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BUILDING A WALL AROUND SCIENCE: THE EFFECT OF U.S.-CHINA TENSIONS ON INTERNATIONAL SCIENTIFIC RESEARCH

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ABSTRACT

This paper examines the impact of rising U.S.-China geopolitical tensions on three main dimensions of science: STEM trainee mobility between these countries, usage of scientific works between scientists in each country, and scientist productivity in each country. We examine each dimension from a “U.S.” perspective and from a “China” perspective in an effort to provide evidence around the asymmetric effects of isolationism and geopolitical tension on science. Using a differences-in-differences approach in tandem with CV and publication data, we find that between 2016 and 2019 ethnically Chinese graduate students became 16% less likely to attend a U.S.-based Ph.D. program, and that those that did became 4% less likely to stay in the U.S. after graduation. In both instances, these students became more likely to move to a non-U.S. anglophone country instead. Second, we document a sharp decline in Chinese usage of U.S. science as measured by citations, but no such decline in the propensity of U.S. scientists to cite Chinese research. Third, we find that while a decline in Chinese usage of U.S. science does not appear to affect the average productivity of China-based researchers as measured by publications, heightened anti-Chinese sentiment in the U.S. appears to reduce the productivity of ethnically Chinese scientists in the U.S. by 2-6%. Our results do not suggest any clear “winner,” but instead indicate that increasing isolationism and geopolitical tension lead to reduced talent and knowledge flows between the U.S. and China, which are likely to be particularly damaging to international science. The effects on productivity are still small but are likely to only grow as nationalistic and isolationist policies also escalate. The results as a whole strongly suggest the presence of a “chilling effect” for ethnically Chinese scholars in the U.S., affecting both the U.S.’s ability to attract and retain talent as well as the productivity of its ethnically Chinese scientists.

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1 Introduction

Over the past few decades, the production of science has become increasingly geographically distributed and interconnected. Graduate students in countries like the U.S., the U.K., and Canada are increasingly born abroad (Bound, Turner and Walsh, 2009; Freeman, 2013) and scientists are a notably mobile group (Franzoni, Scellato and Stephan, 2012). For instance, the percentage of science and engineering Ph.D. degrees granted by U.S. universities earned by foreign-born individuals has nearly doubled since the 1980s, now accounting for 39% of all science and engineering Ph.D. graduates coming out of the United States (NSF NCSES). The diffusion of knowledge and ideas has correspondingly become more international, in large part driven by diaspora networks (Kerr, 2008; Oettl and Agrawal, 2008; Miguelez, 2018), while publications with authors from multiple countries now account for 23% of global publications and 40% of U.S.-based publications (NSF NCSES). Furthermore, there is growing evidence that international collaboration and talent flows lead to higher-impact science (e.g. Hsiehchen, Espinoza and Hsieh, 2015; Freeman and Huang, 2015) while access to frontier knowledge–regardless of its geographic location–is critical for scientific progress (Iaria, Schwarz and Waldinger, 2018).

As science becomes more international, however, it becomes more susceptible to international conflicts and geopolitical tensions. As we know from history, international conflict can deeply negatively impact science. World War I, for instance, led to a reduction in international knowledge flows, reduced international scientific cooperation, and a decline in the productivity of scientists who relied on frontier knowledge from abroad (Iaria, Schwarz and Waldinger, 2018). The expulsion of professors from Germany in the years leading up to World War II changed the trajectory of U.S. science (Moser, Voena and Waldinger, 2014) and damaged German Ph.D. student outcomes (Waldinger, 2010). More recently, the Russian invasion of Ukraine has led to a decline in Ukrainian scientist productivity and has hindered the exchange of scientific knowledge and ideas (Ganguli and Waldinger, 2023).

But broad geopolitical tensions may be different from outright war in the ways in which science is affected. Unlike with warfare, in the presence of geopolitical tension, scientists are not typically forcibly expelled or killed, physical capital is not typically damaged, and cross-border collaborations are often still permitted. Instead, any changes are likely to be driven by a mix of explicit government policy that targets particular foreign groups, where it exists, and nationalist or targeted anti-foreign sentiment. The degree to which such sentiment may affect the production of science–and whether there are important asymmetries in terms of how seriously science in different countries is affected–is not well understood. One might expect that negative sentiment towards foreigners from a particular geopolitical "enemy" could influence whether those individuals are still interested in staying or moving to the country, or whether they'd rather go to a country without such negative sentiment towards them. Such changes in mobility might be most pronounced among the young trainee scientists that make up the largest flow of scientific talent, both when locating to their doctoral program and in choosing their first post-doctoral job. Relatedly, any changes in mobility flows, communication, or collaboration due to increased hostility are likely to also influence the degree to which knowledge can flow between countries. Finally, scientist productivity is likely to be affected, both if negative sentiment reduces available funding and collaboration opportunities or creates a hostile environment in which it is difficult to be productive, and if there is disruption in cross-border knowledge diffusion and information transfer. In short, geopolitical tensions–both those stoked by explicit policies and those stoked by growing negative sentiment–might influence mobility and retention of trainee scientists, the scientific works that scientists are exposed to and can build on, and their resultant productivity.

In recent years, one particular source of geopolitical tension–that between the U.S. and China–has received particularly close attention. In this paper, we examine the impact of the rising geopolitical tensions between the two countries on three dimensions of science–trainee mobility and retention, cross-border knowledge flows, and scientist productivity–using a difference-in-differences style empirical design. Importantly, we examine each dimension from both a "U.S." perspective and from a "China" perspective. Many of the policies tied up in the rise of tensions between the U.S. and China, as will be described in more detail later, were driven by an inherently nationalistic motivation to reduce reliance on the other country and, in the process, to strengthen each country's scientific capabilities. Our goal in examining the impact on each country is to begin to identify whether each country "won" or "lost" in the years since 2016, providing some evidence around the asymmetric effects on science of isolationism and geopolitical tensions.

To quantify the impact of U.S.-China tensions on these three dimensions, we rely on rich data from a collection of publicly posted CVs on ORCID (Open Research and Contributor ID), a website where academics can create and share a digital CV, allowing us to track the employment and education history of researchers. Critically, these data allow us to examine mobility for scientists at early stages of their career, even before they have produced any publications. In addition, we utilize bibliometric data from Dimensions, a database of the metadata from scientific publications, enabling us to track knowledge flows using citation data and changes in scientists' publication productivity over time. In all analyses, we focus on STEM research and trainees given the particular focus of the

American and Chinese governments on STEM.

Understanding the impact of U.S.-China tensions on science is particularly important given that the relationship between the U.S. and China, until recently, was arguably one of the most important scientific relationships in the world. About a third of visa holders enrolled in U.S. Science and Engineering Ph.D. programs are from China (NSF NCSES) while a quarter of U.S.-based Science and Engineering publications have at least one author based in China (NSF NCSES). But around 2016, that relationship began to come undone, as we document in more detail in Section 2. In particular, statements by individuals associated with the Trump campaign, formal policies enacted by the Trump administration, and legal investigations into ethnically Chinese scientists significantly impacted ethnically Chinese scientists in the U.S. A 2021 survey found that 50.7% of Chinese scientists (as defined by ethnicity, regardless of citizenship)–as compared to 11.7% of non-Chinese scientists–reported considerable fear of U.S. government surveillance, which had both affected their plans to stay in the U.S. and their willingness to work with scientists in China (Lee and Li, 2021). At the same time, anti-Chinese sentiment among U.S. adults ticked up from around 55% in 2015 to 66% in 2020 according to the Pew Research Center. In our analysis, we study the impact of this shift in policy and sentiment. We consider the "treatment" to begin in 2016, but we are careful to include dynamic treatment effects to account for the fact that tensions gradually escalated over several years, rather than the treatment being encapsulated in one discrete policy change.

It is important to recognize that the escalation of tensions between the U.S. and China was not solely instigated by the United States. From the outset, the Xi administration adopted a markedly nationalist stance.[1] In turn, many of the U.S. policies emerged as countermeasures to China's practices of forced technology transfers and corporate espionage. However, these measures by the Chinese government were not overtly aimed at the U.S. until recently. Consequently, it appears that the fundamental shift in dynamics primarily stems from changes in U.S. policy.

We employ a difference-in-differences empirical design to quantify the impact of these growing U.S.-China tensions on trainee mobility and retention, knowledge flows, and scientist productivity. Such an approach is critical given the concurrent development of Chinese science during this period. Simply estimating the correlation between U.S.-China geopolitical tensions and, for example, the propensity of Chinese students to study or work in the U.S., could lead to bias; as Chinese science continues to advance, prospective Chinese Ph.D. students may become more likely to stay in or return to China. Hence, for

[1] Made in China 2025, a national strategic plan and industrial policy that aims to achieve independence from foreign suppliers is one of the clearest examples of this policy shift.

each major component of our analysis, we are careful to both select an appropriate control group and to show an event-study plot to examine whether there is a clear trend break around 2016.

Our results and analysis are presented in three sections. In the first part of the article, we focus on trainee mobility and retention. Specifically, we examine whether ethnically Chinese prospective graduate students enroll less in U.S.-based graduate programs (mobility) and then whether they are less likely to stay in the U.S. after graduation if they do attend a U.S.-based graduate program (retention). Here, our treatment group is ethnically Chinese trainees and our control group is non-ethnically Chinese trainees. The choice to focus on ethnically vs. non-ethnically Chinese individuals allows for explicit examination of the effect of anti-Chinese sentiment–as opposed to particular policy changes–on trainee mobility and retention; none of the policies during our time-frame explicitly ban ethnically Chinese trainee scientists. We show that ethnically Chinese graduate students became both less likely (16%) to attend a U.S.-based graduate program and, if they did attend a U.S.-based graduate program, 4% less likely to stay in the U.S. after graduation. In both instances, these students become more likely to move to a non-US anglophone country instead. The results extend to ethnically Chinese students who are not actually from China, suggesting that an important mechanism is a chilling effect resulting from the anti-Chinese sentiment in the U.S.

In the second part of the article, we examine the impact of growing U.S.-China geopolitical tensions on cross-border knowledge flows in both directions. Specifically, we examine whether Chinese scientists become less likely to use scientific research produced by U.S. authors and whether U.S. scientists become less likely to use scientific research produced by Chinese authors. In both cases, the U.K. is the control group.[2] We document a sharp decline in Chinese reliance on U.S. science as measured by citations. Specifically, among Chinese publications, the share of references citing U.S. research declined by about 4-6% after 2016. The impact is more striking for the share of citations to recently published articles, where the share of citations on Chinese publications to U.S. publications declined by 10-12%. However, the decline in cross-border knowledge flows appears to be asymmetric; we see no such decline in the propensity of U.S. scientists to cite Chinese research.

Finally, in the third part of the article, we study the effect on scientist productivity in China and in the U.S. On the China side, we compare the publication counts of "U.S.-reliant" China-based scientists to matched "U.K.-reliant" China-based scientists before and after 2016. Here, we expect China-based scientists that had predominantly built on U.S. scientific work to be the most impacted by growing tensions, given our knowledge

[2]We describe in more detail the choice of the U.K. as a control group in Section 4.

flows results. Surprisingly, however, we find no statistically significant decrease in the amount of scientific output of previously "U.S.-reliant" China-based scientists relative to those who had heavily utilized U.K. science. On the U.S. side, we compare publication counts of ethnically Chinese, U.S.-based scientists to matched non-ethnically Chinese, U.S.-based scientists before and after 2016. The choice to compare ethnically Chinese to non-ethnically Chinese scientists reflects the view that ethnically Chinese scientists in the U.S. are particularly deeply impacted by the growing U.S.-China tensions. In particular, the United States Department of Justice's (DOJ) investigations into ethnically Chinese scientists during the China Initiative and general anti-Chinese sentiment in the U.S. may have impacted the ability of these scientists to continue to be productive. Indeed, we find that the scientific productivity for ethnically Chinese U.S.-based researchers declined by 2-6% relative to the matched non-ethnically Chinese researchers after 2016, suggesting a chilling effect in the U.S.

Our paper builds on existing work on the effect of the China Initiative, an important policy launched in 2018. Specifically, Aghion et al. (2023) and Jia et al. (2022) examine the effect of the China Initiative on the productivity of researchers in China and in the U.S. respectively, with particular emphasis on the mechanism of cross-border collaboration. We contribute to–and differ from–this work in four ways. First, while the aforementioned papers focus on one-sided productivity effects (China alone and the U.S. alone respectively), we explore two-sided effects (the U.S. side and the China side), allowing some evaluation of asymmetries in the ways in which each country's scientific communities are impacted. Second, while we also examine the impact on scientist productivity, we explore different mechanisms: the channels of reduced knowledge flows and of being ethnically Chinese. Third, we also consider the impact on two other key dimensions of science beyond productivity: mobility and knowledge diffusion. Hence, while the emphasis of these earlier papers was on cross-border collaboration, this paper focuses on cross-border human capital and knowledge flows. And fourth, we go beyond the evaluation of the China Initiative to explore the effect of tensions more generally. Our results suggest that a chilling effect on science actually began before the China Initiative formally started, indicating that geopolitical tensions in the absence of formal targeted programs can impact science.

More generally, this paper is related to the broader literature on the effect of war, conflict, and geopolitics on science. We know that major geopolitical events can disrupt international knowledge flows and reduce scientific productivity, as in the case of World War I (Iaria, Schwarz and Waldinger, 2018) or the collapse of the Soviet Union (Abramitzky and Sin, 2014). But what is less clear, and which our results shed light on, is whether general hostility at a scale much lower than either of those events is also likely to have an impact. Our results suggest that it is not just major geopolitical events like war that can disrupt international science; growing nationalist and anti-foreign sentiment can also have a significant impact.

With regard to mobility, prior work has shown that war and conflict cause large emigration flows of academics for instance during World War II (Waldinger, 2012; Becker et al., 2021), after the collapse of the Soviet Union (Borjas and Doran, 2012; Ganguli, 2017), and more recently during Russia's invasion of Ukraine (Ganguli and Waldinger, 2023). Our results build on this literature by showing, as referenced above, that even geopolitical tensions at a much lower level than the formal expulsion of academics or violent warfare can lead to a significant shift in scientist mobility. In addition, while existing work has shown that these types of tensions can result in scientist exit, ours indicates that it can also result in fewer immigrant scientists in the focal countries more generally. Given the large literature linking immigrants to innovation (Bernstein et al., 2022; Hunt and Gauthier-Loiselle, 2010; Moser and San, 2020) and the evidence indicating disastrous long-run effects on universities in the sending countries (Waldinger, 2016) and positive ones on universities and science in the receiving countries (Agrawal, McHale and Oettl, 2017), a shift in where scientists migrate to has major implications for the global geography of science.

Our findings also have significant policy implications. The U.S. and China are currently discussing whether to renew the 45-year-old U.S.-China Science and Technology Cooperation Agreement, which has fostered the close scientific relationship between the two countries since 1979. Our results suggest that further deterioration of this relationship would lead to a loss of young Chinese talent on the U.S. side, reduced access to frontier knowledge on the Chinese side, and a hit to scientific productivity. More generally, as isolationism and geopolitical tensions beyond these two countries continue to increase around the world, our results provide a compass regarding expected broader effects on talent and knowledge flows.

2 Empirical Context

Our study focuses on the years around a significant negative shift in U.S.-China relations. Formal scientific cooperation between the two nations has existed since 1979, when Jimmy Carter and Deng Xiaoping signed the U.S.-China Science and Technology Cooperation Agreement. Today, each country is the other's largest scientific research partner, and three million students from China have studied in the United States (USCET, 2023). However, starting around 2015-2016, the relationship began to deteriorate.

First, the Trump presidential campaign in 2015 and 2016 focused heavily on anti-Chinese sentiment. Indeed, Donald Trump's book Great Again: How to Fix Our Crippled America, which outlined his political agenda, included quotes such as "there are people who wish I wouldn't refer to China as our enemy. But that's exactly what they are. They have destroyed entire industries...cost us tens of thousands of jobs, spied on our businesses, stolen our technology, and have manipulated and devalued their currency." The Trump administration ushered in a transformation in U.S. policy towards China, built on the view that China's rise came at the expense of the United States.

Second, formal policies enacted by the Trump administration increased political and economic tensions between the two countries. In 2018, the Trump administration began setting tariffs on Chinese goods with the goal of reducing the U.S.-China trade deficit and reducing Chinese intellectual property (IP) theft and technology transfer. In response, the Chinese government took retaliatory action, accusing the Trump administration of nationalist protectionism in violation of World Trade Organization (WTO) rules. Tit-for-tat retaliatory measures continued until January 2020 although the tariffs continue to be in place. Although the U.S.-China Trade War was not focused on science explicitly, it amplified economic tensions and negative sentiment more generally and was at least in part a response to the concern that China was stealing American IP.

Finally, and perhaps most relevant to this paper, legal investigations by the FBI and the U.S. DOJ into Chinese and Chinese-American scientists under suspicion of IP theft on behalf of the Chinese government began to take off during this time frame as well. In 2015, for example, seven Chinese and Chinese-American scholars were arrested under suspicion of espionage on behalf of the Chinese government, most notably Xiaoxing Xi, a prominent physicist at Temple University who was later found to be innocent.[3] Starting in 2018, DOJ prosecution of perceived Chinese spies in U.S. research was formalized into a policy known as the "The China Initiative". As the FBI Director stated about the program, "the Chinese government doesn't play by the same rules of academic integrity and freedom that the U.S. does. We know they use some Chinese students in the U.S. as non-traditional collectors of our intellectual property. We know that through their 'Thousand Talents Plan' and similar programs, they try to entice scientists at our universities to bring their knowledge to China." Under the initiative, the DOJ brought charges against 162 defendants according to the MIT Technology Review[4], but after significant criticism that the program used racial profiling and was biased against researchers of Chinese de-

[3] For more detail, see https://www.nytimes.com/2015/05/20/technology/6-chinese-men-indicted-in-theft-of-code-from-us-tech-companies.html and https://www.science.org/content/article/chinese-american-physicist-pleads-not-guilty-technology-theft

[4] https://www.technologyreview.com/2021/12/02/1040656/china-initative-us-justice-department/

scent, it was shut down in 2022. In addition, the FBI barred some Chinese scholars from entering the U.S. altogether[5] and revoked some Chinese student visas.[6] These actions heightened fears about either being a Chinese scientist working in the U.S. or being an American scientist collaborating with Chinese colleagues.

Consistent with this series of events, anti-Chinese sentiment in the U.S. increased substantially starting around 2016 and climbed through the subsequent years. According to the Pew Research Center, anti-Chinese sentiment ticked up from around 55% in 2015 to 66% in 2020 as shown in Figure 1 below.

The changing policy environment and sentiment had a particularly striking impact on the experience of ethnically Chinese scientists working in the U.S. A 2021 survey found that 50.7% of Chinese scientists (as defined by ethnicity, regardless of citizenship)–as compared to 11.7% of non-Chinese scientists–reported considerable fear of U.S. government surveillance, which had both affected their plans to stay in the U.S. and their willingness to work with scientists in China (Lee and Li, 2021). A survey of U.S.-based scientists of Chinese descent found that 72% "do not feel safe as an academic researcher"; 42% are "fearful of conducting research"; and 61% have thought about leaving the United States (Xie et al., 2023). In yet another survey, this one focused on the career plans of Chinese graduate students, the authors found that 34.8% of Chinese students (compared to 17.6% for non-Chinese students) had "experienced professional challenges as a result of race/nationality/country of origin" (Houlette, Lee and Li, 2023). Faculty protests against investigations of Chinese scholars cited concerns regarding a growing "chilling effect" on academic research by creating a hostile environment for Chinese and Chinese-American researchers in the U.S.[7]

Importantly, these changes have not been entirely one-sided. Many of the U.S. policies were a response to, for example, forced technology transfer in China and significant corporate espionage by China in the United States.[8] The Chinese government has also implemented a wide range of nationalist policies intended to improve self-reliance. For example, the Thousand Talents Program, which began to develop in the early 2000s, and the Junior Thousand Talents Program, implemented in 2013, have long aimed to encourage Chinese (senior and junior, respectively) academics to return to China from abroad. As a more recent example, in March 2020, China's government changed its incentive scheme for academics in China to no longer encourage publication in international journals. But

[5] https://www.nytimes.com/2019/04/14/world/asia/china-academics-fbi-visa-bans.html

[6] https://www.nytimes.com/2018/07/25/us/politics/visa-restrictions-chinese-students.html

[7] See, for example, letters by faculty at Stanford, Yale, University of Pennsylvania, and Princeton.

[8] See for example https://www.nytimes.com/2017/08/01/business/trump-china-trade-intellectual-property-section-301.html

these policies have typically not targeted the U.S. explicitly in the same way until recently, and they have been of a more gradual nature. As a result, we view the primary change in treatment, and the significant increase in geopolitical tensions, to be originating on the U.S. side.

In our analysis, we study the impact of the growing U.S.-China tensions and growing anti-Chinese sentiment in the U.S. that we describe above on STEM science and scientists. As is apparent from the description in this section, there was no singular discrete change, and so while we consider the policy "treatment" to begin in 2016, we are careful to include dynamic treatment effects to account for the fact that tensions gradually escalated over several years.

3 Data

Our analysis investigates how the rise of U.S.-China tensions starting in 2016 impacted STEM trainee mobility (graduate student enrollment and retention), usage of scientific works, and scientific productivity in STEM fields. For the first two outcomes, we utilize data from curriculum vitae (CVs) posted on Open Research and Contributor ID (ORCID), a website where academics can publicly post their CV in a standardized format. For the latter two outcomes, we utilize datasets constructed from data about scientific publications listed in Dimensions, a database with metadata about the near-universe of scientific works published in academic journals. From those two raw data sources (CV data and Publications data), we construct six datasets for our analysis. Figure 3 provides an overview of these constructed datasets while Table 1 provides summary statistics for each. Details about their construction is provided below.

3.1 CV Data

We construct two datasets from the curriculum vitaes (CVs) available on ORCID. Each CV in ORCID includes an individual's name as well as their self-reported educational background and employment history.

Utilizing the information on these CVs, we constructed additional variables for our analysis. We marked if and when the individual enrolled in a degree program, if this program was in the U.S., if this program was at the doctoral level, and whether the individual held a job in the U.S. immediately after studying at a U.S. institution. In addition, we assigned them an academic field based on their department affiliation and inferred based on their name if they were of Chinese ethnicity. Details of the procedures for determining field and inferring ethnicity are provided in Appendix A.4.

The ORCID website contains over 14 million CVs. We collected the publicly available

CVs posted on the site as of 2022. We restricted to individuals reporting complete educational backgrounds, which amounts to 1.8 million CVs. We further restrict to those who graduated from STEM programs, a total of 836,495 CVs.[9]

We call the set of individuals who entered doctoral programs between 2008 and 2019 the *Doctoral Student dataset*. Additionally, we require these individuals to have listed at least one prior degree pursued before doctoral study[10]. This dataset includes 128,928 individuals, 16% of whom are ethnically Chinese.

We call the set of individuals who take jobs after graduating from U.S. institutions between 2008 and 2019 the *U.S. Graduates dataset*. We further require these individuals to have received their U.S. degree less than three years before starting their job. That dataset contains information about 50,890 individuals, 18% of whom are ethnically Chinese.

Tables 1a and 1b present simple descriptions of these data. We use these two datasets to track the enrollment of new students into doctoral programs as well as the jobs taken by graduates of U.S. institutions.

The Doctoral Student and U.S. Graduates datasets represent a selected subset of all doctoral students and graduates from these countries and time period. As individuals need to actively sign up to use the ORCID service and fill out a digital CV on the site, the individuals represented in our Doctoral Student and U.S. Graduates datasets are likely to be those who are particularly research active rather than a truly representative sample. Appendix Table A3 makes this clear by comparing the number of publications as well as the probability of having grant funding on publications for authors with ORCID iDs versus those without. As shown in that table, authors with ORCID iDs generally perform stronger on a variety of research measures, including producing publications and earning grants. While our sample is not representative of all doctoral students and graduates, for our analysis we are most interested in the individuals who are most likely to contribute to future science. Therefore, focusing on this group of students and graduates is useful for this purpose.

Given the importance of ethnically Chinese scientists in this paper, we might be concerned that ORCID users who are ethnically Chinese differ from those who are not ethnically Chinese, and specifically, that they might have noticeably different research outcomes prior to the onset of rising tensions in 2016. Appendix Table A3 shows the mean attributes of these two groups. Reassuringly, while ethnically Chinese researchers also

[9]The following 11 fields are considered STEM: Agriculture, Biological Sciences, Biomedical and Clinical Sciences, Chemical Sciences, Earth Sciences, Engineering, Environmental Sciences, Health Sciences, Information and Computing Sciences, Mathematical Sciences, and Physical Sciences (Australian Bureau of Statistics, 2020; Porter, Hawizy and Hook, 2023)

[10]As we will show later, this is important for being able to infer nationality.

appear to achieve stronger research outcomes, we do not observe interactions between ORCID self-selection and being ethnically Chinese.

3.2 Publications Data

We construct three datasets using the bibliometric information about published scientific works available in Dimensions.[11] For each publication in their database, Dimensions provides the names of the authors, the journal of the publication, the scientific field of the publication, the year the article was published, the addresses of the authors, and the list of articles referenced in the citations and bibliography. In addition, Dimensions provides algorithmically disambiguated author identifiers enabling the tracking of authors across publications.

As of 2023, the Dimensions data contains over 140 million publications and 1.8 billion citations in the bibliographies of those publications. Of those articles, we focus on the 51 million published between 2008 and 2019.

For each publication, we construct additional variables based on the publication's metadata. We create a flag for if all of the authors have affiliation addresses in China, the U.S., or the U.K. We refer to these publications as being written by Chinese, U.S., or U.K. research teams respectively. For each author on each publication, we also flag if that author's modal affiliation address country between 2008-2012 was either China or the U.S. If the modal country for an author during that time was China, we call the researcher "China-based." We similarly define "U.S.-based" researchers.

Using this data, we create three datasets. First, for analyzing if China-based scientists changed their usage of U.S.-produced scientific works, we create a dataset which we call the *Publication-Citation Shares dataset*. Following the methodology of Iaria, Schwarz and Waldinger (2018), for each research article in Dimensions, we create two observations. The first observation contains measures of how much the focal publication relies on scientific works produced by research in the U.S., and the second observation contains measures of how much the focal publication relies on scientific works produced by research in the U.K. Articles that do not cite any previous works are removed. Further, we focus only on the observations produced from the references of STEM articles written by China-based research teams between 2011 and 2019. This amounts to 4,285,470 observations from 2,142,735 publications.

We compute multiple measures of the usage of science from these countries: raw, recent, frontier, and recent frontier. We calculate the share of the publication's total citations

[11] Dimensions is similar to other bibliometric databases, such as Web of Science and Scopus, but has been shown to have a wider coverage of scientific journals represented in their data (Singh et al., 2021).

that reference articles produced in the U.S. and the U.K. ("raw"). We also calculate the share of the publication's citations to recent works, defined as papers from the preceding five years, to research from each country ("recent"). Finally, we recalculate each of these measures using only citations to frontier research ("frontier" and "recent frontier" respectively). We follow Iaria, Schwarz and Waldinger (2018) in defining the frontier as research ending up in the top percentile of its field's citation distribution. This reflects the relative importance of these papers among works closer to the scientific frontier. More details on how we construct these usage measures are provided in Appendix A.2.

Second, for examining if U.S.-China tensions impacted the usage of Chinese science by U.S.-based researchers, we create a dataset which we call the *U.S.-U.K. Publications dataset*. This dataset contains STEM papers published by U.S. and U.K. research teams between 2011 and 2019. For each publication, we again compute multiple measures of the usage of science (raw, recent, frontier, and recent frontier) but in reverse: measuring that of Chinese science among U.S. and U.K. publications.[12] This dataset includes 2,847,700 publication observations and enables us to track how researchers in the U.S. and U.K. changed their usage of Chinese-produced scientific knowledge.[13]

Finally, for examining if U.S.-China tensions have impacted the productivity of Chinese and U.S. scientists, we create a panel dataset which we call *the Researcher Panel*. The observations in this dataset are created by constructing a strongly balanced panel of the authors listed on publications in the Dimensions data in the years between 2008 and 2019.[14] For each researcher-year observation, we include the number of publications by that author in that year, as well as quality-adjusted measures, such as the number of publications weighted by the impact factor of the journal that those papers were published in.

When analyzing the effect of the rising U.S.-China tensions on the productivity of China-based researchers, we use a sub-sample of the Researcher Panel. Specifically, to examine the researchers who heavily utilize foreign sciences, we filter the Researcher Panel to China-based STEM researchers[15] who published five or more publications between 2008 and 2012 as well as at least one publication between 2013 and 2019.

When analyzing the effect of the rising U.S.-China tensions on the productivity of U.S. researchers, we again filter the Researcher Panel to a subset of interest. Specifically, we

[12] We define a publication as being produced in China according to the publication's correspondence author. See Appendix A.2 for details.

[13] Unlike the Publication-Citation Shares dataset, the U.S.-U.K. Publications dataset is not disaggregated. This is because we are interested in citations to only one country–China–among these publications.

[14] Our analysis focuses on the 2013-2019 period. We use the years 2008-2012 for computing metrics, such as how active researchers were and where they were located.

[15] Fields are defined by the modal field of their publications.

filter the Researcher Panel to U.S.-based STEM researchers who published at least one publication between 2013 and 2019.

For both panels of China-based STEM researchers and U.S.-based STEM researchers, we apply the Coarsened Exact Matching (CEM) method (Iacus, King and Porro, 2012) respectively to match on pre-analysis observables, as will be described in more detail later, to ensure that the treatment and control researchers are comparable groups. After the CEM procedure, the final China-based STEM researcher panel includes 12,073 unique individuals with 76,605 researcher-year observations. The final U.S.-based STEM researcher panel includes 231,296 unique individuals with 853,087 researcher-year observations.

Table 1, Panels C-E present basic summary statistics of these data. More detailed summary statistics for all five datasets can be found in Appendix A. Appendix A6 and Appendix A8 reports the balance between the treated and control group after the CEM procedure.

4 Analysis and Results

Leveraging the datasets described above, we analyze the effect of the rising U.S.-China tensions starting in 2016 on STEM trainee mobility (doctoral student enrollment and U.S. graduate retention), usage of scientific works, and scientific productivity in STEM fields in the subsequent years. For each outcome, we utilize a difference-in-differences framework for computing the effect. The advantage of this empirical approach is that it allows us to isolate the treatment effect from other contemporaneous changes, such as changes in the appeal of U.S. doctoral programs, the rise in both quantity and quality of Chinese science, and factors impacting the productivity of scientists. In addition to the difference-in-differences estimates, for each analysis, we also estimate and plot event-study models. These models are useful for both assessing the validity of the difference-in-differences parallel trends assumption and for tracing the potentially dynamic nature of the treatment effect. For each outcome, we specify the difference-in-differences model to compare a group likely to have been impacted by the rise in tensions (treated group) with a group that was unlikely to have been unaffected, but whose trend in outcome could plausibly serve as a counterfactual (control group).

In the following sections, we explain our approach to analyzing each outcome in detail. A summary of these approaches can also be found in Table 2.

4.1 STEM Trainee Mobility

4.1.1 Enrollment in U.S. Doctoral Programs

Foreign doctoral students enable and enhance the scientific work done by U.S. universities (Black and Stephan, 2010). Indeed, one of the U.S.'s great advantages in attracting top global STEM talent is derived from its strong higher education system.[16]

Attracting these talented trainees–and retaining them post-graduation–has long been seen as economically and competitively important for the U.S. to retain its edge in scientific research. But the U.S.-China tensions described in Section 2 suggest that the U.S. may have become a less attractive destination for Chinese STEM trainees.

Therefore, we begin by examining how growing U.S.-China tensions starting in 2016 affected the enrollment of ethnically Chinese students in doctoral programs at U.S. universities relative to their non-ethnically Chinese counterparts. Specifically, we estimate the following difference-in-differences model using observations from the Doctoral Student dataset:

$$Y_i = \beta_1 Treat_i + \beta_2 Post_{t(i)} + \beta_3 (Treat_i^* Post_{t(i)}) + \gamma \mathbf{X}_{it} + \epsilon_i \tag{1}$$

In this equation, i is a doctoral student and $t(i)$ is the year that student began their doctoral studies. The outcome of interest is Y_i, which is an indicator for if the student enrolled in a U.S. doctoral program. The treatment group for this analysis are students who are ethnically Chinese, and the control group are students who are not ethnically Chinese. $Post_{t(i)}$ is defined as an indicator for if the student began their doctoral studies in 2016 or later. $\mathbf{X}_{it}$ contains fixed effects for the year, the scientific field of a student's doctoral studies, and the country where the student received their prior academic degree. The parameter of interest from this equation is β_3, which is the effect of the rising U.S.-China tensions on enrollment in U.S. programs.

This approach overcomes many of the obvious empirical challenges that would arise if one simply compared doctoral enrollment at U.S. universities before and after 2016. Enrollment in doctoral programs across the globe and at U.S. universities fluctuates over time for a variety of socio-economic reasons. By using a difference-in-differences approach, we are able to control for general increases and decreases in doctoral program enrollment. Furthermore, by comparing the enrollment of ethnically Chinese students with that of non-ethnically Chinese students, we isolate the treatment effect due to the rise in tensions as opposed to the general fluctuations in the appeal of U.S. universities'

[16] As an illustration of this strength, 19 out of the top 30 positions in the 2023 Times Higher Education Supplements' ranking of the world's universities are held by institutions in the United States.

doctoral programs.

Table 3 presents the results from estimating Equation 1. Column (1) reports the estimated impact on the likelihood of enrolling in a U.S. doctoral program to be -3.7 probability points (SE = 0.78 pp). This amounts to a 16% decline relative to the sample mean.

If ethnically Chinese students were less likely to enroll in U.S. doctoral programs, where did they pursue their degrees? Table 3 Columns (2) and (3) report the estimated effects on the likelihood of enrolling in a U.K. or non-U.S. anglophone university respectively. The estimated treatment effects in both columns are positive and significant. The estimated effect on the likelihood of enrolling in a non-U.S. anglophone university, shown in Column (3), is 2.1 probability points (SE = 0.66 pp). This amounts to a 12% increase over the sample mean. Taken together, these findings are consistent with the explanation that other anglophone universities substituted for U.S. universities among ethnically Chinese Ph.D. students after 2016.

We also estimate an event-study model of the evolving effect of growing U.S.-China tensions on enrollment in U.S. doctoral programs, both to examine the pre-trends and to trace the dynamics effects after 2016. The event-study model specification is the following:

$$Y_i = \beta Treat_i + \sum_{k=2008}^{2014} \delta_k Treat_i + \sum_{k=2016}^{2019} \tau_k Treat_i + \gamma \mathbf{X}_{it} + \epsilon_i \quad (2)$$

The variables in this equation are the same as in Equation 1. From this equation, the δ_k are estimates of the difference in the enrollments of ethnically Chinese students and non-ethnically Chinese students in the years before treatment. If these coefficients are near zero, it provides evidence that these two groups had similar trends in their enrollment in U.S. programs prior to 2016. We are also interested in the τ_k coefficients, which provide the change in enrollment for the ethnically Chinese group relative to the non-ethnically Chinese students in the years after the increase in U.S.-China tensions.

Figure 4 plots the estimated δ_k and τ_k coefficients from Equation 2. Prior to 2016, the rates at which ethnically Chinese and non-ethnically Chinese students enrolled in U.S. doctoral programs followed similar trends. Beginning in 2016, however, the rate that ethnically Chinese students enrolled in U.S. programs began declining (relative to that of non-ethnically Chinese students) and continued declining through at least 2019. For example, in 2018, the probability that an ethnically Chinese Ph.D. student enrolled in a U.S. doctoral program decreased by 5 probability points relative to the rate in 2015.

While the rise in U.S.-China tensions starting in 2016 specifically targeted China, they may have also impacted ethnically Chinese individuals regardless of their nationality due to the possible broader "chilling effect" discussed in Section 2. In order to test this, ideally we would examine if ethnically Chinese students from nations other than China also became less likely to enroll in U.S. programs. Since we do not observe nationality, we proxy it with the location of the institution where a student completed their prior degree.

Table 4, Column (1), shows the estimate of Equation 1 when defining the treatment group as those with a previous degree from a Chinese university. The results in Column (1) reveal an effect size of -4.2 probability points (SE = 1.0 pp) on the probability of attending a U.S. doctoral program. In Column (2), we estimate Equation 1, defining the treatment group to be those with a previous degree from a non-Chinese university. The estimated effect is -1.5 probability points (SE = 0.86 pp). These two coefficients are statistically different from zero and each other at the 10% level. While the difference in the effect on these two groups implies that those of Chinese nationality experienced a larger decline in the rate of enrolling at U.S. doctoral programs, these estimates reveal that growing U.S.-China tensions did not exclusively impact students of Chinese nationality. Indeed, the negative impact on ethnically Chinese students of other nationalities highlights that tensions affected the enrollment of students based on their ethnicity in addition to their nationality.

The effect of U.S.-China tensions may have varied depending on a students' previous experience within the U.S. Therefore, we next test if having previous experience at a U.S. university attenuated the effect of U.S.-China tensions on the probability of enrolling in a U.S. doctoral program.

Table 4, Column (3), shows the results of estimating Equation 1 with the treatment group defined to be those ethnically Chinese students who earned their prior degree from a U.S. university. For this group, the estimated coefficient is slightly negative but not statistically significant. In Column (4), we repeat this exercise but redefine the treatment group to be those whose prior degree was from a non-U.S. university. For this group, the estimated effect is -4.0 probability points (SE = 0.88 pp). These results suggest that U.S.-China tensions may have differentially impacted the enrollment of students without prior experience in the U.S. While both those who had recently attended a degree program in the U.S. and those without that previous experience decreased their rate of entering a U.S. doctoral program, those without prior experience decreased their rate of enrolling in the U.S. by almost four times the probability points.

The results in this section document how U.S.-China tensions emerging in 2016 decreased the enrollment of ethnically Chinese students in U.S. doctoral programs. Instead, in the years following 2016, ethnically Chinese students enrolled in non-U.S. anglophone universities at increased rates. Significantly, the effects extended to those of Chinese ethnicity regardless of their nationality, suggesting the presence of a broader "chilling effect" for all ethnically Chinese trainees. Finally, ethnically Chinese students whose prior degree was in the U.S. did not experience the same decline in enrolling in U.S. doctoral programs as those without this prior experience. The results suggest that the U.S. may be losing STEM talent to other anglophone countries as a result of anti-China policies and hostilities.

4.1.2 Retention of U.S. Graduates

Retaining trained and talented scientists may be equally as important for a nation's economic competitiveness as attracting such talent. We examine if the rise in U.S.-China tensions in 2016 impacted the rate that graduates of U.S. institutions remained in the U.S. upon completing their degrees.

Table 5 displays the results from estimating the difference-in-differences specification of Equation 1 using the U.S. Graduates dataset, where each observation is an individual graduating from a U.S. institution. As in the previous section, we define the treated group as ethnically Chinese graduates and the control group as non-ethnically Chinese graduates. Column (1) reports the estimated impact of treatment on the likelihood that a U.S. graduate's first job remains in the U.S. as -3.6 probability points (SE = 0.95 pp). This amounts to a 4% decline from the sample mean.

In order to study the dynamic effects of U.S.-China tensions, Figure A7 plots the coefficients on the leads and lags from Equation 2 estimated on observations from the U.S. Graduates dataset. The dependent variable is an indicator for whether a U.S. graduate takes a U.S. job following graduation. The plot shows estimates that are not significantly different from zero until after 2016, highlighting that the rate that ethnically Chinese graduates' jobs remained in the U.S. tracked with that of non-ethnically Chinese graduates for many years prior to 2016. Following 2016, the (relative) rate for ethnically Chinese graduates trends downward, becoming statistically significant starting in 2017 and continuing to decline through 2019.

Since the relative rate at which ethnically Chinese graduates of U.S. institutions remain in the U.S. decreased, where did they take jobs instead? Table 5, Columns (2) and (3), report the estimated effects of U.S.-China tensions on the likelihood that a U.S. graduate's first job is in the U.K. or in a non-U.S. anglophone country, respectively. The estimated treatment effect is significant only in the latter case. Column (3) estimates the effect of the treatment on the likelihood that a graduate's job is in a non-U.S. anglophone country as 0.85 probability points (SE = 0.36 pp). This amounts to an increase over the sample mean of nearly 33%. These estimates imply, once again, that some substitution occurred to positions in other anglophone countries.

As before, the changes we observe in the likelihood that a U.S. graduate's first job is in the U.S. may be different for ethnically Chinese individuals from China versus ethnically Chinese individuals from outside of China. To investigate this possibility, we estimate Equation 1 again with the treated group defined as those whose prior degree is from China. The results, shown in Table 5, Column (4), reveal an effect size of -5.9 probability points (SE = 1.6 pp) on the probability of retention following graduation. In Column (5), we define the treated group as those whose prior degree is from an institution outside of China. The estimated effect is very slightly negative and statistically insignificant. These results suggest that the effect of U.S.-China tensions on the professional mobility of ethnically Chinese U.S. graduates is largely driven by (nationally) Chinese diaspora researchers.

These results, while noisier, are consistent with ethnically Chinese U.S. graduates substituting positions with U.S. employers for those in other anglophone countries after 2016. Despite their significance, these estimates, as well as the visual evidence for substitution, are less pronounced than in the doctoral students context from the previous section. We also note that, while Chinese ethnicity appeared to impact trainees' university enrollment outcomes independently of Chinese nationality, we do not find the same pattern in the context of professional outcomes. This may be attributable to the difference in stakes between university outcomes and job market outcomes, with the higher stakes in the latter case limiting choice.

4.2 Building on U.S. and Chinese Research

Prior literature indicates that the mobility of scientists correlates with the diffusion of scientific knowledge (Bernstein et al., 2022; Hunt and Gauthier-Loiselle, 2010; Moser and San, 2020; Agrawal, McHale and Oettl, 2017). In particular, graduates of foreign doctoral programs who return home may bring back new ideas, scientific techniques, and personal connections that may influence the direction of their future work. We investigate if the rise in U.S.-China tensions, and the subsequent decline in the mobility of graduate students and trained scientists, also influenced the usage of scientific knowledge by research teams in the U.S. and China.

We first examine how Chinese researchers' usage of scientific works produced by U.S. research teams changed because of worsening U.S.-China tensions. In the subsequent sub-section, we examine the U.S. side and determine if the usage of Chinese research by U.S. researchers similarly changed after 2016.

In these analyses examining changes in the research that U.S. and Chinese scientists reference in their work, we make comparisons using U.K. research and researchers as controls for their counterparts from the U.S. The U.K. serves as a suitable control for the U.S. in this analysis for a number of reasons. First, the U.S. and the U.K. enjoy similar levels of government support and national preference for research as reflected in their R&D workers per capita (Figure A1). Second, both pursue similar types of research as evidenced in the composition of their publications' fields (Figure A2). Third, both countries are top destinations (i.e., first and second place) for nationally Chinese researchers studying abroad (Figure 2). Beyond these quantitative similarities, the U.S. and the U.K. share a dominant language and cultural lineage. Thus, we assume that the U.K.'s research trajectory in and after 2016 adequately models a U.S. counterfactual in the *Post* period.

4.2.1 Chinese Researchers Building on U.S. Science

Following the approach of Iaria, Schwarz and Waldinger (2018), we estimate a difference-in-differences model using observations from the Publication-Citation Shares dataset in which the focal publications were written by research teams in China. In this analysis, we compare the citations of Chinese researchers to U.S. publications versus to U.K. publications. Specifically, we estimate the following specification:

$$Y_{ij} = \beta_1 Treat_{ij} + \beta_2 Post_{t(i)} + \beta_3 (Treat^*_{ij} Post_{t(i)}) + \gamma \mathbf{X}_{ijt} + \epsilon_{ij} \tag{3}$$

In this equation, i is a scientific publication produced by a Chinese research team, and j represents either the U.S. or U.K. The outcome of interest is Y_{ij}, which is the share of publication i's references citing papers produced in country j. The variable $t(i)$ is the year that publication i was published. The treatment group for this analysis contains the observations in which j = U.S., and the control group contains observations where j = U.K. The variable $Post_{t(i)}$ is defined as an indicator for if publication i came out in 2016 or later. $\mathbf{X}_{it}$ contains fixed effects for the citing publication. The parameter of interest from this equation is β_3, which can be interpreted as the effect of U.S.-China tensions on the share of references among Chinese publications going to U.S.-produced research (versus U.K.-produced research).

This difference-in-differences approach, and setting up the analysis as examining the relative share of citations to U.S. research versus U.K. research, addresses two potential identification concerns. First, norms regarding citing and referencing previous works change over time. By including fixed effects collinear with the year of publication, we negate any concern that these changes are impacting our estimates of the treatment effect. Second, Chinese research has been increasing in quality over time. Therefore, regardless of any changes in international relations, Chinese researchers may be relying more on Chinese-produced research rather than research produced elsewhere over time. By comparing the relative share of U.S.-produced papers to U.K.-produced papers in the reference lists of Chinese publications, we isolate the impact of U.S.-China tensions on the usage of U.S. research from the general trend in Chinese researchers relying less on non-Chinese research.

Table 6 shows estimated coefficients from Equation 3 using publications by Chinese research teams. Column (1) shows the estimated impact of worsening U.S.-China tensions as -1.4 probability points (SE = 0.44 pp). This amounts to a 11% decline from the sample mean and a 6.5% decline from the China-U.S. average citation share to U.S. publications.[17] Column (2) reports the estimated impact of growing U.S.-China tensions on the share of recent references, defined as references to research articles published in the previous five years, to be -1.4 probability points (SE = 0.25 pp) or a 16% decline from the sample mean and a 10% decline from the China-U.S. average. That this decline is greater (in percentage terms) suggests that increasing U.S.-China tensions may have had greater influence on the dissemination of recent research. One might be concerned that the results are driven by a reduction in citing low-quality research. To test if this is the case, we repeat the analyses from Columns (1) and (2) using dependent variables capturing citations to research in the top 1% of its field's citation distribution, which we call "frontier research" and "recent frontier research." Columns (3) and (4) report the estimated impacts on these quality-adjusted shares, revealing a significant reduction in citations to frontier U.S.-based research and suggesting that this concern is unfounded.

We also estimate an event-study model in order to trace the dynamic effects of U.S.-China tensions and to examine the evidence in support of the parallel trends assumption underlying the previous difference-in-differences estimates. The event-study model specification is as follows:

$$Y_{ij} = \beta Treat_{ij} + \sum_{k=2008}^{2014} \delta_k Treat_{ij} + \sum_{k=2016}^{2019} \tau_k Treat_{ij} + \gamma \mathbf{X}_{ijt} + \epsilon_{ij} \tag{4}$$

The variables in this equation are the same as Equation 3. From this equation, the δ_k are estimates of the difference in the citation shares to U.S. research versus U.K. research in the years before the 2016. If these coefficients are near zero, it provides evidence that the

[17]We provide the percentage change relative to the China-U.S. average given the sizable level difference between the average China-U.S. and China-U.K. citation rates.

usage of research from these two countries tracked in the period prior to 2016. The τ_k coefficients document the change in relative citation share to U.S. produced research in the years following 2016, giving insight into the dynamic effect of the rise in U.S.-China tensions.

The event-study coefficients confirm that the change in the citation share of U.S. research on Chinese papers came about as an abrupt change, starting in 2016, and has continued to decline in the years since. Figure 6 shows the estimated coefficients when the dependent variable is the raw share of each paper's total publications. These shares move in parallel in the years prior to 2016, but following that year there is a dramatic decline in the rate of referencing U.S. sources. The coefficient on the year 2018 is -1.4 probability points (SE = 0.43 pp), which indicates that just two years after the U.S.-China tensions really began to take off, the share of citations to U.S. sources in the papers of Chinese teams had already declined by 6.3% relative to 2015. Appendix D includes event studies for recent, frontier, and recent frontier research. The results remain qualitatively unchanged in terms of direction and significance, and the magnitude of the impact for recent frontier references more than doubles. This implies that the impact of U.S.-China tensions on Chinese researchers was particularly pronounced for citations to works on the scientific cutting edge.

4.2.2 U.S. Researchers Building on Chinese Science

Did U.S. research teams similarly change their usage of Chinese-produced scientific knowledge? To investigate that question, we compare the share of references in the publications of U.S. research teams made to works from China with the share of references in the publications of U.K. research teams made to works from China.

This approach is different than the one that we used for analyzing if the usage of U.S. sources by Chinese researchers had changed. In that analysis, we examined the share of citations to U.S. sources versus the share of citations to U.K. sources on Chinese publications, which allowed us to account for secular trends, such as the rising quality and quantity of scientific works produced in China that might decrease the share of citations to foreign works more generally. In analyzing the U.S.-side, a similar approach would not be appropriate, since no other country could serve as a control that could plausibly provide a counterfactual to the unique changes occurring in China's scientific production over the past two decades. Therefore, instead, we examine the share of citations to works from Chinese scientists in the papers of U.S. and U.K. researchers. In doing so, we can control for the changes in Chinese produced science, while isolating the effect of U.S.-China tensions on the usage of China-produced scientific works in the publications of U.S. researchers.

We estimate the difference-in-differences model for this analysis with the specification in Equation 3 and observations from the U.S.-U.K. Publications dataset. Specifically, we estimate the following:

$$Y_i = \beta_1 Treat_i + \beta_2 Post_{t(i)} + \beta_3 (Treat_i^* Post_{t(i)}) + \gamma \mathbf{X}_{it} + \epsilon_i \tag{5}$$

In this equation, i is a scientific publication produced by a U.S. or U.K. research team. The outcome of interest is Y_i, which is the share of publication i's citations that go to papers produced in China. The variable $t(i)$ is the year that publication i was published. The treatment group for this analysis is the set of observations in which publication i is authored by a U.S. research team, and the control group includes observations where publication i is authored by a U.K. research team. The variable $Post_{t(i)}$ is defined as an indicator for if the publication i came out in 2016 or later. $\mathbf{X}_{it}$ contains fixed effects for the year and the scientific field of the publication. The parameter of interest from this equation is β_3, which can be interpreted as the effect of U.S.-China tensions on the share of references to Chinese produced research among publications by U.S. research teams, relative to U.K. research teams.

Table 7 shows the estimates when the dependent variable is the overall share of citations, the share of recent citations, the share of frontier citations, and the share of recent frontier citations. Although all of the coefficients are negative, they are all small in magnitude and none reach statistical significance. Figures 7 and A11, which display the leads and lags from event-study models of the citation shares from U.S. research teams, show a similar pattern. These plots reveal a mild and statistically insignificant decrease in the rate that U.S. papers cite China in 2018 and 2019.

Both Figure 7 and the associated event studies demonstrate that following the rise in U.S.-China tensions, U.S. researchers did not meaningfully change their citation habits with respect to Chinese scientific sources. The small and statistically insignificant coefficients both before and after 2016 demonstrate that the propensities of the U.S. and the U.K. to cite Chinese research moved in parallel throughout this period.

Ultimately, these results demonstrate a shift in the works that Chinese researchers build their publications on. Since 2016, Chinese researchers decreased their usage of U.S. produced science in the citations of their publications. As this decrease can be seen in the relative usage of U.S. produced research versus U.K.-produced research, the shift goes beyond any contemporaneous increase in the quality of Chinese science that may be causing Chinese researchers to rely less on science from non-Chinese science more generally. In contrast, U.S. researchers did not change their usage of Chinese-produced research in a statistically significant manner. This implies that the majority of the effect of U.S.-China tensions after 2016 were felt in the knowledge flows from the U.S. to China and much less so on the knowledge flows from China to the U.S.

4.3 Productivity Impact on STEM Researchers

The rise in U.S.-China tensions may have impacted the productivity of Chinese researchers building on U.S. science as well as U.S. researchers building on Chinese science. There are multiple mechanisms by which productivity could have been affected: because researchers interacted less with researchers from the other country, because fewer graduate students and trainees went back and forth between these countries, because visa restrictions made attending conferences harder, because scientists became more hesitant about collaborating internationally with one another due to fear of legal consequences or outright discrimination, or because of a decline in knowledge flows between the two countries. In this section, we estimate the effect of U.S.-China tensions on productivity, as measured by the number of scientific papers produced by researchers in the years before and after 2016. The mechanisms that we focus on in the analysis are changes in knowledge flows from the U.S. to China on the China side and the increased challenges ethnically Chinese researchers in the U.S. faced with regards to obtaining funding, attending conferences, and collaboration opportunities on the U.S. side. We elaborate in more detail on each below.

Our empirical strategy for estimating the impact of U.S.-China tensions on researchers in China is motivated by our results in the previous section, where we found that publications produced by China-based researchers significantly shifted away from referencing scientific works published by authors in the U.S. Therefore, for examining the productivity of China-based researchers, we define the treated group as the China-based researchers whose work heavily cites scientific works produced by U.S. (but not U.K.) authors in the years prior to 2016. We define the control group, for this analysis, as China-based researchers whose work heavily cites scientific works produced by U.K. (but not U.S.) authors.

Our empirical strategy for estimating the impact of U.S.-China tensions on ethnically Chinese researchers in the U.S. is motivated by our results on STEM trainee mobility. In particular, our previous results demonstrated that ethnically Chinese students significantly changed their mobility patterns following the rise of U.S.-China tensions in 2016. Similar dynamics to the ones that dissuaded or denied ethnically Chinese students from enrolling in U.S. programs and accepting jobs in the U.S. post-graduation may have also impacted the productivity of ethnically Chinese scientists in the U.S. Therefore, for analyzing the productivity of U.S. researchers, we define the treated group as ethnically Chinese researchers in the U.S. and define the control group as non-ethnically Chinese researchers in the U.S.

While the treatment and control groups for studying the changes in productivity among both the Chinese and the U.S. are chosen to provide plausible counterfactual trends, we also match treated researchers with control researchers based on observable characteristics and scientific works in the period before our analytical window. We take this extra step because there is immense heterogeneity across researchers in our data. Comparing researchers who are in different fields of science, at different stages in their careers, or on different trajectories would be unlikely to isolate and provide meaningful estimates of the rise in U.S.-China tensions. Therefore, in investigating the effect on productivity for both the Chinese and U.S. sides, we estimate the difference-in-differences analyses using only the set of researchers who can be matched. We detail the matching procedure below.

4.3.1 Productivity Impact on China-based Researchers

For assessing the impact of rising U.S.-China tensions starting in 2016 on the productivity of Chinese researchers, we again estimate both differences-in-differences and event-study specifications. The data used for this exercise is the sub-sample of observations from the Researcher Panel associated with research-active China-based scientists: researchers who are China-based STEM scientists, who published five or more publications between 2008 and 2012 and at least one publication between 2013 and 2019.

We define the treated group as researchers who predominately cite scientific publications from the U.S., and we define the control group as researchers who predominately cite publications from the U.K. Precisely, the treated group includes researchers who are in the 75th percentile or higher within their field for the portion of their citations that go to publications from the U.S. and are below the 25th percentile for their field for their citation share to publications from the U.K. The control group is similarly defined as being above the 75th percentile in citation share within the field to the U.K. and below the 25th percentile in citation share within the field to the U.S.

In order to isolate the effect of the rise in tensions and boost the precision of our estimates, we further select our sample by matching researchers from the treated and control observations by employing the CEM procedure. Specifically, we match researchers from the treated and control groups based on the following observables: number of publications produced between 2008-2012 (in 10 bins), career age as of 2012 (in 4 bins),[18] the number of actively publishing years between 2008-2012,[19] if the researcher is affiliated with a university, if the researcher is located in a Tier 1 city,[20] and if the researcher is located in a New Tier 1 city.[21] In addition, we included the level and the growth rates for the number of publications and impact-factor-weighted publications between 2013 and 2015 as matching covariates. A comparison of the treatment and control groups across these covariates can be found in Appendix Table A6.Ultimately, the sample on which we analyze the productivity impact on China-based researchers contains 11,975 unique individuals (76,086 observations). Of those, 5,982 are in the treated group (researchers who predominately cite scientific publications from the U.S.) and 5,993 unique individuals in the control group (researchers who predominately cite scientific publications from the U.K.).[22]

We estimate the following differences-in-differences specification:

$$Y_{it} = \beta_1 Treat_i t + \beta_2 Post_{t(it)} + \beta_3 (Treat^*_{it} Post_{it}) + \gamma \mathbf{X}_{it} + \epsilon_i \tag{6}$$

In this equation, i is a researcher and $t(i)$ is the year. The outcome of interest is Y_{it}, which is the number of publications researcher i published in year t in the baseline specification. $Post_{t(i)}$ is defined as an indicator for 2016 or later. $Treat_{it}$ are the researchers who heavily utilize U.S.-produced research. $\mathbf{X}_{it}$ contains individual fixed effects and year fixed effects. Because the outcome of interest is a count variable, we estimate this specification using a Poisson (PPML) model.

For examining the dynamic effects and examining the pre-trends, we estimate the following event-study specification:

$$Y_{ij} = \beta Treat_{ij} + \sum_{k=2013}^{2015} \delta_k Treat_{ij} + \sum_{k=2016}^{2019} \tau_k Treat_{ij} + \gamma \mathbf{X}_{ijt} + \epsilon_{ij} \tag{7}$$

The variables in this equation are the same as Equation 6.

[18]Defined as the number of years since they began actively publishing.

[19]The number of years between 2008-2012 that a person published at least one publication.

[20]Tier 1 cities include Beijing, Shanghai, Guangzhou, Shenzhen.

[21]New Tier 1 Cities include Chengdu, Chongqing, Hangzhou, Wuhan, Nanjing, Tianjin, Suzhou, Xi'an, Changsha, Shenyang, Qingdao, Zhengzhou, Dalian, Dongguan, Ningbo.

[22]The original dataset contains 12,073 unique researchers tracked over the 2013 to 2019 period (76,605 researcher-year observations), but since we use researcher fixed effects, researchers with no variation in the number of publications per year drop from the sample. The sample after fixed effects contains 10,425 unique individuals (54,265 observations). Of those, 5,206 are in the treated group and 5,219 unique individuals in the control group

Table 8 shows the coefficients from estimating the difference-in-differences model on this panel, where the dependent variable varies across each column. Using the number of publications as the dependent variable, Column (1) reports the estimated effect as -0.024 (SE = 0.016). This effect size is not statistically significant and small in magnitude, implying that the average impact of U.S.-China tensions on the productivity of Chinese researchers who heavily relied on U.S. knowledge was negligible relative to those relying on U.K. sources.

While the overall effect on the treated group's productivity is small and not statistically significant, it is possible that researchers changed where they published their papers. For example, these researchers may have found it more challenging to publish in U.S.-based journals after 2016. To test this, Column (2) shows the results of estimating the difference-in-differences specification with a dependent variable of the number of publications in U.S. journals[23]. The coefficient estimate is -0.003 (SE = 0.027), which is again small and not distinguishable from zero. In summary, the rise in U.S.-China tensions–and in particular the change in knowledge flows from the U.S. to China–did not appear to significantly impact the research productivity of China-based researchers who relied on such knowledge flows prior to these tensions.

The result that China-based researchers who built predominantly on U.S. science experienced mostly small or zero decreases in their production of scientific works is confirmed when examining the dynamics. Figure 8 plots the coefficients from estimating the event-study model in Equation 7. The plots show noisy estimates with only a slight decline.

One would not expect researchers in all scientific fields to be impacted equally. In particular, certain fields, such as AI and semiconductors, are seen as being more relevant to national security or to strategic economic competitiveness. Researchers in such fields may have faced particular pressure to become self-reliant, and both governments have placed particular effort at containing knowledge in such strategic areas within national borders. Hence, we expand our analysis to examine field heterogeneity. Unfortunately, due to power concerns, we cannot get to the level of "AI", for example, but we can examine computer science more generally. For this exercise, we assign researchers to a sub-field based on the modal field in which they published.[24].

As expected, there is indeed significant heterogeneity across fields that aggregate effects mask, as shown in Table 9 and Figure 9. While U.S.-reliant China-based researchers

[23]The country of the journal is determined by the location of its publishing house.

[24]Because our sample for this analysis is relatively small, we pool some sub-fields together as indicated in Table 9

in most fields do not experience any productivity changes relative to U.K.-reliant researchers, biology is a clear outlier. U.S.-reliant biologists experienced a decrease in productivity relative to their U.K.-reliant counterparts. The coefficient for these researchers is -0.128 (SE = 0.038) in the number of publications and -0.167 (SE = 0.075) in the number of U.S.-based publications. Similarly, though weak, U.S.-reliant researchers in Engineering and Information and Computing Sciences experienced a relative productivity decrease of 5.7% (SE = 0.031) in the number of publications, and 5.1% (SE = 0.050) in the number of U.S.-based publications. Interestingly, U.S.-reliant Physicists in China experienced an increase in productivity, 17.5% (SE = 0.063) in the number of publications, and 18.8% (SE = 0.084) in the number of U.S.-based publications. We do not detect any statistically significant effects for other STEM fields, as reported in Table A18 and Figure A12. This increase in productivity in the field of Physics may be reflective of investments made by the Chinese government and institutions into specific areas of science, such as those related to materials science and semiconductors.

We also investigate the impact on the quality of publications produced. In this section, we measure quality by weighting publications by the impact factor of the journal the publication appeared in.[25] Table 8, Column (3), shows the estimated effect on the number of impact-factor-weighted publications is -0.005 (SE = 0.018). Column (4) reports that the estimated effect for U.S.-based publication is -0.005 (SE = 0.032). As with the raw productivity outcomes, both estimated coefficients are negative but small in magnitude and not statistically different from zero.

As before, we also examine heterogeneity in quality across sub-fields of science, shown in Table 9 Panel C and Panel D and Figure 9. As before, U.S.-reliant biologists experienced the largest negative effect on productivity, even when adjusting for quality. For these researchers, we estimate an 11.9% (SE = 0.043) decrease in the number of impact-factor-weighted publications and a 14.4% (SE=0.085) decrease in the number of impact-factor-weighted publications in U.S.-based journals. Similarly, U.S.-reliant physicists experienced an 18.5% (SE = 0,071) increase in the number of impact-factor-weighted publications and a 21.3% (SE=0.094) increase in the number of impact-factor-weighted publications in U.S.-based journals relative to the control group. We do not detect any statistically significant effects for other STEM fields, as reported in Table A18 and Figure A12.

Ultimately, these results indicate that the rise in tensions–and more specifically, the decline in knowledge flows from the U.S. to China–did not significantly influence the rate or quality of publications produced by the average Chinese STEM researcher who

[25] We do not use citations to the articles themselves for quality weighting because, given that we are analyzing recent years, the citation data would be truncated.

had previously relied on U.S.-produced research during the time-frame analyzed. However, there is some important field-specific heterogeneity. While China-based researchers in physics saw an increase in the (quality-adjusted) quantity of their publications in the years following the rise of U.S.-China tensions, other fields, notably biology, engineering, and computer science, experienced significant declines. One explanation for the disproportionately large, negative effects on China-based biologists might be the U.S. National Institutes of Health (NIH)'s investigations into biologists that had relationships with China, as documented by Jia et al. (2022).[26] The NIH campaign discouraged collaboration of any kind between U.S.-based and China-based researchers and institutions, which may have both reduced knowledge flows and led to a productivity hit among China-based researchers that had previously relied on those flows and relationships.

4.3.2 Productivity Impact on U.S. Researchers

The rise in U.S.-China tensions may have also impacted the productivity of U.S.-based ethnically Chinese STEM researchers. In this section, we analyze that possibility using another sub-sample of the Researcher Panel dataset. We select the U.S.-based STEM researchers who published at least one publication between 2008 and 2012. For this analysis, we define the treated group as ethnically Chinese researchers and the control group as non-ethnically Chinese researchers.

Again, to increase precision and hone in on the treatment effect of the rising tensions, we match each treated researcher with a control researcher based on various observations from the years 2008-2012: number of publications, career age if the researcher is affiliated with a university, the fraction of the researcher's coauthors who are foreign, number of distinct foreign coauthors if the researcher ever had listed a foreign address if the researcher ever listed funding from a foreign entity, and if the researchers' coauthors list funding from a foreign entity. We also match on the level and growth rate in the number of publications produced by the researcher, the number of impact-factor-weighted publications, the number of collaborators, and the number of China-based collaborators over 2013-2015. Table A8 in the Appendix reports the summary statistics of the covariates and a comparison of these covariates across treatment and control groups. In total, the sample on which we analyze the productivity impact on U.S.-based researchers contains 646,752 observations, with 29,587 unique ethnically Chinese individuals, and 129,032 unique non-ethnically Chinese individuals.[27]

[26]More information about the NIH campaign can also be found here: https://www.science.org/content/article/pall-suspicion-nihs-secretive-china-initiative-destroyed-scores-academic-careers.

[27]The original dataset contains 231,296 unique researchers, but since we use researcher fixed effects, re-

Table 10 shows the results of estimating Equation 6 with the number of publications per year as the dependent variable. As before, we include researcher and year fixed effects. Across all four measures of productivity, shown in Columns 1-4, the same result holds: that the rise in U.S.-China tensions significantly negatively affected the productivity of U.S.-based ethnically Chinese researchers. Specifically, Column (1) shows the estimated effect on the number of publications is -0.020 (SE = 0.007). Column (2) reports that the estimated effect on the number of publications in U.S.-based journals is -0.053 (SE = 0.008). Column (3) shows the estimated treatment effect on impact-factor weighted publications is -0.031 (SE = 0.009). Column (4) reports the estimated effect on impact-factor weighted U.S.-based publications is -0.060 (SE = 0.011). The magnitudes of the estimates reveal that the impact was both statistically and economically meaningful, with the average U.S-based ethnically Chinese researcher experiencing a 2% decrease in overall productivity and 6% decrease in production of impacted-weighted publications in U.S. journals relative to their non-ethnically Chinese colleagues.

Figures 10 display the leads and lags from event-study models of the above four variables of interest. These plots reveal a clear trend break starting in 2016. The decline in the productivity of ethnically Chinese U.S.-based researchers relative to their non-ethnically Chinese colleagues can be seen through 2019, revealing that the effect was not purely transient.

Both Table 10 and Figure 10 demonstrate that following the rise in U.S.-China tensions, both productivity and publication quality of ethnically Chinese STEM scholars in the U.S. decreased, as compared to non-ethnically Chinese STEM scholars. That the estimated impact is found in the relative productivity of ethnically Chinese researchers versus non-ethnically Chinese researchers based in the U.S. provides further evidence that U.S.-China tensions post-2016 have had a chilling effect for ethnically Chinese researchers.

Next, as before, we investigate the heterogeneity of the effect on productivity across scientific sub-fields, highlighting fields considered by both governments to be of national importance. In particular, we show results for the fields at the center of the U.S. CHIPS Act, such as those related to semiconductors, advanced computing, advanced communications technology, advanced energy technologies, quantum information technologies, and biotechnology.[28]. As before, we are limited by sample size and can only look at fields

searchers with no variation in the number of publications per year drop from the sample.

[28] The U.S. CHIPS Act invested $280 billion to bolster U.S. semiconductor capacity on U.S. soil in an effort to bolster supply chain resilience and counter China. More information can be found at https://www.whitehouse.gov/briefing-room/statements-releases/2022/08/09/fact-sheet-chips-and-science-act-will-lower-costs-create-jobs-strengthen-supply-chains-and-counter-china/

at an aggregate level, but this still provides an indication of whether researchers in more sensitive areas experience different changes in productivity.

Table 11 and Figure 11 report the difference-in-difference coefficients for Biological Sciences, Biomedical/Clinical Sciences and Health Sciences, and Engineering, Information, and Computing Sciences. It is clear that, once again, there are significant differences in productivity impact across fields. In particular, ethnically Chinese researchers in Biomed and Health appear to see the largest negative productivity hit. Specifically, the estimated difference-in-differences coefficients for Biomedical/Clinical Science and Health Sciences are -0.039 (SE = 0.009) for number of publications, -0.067 (SE = 0.011) for U.S.-based publications, -0.052 (SE = 0.011) for impact-factor-weighted publications, and -0.080 (SE=0.014) for impact-factor weighted publications in U.S.-based journals. Once again, this is consistent with the NIH investigations discussed in Jia et al. (2022).

We do not detect statistically significant effects for other STEM fields, as reported in Table A22 and Figure A14, with the exception of Engineering, Information, and Computing Sciences which surprisingly saw an increase in productivity.

The results in this section underscore the asymmetry in the effect of the rise of U.S.-China tensions on scientific productivity in the two countries. Whereas the average China-based researcher who relied heavily on U.S. science saw little impact to their productivity, U.S.-based ethnically Chinese researchers experienced a meaningful decrease in their average production of scientific publications. Furthermore, while both U.S. and Chinese researchers saw declines in the production of biology papers, Chinese researchers boosted the quantity and quality of their work in Physics, while U.S. researchers boosted their production of Engineering, Information, and Computer Science publications. These differences in gains and losses by field likely reflect both policy and investment choices made by each country and their respective institutions. The largest effects on both sides appear to be in biology and health, while researchers in other scientific fields that have received special attention from each government due to national security concerns, such as Computer Science and Physics, surprisingly have not seen negative productivity effects.

4.4 Robustness Checks

While our results are consistent across the different analyses conducted above, we also perform a number of additional tests to assess the robustness of our results to different specifications, sample restrictions, and measurement choices.

First, our main empirical specifications define the "treatment" (i.e. the rise of tensions between the U.S. and China) as beginning in 2016 and continuing in the years after. Given that the treatment is not a singular policy change, one might wonder if this choice correctly reflects the timing of the rise in U.S.-China tensions.

There are a variety of reasons that we believe 2016 is the right year to define the treatment as beginning. The chart in Figure 1 shows that sentiment shifted distinctively starting after 2016, with a stark rise in anti-Chinese sentiment. Additionally, for each analysis we ran in the previous section, we estimated event-study models. These event studies display mostly flat pre-trends with sharp trend breaks starting in 2016.

Second, we validate defining ethnically Chinese graduate students as the treatment group in the STEM Trainee Mobility analysis by running a permutation test. In this test, detailed in Appendix B, we compare our estimates of changes in enrollment in U.S. doctoral programs based on the treated group being ethnically Chinese students with the estimates that would result from randomly assigning treatment status among the trainees in our data. In essence, this is a placebo test since if the treatment group is correctly defined then permutations of samples from the untreated group should result in insignificant estimates. After 100 simulations, the estimates from our main analysis fall in the far tail of the distribution of estimates from the simulated treatment statuses. We find this result reassuring that the rise of U.S.-Chinese tensions did specifically impact ethnically Chinese students.

Third, one might wonder if our results are primarily driven by changes in the quality of research being conducted in China rather than a reflection of changes in the tensions between the U.S. and China. Our choice of treatment and control groups for our difference-in-differences analyses specifically seek to address these concerns. For example, when examining the changes in the mobility patterns of STEM graduate students, we examine the differences between ethnically Chinese and non-ethnically Chinese students, thus allowing us to control for changes in the appeal of Chinese graduate programs in STEM. In the analysis of Chinese teams citing U.S. scientific workers, we make comparisons with the citations of U.K. works. Again, this allows us to control for the general increase in the scientific quality of Chinese works, while isolating the differential negative effect on usage of U.S. works beyond the change in usage of U.K. works.

Fourth, we consider the robustness of our analysis to potential measurement error by estimating our main analyses using a variety of different dependent variables. For example, in our analysis of U.S. and Chinese research building on each others' works, we examine the effect of the rise in U.S.-China tensions on the usage of frontier research. While in our main analysis, we define frontier research as that which lands in the top 1% of the field citation distribution, in Appendix D, we show the results if we set this threshold at 3% and 5%. Across these different ways of measuring frontier research, we find similar results. We perform similar robustness checks for our analysis of the mobility of STEM trainees and the productivity of U.S. and Chinese researchers.

In our analysis of the productivity impacts on Chinese sciences, we defined the treatment group as China-based researchers who predominately cite US sciences. In this analysis, we use the threshold for US reliance as above 75th percentile in citation shares to US publications and below 25th percentiles in citation shares to UK publications. As robustness checks, we estimate our main analyses using a variety of different thresholds and apply the CEM procedure. As shown in Appendix A20 we find similar results.

Fifth, we consider the robustness of our results to changes in the sample selection criteria used. For example, our main analysis focuses only on STEM trainees, citations in STEM research articles, and the productivity of STEM researchers. In Appendix D, we relax that restriction and present the results when pooling STEM and Social Sciences together or examining Social Science alone. The results are substantively similar.

Sixth, understanding that applicants to U.S. doctoral programs compete for a limited number of open slots, we consider the possibility that the decline in ethnically Chinese U.S. doctoral students is driven by an increase in qualified applicants from India. Figure A5 presents the raw fraction of incoming U.S. doctoral students that are nationally Chinese or nationally Indian. We do not observe prominent growth in nationally Indian Ph.D. enrollees in and after 2016, alleviating concern about a supply shock of this sort.

Lastly, each of our difference-in-differences estimates of the treatment effect relies on the assumption of parallel trends. If this assumption is violated then it is possible that our estimates are simply spurious noise due to the randomness in the data rather than estimates of the true effect of the rise of U.S.-China tensions.

While the pre-trends estimated in our various analyses are quite flat, we also address this potential concern by estimating the "Honest DiD" approach for each of our difference-in-differences specifications. This approach takes the variation from the pre-treatment period and projects out a worse-case scenario for the post-treatment period. The test then compares the estimated treatment effect against the magnitude of variation projected from the pre-treatment period. This approach is a very high bar to clear. Indeed, it is primarily intended for analyzing difference-in-differences specifications when there is a distinct, discrete, and sharp treatment. Our context does not match that criteria, as our treatment is a combination of changes in sentiment and policy that began in 2016 but evolved in the subsequent years. The results of these tests, which can be found in Appendix B-Appendix G, therefore show predictably noisy estimates. Because of the mismatch of this test with the empirical context studied, we are cautious about interpreting these estimates.

Overall, our results are consistent across analyses, variations in empirical specifications, variations in the measurement of key dependent variables, and variations in sample selection criteria.

5 Discussion and Conclusion

Our results reveal that U.S.-China tensions, by the end of 2019, had already significantly disrupted talent and knowledge flows and led to reduced productivity for scientists in the U.S. Specifically, we have shown, first, regarding STEM trainee mobility and retention, that ethnically Chinese graduate students became both less likely (16%) to attend a U.S.-based Ph.D. program and, if they did attend a U.S.-based program, were less likely (4%) to stay in the U.S. after graduation. In both instances, these students become more likely to move to a different English-speaking country instead. We have also shown a decline in Chinese usage of U.S. science as measured by citations, but no such comparable decline in U.S. usage of Chinese science. And finally, we find negative productivity effects for scientists in the U.S., although not in China: ethnically Chinese scientists in the U.S. were 2-6% less productive after 2016, while China-based scientists that had relied on U.S. frontier knowledge did not appear to be any less productive after 2016, with the exception of biologists. The results as a whole strongly suggest the presence of a "chilling effect" for ethnically Chinese scholars in the U.S., affecting both the U.S.'s ability to attract and retain talent as well as the productivity of its ethnically Chinese scientists. The results on the China side are less clear; while there is less knowledge flowing from the U.S. to China, we do not see any clear productivity impact.

Beyond what we present here, disruptions brought about by geopolitical tensions can have long-lasting effects on scientific productivity. The impact of the movement of top human capital away from U.S. STEM doctoral programs, for example, is likely to take time beyond the time-frame of our data. In addition, tensions have only gotten worse since 2019, with the anti-Asian sentiment that the COVID-19 pandemic inspired and with the increasingly nationalistic policies of both the U.S. and China, such as the 2022 U.S. CHIPS and Science Act which emphasizes domestic research and requires research universities to certify that no researchers or students are participating in a "malign foreign talent recruitment program" or the 2022 Chinese government directive nicknamed "Delete America" aimed at driving U.S. technology out of the country. Our results document some of the negative consequences of growing geopolitical tensions on science and speak to the possible dangers of industrial policies that seek to cut out parts of the world. Efforts by the U.S. and China to improve their innovative capacity through export controls and emphasis on home-grown technology could potentially also lead to some combination of reduced productivity for their own researchers, reduced usage of frontier knowledge, and the loss of top talent. Indeed, other countries that can refrain from aligning into camps may even benefit; For example, as our analysis showed, anglophone countries appear to be attracting ethnically Chinese trainee scientists that are no longer going to the U.S. Given well-established links in the literature between immigrant scientists and innovation, this could also lead to a shift in the location of innovation.

But there is still much to be learned. For instance, although we show declines in enrollment and retention of ethnically Chinese students at U.S. programs, we are unable to quantify the resulting effect on the quality composition of talent in the U.S. using the ORCID sample. Given that uncertainty resulting from a higher student visa refusal rate decreases student quality at U.S. universities (Chen, Howell and Smith, 2023), however, it seems possible that average talent quality would decline in our context as well. We leave a closer examination of the effects on student quality composition to future work.

In addition, although we view our three sets of results to be intimately connected– because the movement of scientists is an effective means of transferring scientific knowledge (Stephan, 2006), and thus a decline in Chinese graduate students in the U.S. is likely to lead to a decline in the knowledge being transmitted between the two countries, which can ultimately impact productivity–the links between the three findings are not precisely pinned down. Future work should more explicitly examine the degree to which cross-border knowledge flow declines are driven by changes in patterns of mobility.

Finally, more work could and should be done to estimate an overall welfare effect. While this paper clearly outlines some adverse effects on scientific progress, these have not been weighed against the imperatives of national security. In certain areas of science, collaboration between the two nations may pose no threat to national security, yet still suffer due to geopolitical strife. Conversely, in other domains, the interruption of knowledge exchange may have significant military implications. Our analysis has already revealed considerable heterogeneity in effects across scientific fields. More finely segmenting science into such domains, a task which may require new methods of classification, will enable policymakers to better analyze the balance of potential national security interests against potential impacts on science.

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6 Figures and Tables

Figure 1: Pew Research Center Survey on Growing Anti-Chinese Sentiment in the U.S.

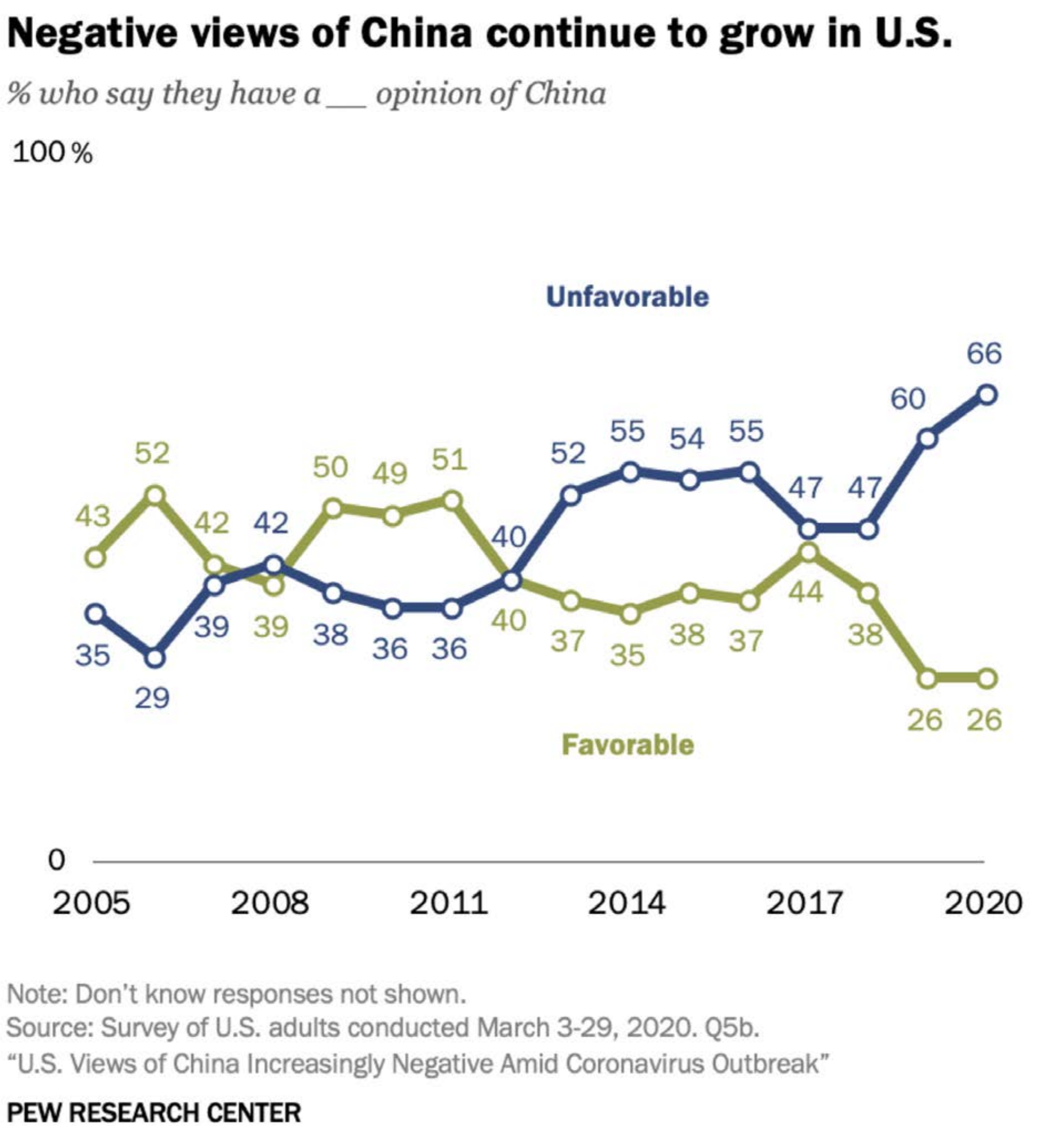


Figure 2: Statista: Chinese Students' Preferred Destinations for Studying Overseas in 2015 and 2022

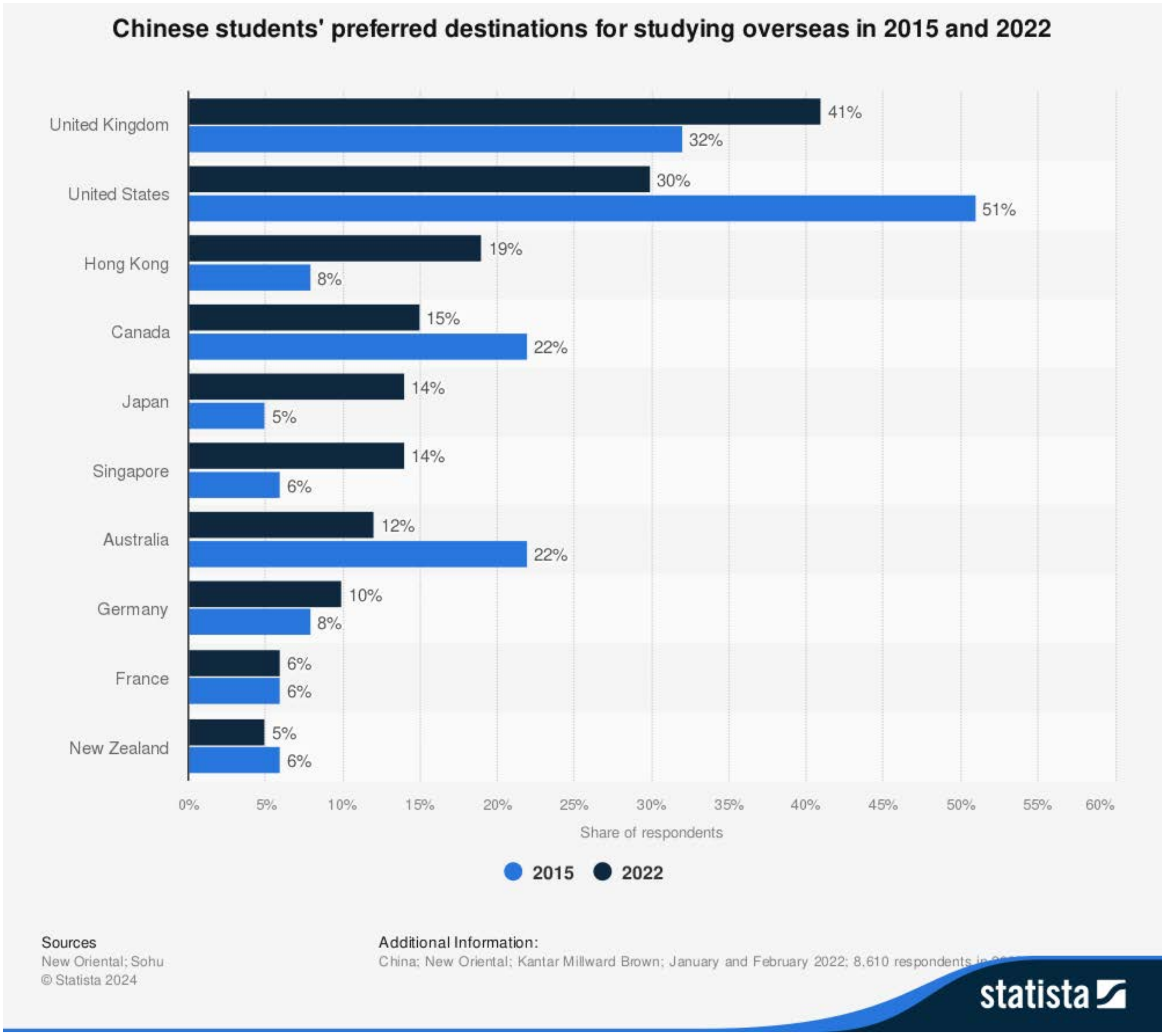
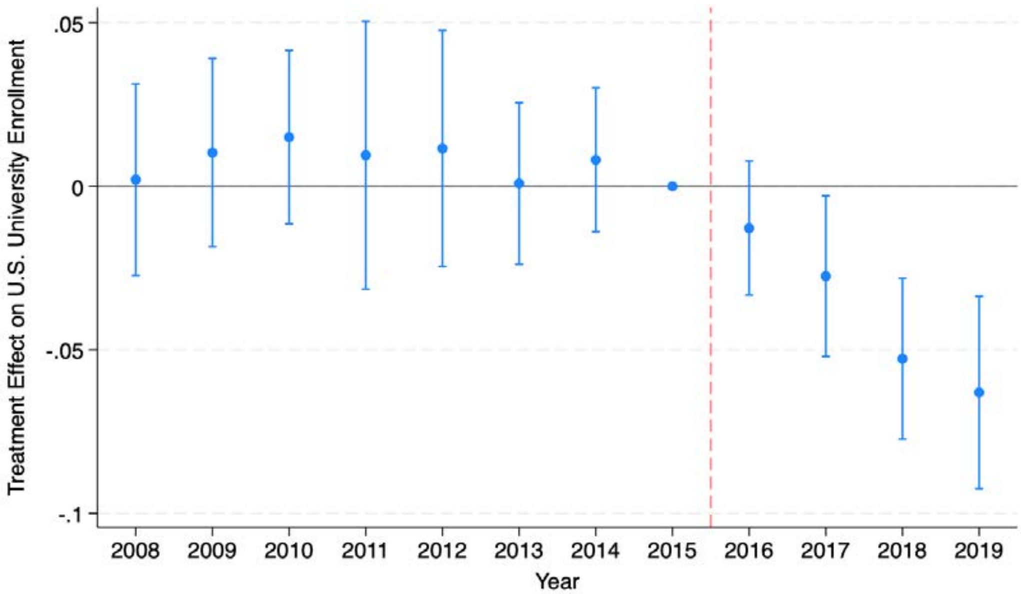


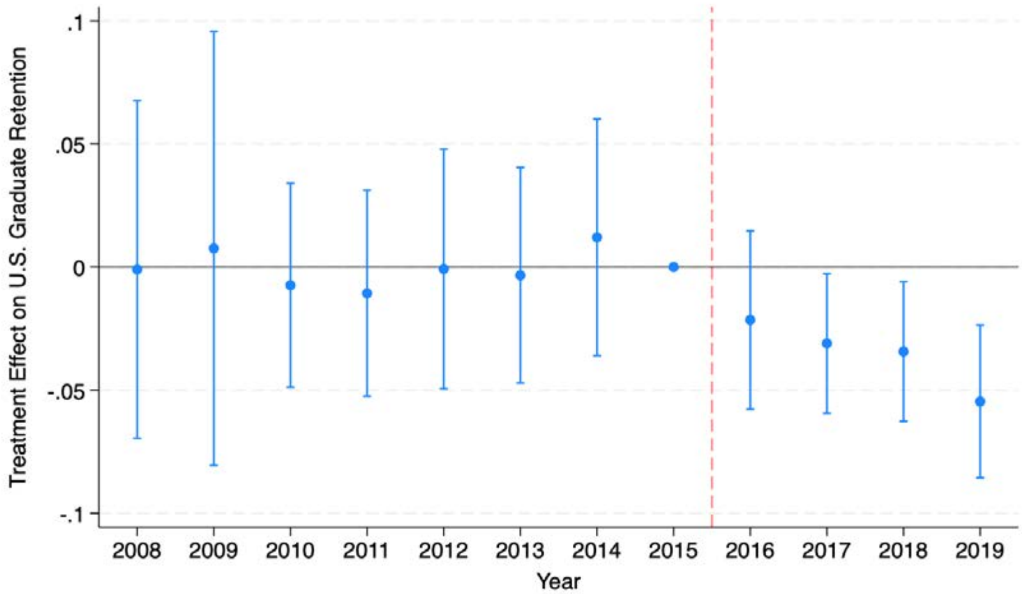
Figure 3: Summary of Data Sources & Sample Construction

Figure 4: Event Study for Propensity to Enroll in a U.S. University



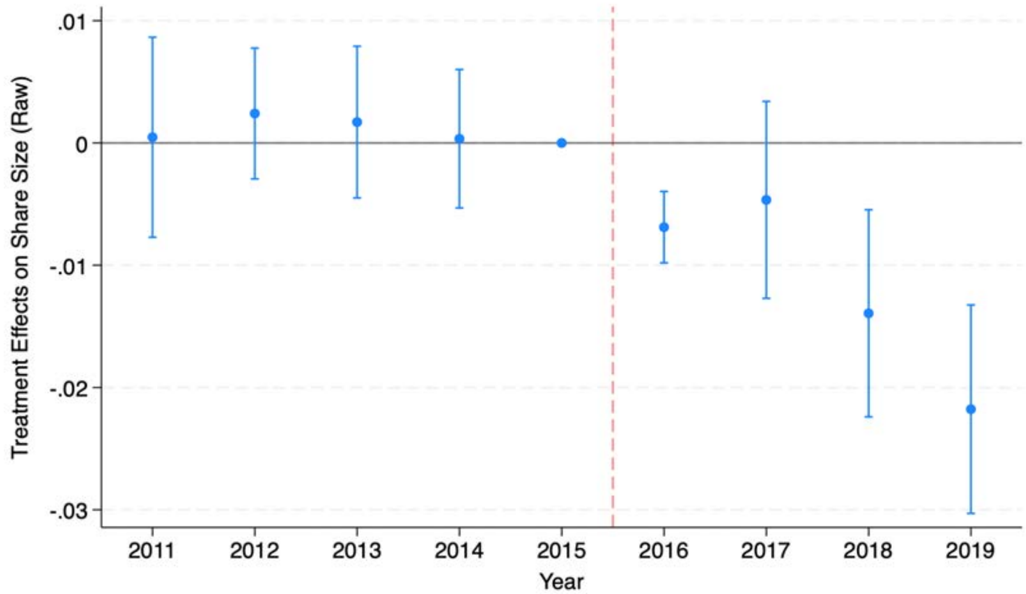
Notes: This plot reports event-study coefficients from a regression predicting enrollment in a U.S. university. The treated group is ethnically Chinese doctoral students, and the control group is non-ethnically Chinese doctoral students. The regression includes cohort, prior degree country, and field fixed effects. Standard errors are clustered at the field-year level.

Figure 5: Event Study for Likelihood of U.S. Retention



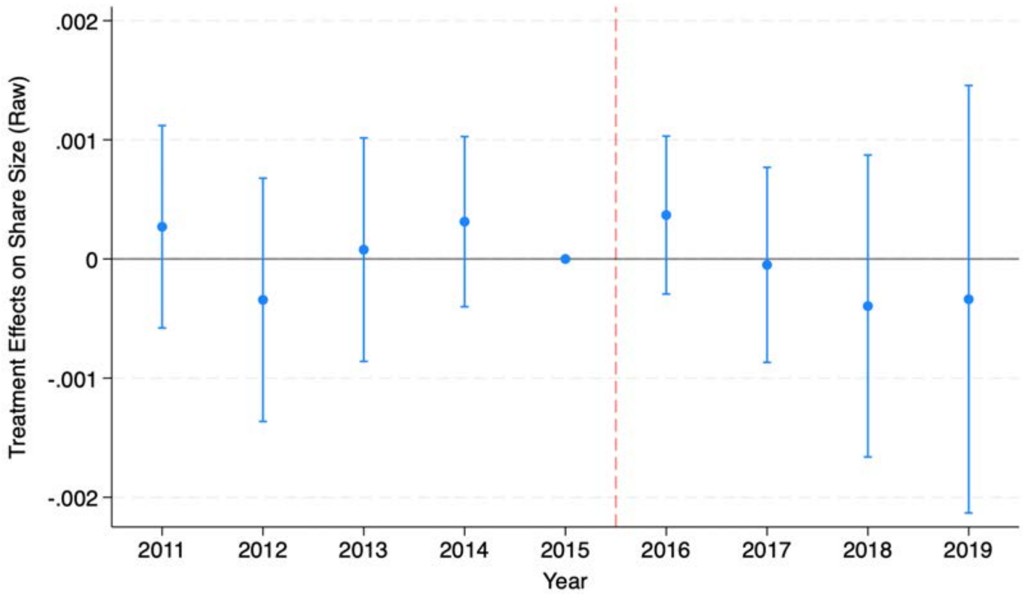
Notes: This plot reports event-study coefficients from a regression predicting whether post-graduation jobs remain in the U.S. The treated group is ethnically Chinese U.S. graduates, and the control group is non-ethnically Chinese U.S. graduates. The regression includes cohort and field fixed effects. Standard errors are clustered at the field-year level.

Figure 6: Event Study for Chinese Researchers Building on U.S. Science



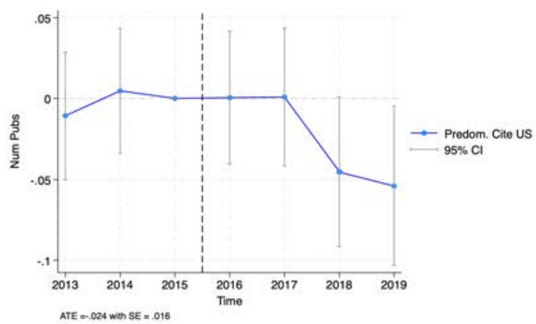
Notes: This plot reports event-study coefficients from a regression predicting the unadjusted size of reference shares on Chinese papers. The treated group is reference shares citing the U.S., and the control group is reference shares citing the U.K. The regressions include fixed effects for the citing paper. Standard errors are clustered at the field level.

Figure 7: Event Study for U.S. Researchers Building on Chinese Science

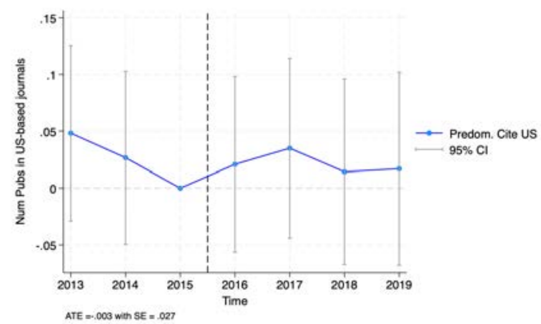


Notes: This plot reports event-study coefficients from a regression predicting the unadjusted share of references citing Chinese research using U.S. and U.K. publications. The treated group is U.S. papers, and the control group is U.K. papers. The regressions include fixed effects for publication years and research fields. Standard errors are clustered at the field level.

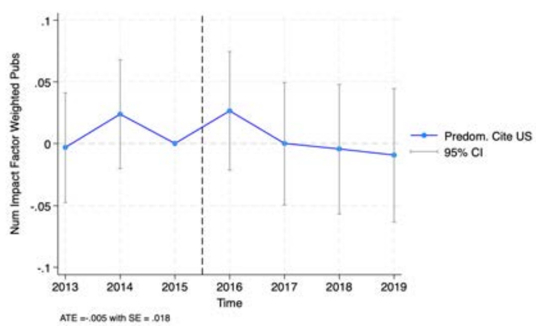
Figure 8: Event-Study Plots for Productivity Change among China-based Researchers



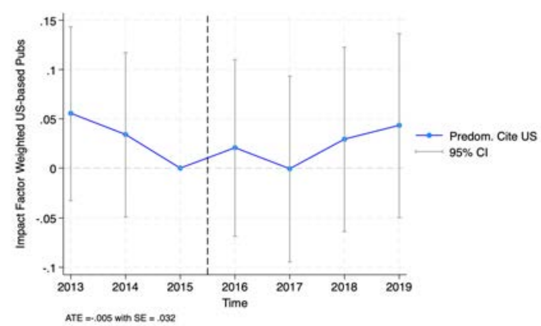
(a) DV:Pubs



(b) DV: U.S. Pubs



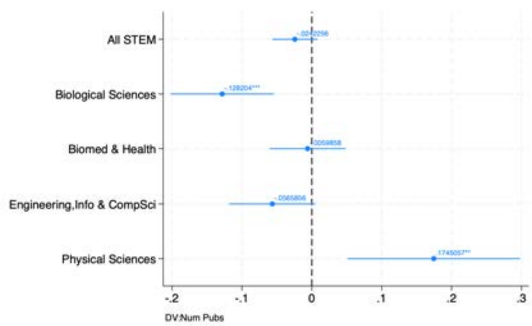
(c) DV: IF wt Pubs



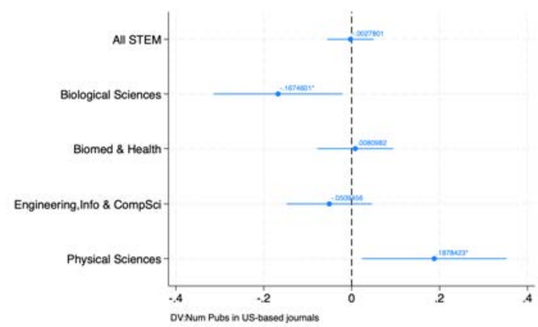
(d) DV:IF wt U.S. Pubs

Notes: This plot reports event-study coefficients from the Poisson regression using the China-based researcher panel. The dependent variable is in subfigure title. The treated group is the China-based researchers predominately citing US sciences, and the control group is the China-based researchers predominately citing UK sciences. The regressions include individual fixed effect and year fixed effect. Standard errors are clustered at the individual level.

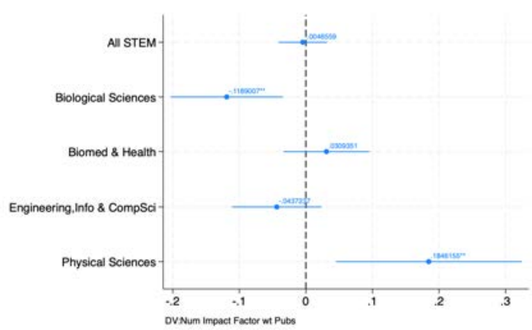
Figure 9: Coefficient Plots for Productivity Change among China-based Researchers, by Researcher's Modal Field



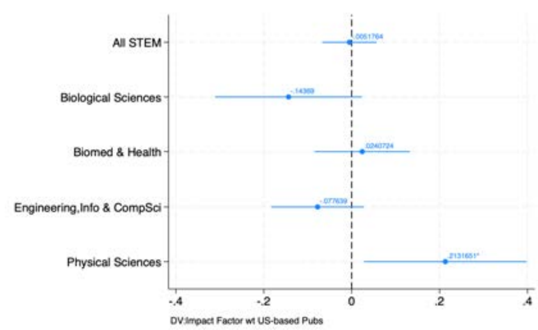
(a) DV:Pubs



(b) DV: U.S. Pubs



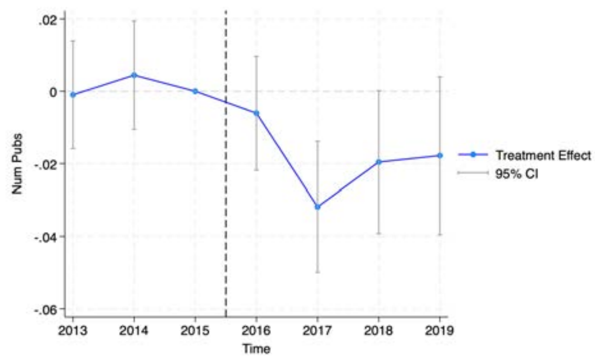
(c) DV: IF wt Pubs



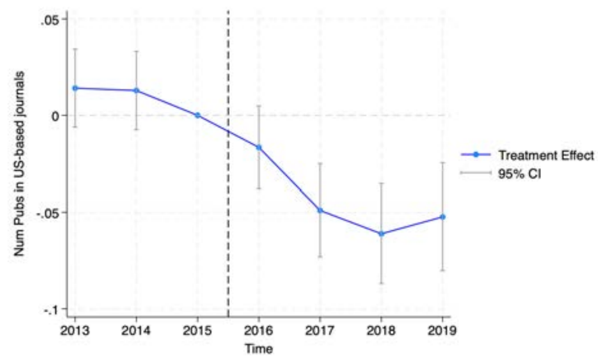
(d) DV:IF wt U.S. Pubs

Notes: This plot reports coefficient from the Poisson regression using the China-based researcher panel for each field. The dependent variable is in subfigure title. The treated group is the China-based researchers predominately citing US sciences, and the control group is the China-based researchers predominately citing UK sciences. The regressions include individual fixed effect and year fixed effect. Standard errors are clustered at the individual level.

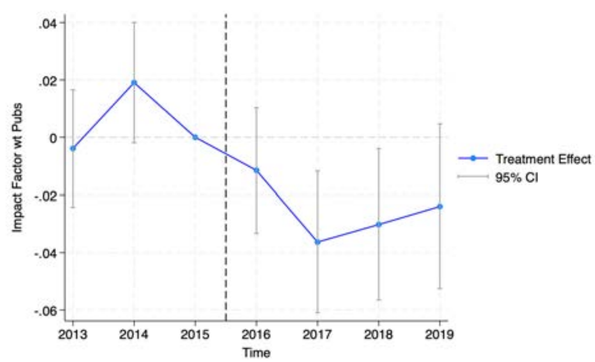
Figure 10: Event-Study Plots for Productivity Change among U.S.-based Researchers



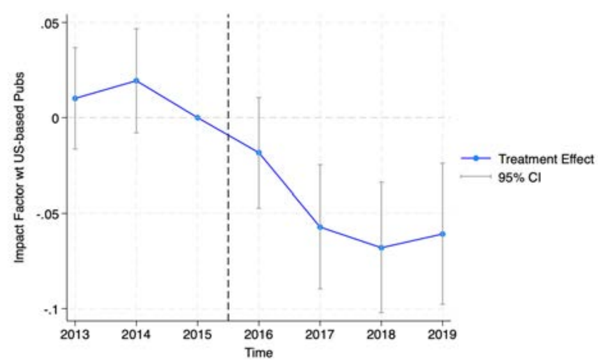
(a) DV:Pubs



(b) DV: U.S. Pubs



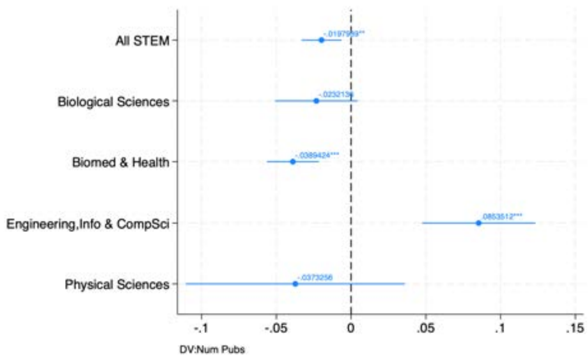
(c) DV: IF wt Pubs



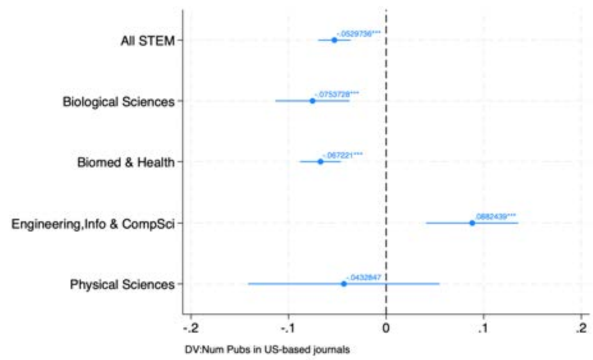
(d) DV:IF wt U.S. Pubs

Notes: This plot reports event-study coefficients from the Poisson regression using the U.S.-based researcher panel. The dependent variable is in subfigure title. The treated group is the U.S.-based ethnically Chinese researchers, and the control group is the matched non-ethnically Chinese researchers. The regressions include individual fixed effect and year fixed effect. Standard errors are clustered at the individual level.

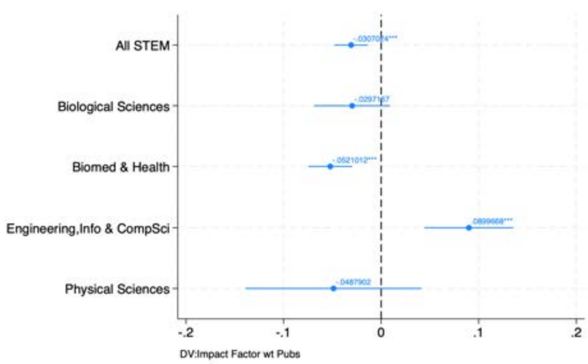
Figure 11: Coefficient Plots for Productivity Change among U.S.-based Researchers, by Researcher's Modal Field



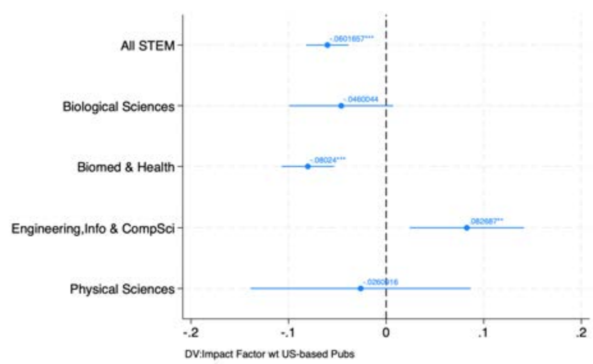
(a) DV:Pubs



(b) DV: U.S. Pubs



(c) DV: IF wt Pubs



(d) DV:IF wt U.S. Pubs

Notes: This plot reports coefficient from the Poisson regression using the U.S.-based researcher panel for each field. The dependent variable is in subfigure title. The treated group is the U.S.-based ethnically Chinese researchers, and the control group is the matched non-ethnically Chinese researchers. The regressions include individual fixed effect and year fixed effect. Standard errors are clustered at the individual level.

Table 1: Basic Summary Statistics Across Datasets

Panel A: Doctoral Student Dataset	Mean	SD	Min	p50	Max
Ph.D. first year	2,012.79	2.88	2,008	2,013	2,019
Enrolls in U.S. university	0.24	0.43	0	0	1
Enrolls in U.K. university	0.09	0.29	0	0	1
Enrolls in non-U.S. anglo. university	0.17	0.37	0	0	1
Treatment = ethnically Chinese	0.16	0.37	0	0	1
Observations	128,928				

Panel B: U.S. Graduates Dataset	Mean	SD	Min	p50	Max
Job first year	2,014.92	3.16	2,008	2,016	2,019
Job in U.S.	0.85	0.35	0	1	1
Job in U.K.	0.01	0.10	0	0	1
Job in non-U.S. anglo. country	0.03	0.16	0	0	1
Ethnically CN	0.18	0.38	0	0	1
Observations	50,890				

Panel C: Publication-Citation Shares	Mean	SD	Min	p50	Max
Citing U.S.	0.50	0.50	0	.5	1
Share of raw references	0.13	0.15	0	.0667	1
Share of recent references	0.09	0.15	0	0	1
Share of frontier references (1%)	0.19	0.28	0	0	1
Share of recent frontier references (1%)	0.16	0.29	0	0	1
Observations	4,247,176				

Panel D: U.S.-U.K. Publications Dataset	Mean	SD	Min	p50	Max
U.S. publication	0.83	0.38	0	1	1
Share of raw citations to China	0.02	0.04	0	0	1
Share of recent citations to China	0.03	0.07	0	0	1
Share of frontier citations to China (1%)	0.01	0.06	0	0	1
Share of recent frontier citations to China (1%)	0.02	0.09	0	0	1
Observations	2,847,700				

Panel E: China-based Researcher Panel	Mean	SD	Min	P50	Max
Num Pubs	3.68	3.56	1	3	72
Num Pubs in US-based journals	1.06	1.59	0	1	52
Num Impact Factor wt Pubs	7.94	9.17	1	5.03	294
Impact Factor wt US-based Pubs	2.62	4.96	0	1.46	241
Predom. Cite US	0.50	0.50	0	1	1
Observations	76,086				

Panel F: U.S.-based Researcher Panel	Mean	SD	Min	p50	Max
Num Pubs	2.61	2.92	1	2	175
Num Pubs in US-based journals	1.52	2.04	0	1	58
Impact Factor wt Pubs	7.58	11.02	1	3.92	515
Impact Factor wt US-based Pubs	4.85	8.55	0	2.32	335
Ethnic CN	0.19	0.39	0	0	1
Observations	853,087				

Notes: This table provides basic descriptive statistics for the data we construct in Section 3. The panel title describes the unit of analysis for each dataset. Panels A and B summarize the data for analyzing student mobility (student level), Panels C and D for scientific knowledge flows (publication-share and publication level), and Panels E and F for researcher productivity (researcher by year level).

Table 2: Applications of Differences-in-Differences Across Analyses

		Sample	**Main DV**	**Treated**	**Control**
Student Mobility	*China*	Doctoral Students	Enrolls in U.S.	Ethnically Chinese	Non-ethnically Chinese
	U.S.	U.S. Graduates	Job in U.S.	Ethnically Chinese	Non-ethnically Chinese
Knowledge Flows	*China*	Publication-Citation Shares	Size	Citing U.S.	Citing U.K.
	U.S.	U.S.-U.K. Publications	Citation Share to Chinese Research	U.S. Publication	U.K Publication
Researcher Productivity	*China*	China-Based Researchers	# of publications	Predominantly Citing U.S.	Predominantly Citing U.K.
	U.S.	U.S.-Based Researchers	# of publications	Ethnically Chinese	Non-ethnically Chinese

Notes: This table describes the differences-in-differences components for each analysis. Treatment is modeled as taking effect for the treated group in and after 2016. Additional considerations for each specification are described in Section 4.

Table 3: Main Treatment Effects on Student Mobility Among Ethnically Chinese Researchers

	(1) Enrolls in U.S.	(2) Enrolls in U.K.	(3) Enrolls in Anglo.
Treatment = ethnically Chinese=1	0.0319***	-0.0197***	-0.0234***
	(0.00456)	(0.00376)	(0.00490)
Treatment = ethnically Chinese=1 × Post-2016=1	-0.0371***	0.00851**	0.0208***
	(0.00778)	(0.00388)	(0.00656)
Field FE	Y	Y	Y
Cohort FE	Y	Y	Y
Prior Country FE	Y	Y	Y
Model	OLS	OLS	OLS
Mean DV	0.239	0.0910	0.169
Observations	128910	128910	128910

Notes: This table presents difference-in-differences coefficients describing the impact of Chinese ethnicity on the probability of enrolling in a U.S. university after 2016. Standard errors are clustered at the field-year level. The dependent variable for each model is in the column heading. The sample includes all doctoral students in STEM fields between 2008 and 2019, with the post-treatment period being after 2016. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

Table 4: Treatment Effect Heterogeneity by Prior Institutional Affiliation Country

	(1) Enrolls in U.S.	(2) Enrolls in U.S.	(3) Enrolls in U.S.	(4) Enrolls in U.S.
Treatment = ethnically Chinese from China=1	0.132***			
	(0.0119)			
Treatment = ethnically Chinese from China=1 × Post-2016=1	-0.0423***			
	(0.0102)			
Treatment = ethnically Chinese not from China=1		0.0116***		
		(0.00407)		
Treatment = ethnically Chinese not from China=1 × Post-2016=1		-0.0150*		
		(0.00856)		
Treatment = ethnically Chinese from U.S.=1			0.00161	
			(0.00675)	
Treatment = ethnically Chinese from U.S.=1 × Post-2016=1			-0.00802	
			(0.0138)	
Treatment = ethnically Chinese not from U.S.=1				0.0455***
				(0.00523)
Treatment = ethnically Chinese not from U.S.=1 × Post-2016=1				-0.0401***
				(0.00871)
Field FE	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y
Prior Country FE	Y	Y	Y	Y
Model	OLS	OLS	OLS	OLS
Mean DV	0.239	0.239	0.239	0.239
Observations	128910	128910	128910	128910

Notes: This table presents difference-in-differences coefficients describing the impact of Chinese ethnicity on the probability of enrolling in a U.S. university after 2016, depending on the country of their prior institutional affiliation. Standard errors are clustered at the field-year level. The sample includes all doctoral students in STEM fields between 2008 and 2019, with the post-treatment period being after 2016. The coefficients in Columns (1) and (2) are statistically different at the 10% level, p = 0.051. The coefficients in Columns (3) and (4) are statistically different at the 10% level, p = 0.062. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

Table 5: Main Treatment Effects on U.S. Retention for Post-U.S. Graduation Jobs

	(1) Job in U.S.	(2) Job in U.K.	(3) Job in Anglo.	(4) Job in U.S.	(5) Job in U.S.
Ethnically CN=1	-0.00119	-0.00613***	-0.0131***		
	(0.00767)	(0.00188)	(0.00308)		
Ethnically CN=1 × Post-2016=1	-0.0360***	0.00330	0.00845**		
	(0.00946)	(0.00222)	(0.00363)		
Treatment = ethnically Chinese from China=1 × Post-2016=1				-0.0591***	
				(0.0161)	
Treatment = ethnically Chinese not from China=1 × Post-2016=1					-0.00524
					(0.0177)
Field FE	Y	Y	Y	Y	Y
Job Year FE	Y	Y	Y	Y	Y
Model	OLS	OLS	OLS	OLS	OLS
Mean DV	0.853	0.00949	0.0255	0.847	0.847
Observations	50890	50890	50890	33899	33899

Notes: This table presents difference-in-differences coefficients describing the impact of Chinese ethnicity on the probability that a post-graduation job is in the U.S after 2016. Standard errors are clustered at the field-year level. The dependent variable for each model is in the column heading. The sample includes all U.S. graduates from STEM programs between 2008 and 2019, with the post-treatment period being after 2016. The coefficients in Columns (4) and (5) are statistically different at the 5% level, $p = 0.044$. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

Table 6: Main Treatment Effects on Knowledge Flows among Chinese Publications

	DV: Share Size			
	(1) Raw	(2) Recent	(3) Frontier	(4) Recent Frontier
Treated = citing U.S.=1	0.182***	0.124***	0.280***	0.247***
	(0.0137)	(0.0150)	(0.0186)	(0.0231)
Treated = citing U.S.=1 × Post-2016=1	-0.0139***	-0.0140***	-0.0143***	-0.0321***
	(0.00438)	(0.00256)	(0.00514)	(0.00552)
Citing Paper FE	Y	Y	Y	Y
Model	OLS	OLS	OLS	OLS
Mean DV	0.126	0.0853	0.193	0.162
Observations	4247176	4051996	3341386	2309406

Notes: Robust standard errors in parentheses with standard errors clustered at the field level. The dependent variable is in the column heading. The analysis sample is reference shares of Chinese publications citing U.S. or U.K. research. The analysis period is 2011-2019, where the post treatment period is 2016-2019. 'Treated' refers to reference shares citing U.S. research, with those citing U.K. research serving as the control group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Main Treatment Effects on Knowledge Flows among U.S. and U.K. Publications

	DV: Share Size			
	(1) Raw	(2) Recent	(3) Frontier	(4) Recent Frontier
Treated = U.S. publication=1	-0.000459	-0.000339	-0.000539	-0.000439
	(0.000587)	(0.000813)	(0.000338)	(0.000568)
Treated = U.S. publication=1 × Post-2016=1	-0.000167	0.000216	-0.000112	-0.000182
	(0.000665)	(0.000986)	(0.000518)	(0.000836)
Field & Year FE	Y	Y	Y	Y
Model	OLS	OLS	OLS	OLS
Mean DV	0.0166	0.0264	0.0109	0.0166
Observations	2847446	2769601	2361126	1836494

Notes: Robust standard errors in parentheses with standard errors clustered at the field level. The dependent variable is in the column heading. The sample is all U.S. and U.K. publications with U.S. or U.K. research teams during the analysis period. The analysis period is 2011-2019, and the post treatment period is 2016-2019. 'Treated' refers to publications in the U.S., with U.K. publications serving as the control group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Main Treatment Effects on Productivity among China-based Researchers

	(1) Pubs	(2) US Pubs	(3) IF wt Pubs	(4) IF wt US Pubs
Predom. Cite US=1 × Post-2016=1	-0.024	-0.003	-0.005	-0.005
	(0.016)	(0.027)	(0.018)	(0.032)
Indiv FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y
Mean DV	3.298	1.120	6.892	2.668
Observations	54,265	48,397	54,265	48,397

Notes: Robust standard errors in parentheses and clustered at the person level. The dependent variable is in column header. The analysis sample is China-based researcher panel. The analysis period is 2013-2019, where the post treatment period is 2016-2019. "Predom Cite US" refers to the Chinese researchers whose fraction of pre-2013 raw citation share is greater than the within-field 75$^{\text{th}}$ percentile to U.S. papers and below the 25$^{\text{th}}$ percentile to U.K. papers. The control group is Chinese researchers with above 75$^{\text{th}}$ percentile within field U.K. citation share and below 25$^{\text{th}}$ percentile within field U.S. citation share. The regression is weighted by the CEM matching weights. All specifications include the post dummy, year fixed effects, and individual fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Main Treatment Effects on Productivity among China-based Researchers, By Focal Researcher's Modal Field

	DV:Num Pubs				
	(1) All STEM	(2) Biological Sciences	(3) Biomed. & Health	(4) Engineering Info & CompSci	(5) Physics
Predom. Cite US=1 × Post-2016=1	-0.024	-0.128***	-0.006	-0.057*	0.175***
	(0.016)	(0.038)	(0.028)	(0.031)	(0.063)
Indiv FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y
Mean DV	3.298	2.956	3.134	3.634	3.150
Observations	54,265	5,342	17,982	16,541	2,858

	DV:Num Pubs in US-based journals				
	(1) All STEM	(2) Biological Sciences	(3) Biomed. & Health	(4) Engineering Info & CompSci	(5) Physics
Predom. Cite US=1 × Post-2016=1	-0.003	-0.167**	0.008	-0.051	0.188**
	(0.027)	(0.075)	(0.044)	(0.050)	(0.084)
Indiv FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y
Mean DV	1.120	0.896	1.091	1.327	1.483
Observations	48,397	4,908	16,843	14,264	2,505

	DV:Num Impact Factor wt Pubs				
	(1) All STEM	(2) Biological Sciences	(3) Biomed. & Health	(4) Engineering Info & CompSci	(5) Physics
Predom. Cite US=1 × Post-2016=1	-0.005	-0.119***	0.031	-0.044	0.185***
	(0.018)	(0.043)	(0.033)	(0.034)	(0.071)
Indiv FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y
Mean DV	6.892	6.324	6.662	7.396	6.481
Observations	54,265	5,342	17,982	16,541	2,858

	DV:Impact Factor wt US-based Pubs				
	(1) All STEM	(2) Biological Sciences	(3) Biomed. & Health	(4) Engineering Info & CompSci	(5) Physics
Predom. Cite US=1 × Post-2016=1	-0.005	-0.144*	0.024	-0.078	0.213**
	(0.032)	(0.085)	(0.055)	(0.054)	(0.094)
Indiv FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y
Mean DV	2.668	2.068	2.663	3.113	3.286
Observations	48,397	4,908	16,843	14,264	2,505

Notes: Robust standard errors in parentheses and clustered at the person level. The dependent variable is in panel header. The analysis sample is China-based researcher panel. The analysis period is 2013-2019, where the post treatment period is 2016-2019. "Predom Cite US" refers to the Chinese researchers whose fraction of pre-2013 raw citation share is greater than the within-field 75th percentile to U.S. papers and below the 25th percentile to U.K. papers. The control group is Chinese researchers with above 75th percentile within field U.K. citation share and below 25th percentile within field U.S. citation share. The regression is weighted by the CEM matching weights. All specifications include the post dummy, year fixed effects, and individual fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$..

Table 10: Main Treatment Effects on Productivity among U.S. based Researchers

	(1) Pubs	(2) US Pubs	(3) IF weighted Pubs	(4) IF weighted US Pubs
Ethnic CN=1 × Post-2016=1	-0.020***	-0.053***	-0.031***	-0.060***
	(0.007)	(0.008)	(0.009)	(0.011)
Indiv FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y
Mean DV	2.667	1.628	7.892	5.286
Observations	646,752	615,735	646,752	615,735

Notes: Robust standard errors in parentheses and clustered at the person level. The dependent variable is in column header.The analysis sample is U.S.-based researcher panel. The analysis period is 2013-2019, where the post treatment period is 2016-2019. '1[Ethnic CN]' refers the treatment group: being ethnically Chinese, as identified by name. The control group is non-ethnically Chinese researchers. The regression is weighted by the CEM matching weight. All specifications include the post dummy, year fixed effects, and individual fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Main Treatment Effects on Productivity among U.S.-based Researchers, By Focal Researcher's Modal Field

	DV:Num Pubs				
	(1) All STEM	(2) Biological Sciences	(3) Biomed. & Health	(4) Engineering Info & CompSci	(5) Physics
Ethnic CN=1 × Post-2016=1	-0.020***	-0.023*	-0.039***	0.085***	-0.037
	(0.007)	(0.014)	(0.009)	(0.019)	(0.037)
Indiv FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y
Mean DV	2.667	1.960	3.030	2.254	2.420
Observations	646,752	81,874	439,524	58,555	12,247

	DV:Num Pubs in US-based journals				
	(1) All STEM	(2) Biological Sciences	(3) Biomed. & Health	(4) Engineering Info & CompSci	(5) Physics
Ethnic CN=1 × Post-2016=1	-0.053***	-0.075***	-0.067***	0.088***	-0.043
	(0.008)	(0.019)	(0.011)	(0.024)	(0.050)
Indiv FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y
Mean DV	1.628	1.105	1.924	1.171	1.554
Observations	615,735	76,857	426,088	52,452	10,882

	DV:Impact Factor wt Pubs				
	(1) All STEM	(2) Biological Sciences	(3) Biomed. & Health	(4) Engineering Info & CompSci	(5) Physics
Ethnic CN=1 × Post-2016=1	-0.031***	-0.030	-0.052***	0.090***	-0.049
	(0.009)	(0.020)	(0.011)	(0.023)	(0.046)
Indiv FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y
Mean DV	7.892	6.621	9.330	5.236	6.357
Observations	646,752	81,874	439,524	58,555	12,247

	DV:Impact Factor wt US-based Pubs				
	(1) All STEM	(2) Biological Sciences	(3) Biomed. & Health	(4) Engineering Info & CompSci	(5) Physics
Ethnic CN=1 × Post-2016=1	-0.060***	-0.046*	-0.080***	0.083***	-0.026
	(0.011)	(0.027)	(0.014)	(0.030)	(0.058)
Indiv FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y
Mean DV	5.286	3.851	6.507	2.961	4.131
Observations	615,735	76,857	426,088	52,452	10,882

Notes: Robust standard errors in parentheses and clustered at the person level. The dependent variable is in column header.The analysis sample is U.S.-based researcher panel. The analysis period is 2013-2019, where the post treatment period is 2016-2019. '1[Ethnic CN]' refers the treatment group: being ethnically Chinese, as identified by name. The control group is non-ethnically Chinese researchers. The regression is weighted by the CEM matching weight. All specifications include the post dummy, year fixed effects, and individual fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$..

Building a Wall Around Science
Online Appendix

Robert Flynn Britta Glennon Raviv Murciano-Goroff Jiusi Xiao

A Data Construction

In this section, we provide additional details on the construction of the datasets used for analysis.

A.1 Enrollment and Retention Dataset

For analyzing the enrollment and retention of students at U.S. institutions, we leveraged data from ORCID. The ORCID website provides annual compilations of all public profiles on their platform. We downloaded the 2022 release of that data. We then parsed the CVs for all listed educational degrees and employment history. The ORCID website contains over 14 million CVs. We restricted to individuals reporting complete educational backgrounds, which amounts to 1.8 million CVs. We further restricted to those who graduated from STEM.[29] programs, a total of 836,495 CVs.

For analyzing changes in the likelihood of enrolling in U.S. doctoral programs, we classified each educational degree by its level based on common words and abbreviations for academic degree titles (e.g., *"Ph.D.," "PhD," "Doctoral,"* or *"Ed.D"*). We discarded individuals lacking terminal degrees at the doctoral level as well as individuals who did not claim at least one degree prior to their doctorate. For each remaining individual, we extracted the location (country) and enrollment year for their doctoral degree as well as the location of their prior degree. This amounts to 128,928 individuals enrolling in doctoral programs between 2008 and 2019.

For analyzing if graduates of U.S. institutions choose to remain in the U.S., we returned to the ORCID CVs, again restricting to individuals with complete educational backgrounds involving STEM. Further, we retained observations only for individuals whose terminal degree was from a U.S. institution. For each individual, we used their employment history to identify jobs started within three years following their U.S. graduation year. We extracted the location and employment start date from the earliest of these post-graduation jobs. This amounts to 50,890 individuals graduating from U.S. institutions beginning a post-graduation job.

Detailed summary statistics on both of these samples are provided in Table A1 and Table A2.

One might wonder how the individuals with ORCID CVs compare to the broader population of scientists and researchers. While there is no comprehensive way to compare these populations, we examine the differences in the number of publications in the

[29] The following 11 fields are considered STEM: Agriculture, Biological Sciences, Biomedical and Clinical Sciences, Chemical Sciences, Earth Sciences, Engineering, Environmental Sciences, Health Sciences, Information and Computing Sciences, Mathematical Sciences, and Physical Sciences (Australian Bureau of Statistics, 2020; Porter, Hawizy and Hook, 2023)

Dimension database for researchers with and without ORCID iDs. As seen in Table A3, individuals with ORCID iDs tend to be more active and have more publications than those without ORCID iDs. While recognizing this contrast is important for evaluating the generalizability of our results, we also think that focusing our analysis on this subset of research active scientists is informative given their significant contribution to science.

In addition, those with ORCID iDs are less likely to be ethnically Chinese. This does not pose a problem for our analysis for a number of reasons. First, our empirical approach estimates and plots event studies showing that the enrollment and employment of ethnically Chinese and non-ethnically Chinese scientists trended similarly in the years prior to 2016. This implies that whatever selection there was among ethnically Chinese scientists with using ORCID, it did not manifest in contrasting trends that would raise concerns about our difference-in-differences estimates. Second, if the lower rate of ethnically Chinese scientists being on ORCID is because ORCID is more popular among U.S.-based scientists, again our analysis would be focused on a sub-population that is particularly relevant for the policy evaluation we conducted.

Table A1: Summary Statistics for Doctoral Students Dataset

	Mean	SD	Min	p25	p50	p75	Max	Count
Ph.D. first year	2,012.79	2.88	2,008	2,010	2,013	2,015	2,019	128,928
Ph.D. last year	2,017.22	2.89	2,008	2,015	2,017	2,019	2,033	128,928
Treatment = ethnically Chinese	0.16	0.37	0	0	0	0	1	128,928
Time since previous degree	1.27	2.08	-18	0	1	2	10	128,928
Origins								
Prior degree in U.S.	0.18	0.38	0	0	0	0	1	128,928
Prior degree in China	0.12	0.33	0	0	0	0	1	128,928
Prior degree in India	0.10	0.30	0	0	0	0	1	128,928
Prior degree in U.K.	0.07	0.26	0	0	0	0	1	128,928
Prior degree in Brazil	0.05	0.22	0	0	0	0	1	128,928
Destinations								
Enrolls in U.S. university	0.24	0.43	0	0	0	0	1	128,928
Enrolls in U.K. university	0.09	0.29	0	0	0	0	1	128,928
Enrolls in Chinese university	0.08	0.27	0	0	0	0	1	128,928
Enrolls in Indian university	0.08	0.27	0	0	0	0	1	128,928
Enrolls in Brazilian university	0.04	0.20	0	0	0	0	1	128,928
Enrolls in non-U.S. anglo. university	0.17	0.37	0	0	0	0	1	128,928
Research fields								
Science & Engineering program	0.79	0.41	0	1	1	1	1	128,928
Medicine/Health program	0.21	0.41	0	0	0	0	1	128,928

Notes: the unit of observation is an individual student enrolling in a Ph.D. program. The sample includes only students enrolling in STEM (Science, Technology, Engineering, and Medicine) programs. We discard observations for students who began Ph.D. programs 10 or more years after finishing their prior degree.

Table A2: Summary Statistics for U.S. Graduates Dataset

	Mean	SD	Min	p25	p50	p75	Max	Count
Job first year	2,014.92	3.16	2,008	2,013	2,016	2,018	2,019	50,890
Graduation year	2,014.46	3.30	2,005	2,012	2,015	2,017	2,019	50,890
Ethnically CN	0.18	0.38	0	0	0	0	1	50,890
Terminal degree is Ph.D.	0.71	0.45	0	0	1	1	1	50,890
Lag from degree to job	0.46	0.80	0	0	0	1	3	50,890
Destinations								
Job in U.S.	0.85	0.35	0	1	1	1	1	50,890
Job in U.K.	0.01	0.10	0	0	0	0	1	50,890
Job in Canada	0.01	0.11	0	0	0	0	1	50,890
Job in Germany	0.01	0.09	0	0	0	0	1	50,890
Job in China	0.02	0.13	0	0	0	0	1	50,890
Job in non-U.S. anglo. country	0.03	0.16	0	0	0	0	1	50,890
Research fields								
Science & Engineering program	0.77	0.42	0	1	1	1	1	50,890
Medicine/Health program	0.23	0.42	0	0	0	0	1	50,890

Notes: the unit of observation is an individual student graduating from a U.S. institution. The sample includes only students graduating from STEM (Science, Technology, Engineering, and Medicine) programs. We retain observations only for graduates whose first post-graduation job begins within three years of graduation.

Table A3: Comparison of Researchers in Dimensions With and Without ORCID iDs

	No ORCID 10,125,703 (84.6%)	Has ORCID 1,841,893 (15.4%)	Total 11,967,596 (100.0%)
Years active after 2008	2.735	5.570	3.171
Publications (lifetime)	4.989	15.308	6.577
Pre-2016 publications	1.801	3.072	1.997
Post-2016 publications	3.187	12.230	4.579
SJR-weighted publications (lifetime)	10.334	34.811	14.102
Pre-2016 SJR-weighted publications	3.675	6.822	4.160
Post-2016 SJR-weighted publications	6.659	27.989	9.942
# of grants (lifetime)	0.071	0.252	0.099
# of research organizations (lifetime)	1.074	2.132	1.237
STEM field	0.755	0.816	0.765
HASS field	0.101	0.161	0.110
Missing field	0.143	0.023	0.125
Missing publications	0.077	0.008	0.066
Ethnically CN	0.198	0.133	0.188

Notes: the unit of observation is a researcher whose first publication in Dimensions was after 2008. We observe that researchers with ORCID profiles have generally stronger research attributes.

A.2 Knowledge Flows Dataset

Dimensions provides the bibliometric data we use to examine the impact of U.S.-China tensions on scientific knowledge flows. The Dimensions data covers over 1.8 billion citations connecting over 140 million publications, providing a comprehensive and global view of the academic citation landscape (Thelwall, 2018; Singh et al., 2021). Publication references serve as a large-scale and observable proxy for scientific knowledge flows in the form of trace data (Iaria, Schwarz and Waldinger, 2018). As such, we derive datasets from Dimensions describing the citation behavior of papers written by Chinese, U.S., and

U.K. research teams between 2011 and 2019, proceeding in two steps: (1) identifying publications by research teams in each nation and (2) quantifying the degree to which each cites prior research from foreign countries.

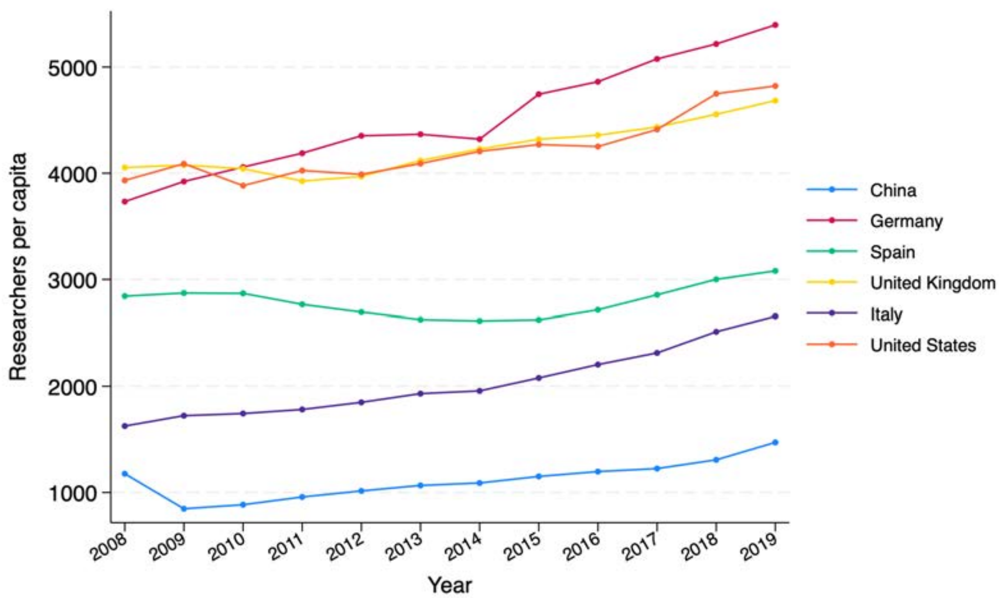
First, for each publication in Dimensions, we create flags for if all of the authors with location data list an affiliation address in China, the U.S., or the U.K. We refer to these publications as being written by Chinese, U.S., or U.K. research teams respectively. We discard publications where authors list addresses from more than one of these three countries (e.g., publications where all authors claim a Chinese address but one author also claims a U.S. address). Further, we discard publications that are not categorized as belonging to a STEM field. This amounts to 2,123,588 publications associated with Chinese research teams and 2,847,700 publications associated with U.S. or U.K. research teams issued between 2011 and 2019.

We then employ four measures of how publications build on research produced in other countries. Given a focal publication (citing paper), we identify the publications on its reference list (cited papers). For each cited paper, we assign an origin based on the affiliation address of its corresponding author. If the cited paper has no corresponding author, but involves researchers exclusively from one country, we assign that country. Otherwise, we leave the cited paper's origin country blank. Then, we use the assigned locations to construct four measures of usage per country. First, we calculate the "raw" usage of a given country's research by taking the simple fraction of cited papers assigned to that country. Second, we calculate the "recent" usage of a country's research by taking the fraction of cited papers published within five years of the citing paper that we assigned to that country. Third, we calculate the "frontier" usage of a country's research by taking the fraction of cited papers landing in the top 1%, 3%, or 5% of its field's citation distribution (using Dimensions' field citation ratio measure) that we assigned to that country. Finally, we calculate the "recent frontier" usage of a country's research by taking the fraction of cited papers satisfying both of these restrictions that we assigned to that country.

In analyzing knowledge flows between the U.S. and China, we make comparisons with U.K. researchers and U.K. produced research. We believe that these comparisons can serve as useful counterfactual trends for a variety of reasons. First, the U.S. and U.K. are top destinations for Chinese students. Second, researchers per capita tracks similarly for the U.S. and the U.K., as shown in Figure A1. Lastly, as shown in Figure A2, U.S. and U.K. researchers have similar distributions across scientific fields of their quality-weighted publications.

In Table A4, we provide summary statistics on the dataset used for analyzing the changing usage of U.S. produced research by China-based researchers. An observation in this dataset is a publication-citation share, where the citation share represents either citations to U.S. produced research or citations to U.K. produced research. These citation shares come from the papers of Chinese research teams.

Figure A1: Per Capita Researchers Across Countries



Notes: This plot presents the number of researchers per capita for various countries between 2008 and 2019. The data is sourced from the World Bank via the UNESCO Institute for Statistics (UIS). We observe that the U.S. and the U.K. exhibit both similar levels and similar trends.

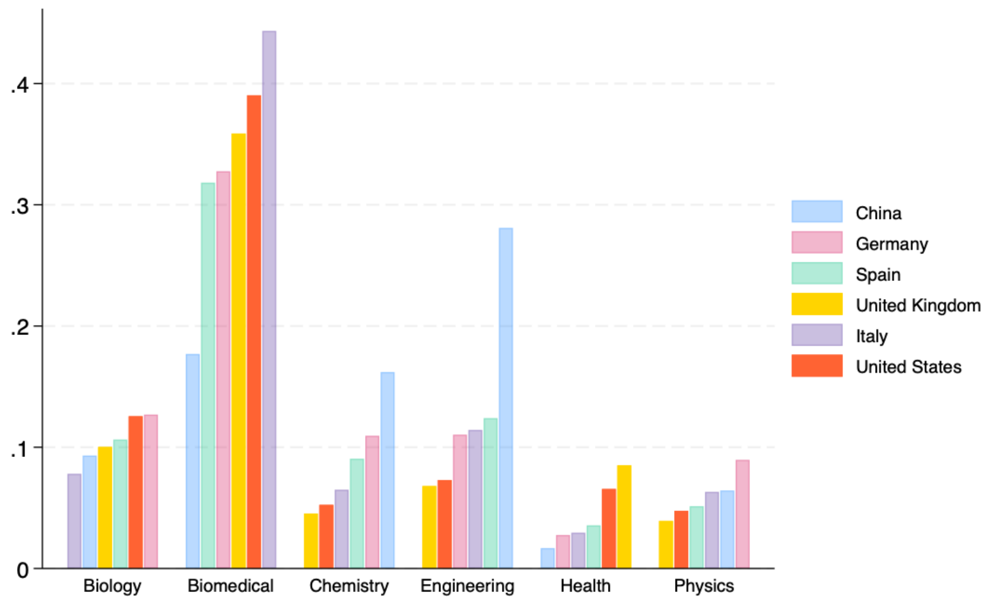
Table A4: Summary Statistics for Publication-Citation Shares Dataset

	Mean	SD	Min	p25	p50	p75	Max	Count
Citing U.S.	0.50	0.50	0	0	.5	1	1	4,247,176
Share of raw references	0.13	0.15	0	0	.0667	.2	1	4,247,176
Share of recent references	0.09	0.15	0	0	0	.125	1	4,051,996
Share of frontier references (1%)	0.19	0.28	0	0	0	.333	1	3,341,386
Share of recent frontier references (1%)	0.16	0.29	0	0	0	.25	1	2,309,406
Citing paper attributes								
Publication year	2,015.69	2.56	2,011	2,014	2,016	2,018	2,019	4,247,176
Number of fields	1.24	0.46	1	1	1	1	5	4,247,176
Field: biology	0.11	0.31	0	0	0	0	1	4,247,176
Field: biomedical	0.21	0.41	0	0	0	0	1	4,247,176
Field: chemistry	0.20	0.40	0	0	0	0	1	4,247,176
Field: engineering	0.38	0.48	0	0	0	1	1	4,247,176
Field: health	0.02	0.15	0	0	0	0	1	4,247,176
Field: physics	0.07	0.26	0	0	0	0	1	4,247,176
Science & Engineering program	0.81	0.40	0	1	1	1	1	4,247,176
Medicine/Health program	0.22	0.42	0	0	0	0	1	4,247,176

Notes: the unit of observation is a publication-citation share citing the U.S. or U.K. All citing papers belong to STEM fields and are written by Chinese research teams.

In Table A5, we provide summary statistics on the dataset used for analyzing the changing usage of China produced research by U.S. research teams. An observation in this dataset is a publication written by a U.S. or U.K. research team, and the outcome of interest is the share of their references citing China produced research.

Figure A2: Fraction of Countries' Quality-Weighted Publications Belonging to Fields (2011-2015)



Notes: This plot graphs the fraction of countries' quality-weighted publications belonging to each of the selected STEM fields. Publications are quality-weighted by the SJR score of their publishing journal. We observe that research in the U.S. distributes among fields similarly to that of the U.K. relative to other countries. The data is constructed using Dimensions.

Table A5: Summary Statistics for U.S.-U.K. Publications Dataset

	Mean	SD	Min	p25	p50	p75	Max	Count
Publication year	2,015.05	2.59	2,011	2,013	2,015	2,017	2,019	2,847,700
Number of fields	1.25	0.48	1	1	1	1	5	2,847,700
U.S. publication	0.83	0.38	0	1	1	1	1	2,847,700
Share of raw citations to China	0.02	0.04	0	0	0	.0137	1	2,847,700
Share of recent citations to China	0.03	0.07	0	0	0	0	1	2,769,843
Share of frontier citations to China (1%)	0.01	0.06	0	0	0	0	1	2,361,343
Share of recent frontier citations to China (1%)	0.02	0.09	0	0	0	0	1	1,836,702
Share of references citing U.S.	0.47	0.22	0	.324	.48	.622	1	2,847,700
Share of references citing U.K.	0.08	0.14	0	0	.0417	.103	1	2,847,700
Research fields								
Field: biology	0.14	0.35	0	0	0	0	1	2,847,700
Field: biomedical	0.48	0.50	0	0	0	1	1	2,847,700
Field: chemistry	0.08	0.27	0	0	0	0	1	2,847,700
Field: engineering	0.13	0.34	0	0	0	0	1	2,847,700
Field: health	0.15	0.35	0	0	0	0	1	2,847,700
Field: physics	0.06	0.24	0	0	0	0	1	2,847,700
Science & Engineering program	0.48	0.50	0	0	0	1	1	2,847,700
Medicine/Health program	0.57	0.50	0	0	1	1	1	2,847,700

Notes: the unit of observation is a publication. The sample includes only publications associated with STEM fields whose authors are based in the U.S. or U.K. Publications with no citations are dropped from the dataset.

A.3 Productivity Dataset

We use Dimensions' bibliometric data to examine the impact of U.S.-China tensions on researcher productivity. The advantages of the Dimensions dataset here are twofold. First, the dataset is comprehensive, with 140 million publications across fields and countries. Second, it links the publications to other valuable information such as researchers, organizations, and research grants. Finally, Dimensions' attention to researcher disambiguation, powered by algorithms, enables the construction of a reliable researcher panel.

For analyzing the productivity effect on China- and U.S.-based scientists, we create a panel dataset which we call *the Researcher Panel*. We define "China-based" ("U.S.-based") researchers as those for whom China (the U.S.) is the majority country reported on publication addresses between 2008 and 2012. To classify the primary field of the focal researcher, we use the all-time modal field of their publications. We again restrict to researchers operating in STEM fields.

The Researcher panel is created by constructing a strongly balanced panel of these authors using their publication records in the years between 2008 and 2019. We choose 2019 as the end year to avoid shocks to scientific productivity associated with COVID-19. For each researcher-year observation, we include the number of publications by that author in that year, as well as quality-adjusted measures, such as the number of publications weighted by the impact factor of the journal that those papers were published in.

When analyzing the effect of the rising U.S.-China tensions on the productivity of Chinese researchers, we focus on a sub-sample of China-based STEM researchers who published five or more publications between 2008 and 2012 as well as at least one publication between 2013 and 2019. For each China-based researcher, we calculated the fraction of references on their 2008-2012 publications that cited the U.S., U.K., and China, locating cited papers using the same approach as in Section A.2. We use the citation measures to construct the treatment and control group in our China side analysis. Specifically, the treated group includes researchers who are in the 75th percentile or higher within their field for the portion of their citations that go to publications from the U.S. and are below the 25th percentile for their field for their citation share to publications from the U.K. The control group is similarly defined as being above the 75th percentile in citation share within field to the U.K. and below the 25th percentile in citation share within the field to the U.S.

Due to the heterogeneity in prolificacy and quality, a direct comparison between China-based researchers who predominantly cite U.S. science and those who predominantly cite U.K. sciences may not be appropriate. To construct a more suitable comparison group, we employed the coarsened exact matching (CEM) method described in Iacus, King and Porro (2012). CEM coarsens the covariates into strata and matches the treated and untreated units based on the strata. In the China-based researcher analysis, we use the following covariates in the matching process: the number of publications before 2013, proxied career age as of 2012, the number of actively publishing years between 2008 and 2012, whether the researcher has a university affiliation, whether the researcher is located in a Tier 1 City, or New Tier 1 Cities, the average and growth rate of the number of publications between 2013 and 2015, the level and the growth rate of the number of impact-factor-weighted publications between 2013 and 2015 [30]. The descriptive statistics of the matching covariates are shown in Table A6. The CEM algorithm matched 11,975 individuals, out of which 5,982 who predominately cite scientific publications from the U.S. and 5,993 who predominately cite publications from the U.K. We use matching weights generated by the CEM algorithm in the associated regression analyses.

To demonstrate the balance between our treated and matched control groups for China-based researchers, we provide summary statistics on the attributes of these groups in Table A6. In addition, we show summary statistics on the publications of these groups in Table A7.

[30] The career age and the number of publications produced between 2008-2012 are evenly split in 4 and 10 bins respectively when matching.

Table A6: China-based Researcher Panel Descriptive Statistics: CEM Matching Variables

	(1) All	(2) Matched	(3) Matched-Untreated	(4) Matched-Treated
Num Pubs in 2008-2012	13.38	8.081	8.135	8.027
	(10.41)	(4.124)	(4.147)	(4.101)
Career Age	7.322	5.895	5.953	5.837
	(4.419)	(3.450)	(3.533)	(3.363)
Num Active Years in 2008-2012	3.825	3.429	3.429	3.430
	(1.076)	(1.012)	(1.013)	(1.011)
1[University]	0.655	0.656	0.657	0.656
	(0.475)	(0.475)	(0.475)	(0.475)
1[Tier 1 Cities]	0.352	0.348	0.326	0.370
	(0.477)	(0.476)	(0.469)	(0.483)
1[New Tier 1 Cities]	0.344	0.351	0.351	0.352
	(0.475)	(0.477)	(0.477)	(0.478)
Growth Rate of Num Pubs 2008-2012	-0.000222	0.0135	0.0130	0.0140
	(0.194)	(0.190)	(0.196)	(0.184)
Num Pubs	4.481	2.404	2.391	2.418
	(5.120)	(1.546)	(1.552)	(1.539)
Growth Rate of IF-wt Pubs 2008-2012	0.0114	0.0300	0.0283	0.0316
	(0.254)	(0.248)	(0.253)	(0.244)
Num Impact Factor Weighted Pubs	9.680	4.605	4.403	4.807
	(13.20)	(3.458)	(3.332)	(3.568)
Observations	132,272	11,975	5,993	5,982

Notes: Standard deviation in parentheses.

Table A7: China-based Researcher Panel Descriptive Statistics: Outcome Variables

	(1) All	(2) Matched	(3) Matched-Treated	(4) Matched-Untreated
Num Pubs	4.481	2.404	2.391	2.418
	(5.120)	(1.546)	(1.552)	(1.539)
Num Pubs in US-based journals	1.312	0.717	0.621	0.813
	(1.895)	(0.843)	(0.776)	(0.895)
Num Impact Factor Weighted Pubs	9.680	4.605	4.403	4.807
	(13.20)	(3.458)	(3.332)	(3.568)
Impact Factor Weighted US-based Pubs	3.315	1.583	1.277	1.889
	(6.058)	(2.123)	(1.788)	(2.373)
Observations	132,272	11,975	5,993	5,982

Notes: Standard deviation in parentheses.

For analyzing the relative productivity effect on U.S.-based STEM researchers, we subset the Researcher Panel to the U.S.-based researchers who published at least one publication between 2008 and 2013. We included the same fields, as well as the same sets of covariates. Additionally, we constructed a set of variables to proxy the propensity toward foreign collaboration for the U.S.-based researchers: whether the focal person listed any foreign address, whether the focal researcher cited any foreign funding sources, the number and fraction of distinct foreign coauthors, and whether the focal person has coauthors who have foreign funding. We imputed their ethnicity (see Section A.4) from their name and created a binary indicator for being ethnically Chinese as our treatment indicator.

For the U.S. side, we are interested in examining ethnically Chinese researchers, as the China Initiative disproportionally prosecuted and discriminated against ethnic Chinese researchers in the U.S. However, active U.S. researchers who are ethnic Chinese behave very differently from non-ethnic Chinese, in terms of prolificacy, impact, size and composition of collaborator pool, and topic. Similar to the China side, to construct the appropriate control group, we employed the CEM technique. With ethnic Chinese as treatment status, we used all pre-analysis covariates and pretreatment characteristics between 2011 and 2015 and matched within the modal field. The pre-analysis covariates include the number of publications before 2013, proxied career age as of 2012, the number of actively publishing years between 2008 and 2012, whether the researcher has a university affiliation, fraction of the coauthors that are foreign, number of distinct foreign coauthors, whether the researcher has a Chinese coauthor, whether the researcher listed any foreign address, whether the researcher listed any foreign funding, and whether the researcher has coauthors with foreign funding. The pretreatment characteristics include the average and growth rate of the number of publications between 2013 and 2015, the level and the growth rate of the number of impact-factor-weighted publications between 2013 and 2015, the level and the growth rate of number of collaborators between 2013 and 2015, and the level and the growth rate of number of Chinese collaborators between 2013 and 2015. Table A8 reports the summary statistics of the covariates. The algorithm matched 231,296 individuals, out of which 129,032 individuals are non-ethnically Chinese and 29,587 individuals are ethnically Chinese. The generated CEM weight will be applied in the regression analysis.

To demonstrate the balance between our treated and matched control groups for U.S.-based researchers, we provide summary statistics on the attributes of these groups in Table A8. In addition, we show summary statistics on the publications of these groups in Table A9.

Table A8: U.S.-based Researcher Panel Descriptive Statistics : CEM Matching Variables

	(1) All	(2) Matched	(3) Matched-Untreated	(4) Matched-Treated
Num Pubs in 2008-2012	9.604	4.057	3.900	4.756
	(16.44)	(5.261)	(5.095)	(5.892)
Career Age	10.53	4.491	4.355	5.097
	(9.885)	(4.378)	(4.228)	(4.945)
Num Active Years in 2008-2012	2.921	2.070	2.020	2.291
	(1.509)	(1.250)	(1.225)	(1.336)
1[University]	0.442	0.428	0.419	0.465
	(0.497)	(0.495)	(0.493)	(0.499)
Fraction of Foreign Coauthors	0.115	0.0163	0.0135	0.0288
	(0.197)	(0.0709)	(0.0643)	(0.0935)
Num of Distinct Foreign Coauthors	3.980	0.311	0.248	0.593
	(11.66)	(1.541)	(1.327)	(2.237)
1[Have Foreign Address]	0.242	0.0283	0.0235	0.0494
	(0.428)	(0.166)	(0.152)	(0.217)
Fraction of Foreign Coauthors	0.115	0.0163	0.0135	0.0288
	(0.197)	(0.0709)	(0.0643)	(0.0935)
1[Have Foreign Funding]	0.280	0.0476	0.0378	0.0909
	(0.449)	(0.213)	(0.191)	(0.288)
1[Have Coauthors with Foreign Funding]	0.811	0.738	0.722	0.808
	(0.392)	(0.440)	(0.448)	(0.394)
Growth Rate of Num Pubs 2008-2012	-0.00147	-0.00387	-0.00226	-0.0101
	(0.345)	(0.315)	(0.314)	(0.318)
Num Pubs	2.818	1.739	1.717	1.836
	(3.725)	(1.343)	(1.325)	(1.416)
Growth Rate of IF-wt Pubs 2008-2012	-0.00813	-0.0145	-0.0135	-0.0184
	(0.540)	(0.524)	(0.521)	(0.535)
Num Impact Factor Weighted Pubs	8.589	4.713	4.558	5.400
	(15.96)	(5.138)	(4.984)	(5.725)
Growth Rate of Num CN Collab 2008-2012	0.0157	0.00411	0.00202	0.0122
	(0.246)	(0.144)	(0.0964)	(0.254)
Num Chinese Collaborator	0.287	0.0552	0.0190	0.216
	(1.990)	(0.557)	(0.284)	(1.139)
Growth Rate of Num Collab 2008-2012	0.0347	0.0334	0.0337	0.0324
	(0.562)	(0.539)	(0.544)	(0.519)
Num Collaborator	12.66	7.891	7.699	8.742
	(17.97)	(6.759)	(6.575)	(7.465)
Observations	675,195	231,296	188,790	42,506

Notes: Standard deviation in parentheses.

Table A9: U.S.-based Researcher Panel Descriptive Statistics :Outcome Variables

	(1) All	(2) Matched	(3) Matched-Untreated	(4) Matched-Treated
Num Pubs in 2008-2012	9.604	4.057	3.900	4.756
	(16.44)	(5.261)	(5.095)	(5.892)
Career Age	10.53	4.491	4.355	5.097
	(9.885)	(4.378)	(4.228)	(4.945)
Num Active Years in 2008-2012	2.921	2.070	2.020	2.291
	(1.509)	(1.250)	(1.225)	(1.336)
1[University]	0.442	0.428	0.419	0.465
	(0.497)	(0.495)	(0.493)	(0.499)
Fraction of Foreign Coauthors	0.115	0.0163	0.0135	0.0288
	(0.197)	(0.0709)	(0.0643)	(0.0935)
Num of Distinct Foreign Coauthors	3.980	0.311	0.248	0.593
	(11.66)	(1.541)	(1.327)	(2.237)
1[Have Foreign Address]	0.242	0.0283	0.0235	0.0494
	(0.428)	(0.166)	(0.152)	(0.217)
Fraction of Foreign Coauthors	0.115	0.0163	0.0135	0.0288
	(0.197)	(0.0709)	(0.0643)	(0.0935)
1[Have Foreign Funding]	0.280	0.0476	0.0378	0.0909
	(0.449)	(0.213)	(0.191)	(0.288)
1[Have Coauthors with Foreign Funding]	0.811	0.738	0.722	0.808
	(0.392)	(0.440)	(0.448)	(0.394)
Growth Rate of Num Pubs 2008-2012	-0.00147	-0.00387	-0.00226	-0.0101
	(0.345)	(0.315)	(0.314)	(0.318)
Num Pubs	2.818	1.739	1.717	1.836
	(3.725)	(1.343)	(1.325)	(1.416)
Growth Rate of IF-wt Pubs 2008-2012	-0.00813	-0.0145	-0.0135	-0.0184
	(0.540)	(0.524)	(0.521)	(0.535)
Num Impact Factor Weighted Pubs	8.589	4.713	4.558	5.400
	(15.96)	(5.138)	(4.984)	(5.725)
Growth Rate of Num CN Collab 2008-2012	0.0157	0.00411	0.00202	0.0122
	(0.246)	(0.144)	(0.0964)	(0.254)
Num Chinese Collaborator	0.287	0.0552	0.0190	0.216
	(1.990)	(0.557)	(0.284)	(1.139)
Growth Rate of Num Collab 2008-2012	0.0347	0.0334	0.0337	0.0324
	(0.562)	(0.539)	(0.544)	(0.519)
Num Collaborator	12.66	7.891	7.699	8.742
	(17.97)	(6.759)	(6.575)	(7.465)
Observations	675,195	231,296	188,790	42,506

Notes: Standard deviation in parentheses.

A.4 Ethnicity & Field Imputation

This paper uses measures of ethnicity and scientific field distilled from self-reported names and departments, respectively. To impute ethnicity, we employ the Python package *ethnicseer* using individuals' full names. We use *ethnicseer* specifically because it can classify ethnicity with the granularity our analysis requires (e.g., Chinese ethnicity instead of Asian). In addition, Torvik and Agarwal (2016) find that *ethnicseer* agrees with Ethnea (another popular ethnicity imputation package) 94% of the time for ethnically Chinese names, suggesting our approach is comparable with that of other researchers. We do not use the non-Chinese ethnicities imputed by *ethnicseer* other than to classify individuals as "non-ethnically Chinese."

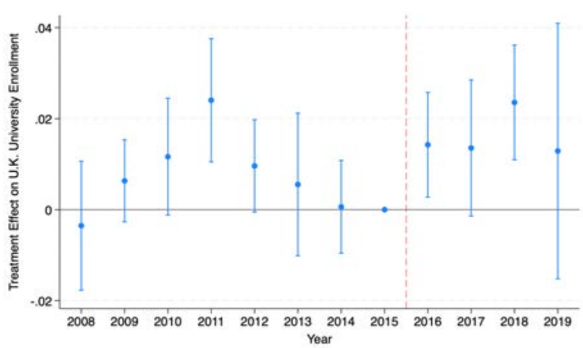
To infer scientific fields for ORCID researchers, we leverage academic department data self-reported on education spells. We use the FoR (Field of Research) framework from ANZSRC (Australian and New Zealand Standard Research Classification) to map unstructured department data onto 22 distinct research fields (Australian Bureau of Statistics, 2020). For example, a researcher whose department contained the substring *"biolog"* might be assigned to the field "biological sciences." When a researcher's listed department contains multiple relevant substrings, we rely on the last one to infer field. For example, a researcher listing their department as "computational biology" would be assigned to the field "biological sciences" by the substring *"biolog"* (as opposed to "computer sciences" by the substring *"comput"*).

B Additional Enrollment Results and Robustness Checks

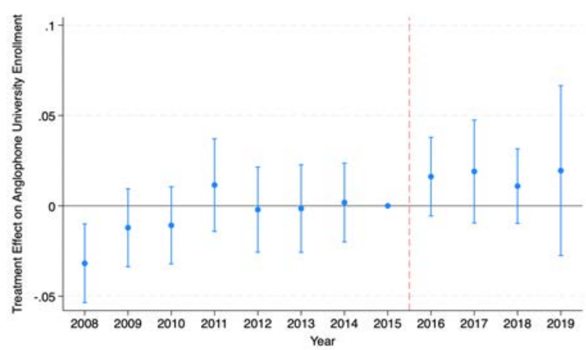
In this section, we provide additional results regarding the enrollment of graduate students in U.S. doctoral programs.

In Table 3, we documented that following the rise in U.S.-China tensions, an increasing share of ethnically Chinese doctoral students enrolled in non-U.S. anglophone programs relative to non-ethnically Chinese doctoral students. In Figures A3(a) and A3(b), we estimate and plot event studies for the enrollment in U.K. universities and all non-U.S. anglophone universities. While the pre-trends are noisy and not perfectly flat for enrollment in U.K. universities, the event study for non-U.S. anglophone universities reveals a distinctive increase in enrollment in the years following 2016.

Figure A3: Event Studies for Propensity to Enroll in English Speaking Alternative Universities



(a) Enrolls in U.K. University



(b) Enrolls in Non-U.S. anglophone University

Notes: These plots report event-study coefficients from regressions predicting enrollment in U.K. or non-U.S. anglophone universities. The treated group is ethnically Chinese doctoral students, and the control group is non-ethnically Chinese doctoral students. The regressions includes cohort, prior degree country, and field fixed effects. Standard errors are clustered at the field-year level.

We conduct a series of additional analyses and demonstrate the robustness of our findings regarding enrollment in U.S. programs. In Table A10, we repeat our analysis of enrollment in U.S. programs for subsets of areas of study. In Column (1), we show the results for Social Science. In Column (2), we show the results for Social Science and STEM together. In Column (3), we show the results for Engineering. The estimated coefficients on the interaction between the student being ethnically Chinese and the observation coming from after 2016 are all negative and significant at the 5% level. This implies that across these different areas of study the negative impact on enrollment occurred.

Table A10: Main Treatment Effects on Mobility among Ethnically Chinese Researchers Across Fields of Study

	(1) Enrolls in U.S.	(2) Enrolls in U.S.	(3) Enrolls in U.S.
Treatment = ethnically Chinese=1	0.0161	0.0297***	0.0426***
	(0.0105)	(0.00415)	(0.00629)
Treatment = ethnically Chinese=1 × Post-2016=1	-0.0498**	-0.0386***	-0.0323***
	(0.0196)	(0.00757)	(0.0108)
Field FE	Y	Y	Y
Cohort FE	Y	Y	Y
Prior Country FE	Y	Y	Y
Model	OLS	OLS	OLS
Sample	Social Sciences	Social + STEM	Engineering
Errors	Clustered	Clustered	Robust
Mean DV	0.214	0.234	0.243
Obs	30283	159210	35250

Notes: Standard errors in parentheses, either clustered at the field-year level or robust. The dependent variable is a binary variable capturing whether the student enrolled in a U.S. university. The analysis sample is all doctoral students. The analysis period is 2008-2019, where the post treatment period is 2016-2019. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, in Table A11, we re-run our difference-in-differences estimates for the enrollment in U.S. programs while varying the maximum number of years permitted between a researcher's Ph.D. and their prior degree. Reassuringly, the estimated coefficients on the main effect and interaction terms are largely unchanged.

Table A11: Main Treatment Effects on Enrollment among Ethnically Chinese Researchers with Lag Sensitivity Checks

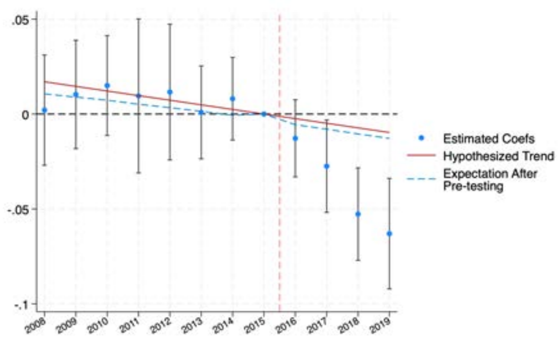
	(1) Enrolls in U.S.	(2) Enrolls in U.S.	(3) Enrolls in U.S.	(4) Enrolls in U.S.
Treatment = ethnically Chinese=1	0.0319***	0.0321***	0.0320***	0.0342***
	(0.00456)	(0.00460)	(0.00431)	(0.00494)
Treatment = ethnically Chinese=1 × Post-2016=1	-0.0371***	-0.0371***	-0.0367***	-0.0394***
	(0.00778)	(0.00782)	(0.00773)	(0.00814)
Field FE	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y
Prior Country FE	Y	Y	Y	Y
Model	OLS	OLS	OLS	OLS
Max Time Since Prior Degree	10 Years	15 Years	5 Years	1 Year
Mean DV	0.239	0.237	0.244	0.259
Obs	128910	130838	121608	91649

Notes: Standard errors clustered at the field-year level in parentheses. The dependent variable is in the column heading. The analysis sample is all global Ph.D. "seekers." Each column varies the maximum number of years permitted between a researcher's Ph.D. and their prior degree. The analysis period is 2008-2019, where the post treatment period is 2016-2019. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

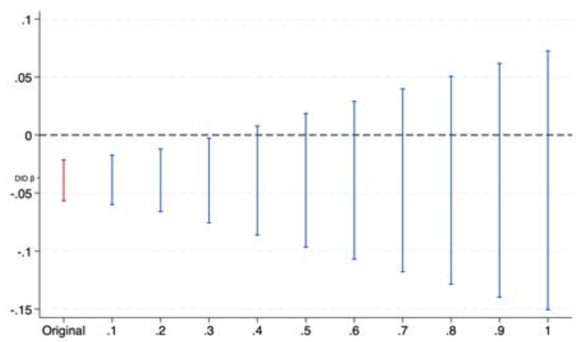
Given that we implement a difference-in-differences empirical approach, we run additional analyses to test our estimates robustness to the possibility of non-parallel trends. We do this using three methods. First, in Figure A4(a) we visualize the possibility of a parallel trends violation using the Stata *pretends* package based on the work of Roth (2022). Second, in Figure A4(b), we run the HonestDiD estimation procedure for sensitivity analysis based on Rambachan and Roth (2023). Finally, in Figure A4(c), we run a permutation test.

Figure A4: Parallel Trends Tests for Enrollment in U.S. Doctoral Programs Results

(a) *pretrends* Test



(b) *honestdid* Test



(c) *ritest* Test

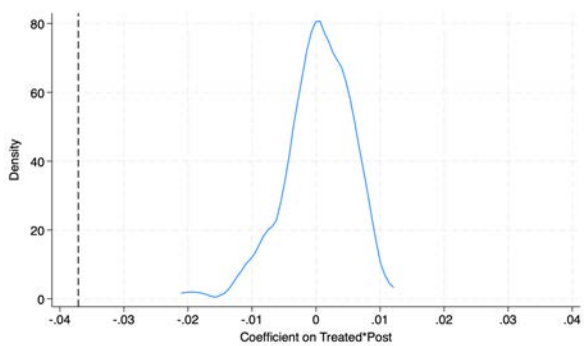
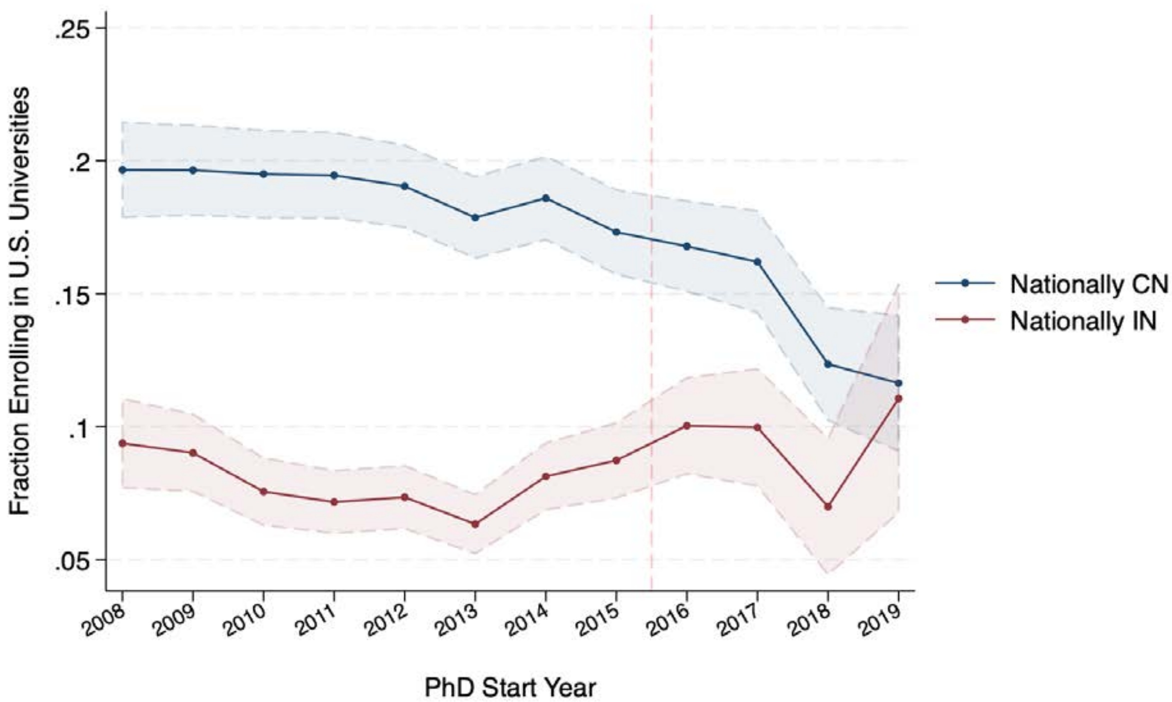


Figure A5: Raw Fraction of New Doctoral Students Enrolling in U.S. By Nationality



Notes: This figure plots the raw fraction of new doctoral students enrolling in U.S. universities by nationality. We infer the nationality of an incoming doctoral student based on the country of their prior degree. We include plots for nationally Chinese and nationally Indian doctoral students.

C Additional Retention Results and Robustness Checks

In Table 5, we documented that following the rise in U.S.-China tensions, an increasing share of ethnically Chinese graduates of doctoral programs took positions in non-U.S. anglophone universities. In Figures A6(a) and A6(b), we estimate and plot event studies for taking jobs in the U.K. and all non-U.S. anglophone countries. These plots are noisy, and any change in years after 2016 are less obvious.

We conduct a series of additional analyses and demonstrate the robustness of our findings regarding retention of grad students in U.S. programs.

First, in Table A12, we repeat our analysis of taking a position in the U.S. after graduation for subsets of graduates based on the area of study. In Column (1), we show the results for Social Science. In Column (2), we show the results for Social Science and STEM together. In Column (3), we show the results for Engineering. The estimated coefficients on the interaction between the student being ethnically Chinese and the observation coming from after 2016 negative and significant in Columns (2) and (3), but positive and significant in Column (1). This implies that graduates of STEM programs experienced qualitatively different effects than those in the social sciences.

Table A12: Main Treatment Effects on Mobility among Ethnically Chinese U.S. Graduates Beyond STEM

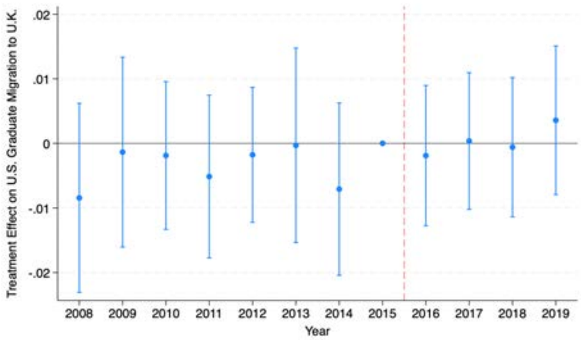
	(1) Job in U.S.	(2) Job in U.S.	(3) Job in U.S.
Ethnically CN=1	-0.181***	-0.0293***	0.0286
	(0.0178)	(0.00955)	(0.0183)
Ethnically CN=1 ×	0.0467**	-0.0217*	-0.0635***
Post-2016=1	(0.0235)	(0.0115)	(0.0210)
Field FE	Y	Y	Y
Cohort FE	Y	Y	Y
Prior Country FE	Y	Y	Y
Model	OLS	OLS	OLS
Sample	Social Sciences	Social + STEM	Engineering
Errors	Clustered	Clustered	Robust
Mean DV	0.786	0.839	0.809
Obs	13423	64313	7778

Notes: Standard errors in parentheses, either clustered at the field-year level or robust. The dependent variable is a binary variable capturing whether the student's post-graduation job was in the U.S. The analysis sample is all global Ph.D. "seekers." The analysis period is 2008-2019, where the post treatment period is 2016-2019. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

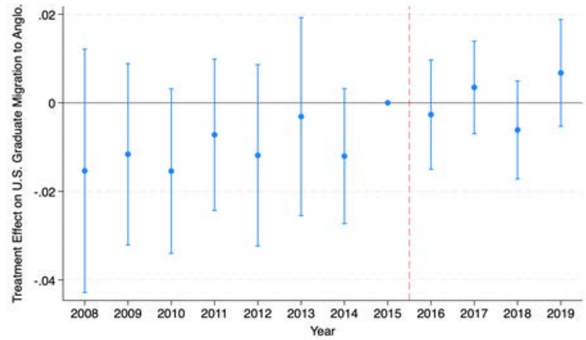
Next, we examine the subset of graduate students who completed a doctoral degree and look at the probability of remaining in the U.S. after completion of that degree. Figure A7 shows the event study for these individuals. The pattern, similar to the full sample used in the main text, shows flat pre-trends and a distinctive trend break following 2016.

Table A13 confirms these results by estimating the difference-in-differences specification using the subset of individuals graduating with a doctoral degree. Column (1) shows the results for taking a job in the U.S. Column (2) shows the results for taking a job in the U.K. Column (3) shows the results for taking a job in a non-U.S. anglophone country. The significant coefficient on the interaction terms in Column (1) and Column (3) reveals that these doctoral grads are relatively less likely to take a position in the U.S and relatively

Figure A6: Event Studies for Likelihood of Migration to English Speaking Alternative Employers



(a) Job at U.K. Employer



(b) Job at Non-U.S. anglophone Employer

Notes: These plots report event-study coefficients from regressions predicting whether a post-graduation job at a U.K. or non-U.S. anglophone employer. The treated group is ethnically Chinese U.S. graduates, and the control group is non-ethnically Chinese U.S. graduates. The regressions include cohort and field fixed effects. Standard errors are clustered at the field-year level.

more likely to take a position in a non-U.S. anglophone country. The results do not show an increasing migration to the U.K.

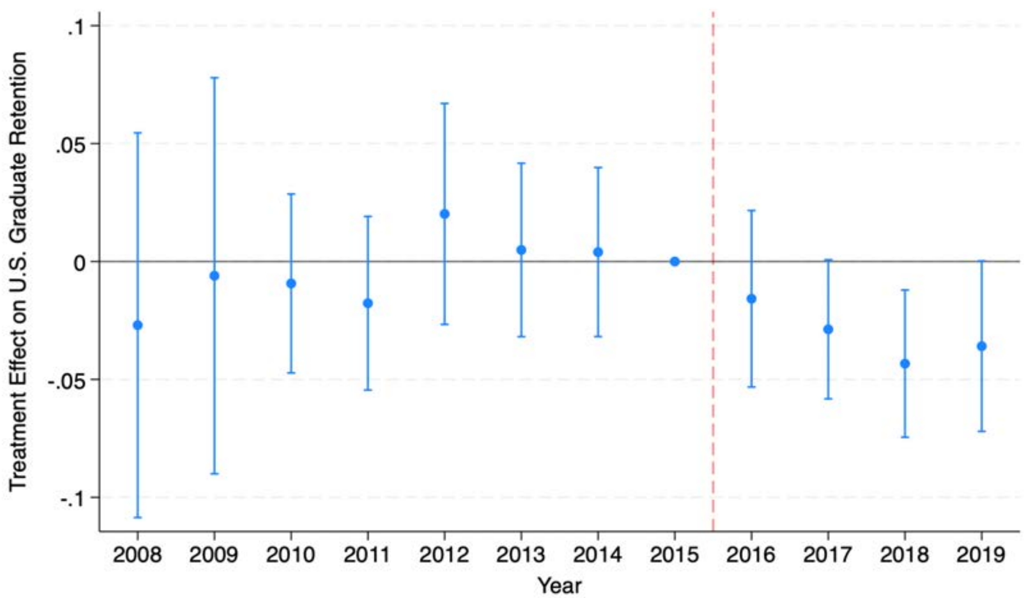
Table A13: Main Treatment Effects on Mobility among Ethnically Chinese U.S. Graduates (Ph.D. Only)

	(1) Job in U.S.	(2) Job in U.K.	(3) Job in Anglo.
Ethnically CN=1	0.0206***	-0.00825***	-0.0158***
	(0.00689)	(0.00223)	(0.00351)
Ethnically CN=1 ×	-0.0304***	0.00396	0.00820*
Post-2016=1	(0.00955)	(0.00264)	(0.00424)
Field FE	Y	Y	Y
Job Year FE	Y	Y	Y
Model	OLS	OLS	OLS
Mean DV	0.845	0.0121	0.0297
Observations	36015	36015	36015

Notes: Robust standard errors in parentheses without clustering. The dependent variable is in the column heading. The analysis sample is all jobs taken after 2008 by U.S. graduates earning degrees after 2005. The analysis period is 2008-2019, where the post treatment period is 2016-2019. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table A14, we re-run our difference-in-differences estimates for taking a job in the U.S. while varying the maximum number of years permitted between a researcher's job and graduate degree. Reassuringly, the estimated coefficients on the main effect and interaction terms are largely unchanged.

Figure A7: Event Study for Likelihood of U.S. Retention (Ph.D. Only)



Notes: This plot reports event-study coefficients from a regression predicting whether post-graduation jobs remain in the U.S among Ph.D. graduates only. The treated group is ethnically Chinese U.S. graduates, and the control group is non-ethnically Chinese U.S. graduates. The regression includes cohort and field fixed effects. Standard errors are clustered at the field-year level.

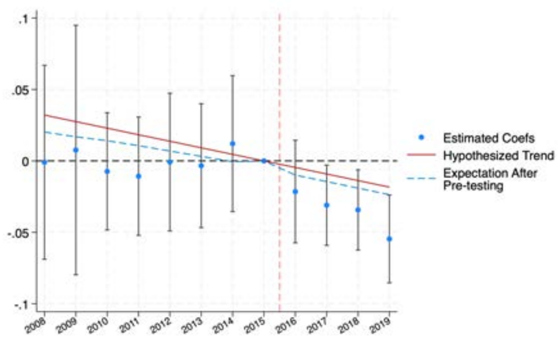
Table A14: Main Treatment Effects on Mobility among Ethnically Chinese U.S. Graduates with Lag Sensitivity

	(1) Job in U.S.	(2) Job in US	(3) Job in US
Ethnically CN=1	-0.00119	0.00251	0.00592
	(0.00767)	(0.00769)	(0.00748)
Ethnically CN=1 × Post-2016=1	-0.0360***	-0.0372***	-0.0385***
	(0.00946)	(0.00949)	(0.00960)
Field FE	Y	Y	Y
Cohort FE	Y	Y	Y
Prior Country FE	Y	Y	Y
Model	OLS	OLS	OLS
Max Time Since Prior Degree	3 Years	2 Years	1 Year
Mean DV	0.853	0.857	0.863
Obs	50890	48634	45537

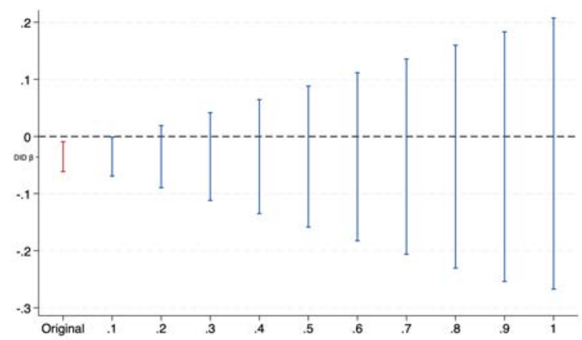
Notes: Standard errors clustered at the field-year level in parentheses. The dependent variable is in the column heading. The analysis sample is all jobs taken after 2008 by U.S. graduates earning degrees after 2005. Each column varies the maximum number of years permitted between a researcher's job and their graduate degree. The analysis period is 2008-2019, where the post treatment period is 2016-2019. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Lastly, we run additional analyses to test our estimates robustness to the possibility of non-parallel trends. We do this using three methods. First, in Figure A4(a) we visualize the possibility of a parallel trends violation using the Stata *pretends* package based on the work of Roth (2022). Second, in Figure A4(b), we run the HonestDiD estimation procedure for sensitivity analysis based on Rambachan and Roth (2023). Finally, in Figure A4(c), we run a permutation test.

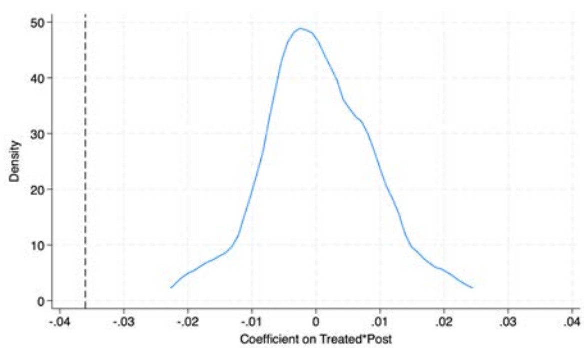
(a) *pretrends* Test for U.S. Graduate Jobs



(b) *honestdid* Test for U.S. Graduate Jobs



(c) *ritest* Test for U.S. Graduate Jobs



D Additional Knowledge Flows Results and Robustness Checks for Chinese Researchers Building on Science Produced in U.S.

In our main analysis, we investigate if Chinese researchers changed their usage of scientific works produced in the U.S. in the years following 2016. In the plots below, we plot event-study coefficients predicting the share of citations on the papers of researchers in China that cites U.S. sources relative to U.K. sources. Figure A9(a) uses a dependent variable of recent publications, which are defined as publications produced in the previous five years. Figure A9(b) uses a dependent variable of frontier publications, defined as top cited papers in a scientific field. Finally, Figure A9(c) shows the results with a dependent variable of recent-frontier works. All of the figures show a distinctive trend break at the 2016.

We also run our analysis on subsets of publications from outside of STEM fields in order to test if the effect is more-widespread. In Table A15, we show the estimated difference-in-differences results for Social Science papers. We estimate this with a dependent variable of the raw share of citations, the share of recent citations, frontier citations, and recent-frontier citations. Except for the raw share of citations, all of the other interaction terms reveal negative and significant effects on the share of U.S. social science works being cited.

Table A15: Main Treatment Effects on Knowledge Flows among Chinese Publications (Social Sciences)

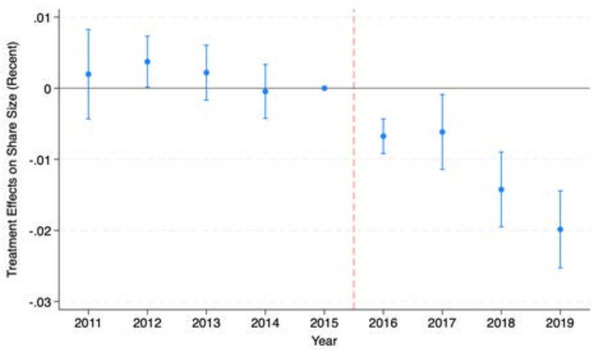
	DV: Share Size			
	(1) Raw	(2) Recent	(3) Frontier	(4) Recent Frontier
Treated = citing U.S.=1	0.202***	0.148***	0.279***	0.246***
	(0.0231)	(0.0200)	(0.0327)	(0.0306)
Treated = citing U.S.=1 × Post-2016=1	-0.00467	-0.0191***	-0.0101**	-0.0517***
	(0.00327)	(0.00551)	(0.00439)	(0.00818)
Citing Paper FE	Y	Y	Y	Y
Model	OLS	OLS	OLS	OLS
Sample	Social Sciences	Social Sciences	Social Sciences	Social Sciences
Mean DV	0.158	0.116	0.209	0.176
Observations	179782	161124	142528	100140

Notes: Robust standard errors in parentheses with standard errors clustered at the field level. The dependent variable is in the column heading. The analysis sample is reference shares of Chinese publications citing U.S. or U.K. research. The analysis period is 2011-2019, where the post treatment period is 2016-2019. 'Treated' refers to reference shares citing U.S. research, with those citing U.K. research serving as the control group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

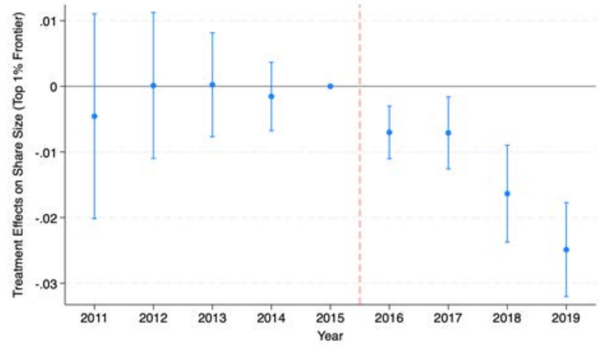
We conduct a series of additional analyses and demonstrate the robustness of our findings.

In Table A16, we highlight that our results regarding citations to frontier works are not driven by the cutoff point at which we define a paper as being a frontier work. In this table, we repeat our analysis for frontier works with a threshold of the work being in the

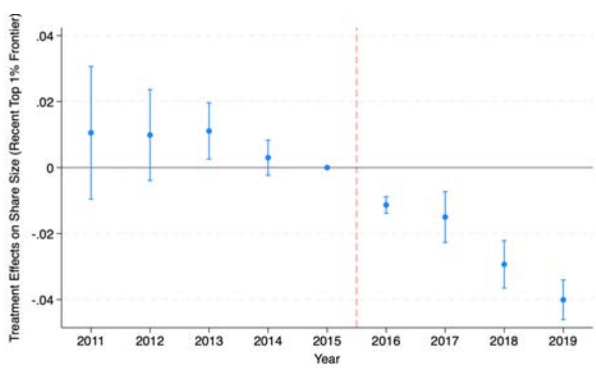
Figure A9: Event-Study Plots for Chinese Researchers Building on U.S. Science



(a) Predicting Share Size (Recent)



(b) Predicting Share Size (Frontier)



(c) Predicting Share Size (Recent Frontier)

Notes: These plots report event-study coefficients from regressions predicting adjusted sizes of reference shares on Chinese papers. The treated group is reference shares citing the U.S., and the control group is reference shares citing the U.K. The regressions include fixed effects for the citing paper. Standard errors are clustered at the field level.

top 3% or 5% of works in its field of science. The results are fairly similar across these specifications.

Table A16: Main Treatment Effects on Knowledge Flows among Chinese Publications (Other Frontier Thresholds)

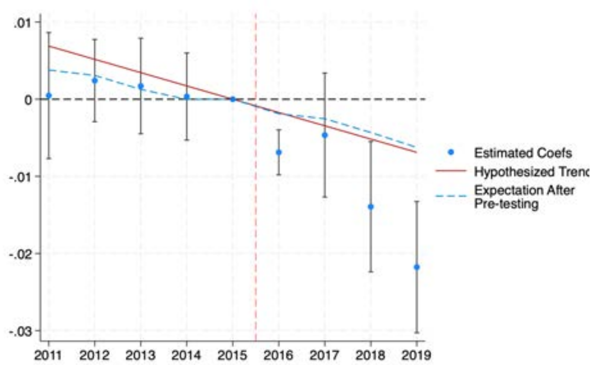
	DV: Share Size			
	(1) Frontier (3%)	(2) Recent Frontier (3%)	(3) Frontier (5%)	(4) Recent Frontier (5%)
Treated = citing U.S.=1	0.247***	0.211***	0.231***	0.194***
	(0.0188)	(0.0223)	(0.0182)	(0.0211)
Treated = citing U.S.=1 × Post-2016=1	-0.0131***	-0.0273***	-0.0125***	-0.0256***
	(0.00463)	(0.00455)	(0.00449)	(0.00445)
Citing Paper FE	Y	Y	Y	Y
Model	OLS	OLS	OLS	OLS
Mean DV	0.172	0.140	0.161	0.130
Observations	3727442	2946932	3863692	3232964

Notes: Robust standard errors in parentheses with standard errors clustered at the field level. The dependent variable is in the column heading. The analysis sample is reference shares of Chinese publications citing U.S. or U.K. research. The analysis period is 2011-2019, where the post treatment period is 2016-2019. 'Treated' refers to reference shares citing U.S. research, with those citing U.K. research serving as the control group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

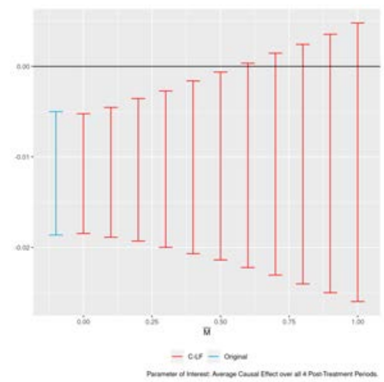
Given that we implement a difference-in-differences empirical approach, we run additional analyses to test our estimates robustness to the possibility of non-parallel trends. We do this using three methods. First, in Figure A10(a) we visualize the possibility of a parallel trends violation using the Stata *pretends* package based on the work of Roth (2022). Second, in Figure A10(b), we run the HonestDiD estimation procedure for sensitivity analysis based on Rambachan and Roth (2023). Finally, in Figure A10(c), we run a permutation test.

Figure A10: Parallel Trends Tests for Chinese Reliance on U.S. Science Results

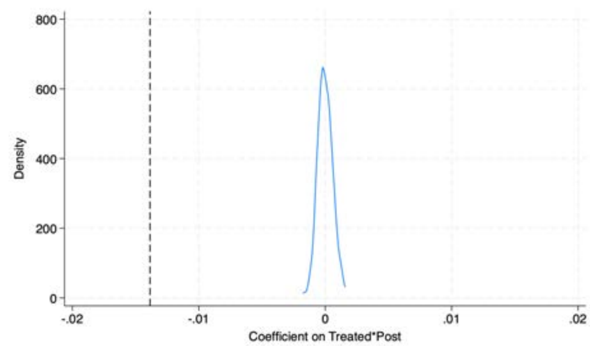
(a) *pretrends* Test



(b) *honestdid* Test



(c) *ritest* Test



E Additional Knowledge Flows Results and Robustness Checks for U.S. Researchers Building on Science Produced in China

In our main analysis, we investigate if U.S. researchers changed their usage of scientific works produced in China in the years following 2016. In the plots below, we plot event-study coefficients predicting the share of citations to the papers of researchers in China when comparing U.S. versus U.K. researchers. Figure A11(a) uses a dependent variable of recent publications, which are defined as publications produced in the previous five years. Figure A11(b) uses a dependent variable of frontier publications, defined as top cited papers in a scientific field. Finally, Figure A11(c) shows the results with a dependent variable of recent-frontier works. All of the figures show relatively flat plots across years.

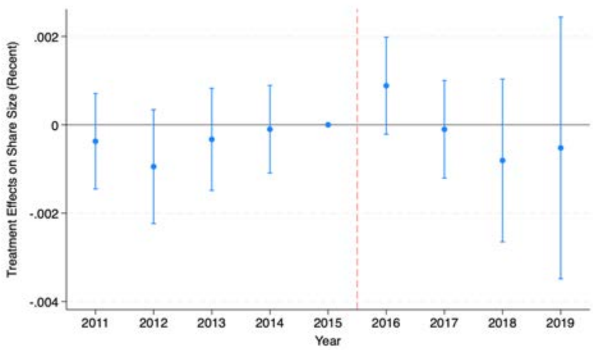
We also run our analysis on subsets of publications from outside of STEM fields in order to test if the effect is more-widespread. In Table A17, we show the estimated difference-in-differences results for Social Science papers. We estimate this with a dependent variable of the raw share of citations, the share of recent citations, frontier citations, and recent-frontier citations. Again, the insignificant and small estimated interaction terms do not indicate meaningful changes in the usage of Chinese research.

Table A17: Main Treatment Effects on Knowledge Flows among U.S.-U.K. Publications (Social Sciences)

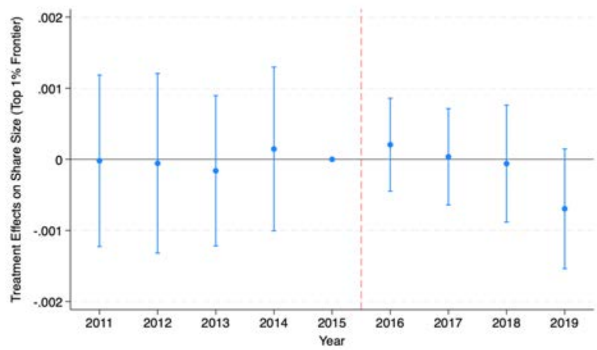
	DV: Share Size			
	(1) Raw	(2) Recent	(3) Frontier	(4) Recent Frontier
Treated = U.S. publication=1	-0.000456 (0.000331)	-0.000209 (0.000493)	-0.000784* (0.000475)	-0.000713 (0.000577)
Treated = U.S. publication=1 × Post-2016=1	0.000138 (0.000271)	0.000398 (0.000511)	0.000336 (0.000260)	-0.000110 (0.000517)
Field & Year FE	Y	Y	Y	Y
Model	OLS	OLS	OLS	OLS
Sample	Social Sciences	Social Sciences	Social Sciences	Social Sciences
Mean DV	0.00581	0.00954	0.00512	0.00808
Observations	662080	629124	557060	410616

Notes: Robust standard errors in parentheses with standard errors clustered at the field level. The dependent variable is in the column heading. The analysis sample is reference shares of Chinese publications citing U.S. or U.K. research. The analysis period is 2011-2019, where the post treatment period is 2016-2019. 'Treated' refers to reference shares citing U.S. research, with those citing U.K. research serving as the control group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

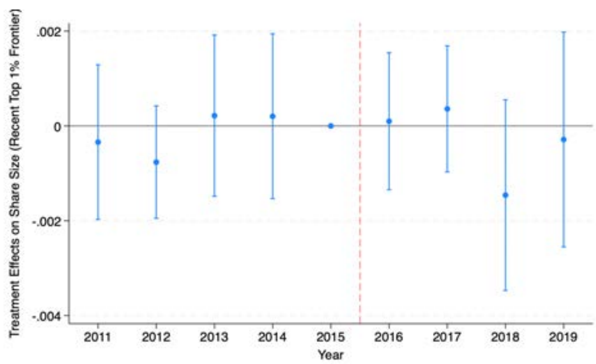
Figure A11: Event-Study Plots for U.S. Researchers Building on Chinese Science



(a) Predicting Share Size (Recent)



(b) Predicting Share Size (Frontier)



(c) Predicting Share Size (Recent Frontier)

Notes: These plots report event-study coefficients from regressions predicting adjusted shares of references citing Chinese research using U.S. and U.K. publications. The treated group is U.S. papers, and the control group is U.K. papers. The regressions include fixed effects for publication years and research fields. Standard errors are clustered at the field level.

F Additional Productivity Results and Robustness Checks for Chinese Researchers

We report the heterogeneity by field analysis of each STEM field below in Figure A12 and Table A18.

While our main results on the effect do not show significant changes in Chinese researcher productivity, we probe this result with variations of the empirical specification and sample.

First, we examine if the results hold when also examining social science research. In Table A19, we run the analysis pooling social science and STEM researchers together. The results are consistent with the main analysis and does not show a significant change in the productivity of these researchers after 2016.

Table A19: Main Treatment Effects on Publications among Researchers in China, STEM + Social Sciences

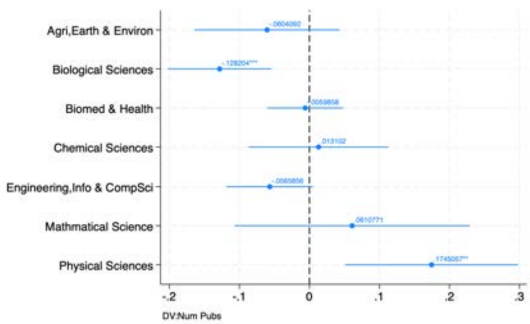
	(1) Pubs	(2) US Pubs	(3) CN Pubs	(4) IF weighted Pubs
Predom. Cite US=1 × Post-2016=1	-0.025	-0.003	-0.005	-0.005
	(0.016)	(0.027)	(0.018)	(0.031)
Indiv FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y
Mean DV	3.292	1.118	6.883	2.666
Observations	54,605	48,677	54,605	48,677

Robust standard errors in parentheses and clustered at the person level. The dependent variable is in column header. The analysis sample is China-based researcher panel. The analysis period is 2013-2019, where the post treatment period is 2016-2019. "Predom Cite US" refers to the Chinese researchers whose fraction of pre-2013 raw citation share is greater than the within-field 75^{th} percentile to U.S. papers and below the 25^{th} percentile to U.K. papers. The control group is Chinese researchers with above 75^{th} percentile within field U.K. citation share and below 25^{th} percentile within field U.S. citation share. The regression is weighted by the CEM matching weights. All specifications include the post dummy, year fixed effects, and individual fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

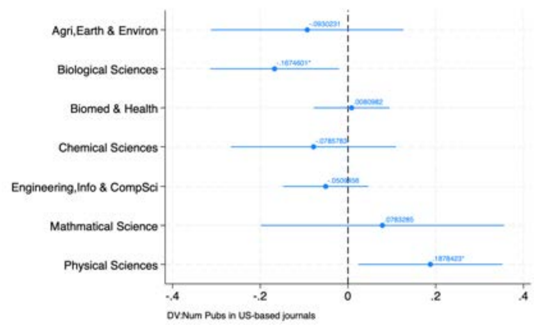
Next, we examine the robustness of our findings when varying the definition of the treatment and control. We begin by running our main specification but change the share of citations thresholds at which we define a Chinese researcher to be reliant on U.S. or U.K. produced research. Table A20 shows the results for the thresholds of 75%, 50%, and 90%. Each of these results show not statistically significant effects on productivity.

Lastly, we consider if the results would be different if we defined the treatment and control group based on their usage of only recently published works. In Table A21, we repeat the estimation in that way and again find not significant change in productivity. We also estimate the event study for this definition of treatment and control group and plot the coefficient in Figure A13. These plots do not show significant declines overall. The total number of publications does show a slight decrease in the years following 2016, however, this decrease is not statistically significant.

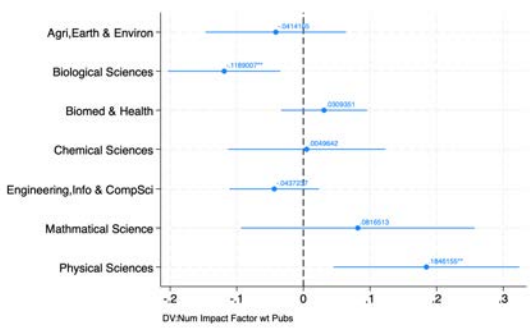
Figure A12: Coefficient Plots for Productivity Change among China-based Researchers, by Researcher's modal field



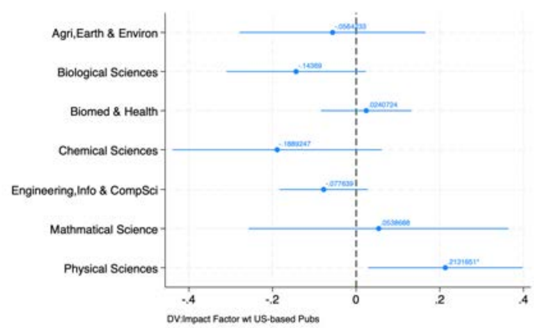
(a) DV:Pubs



(b) DV: U.S. Pubs



(c) DV: IF wt Pubs



(d) DV:IF wt U.S. Pubs

Notes: This plot reports coefficient from the Poisson regression using the China-based researcher panel for each field. The dependent variable is in subfigure title. The treated group is the China-based researchers predominately citing US sciences, and the control group is the China-based researchers predominately citing UK sciences. The regressions include individual fixed effect and year fixed effect. Standard errors are clustered at the individual level.

Table A18: Main Treatment Effects on Productivity among China-based Researchers, By Focal Researcher's Modal Field

Panel A:	DV:Num Pubs						
	(1) Agri, Earth & Environment	(2) Biological Sciences	(3) Biomed. & Health	(4) Chemical Sciences	(5) Engineering Info & CompSci	(6) Math	(7) Physics
Predom. Cite US=1 × Post-2016=1	-0.060	-0.128***	-0.006	0.013	-0.057*	0.061	0.175***
	(0.053)	(0.038)	(0.028)	(0.051)	(0.031)	(0.086)	(0.063)
Indiv FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y	Y	Y
Mean DV	3.376	2.956	3.134	3.342	3.634	2.552	3.150
Observations	4,692	5,342	17,982	5,401	16,541	1,449	2,858

Panel B:	DV:Num Pubs in US-based journals						
	(1) Agri, Earth & Environment	(2) Biological Sciences	(3) Biomed. & Health	(4) Chemical Sciences	(5) Engineering Info & CompSci	(6) Math	(7) Physics
Predom. Cite US=1 × Post-2016=1	-0.093	-0.167**	0.008	-0.079	-0.051	0.078	0.188**
	(0.112)	(0.075)	(0.044)	(0.096)	(0.050)	(0.142)	(0.084)
Indiv FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y	Y	Y
Mean DV	0.836	0.896	1.091	0.884	1.327	1.010	1.483
Observations	3,946	4,908	16,843	4,571	14,264	1,360	2,505

Panel C:	DV:Num Impact Factor wt Pubs						
	(1) Agri, Earth & Environment	(2) Biological Sciences	(3) Biomed. & Health	(4) Chemical Sciences	(5) Engineering Info & CompSci	(6) Math	(7) Physics
Predom. Cite US=1 × Post-2016=1	-0.041	-0.119***	0.031	0.005	-0.044	0.082	0.185***
	(0.054)	(0.043)	(0.033)	(0.060)	(0.034)	(0.089)	(0.071)
Indiv FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y	Y	Y
Mean DV	7.301	6.324	6.662	7.029	7.396	4.873	6.481
Observations	4,692	5,342	17,982	5,401	16,541	1,449	2,858

Panel D:	DV:Impact Factor wt US-based Pubs						
	(1) Agri, Earth & Environment	(2) Biological Sciences	(3) Biomed. & Health	(4) Chemical Sciences	(5) Engineering Info & CompSci	(6) Math	(7) Physics
Predom. Cite US=1 × Post-2016=1	-0.056	-0.144*	0.024	-0.189	-0.078	0.054	0.213**
	(0.113)	(0.085)	(0.055)	(0.128)	(0.054)	(0.159)	(0.094)
Indiv FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y	Y	Y
Mean DV	2.051	2.068	2.663	2.279	3.113	2.055	3.286
Observations	3,946	4,908	16,843	4,571	14,264	1,360	2,505

Notes: Robust standard errors in parentheses and clustered at the person level. The dependent variable is in panel header. The analysis sample is China-based researcher panel. The analysis period is 2013-2019, where the post treatment period is 2016-2019. "Predom Cite US" refers to the Chinese researchers whose fraction of pre-2013 raw citation share is greater than the within-field 75th percentile to U.S. papers and below the 25th percentile to U.K. papers. The control group is Chinese researchers with above 75th percentile within field U.K. citation share and below 25th percentile within field U.S. citation share. The regression is weighted by the CEM matching weights. All specifications include the post dummy, year fixed effects, and individual fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$..

Table A20: Main Treatment Effects on Productivity among China-based Researchers, By Different Threshold Definitions of Reliance

Panle A:	Treatment: Cite Share to US above 75pctile and to UK below 25pctile			
	(1)	(2)	(3)	(4)
	Pubs	US Pubs	IF wt Pubs	IF wt US Pubs
Predom. Cite US (>75pct)=1 × post=1	-0.024	-0.003	-0.005	-0.005
	(0.016)	(0.027)	(0.018)	(0.032)
Indiv FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y
Mean DV	3.298	1.120	6.892	2.668
Observations	54,265	48,397	54,265	48,397

Panel B:	Treatment: Cite Share to US above 50pctile and to UK below 50pctile			
	(1)	(2)	(3)	(4)
	Pubs	US Pubs	IF wt Pubs	IF wt US Pubs
Predom. Cite US (>50pct)=1 × post=1	-0.006	-0.004	0.001	-0.018
	(0.007)	(0.010)	(0.008)	(0.012)
Indiv FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y
Mean DV	4.904	1.551	10.921	3.962
Observations	307,413	286,030	307,413	286,030

Panel C:	Treatment: Cite Share to US above 90pctile and to UK below 10pctile			
	(1)	(2)	(3)	(4)
	Pubs	US Pubs	IF wt Pubs	IF wt US Pubs
Predom. Cite US (>90pct)=1 × post=1	0.034	0.069	0.055	0.066
	(0.042)	(0.074)	(0.047)	(0.083)
Indiv FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y
Mean DV	2.682	0.908	5.223	2.024
Observations	7,843	6,676	7,843	6,676

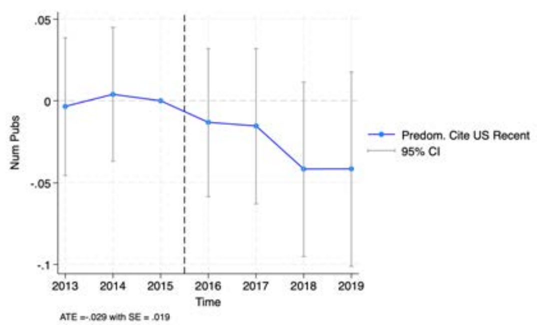
Notes: Robust standard errors in parentheses and clustered at the person level. The dependent variable is in panel header. The analysis sample is China-based researcher panel. The analysis period is 2013-2019, where the post treatment period is 2016-2019. "Predom Cite US" refers to the Chinese researchers whose fraction of pre-2013 raw citation share is greater than the within-field 75th percentile to U.S. papers and below the 25th percentile to U.K. papers. The control group is Chinese researchers with above 75th percentile within field U.K. citation share and below 25th percentile within field U.S. citation share. The regression is weighted by the CEM matching weights. All specifications include the post dummy, year fixed effects, and individual fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$..

Table A21: Main Treatment Effects among Chinese Researchers, using recent citation share as treatment

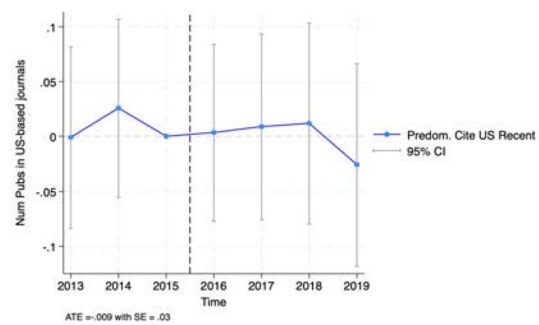
	(1) Pubs	(2) US Pubs	(3) IF wt Pubs	(4) IF wt US Pubs
Predom. Cite US Recent=1 $\times$ Post-2016=1	-0.029	-0.009	-0.016	-0.016
	(0.019)	(0.030)	(0.021)	(0.034)
Indiv FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y
Mean DV	3.119	1.041	6.324	2.386
Observations	45,956	41,062	45,956	41,062

Notes: Robust standard errors in parentheses and clustered at the person level. The dependent variable is in column header. The analysis sample is China-based researcher panel. The analysis period is 2013-2019, where the post treatment period is 2016-2019. "Predom Cite US" refers to the Chinese researchers whose fraction of pre-2013 recent citation share is greater than the within-field 75^{th} percentile to U.S. papers and below the 25^{th} percentile to U.K. papers. The control group is Chinese researchers with above 75^{th} percentile within field U.K. citation share and below 25^{th} percentile within field U.S. citation share. The regression is weighted by the CEM matching weights. All specifications include the post dummy, year fixed effects, and individual fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

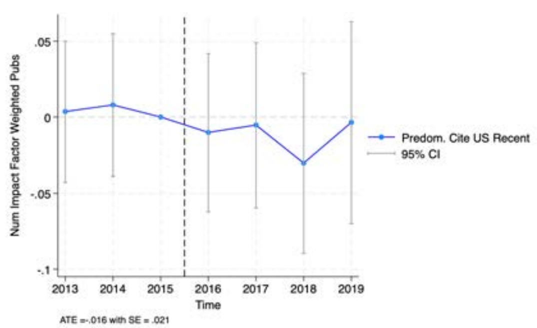
Figure A13: Productivity Change among Chinese Researchers, using recent citation share to define treatment



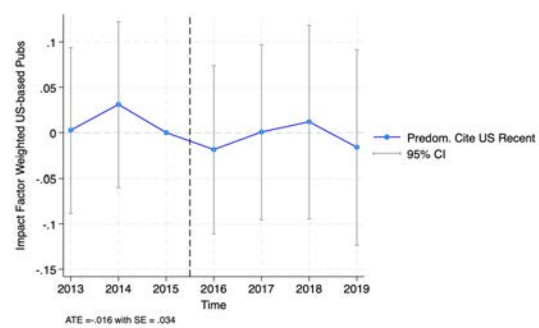
(a) DV:Num Pubs



(b) DV: U.S. Pubs



(c) DV: IF Weighted Pubs



(d) DV:IF Weighted U.S. Pubs

Notes: This plot reports event-study coefficients from the Poisson regression using the China-based researcher panel. The dependent variable is in subfigure title. The treated group is the China-based researchers predominately citing US sciences, as defined by recent citation share, and the control group is the China-based researchers predominately citing UK sciences. The regressions include individual fixed effect and year fixed effect. Standard errors are clustered at the individual level.

G Additional Productivity Results and Robustness Checks for U.S. Researchers

We report the heterogeneity by field analysis for each STEM field below in Figure A14 and TableA22.

We examine if the results regarding changes in ethnically Chinese U.S.-based researchers hold when also examining social science research. In Table A23, we run the analysis when pooling social science and STEM researchers. The results show a significant change in the productivity of these researchers, demonstrating our main results are not driven by excluding social science researchers.

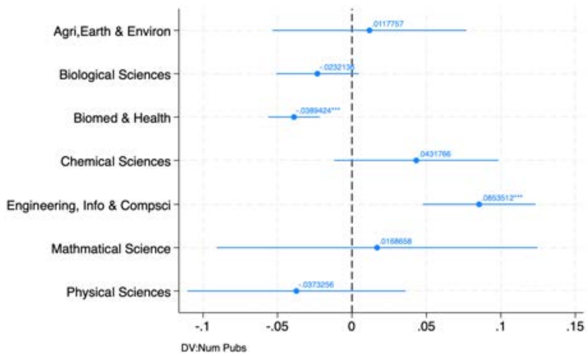
Table A23: Main Treatment Effects on Publications among U.S.-based researchers, STEM + Social Sciences

	(1) Pubs	(2) US Pubs	(3) IF weighted Pubs	(4) IF weighted US Pubs
Ethnic CN=1 $\times$ Post-2016=1	-0.018***	-0.052***	-0.030***	-0.060***
	(0.007)	(0.008)	(0.009)	(0.011)
Indiv FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y
Mean DV	2.628	1.599	7.726	5.170
Observations	674,045	638,616	674,045	638,616

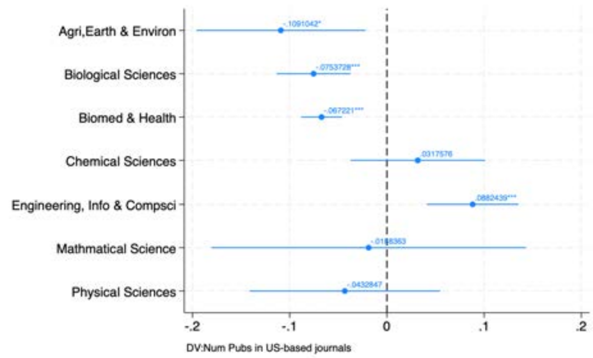
Notes: Robust standard errors in parentheses and clustered at the person level. The dependent variable is in column header.The analysis sample is all active U.S.-based researchers in STEM fields. The analysis period is 2013-2019, where the post treatment period is 2016-2019. '1[Ethnic CN]' refers the treatment group: being ethnically Chinese, as identified by name. The control group is non-ethnically Chinese researchers. The regression is weighted by the CEM matching weight. All specifications include the post dummy, year fixed effects, and individual fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We also examine the robustness of our findings by implementing both a permutation test as well as the HonestDiD estimation procedure for sensitivity analysis based on Rambachan and Roth (2023). Figure A15 shows the results of the permutation test, while Figure A16 shows the results of HonestDiD.

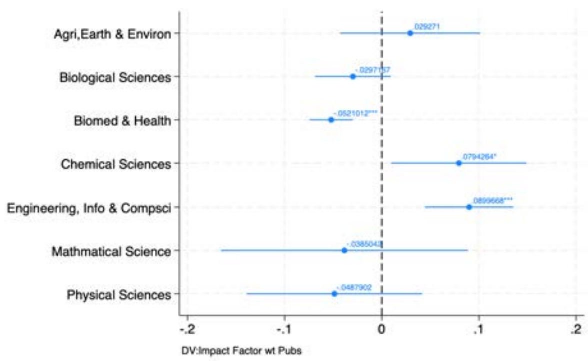
Figure A14: Coefficient Plots for Productivity Change among U.S.-based Researchers, by Researcher's modal field



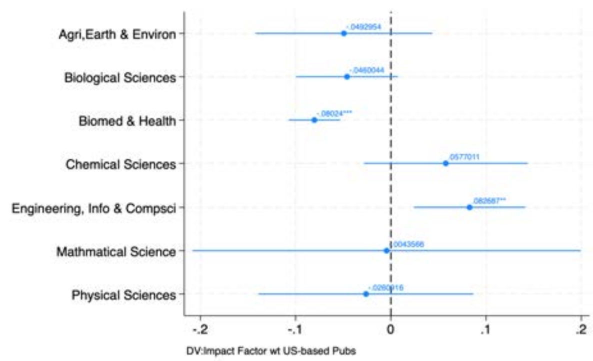
(a) DV:Pubs



(b) DV: U.S. Pubs



(c) DV: IF wt Pubs



(d) DV:IF wt U.S. Pubs

Notes: This plot reports coefficient from the Poisson regression using the U.S.-based researcher panel for each field. The dependent variable is in subfigure title. The treated group is the U.S.-based ethnically Chinese researchers, and the control group is the matched non-ethnically Chinese researchers. The regressions include individual fixed effect and year fixed effect. Standard errors are clustered at the individual level.

Table A22: Main Treatment Effects on Productivity among U.S.-based Researchers, By Focal Researcher's Modal Field

	DV:Num Pubs						
	(1) Agri, Earth & Environment	(2) Biological Sciences	(3) Biomed. & Health	(4) Chemical Sciences	(5) Engineering Info & CompSci	(6) Mathmatical Sciences	(7) Physical Sciences
Ethnic CN=1 × Post-2016=1	0.012	-0.023*	-0.039***	0.043	0.085***	0.017	-0.037
	(0.033)	(0.014)	(0.009)	(0.028)	(0.019)	(0.055)	(0.037)
Indiv FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y	Y	Y
Mean DV	2.353	1.960	3.030	2.167	2.254	1.794	2.420
Observations	24,208	81,874	439,524	27,035	58,555	3,309	12,247

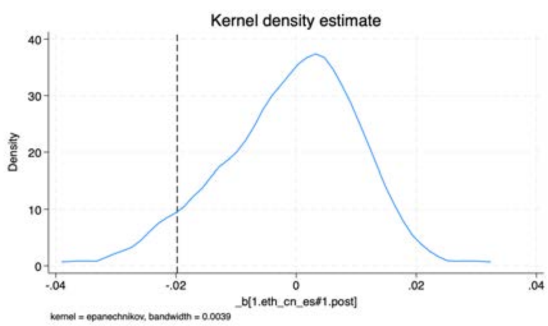
	DV:Num Pubs in US-based journals						
	(1) Agri, Earth & Environment	(2) Biological Sciences	(3) Biomed. & Health	(4) Chemical Sciences	(5) Engineering Info & CompSci	(6) Mathmatical Sciences	(7) Physical Sciences
Ethnic CN=1 × Post-2016=1	-0.109**	-0.075***	-0.067***	0.032	0.088***	-0.019	-0.043
	(0.044)	(0.019)	(0.011)	(0.035)	(0.024)	(0.083)	(0.050)
Indiv FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y	Y	Y
Mean DV	1.298	1.105	1.924	1.188	1.171	0.897	1.554
Observations	21,945	76,857	426,088	24,622	52,452	2,889	10,882

	DV:Impact Factor wt Pubs						
	(1) Agri, Earth & Environment	(2) Biological Sciences	(3) Biomed. & Health	(4) Chemical Sciences	(5) Engineering Info & CompSci	(6) Mathmatical Sciences	(7) Physical Sciences
Ethnic CN=1 × Post-2016=1	0.029	-0.030	-0.052***	0.079**	0.090***	-0.039	-0.049
	(0.037)	(0.020)	(0.011)	(0.036)	(0.023)	(0.065)	(0.046)
Indiv FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y	Y	Y
Mean DV	4.850	6.621	9.330	6.048	5.236	3.974	6.357
Observations	24,208	81,874	439,524	27,035	58,555	3,309	12,247

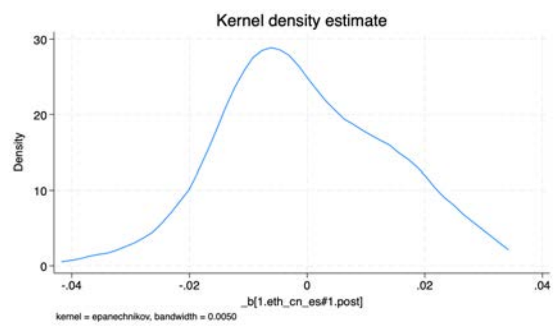
	DV:Impact Factor wt US-based Pubs						
	(1) Agri, Earth & Environment	(2) Biological Sciences	(3) Biomed. & Health	(4) Chemical Sciences	(5) Engineering Info & CompSci	(6) Mathmatical Sciences	(7) Physical Sciences
Ethnic CN=1 × Post-2016=1	-0.049	-0.046*	-0.080***	0.058	0.083***	-0.004	-0.026
	(0.047)	(0.027)	(0.014)	(0.044)	(0.030)	(0.104)	(0.058)
Indiv FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y	Y	Y
Mean DV	2.793	3.851	6.507	3.826	2.961	2.197	4.131
Observations	21,945	76,857	426,088	24,622	52,452	2,889	10,882

Notes: Robust standard errors in parentheses and clustered at the person level. The dependent variable is in column header.The analysis sample is U.S.-based researcher panel. The analysis period is 2013-2019, where the post treatment period is 2016-2019. '1[Ethnic CN]' refers the treatment group: being ethnically Chinese, as identified by name. The control group is non-ethnically Chinese researchers. The regression is weighted by the CEM matching weight. All specifications include the post dummy, year fixed effects, and individual fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$..

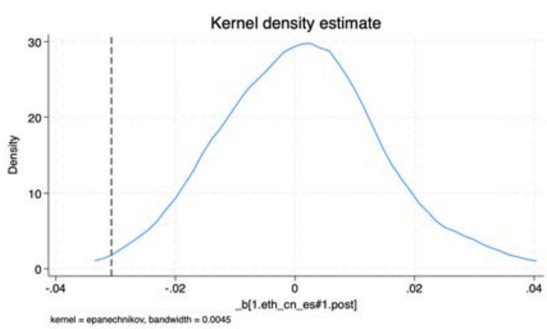
Figure A15: *ritest* Robustness Check for Productivity Change among U.S.-based Researchers



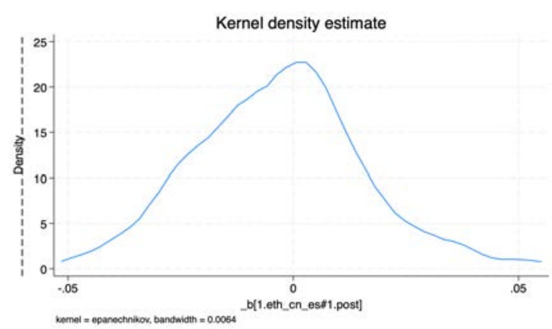
(a) DV:Pubs



(b) DV: U.S. Pubs

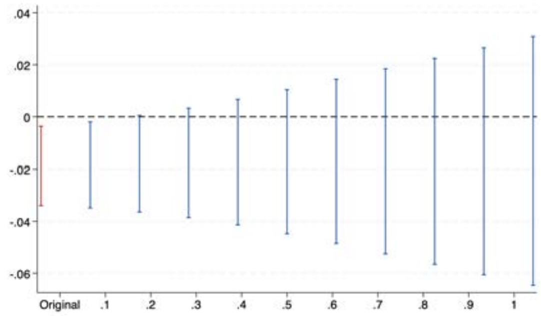


(c) DV: IF wt Pubs

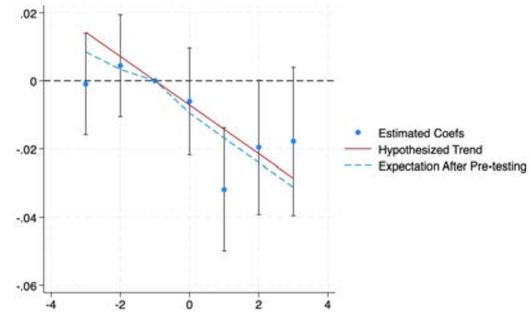


(d) DV:IF wt U.S. Pubs

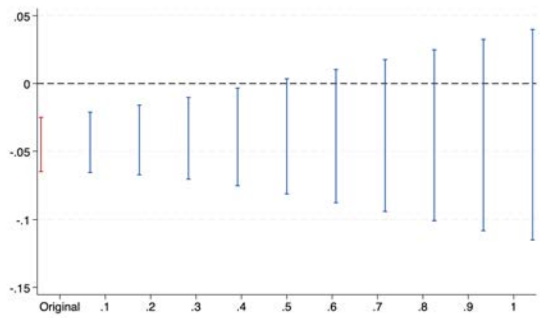
Figure A16: *honestdid* Robustness Check for Productivity Change among U.S.-based Researchers



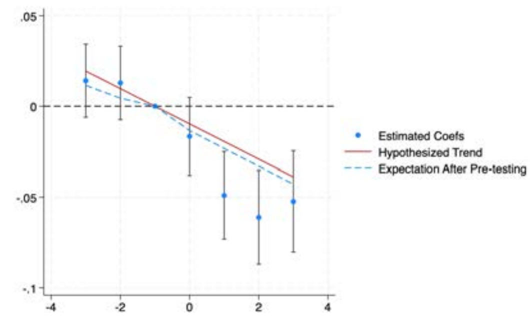
(a) DV:Pubs



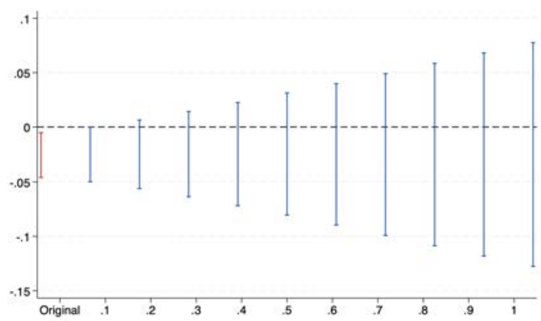
(b) DV: Pubs



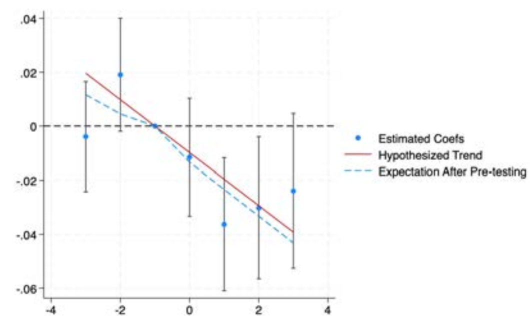
(c) DV:US Pubs



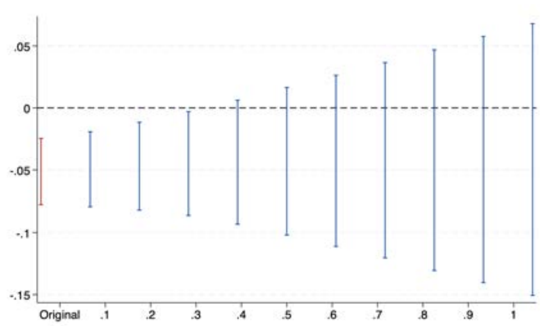
(d) DV: U.S. Pubs



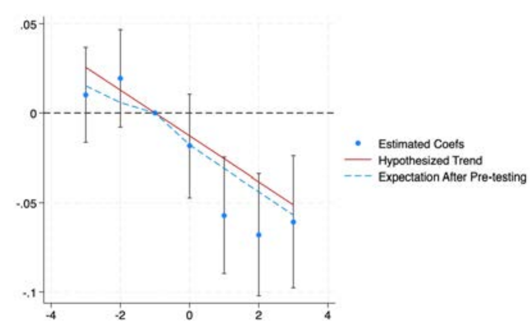
(e) DV:IF wt Pubs



(f) DV: IF wt Pubs



(g) DV:IF wt U.S. Pubs



(h) DV:IF wt U.S. Pubs