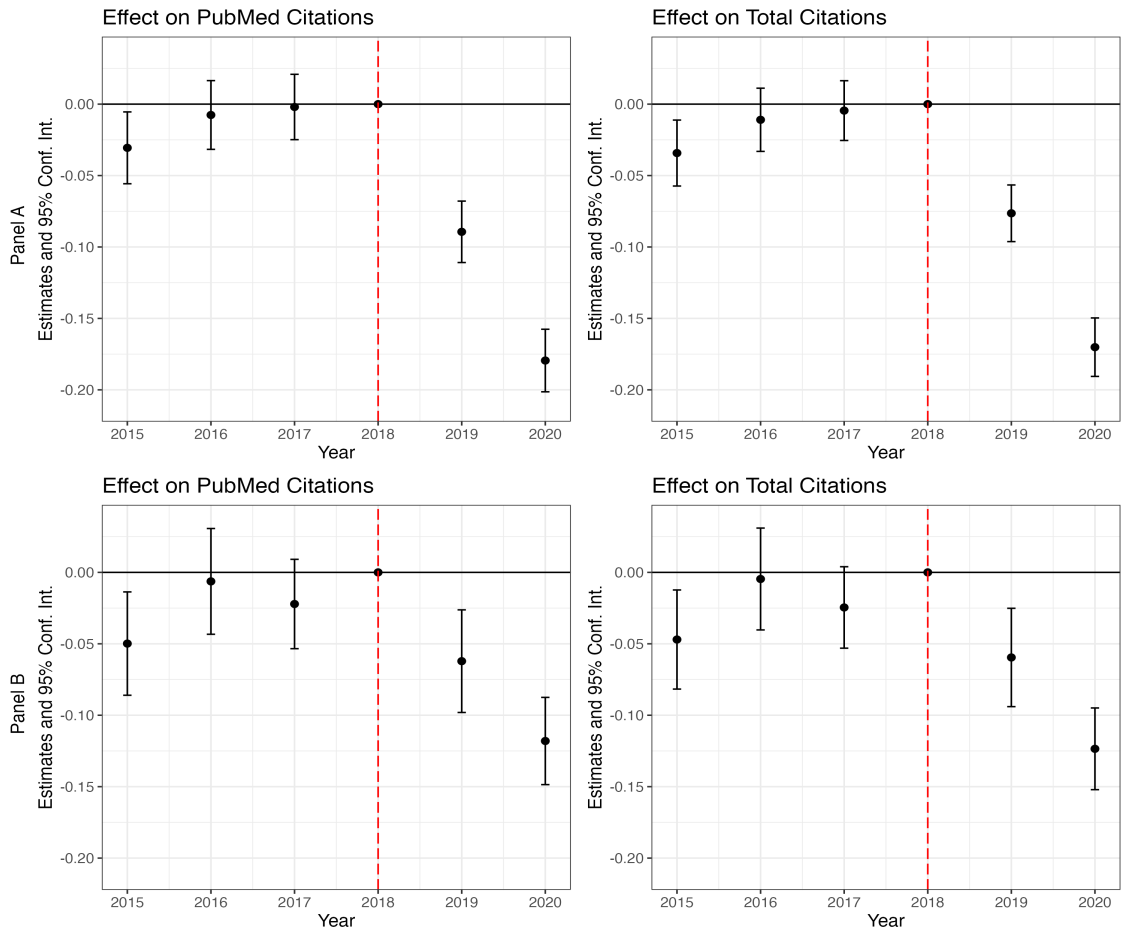
In Appendix A.4, we separate publications based on their funding sources. We find that the citation decline applies to both NIH-funded publications and non-NIH-funded publications and the former appears larger. Similarly, the citation decline applies to both China-funded publications and non-China-funded publications and the former is larger. These results show that the adverse impacts on treated scientists are not limited to the publications funded by NIH or China. Instead, the productivity effect is reflected by different types of publications. Overall, these findings demonstrate that the investigations had broad negative impacts on the treated scientists. The impacts are multidimensional, reflected by both the quantity and quality of the research.

Table 2. The Impacts on Productivity: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	PubMed Publications			PubMed Citations		
Ties to China × Post	-0.020	-0.018	-0.019	-0.124	-0.066	-0.071
	(0.003)	(0.004)	(0.005)	(0.008)	(0.009)	(0.011)
Pre-treatment avg.	1.557	1.557	1.557	4.17	4.17	4.17
R2	0.754	0.754	0.81	0.687	0.688	0.735
No. of obs.	616812	616812	616812	616812	616812	616812
Scholar FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Baseline Covariates*Year FE		Y			Y	
Entropy Balancing			Y			Y
Panel B	Non-PubMed Publications			Non-PubMed Citations		
Ties to China × Post	0.035	0.017	0.017	-0.052	-0.059	-0.054
	(0.004)	(0.004)	(0.008)	(0.006)	(0.006)	(0.016)
Pre-treatment avg.	1.011	1.011	1.011	1.394	1.394	1.394
R2	0.69	0.693	0.734	0.685	0.69	0.691
No. of obs.	616812	616812	616812	616812	616812	616812
Scholar FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Baseline Covariates*Year FE		Y			Y	
Entropy Balancing			Y			Y
Panel C	Total Publications			Total Citations		
Ties to China × Post	0.001	-0.004	-0.007	-0.111	-0.071	-0.072
	(0.003)	(0.004)	(0.006)	(0.007)	(0.008)	(0.011)
Pre-treatment avg.	1.943	1.943	1.943	4.48	4.48	4.48
R2	0.772	0.772	0.818	0.703	0.704	0.746
No. of obs.	616812	616812	616812	616812	616812	616812
Scholar FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Baseline Covariates*Year FE		Y			Y	
Entropy Balancing			Y			Y

Note: All outcomes are log-transformed. For Columns (1) to (6), the models always control for scholar and year fixed effects. In Columns (2) and (5), we include the interactions between year dummies and four baseline covariates: 1) total number of publications in 2010-2014, 2) total citations in 2010-2014, 3) number of NIH-funded publications in 2010-2014, and 4) indicator for Asian researcher. In Columns (3) and (6), we use entropy balancing to balance all four covariates before running the regression. Standard errors are clustered at the scholar level.

Figure 3. The Impacts on Productivity: Results from Event Study



Note: Plots in this figure present the effect estimates of "leads and lags" of the treatment. Panel A presents the results controlling for scholar fixed effects and year fixed effects; Panel B presents the estimates using entropy balancing. Each segment represents the 95% confidence interval of the estimate. The outcome in the left column is the logged number of citations for PubMed publications. In the right column, it is the logged number of citations for all publications.

In Appendix A.5, we examine the publications by collaboration types—collaborations within the U.S., collaborations with non-China countries, and collaborations with China. We note that the decline in China-collaborated publications in the treated group seems to be offset in part by an increase in domestic-only publications relative to the control group, and not offset by an increase in collaborations with other countries. In terms of citations, we find all three types of collaborations were negatively affected for the treated group in comparison to the control group. These patterns suggest that the treated scientists may not have been able to use other types of collaborations to compensate for their loss in productivity.

4.2. Results by Ethnicity and Institutions

Existing media reports on these investigations often highlight the role of ethnicity and focus on investigations at particular universities (Dolgin, 2019). Motivated by these discussions, we take a closer look at the ethnicity of scientists and the impacts across universities.

Using the algorithm developed by Imai and Khanna (2016),[12] we split the sample into Asian and non-Asian scientists and estimate a triple-difference design. On average, we find that both Asian and non-Asian scientists are adversely affected and the difference is small, as shown in Column (1) of Table 3. However, once we separate the publications to be those funded by NIH or not, we find that Asian scientists were more adversely affected in terms of NIH funded publications whereas the difference between Asian and non-Asian scientists is small but positive for non-NIH funded publications (Columns (2)–(3)). Moreover, we find that Asian scientists were also more adversely affected in terms of China funded publications (Columns (4)–(5)).

[12] More details on the implementation of this algorithm are in the Appendix.

Table 3. Heterogeneous Treatment Effects by Ethnicity

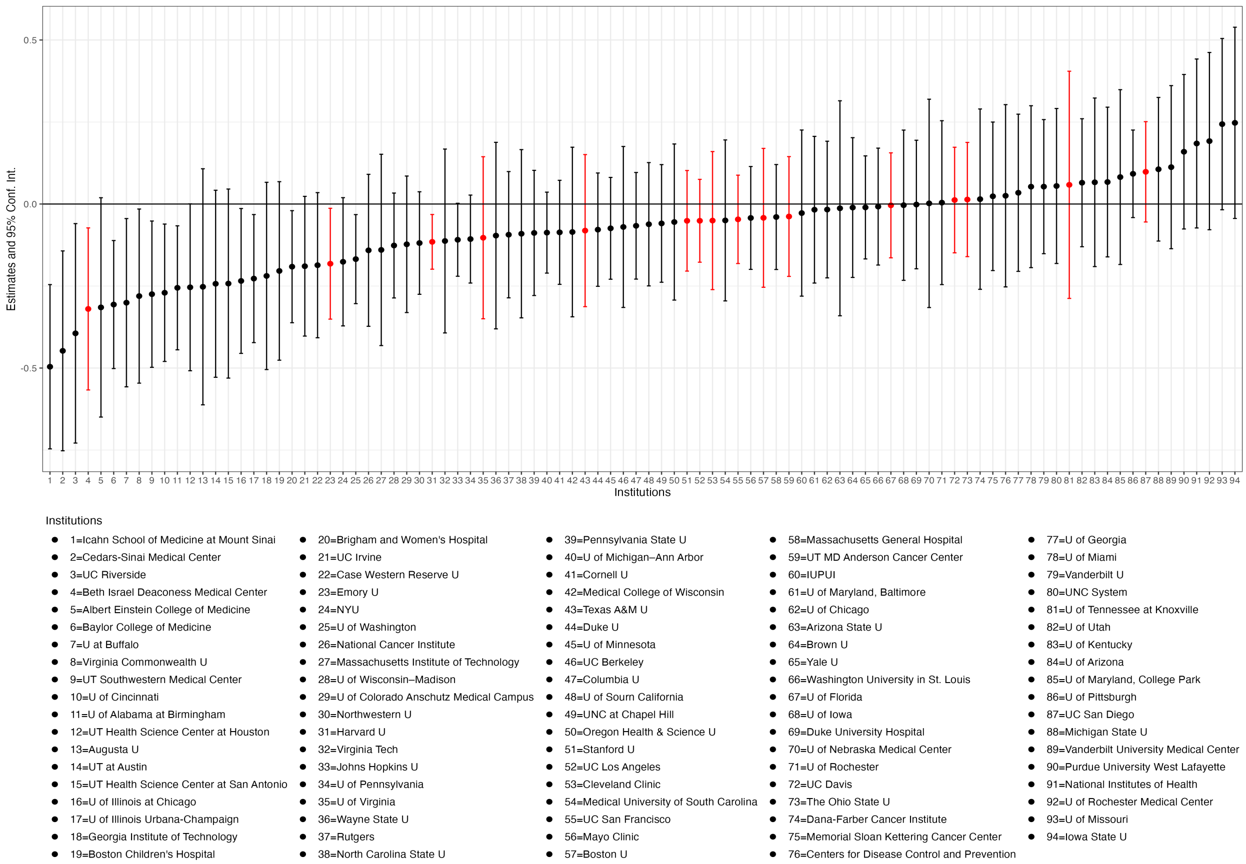
	Citations by Nature of Publication				
	(1) All	(2) NIH-Funded	(3) Non NIH-Funded	(4) China-Funded	(5) Non China-Funded
Ties to China × Post × Asian	-0.008	-0.070	0.034	-0.196	-0.004
	(0.019)	(0.020)	(0.020)	(0.013)	(0.020)
Ties to China × Post	-0.070	-0.057	-0.043	-0.117	-0.058
	(0.009)	(0.010)	(0.010)	(0.006)	(0.009)
Post × Asian	0.058	0.019	0.078	0.009	0.056
	(0.014)	(0.014)	(0.014)	(0.003)	(0.014)
R2	0.704	0.712	0.683	0.657	0.698
No. of obs.	616812	616812	616812	616812	616812
Scholar FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Baseline Covariates*Year FE	Y	Y	Y	Y	Y

Note: In all columns, outcomes are log-transformed and we control for scholar and year fixed effects, as well as the interactions of year dummies with the baseline covariates: 1) total number of publications in 2010-2014, 2) total citations in 2010-2014, and 3) number of NIH-funded publications in 2010-2014. Standard errors are clustered at the scholar level.

We then examine the impacts by institution. In Figure 4, we plot the heterogeneity of treatment effects for institutions in the sample that have more than 100 scholars in both the treated group and the control group. We find that the adverse effect applies to most of the institutions. In addition, we mark the institutions whose investigations were reported by the media in red.[13] We do not find that the impacts on scholars in these institutions are different from those in other institutions. These results suggest that the impact is general and not institution-specific.

[13]We identify institutions with public investigations using data from APA Justice `https://www.apajustice.org/china-initiative-scientist-cases.html` and the *MIT Technology Review* `https://www.technologyreview.com/2021/12/02/1040656/china-initative-us-justice-department/` (*The US crackdown on Chinese economic espionage is a mess. We have the data to show it.*, N.d.)

Figure 4. Heterogeneous Treatment Effects Over Institutions



Note: The figure presents the heterogeneity of treatment effects within the treated group across institutions in the sample that contain more than 100 scholars in both the treated group and the control group. Each point and error bar represent the estimated ATT at a given institution and the corresponding 95% confidence interval. Those in red represent institutions that are known to have scientist(s) investigated by the NIH.

4.3. Results by Fields and Aggregate Implications

We then decompose the effect by field of research. Given that the investigations were primarily at the NIH and focused mainly on U.S.-China collaborations, we expect that the findings are particularly relevant for the fields with more U.S.-China collaborations and the fields that receive a lot of funding from the NIH.[14]

[14]Field-specific effects were reflected in our interviews with scientists. Scientists who were in fields with high NIH-funding but low overall levels of U.S.-China collaboration, for example public health and clinical sciences, felt much less pressure to stop their U.S.-China collaborations than those in fields with higher levels of U.S.-China collaboration, such as in chemistry and the biological sciences.

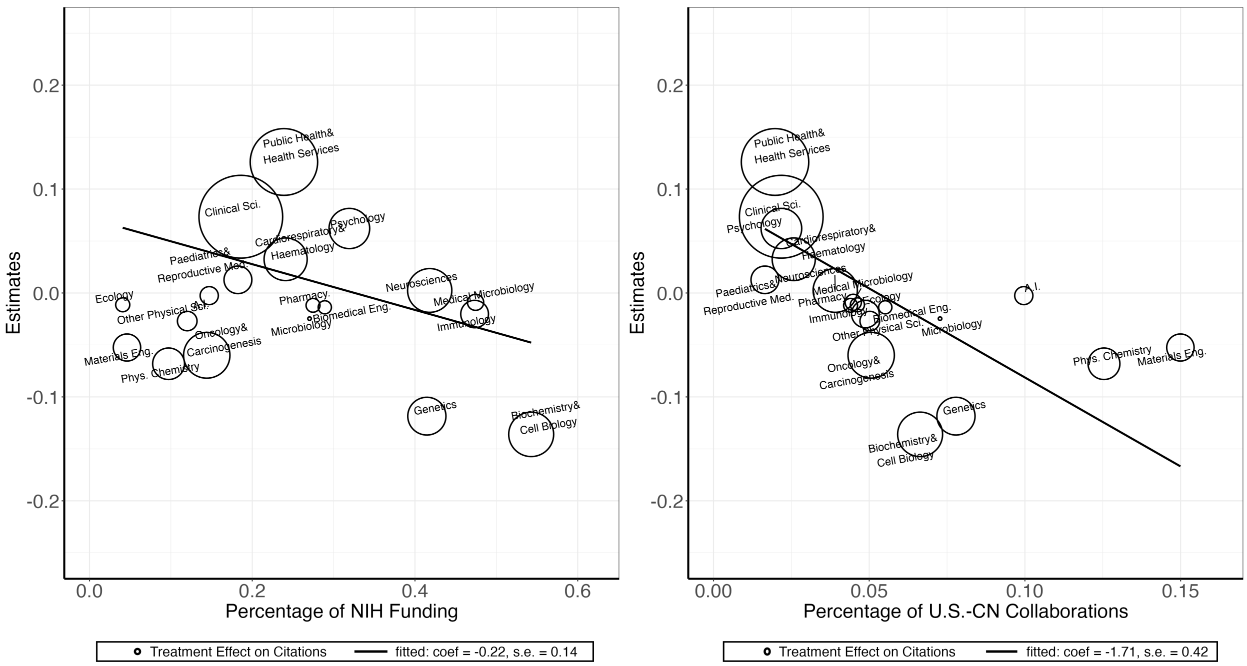
Estimates by fields. We define research field using Dimensions metadata, which puts each publication into a "field of research" using the Australian and New Zealand Standard Research Classification.[15] For each field, we create two measures using our publication data from 2010–2020. The first is the share of publications with NIH funding support in each field, the second the share of U.S.-China collaborations among total publications in each field. The top fields in terms of NIH funding in our data are biochemistry and cell biology, medical microbiology, and immunology, whereas the top fields in terms of U.S.-China collaborations are materials engineering, physical chemistry, and molecular and materials chemistry. We present these two measures by fields in Appendix Tables A.6 and A.7.

We estimate the impacts of NIH investigations on citations by field (i.e., quality-adjusted productivity) and correlate these estimates with the two measures above. As shown in Figure 5, scientists with collaborations with institutions in China in the fields where NIH funding is more important experienced a larger decline relative to those in fields with less NIH funding. Specifically, a one-standard-deviation increase in the NIH funding (0.15) is associated with a 3.2 percentage point decline in the treatment effect. Similarly, scientists with collaborations with institutions in China in the fields where U.S.-China collaboration is more important experienced a larger decline relative to those in fields with less U.S.-China collaboration. The magnitude is even larger and more precisely estimated: a one-standard-deviation increase in the share of U.S.-China collaboration (0.04) is associated with a 6.2 percentage point decline in the treatment effect.

Aggregate implications by fields. Last, we provide a preliminary analysis of the effect of these investigations on the development of science in the U.S. and China more broadly. Did the NIH investigations matter for the development of science in the U.S. or China? It is challenging to provide a definite answer to this broad question. Nevertheless, the fact that we find that some fields were more affected by these investigations than others allows us to get some leverage on this question.

[15] https://www.abs.gov.au/ausstats/abs@.nsf/0/6bb427ab9696c225ca2574180004463e

Figure 5. Citation Estimates vs. NIH Funding and US-China Collaborations



Note: Each bubble represents a field. The size of the bubbles is scaled by their number of publications in the data. Y-axis is the estimated treatment effect on citations. The sample is restricted to fields with greater than $50,000$ publications in our dataset.

Conceptually, we would like to know how the progress of science by field in China and the U.S. in the last several years correlates with our findings by fields. Have fields that were most affected by the investigations according to our analysis slowed their progress in the U.S. and China in comparison to the rest of the world? Empirically, we measure the progress by fields in China and the U.S. relative to other countries using a difference-in-differences design. We first use Dimensions to collect data on the yearly number of publications by field for the top 50 countries (including China and the U.S.) in natural sciences research.[16]

Mirroring our main design, we consider the research output during 2015–2018 as the pre-treatment progress and the output during 2019–2020 as the post-treatment progress. Using the difference-in-differences design, for each field, we measure the increase or decrease in research output by field (f) for China and the U.S., relative to the other 48 countries and the pre-treatment period, estimated as follows:

$$Y_{c,t} = \mu + \beta_{f,China}\mathbf{1}\{China\} * \mathbf{1}\{Post_t\} + \alpha_c + \xi_t + \varepsilon_{c,t} \quad (2)$$

$$Y_{c,t} = \mu + \beta_{f,US}\mathbf{1}\{US\} * \mathbf{1}\{Post_t\} + \alpha_c + \xi_t + \varepsilon_{c,t}, \quad (3)$$

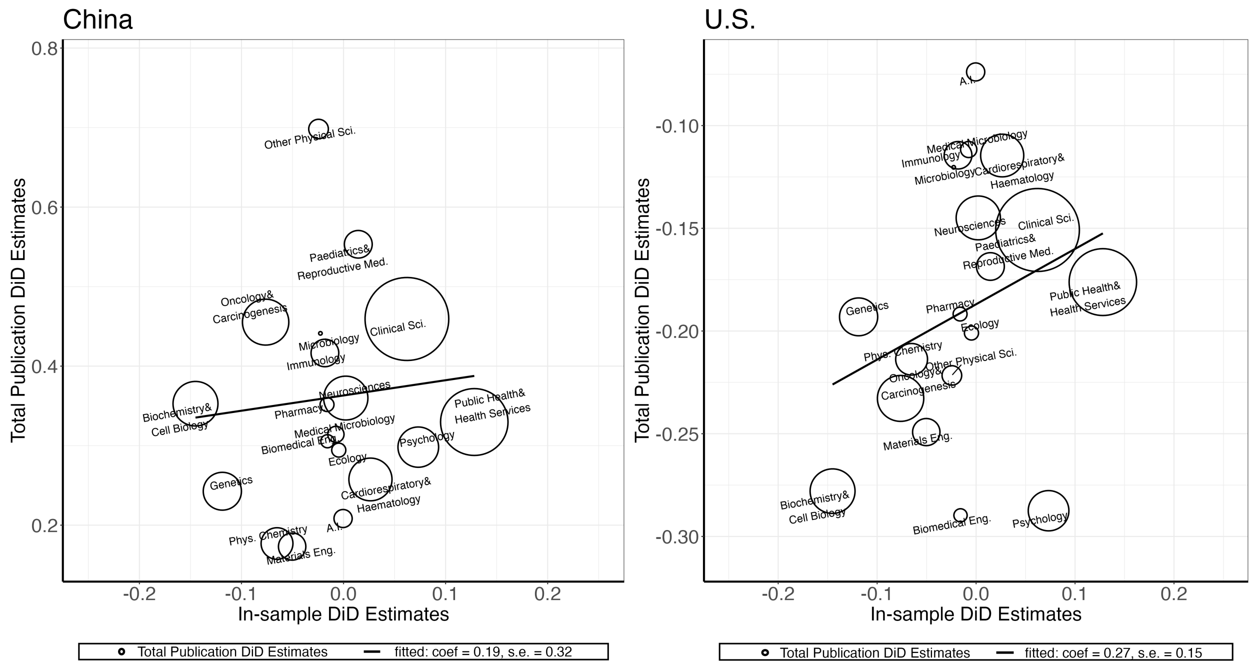
where $Y_{c,t}$ is the logged total number of publications in the field for country c in year t.[17] $China$ is an indicator for China and US is an indicator for the U.S. We include country-level fixed effects (α_c) and year fixed effects (ξ_t). For each field f, we then extract the estimate $\beta_{f,China}$ and $\beta_{f,US}$ as an estimate of how China and the U.S., respectively have fared in terms of productivity during 2019–2020 in comparison to the rest of the world.

Figure 6 shows the correlation between the estimates of the impact of NIH investigations on citations (x-axis) and the estimates on research progress based on the difference-in-differences design. This correlation can be interpreted as the elasticity of the scientific

[16] We use the 2021 Nature Index (`https://www.natureindex.com/annual-tables/2021/country/all`) to select these 50 countries.

[17] To calculate the number of publications by field, country, and year, we queried Dimensions for total publications by country, year, and field. These totals thus reflect overall publications in the field, not just publication numbers by the scientists in our data described above.

FIGURE 6. CITATION ESTIMATES VS. PROGRESS BY FIELD IN U.S. AND CHINA



Note: Each dot represents a field. The X-axis is the estimated treatment effects on citations and the Y-axis is the estimated post-treatment research progress for China and the U.S., relative to the other 48 countries and the pre-treatment period. The figure shows the relationship between how much treated scientists' publication citations in a field are impacted by the investigations (x-axis) and how much U.S. and China's overall publications in that field are impacted. The sample is restricted to fields with greater than $50,000$ publications in the data.

progress of the U.S. (and China) in response to the impacts of the investigations. As shown, there exists a positive correlation between our estimates and the increases in publications by field, indicating that the fields that are more affected by the U.S.-China political tensions have produced fewer new publications during 2019 and 2020 relative to the rest of the world. Interestingly, this positive relationship holds for both the U.S. and China, suggesting that both countries appear to lose from these political tensions. The slope is 0.29 for the U.S. and 0.26 for China and is more precisely estimated for the U.S. Therefore, if anything, the loss of the U.S. appears to be more sensitive to the impacts of the investigations.

5. Discussion Based on Interviews

As a design complementary to our quantitative analyses, we have interviewed 12 scientists about their experience and perspectives.[18] The majority of the scientists we talked to had previous, existing or planned research collaborations with scientists in China. These interviews help us better understand underlying mechanisms for our finding that scholars with previous collaborations with China have seen a decrease in publications related to the life sciences and overall quality of publications following the NIH investigations.

Overwhelmingly, the scientists we interviewed felt affected by the investigations and recent U.S.-China tensions, and were reluctant to start new or continue existing collaborations with institutions in China. Most of the scientists reported that their research had been negatively affected by the investigations. For some scientists, the investigations had a direct effect on their research productivity. Two scientists we interviewed had had their NIH funding suspended for several years as a direct result of the investigations. This direct effect had a clear negative impact on their research, and in one case forced them to all but close their lab.

Even for those who were not directly affected by the investigations, some scientists saw a tradeoff between applying for U.S. government funding and continuing their international collaborations with institutions in China. These scientists reported that although they could technically continue their collaborations with U.S. government funding, doing so was risky as any mistake in reporting might be subject to intense scrutiny. Continuing collaborations with institutions in China, they reported also had a new costly administrative overhead, including frequently consulting with their university's administration to navigate constantly changing regulations about collaboration. They, therefore, felt they had to choose between access to U.S. research dollars and their collaborations with scientists in China.

This new reticence to stop or wind down collaborations with research groups in China

[18] These interviews were approved by the UC San Diego Institutional Review Board.

was costly to productivity in several ways. Several scientists mentioned that the loss of collaboration with institutions in China meant loss of access to human capital, labs, and machines that were essential for their current work. Several scientists who we interviewed directly relied on equipment and labs in China as an input to their work. Many of the scientists reported using their collaborations as a way to recruit talented graduate students and postdocs.

Ceasing to collaborate with researchers in China often required U.S. researchers to change their research direction. Several mentioned that they were pursuing new research directions as a result of the policies. Two mentioned that they had felt that their best research had been conducted with their colleagues in China and they worried that their future work in the absence of these collaborations would be less impactful.

We found that scientists with Chinese heritage experienced this chilling effect more acutely than those without. The few scientists we interviewed who felt that their research had not been affected much by recent tensions were not of Chinese heritage. Several scientists we interviewed who were of Chinese heritage reported feeling under increased scrutiny because of their ethnicity.

These qualitative discussions support the findings from our quantitative investigations and reveal that the scientists are affected in multiple dimensions. Consistent with our finding on the aggregation implications by fields, the scientists in our interviews also conjecture that these investigations have negative impacts beyond their own productivity. Importantly, most of them reported that they believe U.S.-China tensions are likely to last and thus have consequences in the long run. While the China Initiative has officially ended, funding agencies' investigations of researchers are ongoing and universities' policies with respect to collaborations with scientists in China is still in flux. We hope that our study serves as a first step to understanding the consequences of the ongoing political tensions and opening up new avenues for future research.

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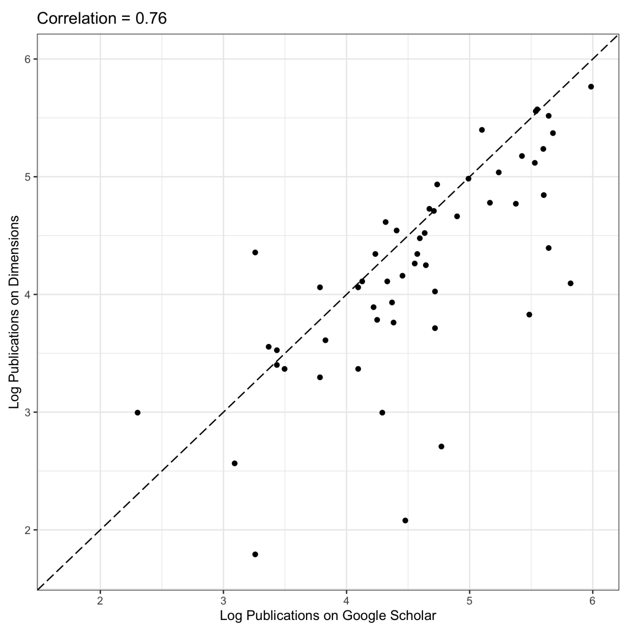
A. Supplementary Materials

A.1. Data Validation

A.1.1. Publication Data Validation

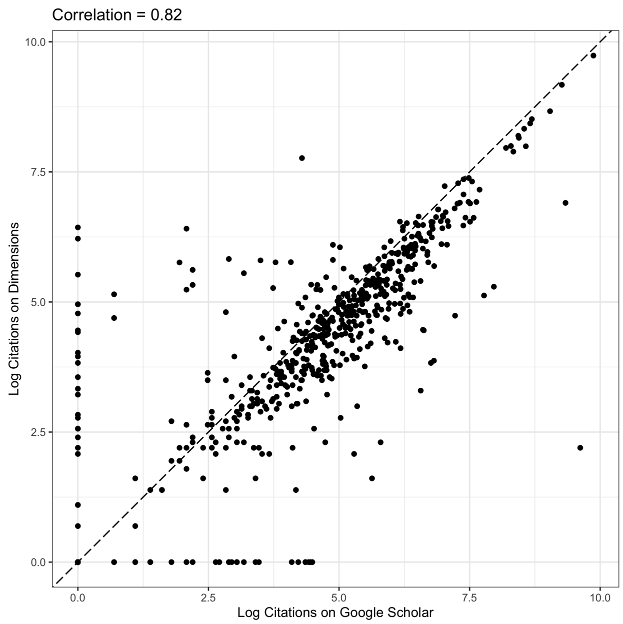
Figure A1. Correlation of Publication Data Between Dimensions and Google Scholar



Note: Each dot represents an author. The X-axis is logged number of publications in 2010-2020 from Google Scholar and the Y-axis is logged number of publications in 2010-2020 from Dimensions. Dashed line is the 45 degree line representing perfect correlation. The sample is based on 54 match authors and for the period 2010-2020.

A.1.2. Citation Data Validation

FIGURE A2. CORRELATION OF AUTHOR-YEAR CITATION DATA BETWEEN DIMENSIONS AND GOOGLE SCHOLAR



Note: Each dot represents an author-year. The X-axis is logged number of citations in from Google Scholar and the Y-axis is logged number of citations from Dimensions. Dashed line is the 45 degree line representing perfect correlation. The sample is based on 54 match authors and for the period 2010-2020.

A.2. Predicting Asian Surnames using Imai and Khanna (2016)

We predict the ethnicity of each scientist in our sample using the methodology developed by Imai and Khanna (2016). The authors construct their training set by combining Census Bureau's Surname List with various information from voter registration records. They then use Bayes' rule to predict the posterior probability of each individual with given demographic information to belong to each of the five ethnic groups: White, Black, Hispanic, Asian and Other. We implement the method using the R package *wru*, which generates probability estimates for each surname in our sample. The most frequent surnames that are considered Asian by the method include *Wang* (578), *Chen* (447), and *Zhang* (400). It is worth noting that the method cannot distinguish Chinese surnames from other Asian surnames. Hence, the most common Asian surnames also include Korean ones (e.g. *Kim*) or South Asian ones (e.g. *Singh*).

A.3. Outcome with Inverse Hyperbolic Sine Transformation

Impacts on Productivity: Inverse Hyperbolic Sine Transformation

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	PubMed Publications			PubMed Citations		
Ties to China × Post	-0.022	-0.021	-0.022	-0.102	-0.058	-0.061
	(0.004)	(0.004)	(0.006)	(0.009)	(0.010)	(0.012)
Pre-treatment avg.	1.968	1.968	1.968	4.753	4.753	4.753
R2	0.744	0.744	0.797	0.675	0.675	0.721
No. of obs.	616812	616812	616812	616812	616812	616812
Scholar FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Baseline Covariates*Year FE		Y			Y	
Entropy Balancing			Y			Y
Panel B	Non-PubMed Publications			Non-PubMed Citations		
Ties to China × Post	0.043	0.022	0.022	-0.044	-0.054	-0.049
	(0.004)	(0.005)	(0.010)	(0.007)	(0.008)	(0.020)
Pre-treatment avg.	1.286	1.286	1.286	1.660	1.660	1.660
R2	0.682	0.686	0.726	0.673	0.677	0.680
No. of obs.	616812	616812	616812	616812	616812	616812
Scholar FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Baseline Covariates*Year FE		Y			Y	
Entropy Balancing			Y			Y
Panel C	Total Publications			Total Citations		
Ties to China × Post	0.004	-0.004	-0.007	-0.083	-0.060	-0.060
	(0.004)	(0.005)	(0.007)	(0.008)	(0.009)	(0.012)
Pre-treatment avg.	2.428	2.428	2.428	5.096	5.096	5.096
R2	0.760	0.761	0.805	0.691	0.691	0.732
No. of obs.	616812	616812	616812	616812	616812	616812
Scholar FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Baseline Covariates*Year FE		Y			Y	
Entropy Balancing			Y			Y

Note: All outcomes are transformed with inverse hyperbolic sine. For Columns (1) to (6), the models always control for scholar and year fixed effects. In Columns (2) and (5), we include the interactions between year dummies and four baseline covariates: 1) total number of publications in 2010-2014, 2) total citations in 2010-2014, 3) number of NIH-funded publications in 2010-2014, and 4) indicator for Asian researcher. In Columns (3) and (6), we use entropy balancing to balance all four covariates before running the regression. Standard errors are clustered at the scholar level.

A.4. Citation Effects by Funding Sources

	Citation Effects by Nature of Publication				
	All	NIH-Funded	Non NIH-Funded	China-Funded	Non China-Funded
Ties to China × Post	-0.071	-0.071	-0.036	-0.157	-0.059
	(0.008)	(0.009)	(0.009)	(0.005)	(0.008)
Pre-treatment avg.	4.48	2.666	3.264	0.759	4.353
R2	0.704	0.712	0.683	0.657	0.698
No. of obs.	616812	616812	616812	616812	616812
Scholar FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Baseline Covariates*Year FE	Y	Y	Y	Y	Y

Note: In all columns, outcomes are log-transformed and we control for scholar and year fixed effects, as well as the interactions of year dummies with the baseline covariates: 1) total number of publications in 2010-2014, 2) total citations in 2010-2014, 3) number of NIH-funded publications in 2010-2014, and 4) indicator for being Asian researcher. Standard errors are clustered at the scholar level.

A.5. Effects by Collaboration Types

	Effects by Collaboration Types					
	U.S. Publications	Intl (Non-China) Publications	China-Collab Publications	U.S. Citations	Intl (Non-China) Citations	China-Collab Citations
Ties to China × Post	0.010	-0.014	-0.049	-0.016	-0.100	-0.421
	(0.004)	(0.003)	(0.002)	(0.009)	(0.009)	(0.007)
Pre-treatment avg.	1.533	0.852	0.417	3.372	2.549	1.402
R2	0.738	0.682	0.748	0.653	0.592	0.654
No. of obs.	616812	616812	616812	616812	616812	616812
Scholar FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Baseline Covariates*Year FE	Y	Y	Y	Y	Y	Y

Note: In all columns, outcomes are log-transformed and we control for scholar and year fixed effects, as well as the interactions of year dummies with the baseline covariates: 1) total number of publications in 2010-2014, 2) total citations in 2010-2014, 3) number of NIH-funded publications in 2010-2014, and 4) indicator for being Asian researcher. Standard errors are clustered at the scholar level.

A.6. Fields with Highest % of U.S.-CN Collaboration

Field Name	Percentage
Materials Engineering	15.0 %
Physical Chemistry (incl. Structural)	12.5 %
Artificial Intelligence and Image Processing	10.0 %
Genetics	7.8 %
Microbiology	7.3 %
Biochemistry and Cell Biology	6.6 %
Biomedical Engineering	5.5 %
Oncology and Carcinogenesis	5.1 %
Other Physical Sciences	5.0 %
Immunology	4.9 %
Ecology	4.6 %
Medical Microbiology	4.5 %
Pharmacology and Pharmaceutical Sciences	4.4 %
Neurosciences	3.9 %
Cardiorespiratory Medicine and Haematology	2.6 %
Psychology	2.2 %
Clinical Sciences	2.2 %
Public Health and Health Services	2.0 %
Paediatrics and Reproductive Medicine	1.7 %

A.7. Fields with Highest % of NIH Funding

Field Name	Percentage
Biochemistry and Cell Biology	54.3 %
Medical Microbiology	47.4 %
Immunology	47.3 %
Neurosciences	41.8 %
Genetics	41.5 %
Psychology	31.9 %
Biomedical Engineering	28.9 %
Pharmacology and Pharmaceutical Sciences	27.5 %
Microbiology	27.0 %
Cardiorespiratory Medicine and Haematology	24.1 %
Public Health and Health Services	23.9 %
Clinical Sciences	18.6 %
Paediatrics and Reproductive Medicine	18.2 %
Artificial Intelligence and Image Processing	14.7 %
Oncology and Carcinogenesis	14.4 %
Other Physical Sciences	12.0 %
Physical Chemistry (incl. Structural)	9.7 %
Materials Engineering	4.6 %
Ecology	4.1 %