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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 15% 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 active scientists in the U.S. by 2-6% and is associated with an increased hazard of 7% that ethnically Chinese scientists stop publishing altogether. 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 scientists' 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 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 enrolling in a 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—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 from Digital Science, 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 presidential 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. Until recently, however, these measures by the Chinese government were not overtly aimed at the U.S. 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 (15%) 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. The distinction between nationally Chinese (i.e., originating from mainland China, as inferred by university or current location) and ethnically Chinese (i.e. part of the Chinese diaspora, regardless of location, as inferred by their name) is one that we make throughout the paper, depending on the focus of any given item of analysis.

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. papers declined by about 4-7% after 2016. The impact is more striking for the share of references to recently published papers, where the share of references on Chinese publications to U.S. papers 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.

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

Finally, in the third part of the article, we study the effect on scientist productivity in China and in the U.S., both on the intensive and the extensive margin. 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 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. Furthermore, following the growth in U.S.-China tensions, the rate at which ethnically Chinese U.S.-based researchers stopped publishing altogether increased by 7%.

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 change international knowledge flows and 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 leading up to 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). Starting around 2015-2016, however, 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 (typically) Chinese and Chinese-American scientists under suspicion of IP theft on behalf of the Chinese government began to take off around 2016 as well, as is visible in Figure 1. The figure tallies annual cases charged under the so-called "China Initiative", which was a formal policy under which the DOJ prosecuted perceived Chinese spies in U.S. research. 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 across 77 cases according to the MIT Technology Review,[3] but after significant criticism that the program used racial profiling and was biased against researchers of Chinese descent, it was shut down in 2022. In addition, the FBI barred some Chinese scholars from entering the U.S. altogether[4] and revoked some Chinese student visas.[5] These actions heightened fears about either being a Chinese scientist working in the U.S. or being an American scientist with connections to China.

Consistent with this series of events, anti-Chinese sentiment in the U.S. increased substantially during this timeframe. According to the Pew Research Center, anti-Chinese sentiment ticked up from around 55% in 2015 to 66% in 2020 as shown in Figure 2 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.[6]

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.[7] 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

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

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

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

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

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

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 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, revealed through both policy changes 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 five 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 are 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 listed department and inferred based on their name if they were ethnically Chinese. Specifically, we imputed each individual's ethnicity using an algorithmic name classifier and created a flag for if this ethnicity was Chinese. Details of the procedures for determining field and inferring ethnicity are provided in Appendix A.4.

The ORCID website contains over 15 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.[8]

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, and we use the location of this degree to proxy for their nationality. As this measure is constructed using an individual's prior degree location, it is conceptually and empirically distinct from our measure of ethnicity, which is inferred based on their name. This dataset includes 129,223 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 periods. 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

[8]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).

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 A4 shows the mean attributes of these two groups. Reassuringly, while ethnically Chinese researchers also appear to achieve stronger research outcomes, we do not observe interactions between ORCID self-selection and being ethnically Chinese.

As an additional check on the validity of our constructed data, we compare our insights to those provided by publicly available established sources. Reassuringly, doctoral stay rates inferred from our U.S. graduates data set are similar to those reported by NSF. Specifically, for the cohort of nationally Chinese STEM doctoral students graduating from U.S. universities in 2012,[9] the NSF reported a stay rate of 83%; we similarly observe that 83% of post-graduation jobs taken in 2012 by Chinese doctoral graduates were in the U.S. For nationally Indian graduates, the rates are 83% and 79.1% respectively. That these rates are comparable validates our retention measure and underlying data.

3.2 Publications Data

We construct three datasets using the bibliometric information about published scientific works available in Dimensions.[10] For each publication in their database, Dimensions provides the names of the authors, the publishing journal, the scientific field of the publication, the publishing year, the addresses of the authors, and the list of papers 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 1.8 billion citations across 140 million publications. Of those, 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,[11] 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 and 2012 was either China or the

[9] 2012 is the last year before our treatment year (2016) for which complete data on this outcome is available from NSF.

[10] 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).

[11] In all of our analyses, when we refer to researchers located in "China", we are referring to mainland China.

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 publication in Dimensions, we create two observations. The first observation contains measures of how much the focal publication references scientific papers produced by research in the U.S., and the second observation contains measures of how much the focal publication references scientific papers produced by research in the U.K. Publications that do not reference any previous works are removed. Further, we focus only on the observations produced from the references of STEM publications written by Chinese research teams between 2011 and 2019. This amounts to 4,247,176 observations from 2,123,588 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 that reference papers 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, to examine 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 publications 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 China-produced scientific knowledge.[13]

Finally, to examine 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 obser-

[12]We define a publication as being produced in China according to the publication's corresponding 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.

vations in this dataset are created by constructing a strongly balanced panel of the authors listed in 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 factors of the publishing journals.

When analyzing the effect of the rising U.S.-China tensions on the productivity of Chinese 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 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-F present basic summary statistics of these data. More detailed summary statistics for all five datasets can be found in Appendix A. Appendix Tables A7 and Appendix A9 report 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

[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] We define a researcher's field as the modal field of their publications.

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

[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.

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' 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 -3.5 probability points (SE = 0.78 pp). This amounts to a 15% 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 university based in the U.K. or non-U.S. anglophone country 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 2.2 probability points (SE = 0.67 pp). This amounts to a 13% 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. They also suggest that the results are not due to an increase in Chinese university quality; the Chinese STEM trainees not going to the U.S. appear to attend other anglophone universities rather than staying in China. An additional robustness check (Appendix Figure A8) showing no increase in the propensity to enroll in China after 2016 further supports this view.

The results so far simply observe the change in the fraction of ethnically Chinese students entering U.S. doctoral programs. They do not consider whether there was a compositional change in the quality of such students. To examine this, we use the rank of each Chinese student's prior university as a proxy for their quality. Appendix Figure A7 shows that the fraction of students enrolling in doctoral programs from prominent Chinese universities is falling over time. More formally, Table 3 Column (4) repeats the analysis from Column (1) while controlling for students' prior degree university rank by decile. With this adjustment, the estimated impact of U.S.-China tensions on the likelihood of enrolling in a U.S. doctoral program is -3.1 probability points (SE = 0.80 pp). In Column (5), we redefine the treatment group to be those ethnically Chinese doctoral students whose prior degree was from a top decile university. Among these students, the estimated impact on the likelihood of enrolling in a U.S. doctoral program grows to -5.8 probability points (SE = 1.7 pp). This suggests that the impact was strongest among students from top quality universities.

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 dynamic effects after 2016. The event-study model specification is the following:

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

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 group 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 five 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 ethnically Chinese with a previous degree from a university in China. The results in Column (1) reveal an effect size of -3.6 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 ethnically Chinese with a previous degree from a university outside of China. The estimated effect is -2.3 probability points (SE = 0.89 pp). These estimates reveal that growing U.S.-China tensions did not exclusively impact ethnically Chinese students of Chinese nationality.[17] 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 -3.7 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 that U.S.-China tensions emerging in 2016 decreased the enrollment of ethnically Chinese students in U.S. doctoral programs, but the economic significance of our results can be difficult to interpret. A back-of-the-envelope estimate of the number of nationally Chinese doctoral students displaced during our treatment period leverages the coefficient from Table 3 Column 1 combined with NSF NCSES data provides us with an estimate of 5,760 nationally Chinese STEM students that did not attend U.S. doctoral programs between 2016 and 2019 as a result of U.S.-China tensions.[18]

[17]In unreported regressions, we find that these results are driven by ethnically Chinese students from other Asian countries.

[18]We restrict our estimation to nationally Chinese doctoral students given the absence of annual data on ethnically Chinese matriculation patterns, understanding the former to be an approximate subset of the latter. We assume that the 34,510 nationally Chinese students enrolled in U.S. doctoral programs in 2015, per NSF, were at that point evenly split across cohorts in five-year doctoral programs. Since nationally Chinese students are a smaller group than ethnically Chinese students, and having established that eth-

We also observed that ethnically Chinese students enrolled in non-U.S. anglophone universities at increased rates in the years following 2016. 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. In addition, the fact that our results extended to those of Chinese ethnicity regardless of their nationality suggests the presence of a broader "chilling effect" for all ethnically Chinese trainees.

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. We include fixed effects for the year of the graduate's first post-graduation job and the scientific field of their doctoral studies. 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, Appendix Figure 5 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 es-

nically Chinese students outside of China also experienced the impact of U.S.-China tensions, we should consider this projection as a lower bound. At the same time, given the selected nature of the ORCID sample and the data we draw from it, we generalize our results to broader populations with caution.

timated 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 use 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 field composition of their publications (Figure A2). Third, both countries are top destinations (i.e., first and second place) for nationally Chinese researchers studying abroad (Figure A3). 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 references on Chinese publications to U.S. papers versus to U.K. papers. 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 papers (versus U.K.-produced papers).

This difference-in-differences approach, and setting up the analysis as examining the relative share of references to U.S. papers versus U.K. papers, 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 China-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. papers.[19] Column (2) reports the estimated impact of growing U.S.-China tensions on the share of recent references, defined as references to papers published in the previous five years, to be -1.4 probability points (SE = 0.26 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 papers in the top 1% of their 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:

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

[19]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.

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. papers versus U.K. papers in the years before 2016. If these coefficients are near zero, it provides evidence that the 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 papers 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 citations to U.S. papers by Chinese publications 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 publication's reference list. These shares move in parallel in the years prior to 2016, but following that year there is a dramatic decline in the rate of citing U.S. papers. 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 references to U.S. papers in the publications of Chinese teams had already declined by 6.3% relative to 2015. Appendix D includes event studies for citations to 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 research 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 China-produced scientific knowledge? To investigate that question, we compare the share of references in the publications of U.S. research teams made to papers from China with the share of references in the publications of U.K. research teams made to papers from China.

This approach is different than the one that we used for analyzing if the usage of U.S. research by Chinese researchers had changed. In that analysis, we examined the share of references to U.S. papers versus the share of references to U.K. papers 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 references 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 references to papers from Chinese scientists in the publications of U.S. and U.K. researchers. In doing so, we can control for the changes in China-produced science, while isolating the effect of U.S.-China tensions on the usage of China-produced scientific works in U.S. research.

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 references 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 China-produced papers among publications by U.S. research teams, relative to U.K. research teams.

Table 7 shows the estimates when the dependent variable is the raw share of references, the share of recent references, the share of frontier references, and the share of recent frontier references. Although all of the coefficients are negative, they are all small in magnitude and none reach statistical significance. Figures 7 and A15, 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. publications 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 sources more generally. In contrast, U.S. researchers did not change their usage of China-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 publications 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 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 Chinese research teams significantly shifted away from referencing scientific papers 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 papers 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 papers 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 China 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 papers from the U.S., and we define the control group as researchers who predominately cite papers from the U.K. Precisely, the treated group includes researchers who are above the 75^{th} percentile within their field for the portion of their citations that go to papers from the U.S. and are below the 25^{th} percentile for their field for their citation share to papers from the U.K. The control group is similarly defined as being above the 75^{th} percentile in citation share within the field to the U.K. and below the 25^{th} percentile in citation share within the field to the U.S.

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 and 2012 (in 10 bins), career age as of 2012 (in 4 bins),[20] the number of actively publishing years between 2008 and 2012,[21] if the researcher is affiliated with a university, if the researcher is located in a Tier 1 city,[22] and if the researcher is located in a New Tier 1 city.[23] 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 A7. 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 papers from the U.S.) and 5,993 unique individuals in the control group (researchers who predominately cite scientific papers from the U.K.).[24]

We are interested in the effect of U.S.-China tensions on both the extensive margin (scientists stopping research altogether) and the intensive margin (a change in the count of publications among active researchers) and estimate a separate model for each.

First, to examine the treatment effects on the extensive margin (scientists stopping research altogether), we estimate the following Cox Proportional Hazard model:

$$h(t \mid Treat_i) = h_0(t)\exp(\beta \cdot Treat_i) \tag{6}$$

In Equation 6, $h(t \mid Treat_i)$ is the the hazard function of failure at time t, conditional on the treatment status. The failure event is defined by the researcher stopping publication. $h_0(t)$ is the baseline hazard function, $Treat_i$ is a binary indicator of treatment status. In the China-based researcher analysis, $Treat_i$ equals one if the China-based researcher predominantly cites U.S. science, zero if the China-based researcher predominantly cites U.K. science. β is the coefficient of interest that measures the hazard of stopping publication associated with treatment status.

We estimate the following differences-in-differences specification to examine the treatment effects on the intensive margin (the change in the count of publications for active researchers):

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

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

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

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

[24] 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.

$$Y_{it} = \beta_1 Treat_i t + \beta_2 Post_{t(it)} + \beta_3 (Treat^*_{it} Post_{it}) + \gamma \mathbf{X}_{it} + \epsilon_i \tag{7}$$

In Equation 7, 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:

$$Y_{ij} = \beta Treat_{ij} + \sum_{k=2013}^{2015} \delta_k Treat_{ij} + \sum_{k=2016}^{2019} \tau_k Treat_{ij} + \gamma \mathbf{X}_{ijt} + \epsilon_{ij} \tag{8}$$

The variables in this equation are the same as Equation 7.

Table 8 contains the results. The first two columns report the Cox Hazard Proportional Model coefficients highlighting the extensive margin. Column (1) reports that China-based researchers who predominantly cited U.S. papers saw an increased but not statistically significant hazard of stopping publication altogether (β = 0.079, SE = 0.049). Column (2) reports the estimated hazard when the failure event is defined by stopping publication in U.S.-based journals. Being U.S.-reliant is associated with an increased hazard of stopping publication in U.S.-based journals due to U.S.-China tensions (β = 0.115, SE = 0.062). This is equivalent to a hazard ratio of 1.12, or a 12% increased hazard of stopping publishing in the U.S. for the treated group. Figure A16 reports the Kaplan-Meier Curves that show survival step function curves for the treated and control groups.

Columns (3)-(6) of Table 8 show the intensive margin results using a differences-in-differences model, where the dependent variable varies across each column. Column (3) reports the estimated effect on the number of publications as -0.024 (SE = 0.016). This effect size is not statistically significant and is 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 works. For example, these researchers may have found it more challenging to publish in U.S.-based journals after 2016. To test this, Column (4) shows the results of estimating the difference-in-differences specification with a dependent variable of the number of publications in U.S. journals[25]. 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 8. Given the average treatment effect is not statistically significant, the event study shows noisy estimates with only a slight decline, suggesting that the productivity impact among China-based researchers could become more negative if the trend continues.

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.[26].

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 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 -0.130 (SE = 0.038) in the number of publications and -0.169 (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 19.0% (SE = 0.084) in the number of U.S.-based publications. We do not detect any statistically signifi-

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

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

cant effects for other STEM fields, as reported in Table A17 and Figure A17. 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.[27] Table 8, Column (5), shows the estimated effect on the number of impact-factor-weighted publications is -0.005 (SE = 0.018). Column (6) 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 12.0% (SE = 0.043) decrease in the number of impact-factor-weighted publications and a 14.5% (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 21.4% (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 A17 and Figure A17.

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 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).[28] The NIH campaign discouraged collaboration of any kind between U.S.-based and China-based researchers and institutions,

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

[28] 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.

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 A9 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.[29]

As before, we begin with the extensive margin results. Table 10 Column (1)-(2) report the effects on extensive margin from estimating Equation 6 using a Cox hazard model. Column(1) reports that U.S.-China tensions increased the hazard of stopping publishing altogether for ethnically Chinese scientists in the U.S. by 7% (β = 0.079, SE = 0.049, which is equivalent to a hazard ratio of 1.073). Column (2) repeats the same analysis but for U.S.-based journals, finding a 6.1% increased hazard of stopping publishing in the U.S. for ethnically Chinese researchers after 2016 (β = 0.115, SE = 0.062, equivalent to a hazard ratio of 1.061). Both estimates are statistically significant at the 1% level. Figure A19 reports the Kaplan-Meier Curves that show survival step function curves for the treated and control groups.

[29] The original dataset contains 231,296 unique researchers, but since we use researcher fixed effects, researchers with no variation in the number of publications per year drop from the sample.

A back-of-the-envelope calculation of the magnitude of this effect estimates the additional number of ethnic Chinese researchers who exit academia due to the increased hazard. Specifically, we multiply the number of ethnically Chinese researchers who would have dropped out in the absence of rising tensions by the 7% hazard.[30] This calculation estimates that the U.S.-China tensions caused 1,286 ethnically Chinese researchers to stop publishing entirely.

Table 10 Column (3)-(6) shows the results of estimating Equation 7 on the intensive margin using the differences-in-differences approach. Across all four measures of productivity, shown in Columns (3)-(6), 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 (3) shows the estimated effect on the number of publications is -0.020 (SE = 0.007). Column (4) reports that the estimated effect on the number of publications in U.S.-based journals is -0.054 (SE = 0.008). Column (5) shows the estimated treatment effect on impact-factor weighted publications is -0.031 (SE = 0.009). Column (6) reports the estimated effect on impact-factor weighted U.S.-based publications is -0.061 (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-factor-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

[30] To calculate the number of ethnically Chinese who would have dropped out in the absence of rising tensions, we first calculate the baseline dropout rate $r = 1 - \frac{\text{number of researchers in 2013}}{\text{number of researches in 2019}}$, and percent Chinese $p = \frac{\text{number of ethnically Chinese researchers in 2013}}{\text{number of researchers in 2013}}$. The number of ethnically Chinese who would have dropped out is calculated by $N \times r \times p$, where N is the sample size

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.[31] As before, we are limited by sample size and can only look at fields 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, -0.068 (SE = 0.011) for U.S.-based publications, -0.052 (SE = 0.011) for impact-factor-weighted publications, and -0.081 (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 A20 and Figure A20, 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.

[31] 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/

We also perform a back-of-envelope calculation for estimating the decline in the number of publications among active ethnically Chinese researchers. Specifically, we multiple the estimated coefficient by each post-treatment year's total publications produced by ethnically Chinese researchers. Summing these products, a two percent decrease in productivity equates to 22,487 publications that could have been published by ethnically Chinese researchers after 2015. The effect is stronger for publications in U.S. based journals: 29,163 papers. When adjusting for quality, our estimates equate to a loss of 113,339 impact-factor weighted publications, and 61,309 impact-factor weighted U.S.-based publications.

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 2 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 publications citing U.S. papers, we make comparisons with the citations to U.K. papers. 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.

We also address this concern by including additional controls. In Appendix D, we estimate specifications including time trends at the field-by-country level. The resulting estimates are largely unchanged. This allows us to alleviate any question about whether specific fields of Chinese science have significantly different changes in relative quality during the window of our analysis.

Finally, if our mobility results were driven by the Thousand Talents program or by an increase in Chinese university quality, we would expect that those ethnically Chinese students no longer enrolling in U.S. Ph.D. programs would be going to China instead. However, our analysis of the propensity to enroll in Chinese universities, shown in Appendix Figure A8, finds no such result.

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 its field's 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 science, we defined the treatment group as China-based researchers who predominately cite U.S. science. In this analysis, we use the threshold for U.S. reliance as above 75^{th} percentile in citation shares to U.S. papers and below 25^{th} percentiles in citation shares to U.K. papers. As robustness checks, we estimate our main analyses using a variety of different thresholds and apply the CEM procedure. As shown in Appendix Table A18, we find similar results.

Fifth, 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 A6 presents the raw fraction of incoming U.S. doctoral students that are nationally Chinese or nationally Indian. We do not observe an uptick in nationally Indian Ph.D. enrollees after 2016, alleviating concern about a supply shock of this sort.

Sixth, we address the possibility that the observed decline in ethnically Chinese U.S. enrollment is part of a greater trend of increasing visa refusals (Chen, Howell and Smith, 2023) and emerging alternative destinations for tertiary students, and not actually due to U.S.-China tensions. In particular, Ganguli and MacGarvie (2024) document a decline in the issuance of U.S. visas to international students from India, Iran, and South Korea as well as China, in parallel with an increase in issuance of non-U.S. anglophone country visas. To address the concern that our results reflect these broader trends, Table A12 repeats the main regression from Section 4.1.1 but restricts the control group to students whose prior degree was in these three countries. The results remain strongly negative and significant, suggesting that the impact we document here is distinct from broader changes in mobility flows. Similarly, Figure A12 presents the raw fraction of post-graduation jobs taken with U.S. employers by nationally Chinese and nationally Indian U.S. graduates respectively. The figure suggests that the decline in stay rates for Chinese U.S. graduates are not simply reflecting a broader trend; stay rates for Indian graduates appear to increase slightly after 2016.

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 (15%) 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 and many even stopped producing research altogether, 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 prior work has established that uncertainty resulting from a higher student visa refusal rate decreases student quality at U.S. universities (Chen, Howell and Smith, 2023), 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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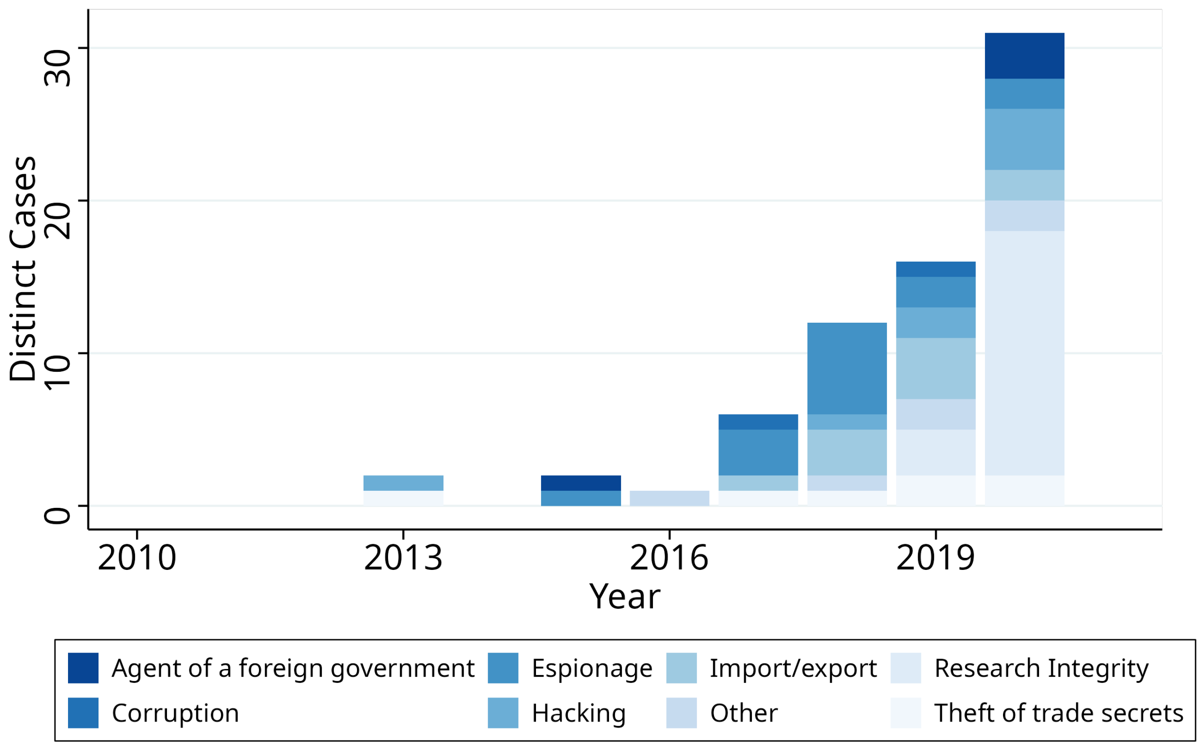
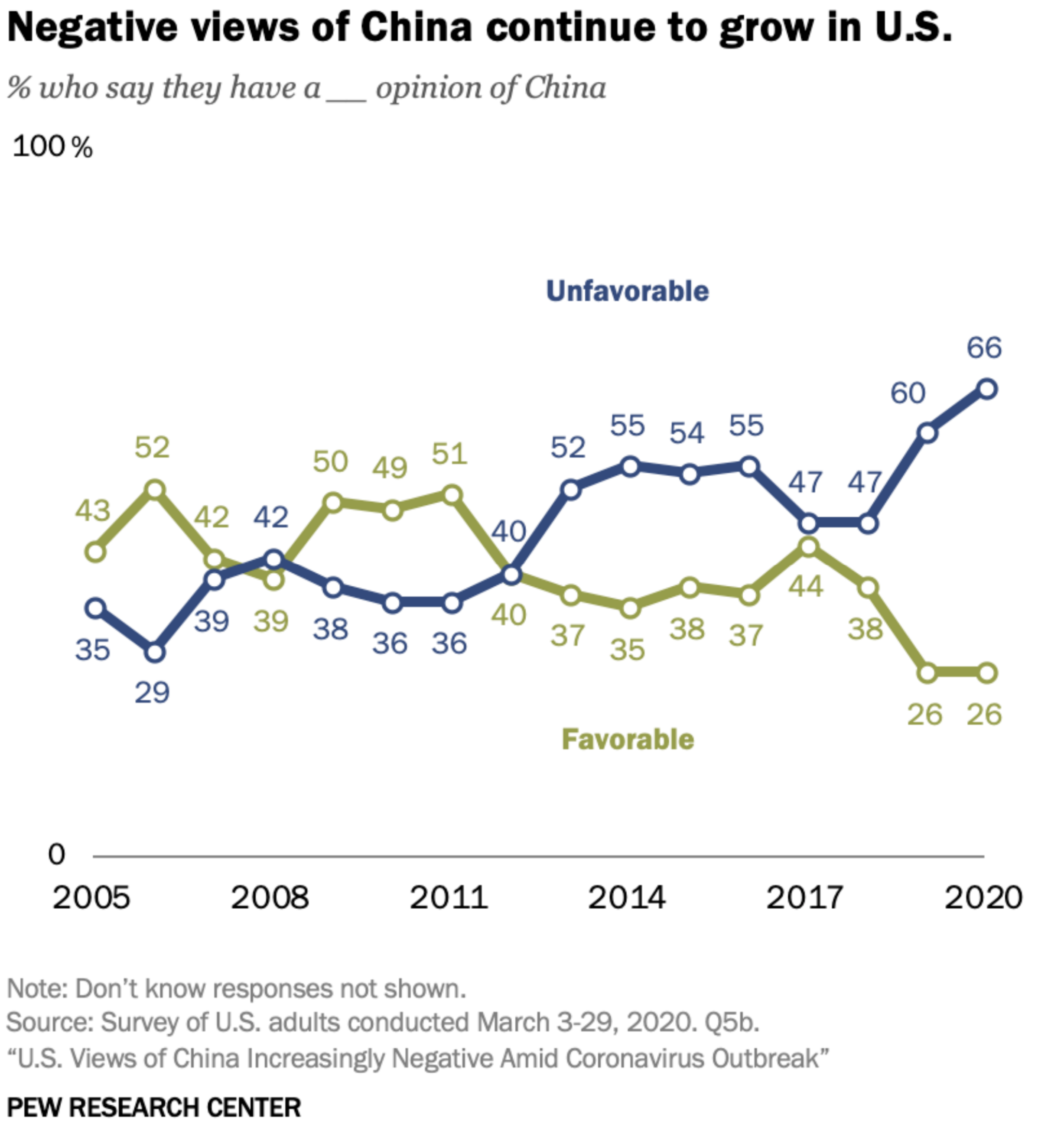
6 Figures and Tables

Figure 1: China Initiative Cases Collected by MIT Technology Review's China Initiative Database



Notes: This figure graphs the number of distinct cases listed in the MIT Technology Review's China Initiative database for the years 2010 to 2021. The count of cases are displayed according to the category of legal issue in the case. We bin cases involving any type of espionage, research integrity issue, or hacking into respective categories. Distinct cases are defined as legal cases with distinct court docket numbers. This figure utilizes data from the following article: Eileen Guo, Jess Aloe, and Karen Hao, "The US crackdown on Chinese economic espionage is a mess. We have the data to show it," *MIT Technology Review*, December 2, 2021, https://www.technologyreview.com/2021/12/02/1040656/china-initative-us-justice-department/.

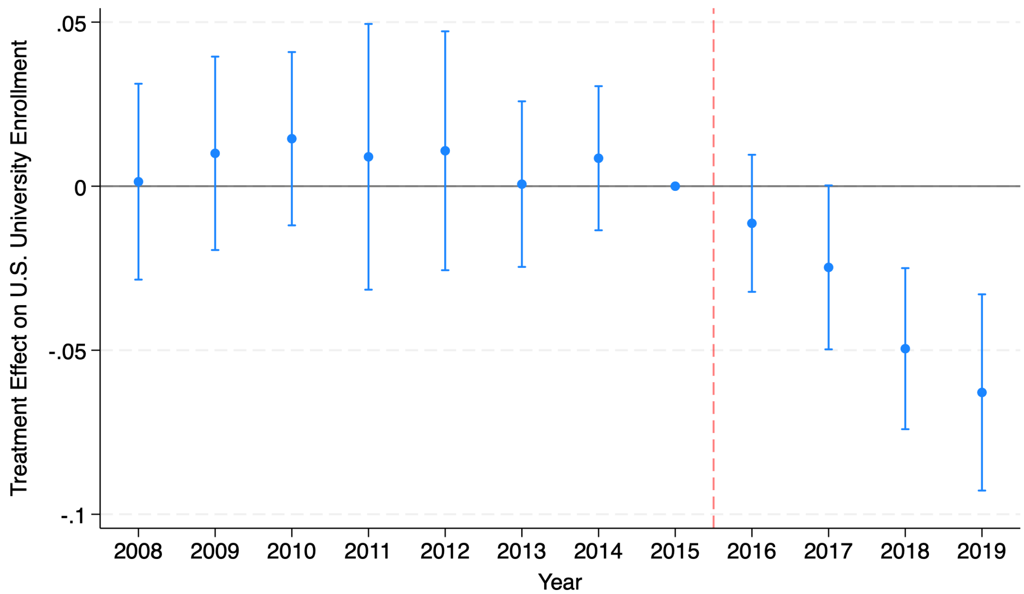
Figure 2: Pew Research Center Survey on Growing Anti-Chinese Sentiment in the U.S.



Notes: This figure graphs the fraction of surveyed U.S. adults reporting favorable or unfavorable views of China annually between 2005 and 2020. Anti-Chinese sentiment in the U.S. increased substantially starting around 2016 and climbed through the subsequent years.

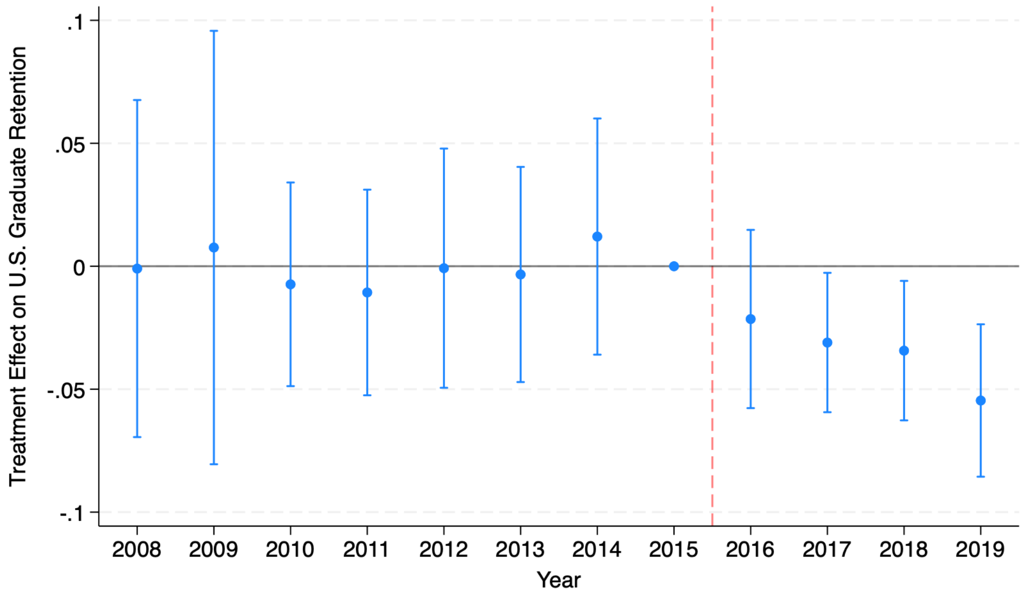
Figure 3: Summary of Data Sources & Sample Construction

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



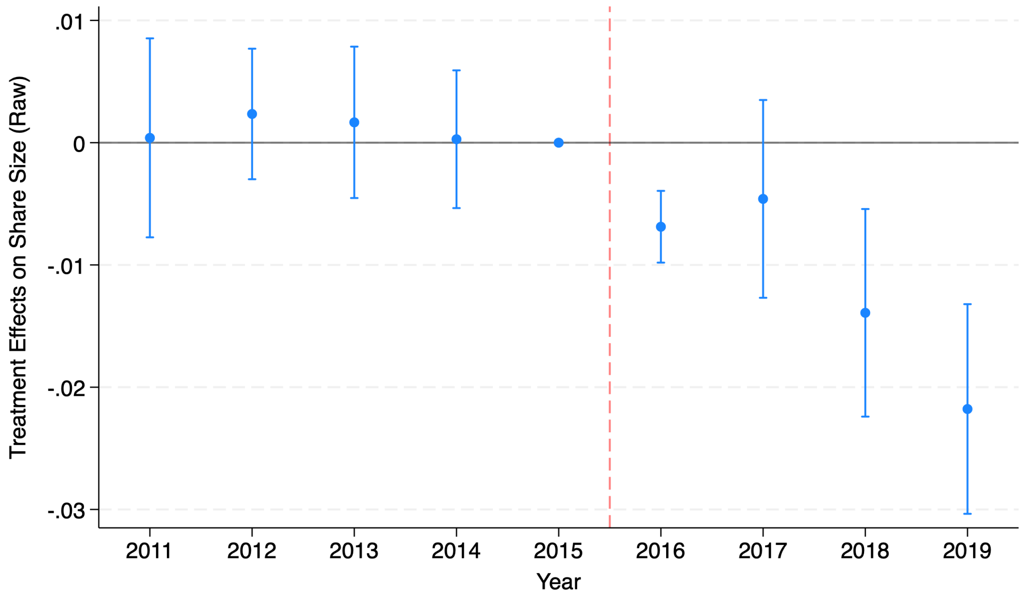
Notes: This plot reports event-study coefficients from a regression predicting enrollment in a U.S. university. The treated group is ethnically Chinese doctoral students, and the control group is non-ethnically Chinese doctoral students. The regression includes cohort, prior degree country, and field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

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



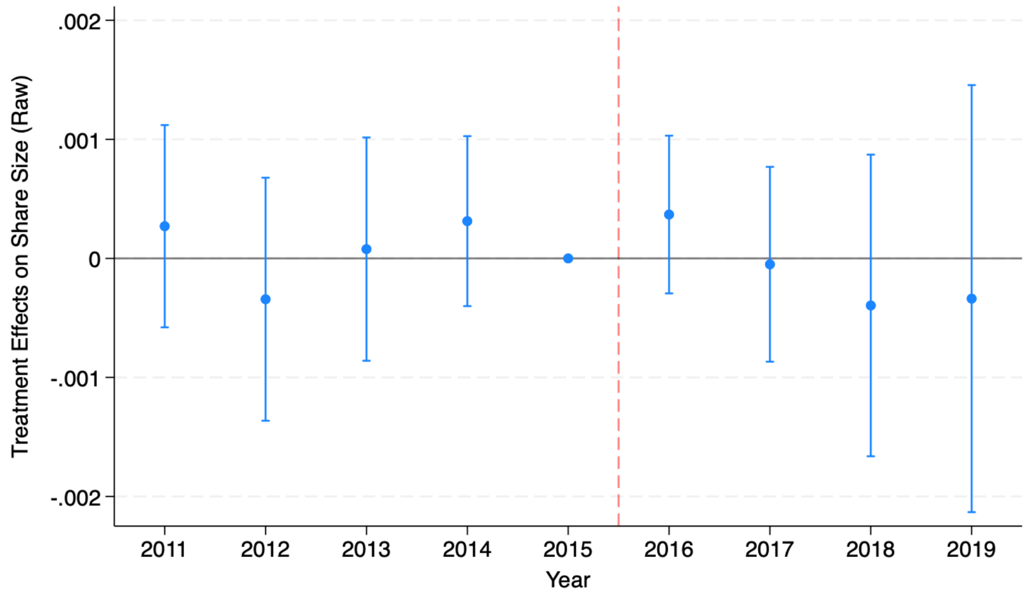
Notes: This plot reports event-study coefficients from a regression predicting whether post-graduation jobs taken by U.S. graduates remain in the U.S. The treated group is ethnically Chinese U.S. graduates, and the control group is non-ethnically Chinese U.S. graduates. The regression includes cohort 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



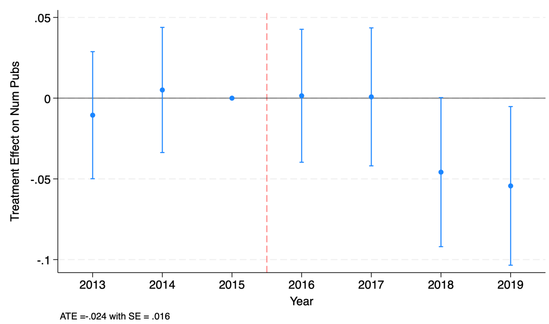
Notes: This plot reports event-study coefficients from a regression predicting the size of citation shares on Chinese publications. The treated group is citation shares to the U.S., and the control group is citation shares to the U.K. The regressions include fixed effects for the citing publication.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

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

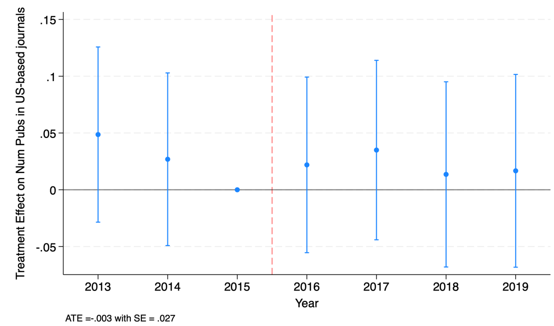


Notes: This plot reports event-study coefficients from a regression predicting the unadjusted share of references to Chinese papers on U.S. and U.K. publications. The treated group is U.S. publications, and the control group is U.K. publications. The regressions include fixed effects for publication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

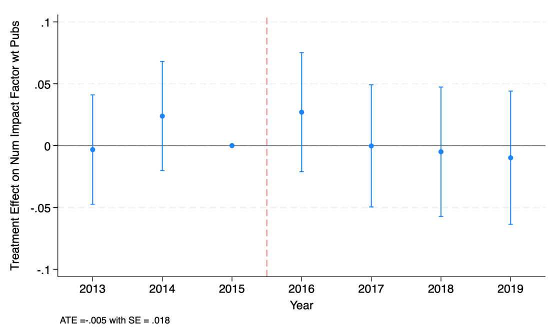
Figure 8: Event-Study Plots for Productivity Change among China-based Researchers



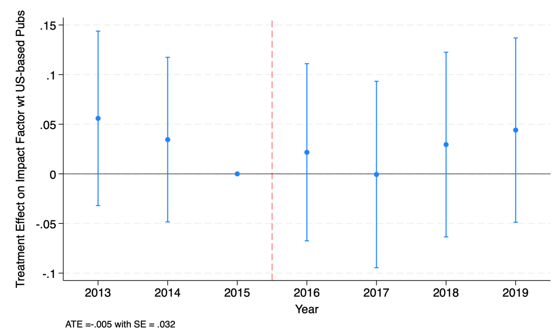
(a) DV: Pubs



(b) DV: U.S. Pubs



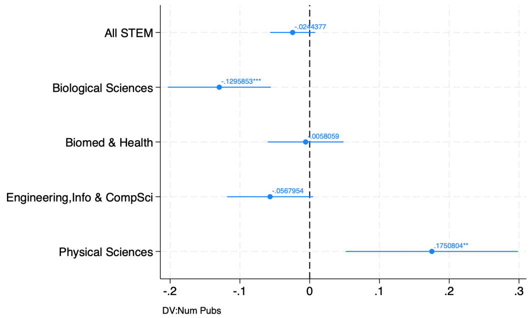
(c) DV: IF wt Pubs



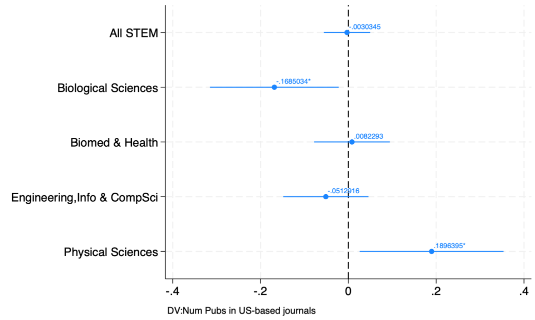
(d) DV: IF wt U.S. Pubs

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 U.S. papers, and the control group is the China-based researchers predominately citing U.K. papers. The regressions include individual fixed effect and year fixed effect. Standard errors are clustered at the individual level.

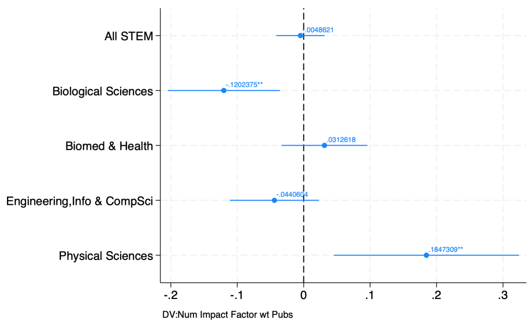
Figure 9: Coefficient Plots for Productivity Change among China-based Researchers, by Researcher's Modal Field



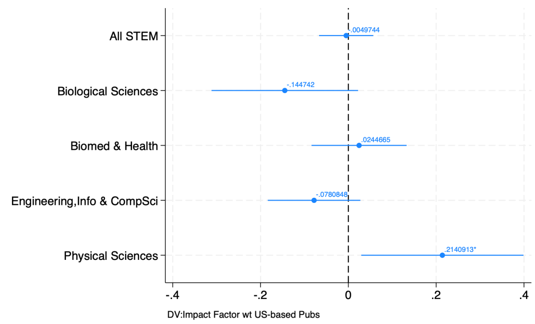
(a) DV: Pubs



(b) DV: U.S. Pubs



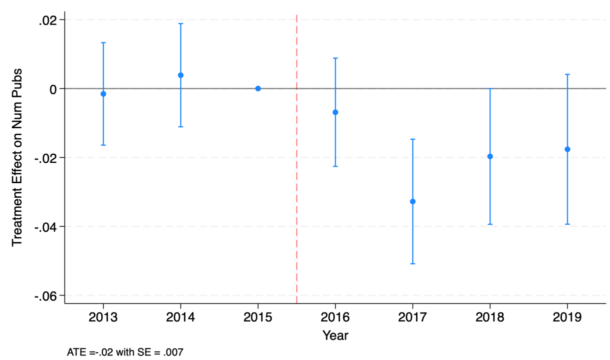
(c) DV: IF wt Pubs



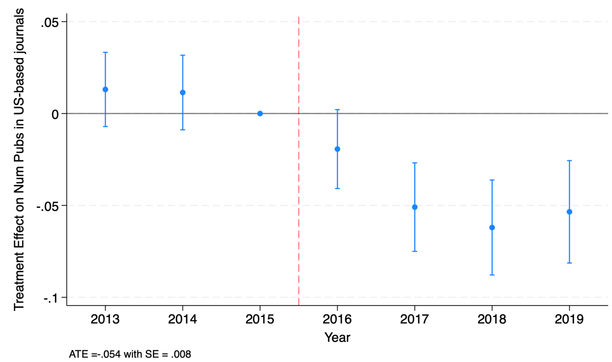
(d) DV: IF wt U.S. Pubs

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

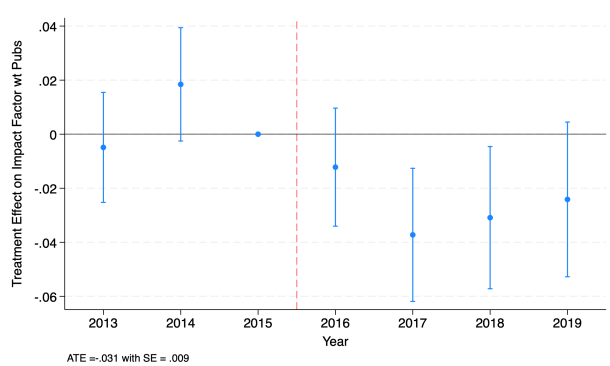
Figure 10: Event-Study Plots for Productivity Change among U.S.-based Researchers



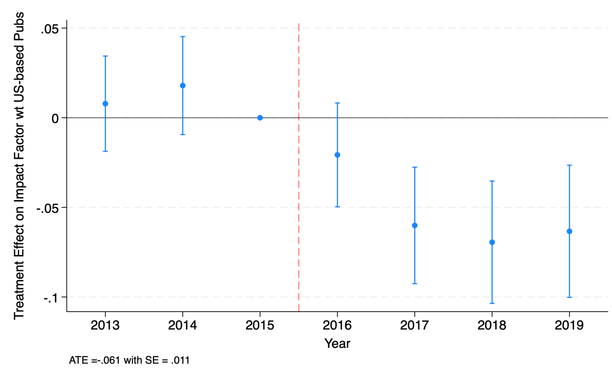
(a) DV: Pubs



(b) DV: U.S. Pubs



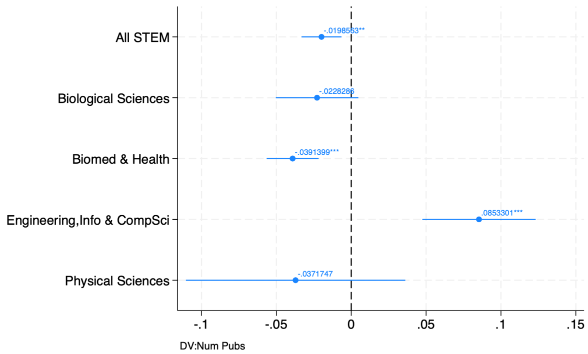
(c) DV: IF wt Pubs



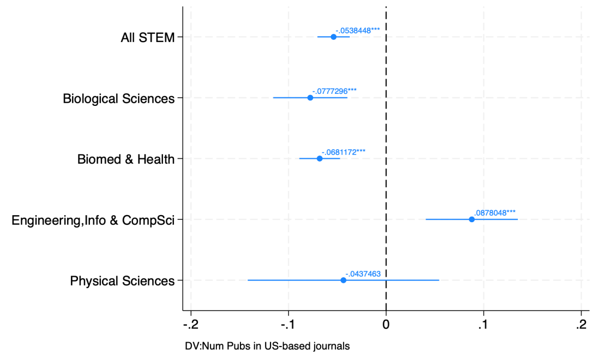
(d) DV: IF wt U.S. Pubs

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.

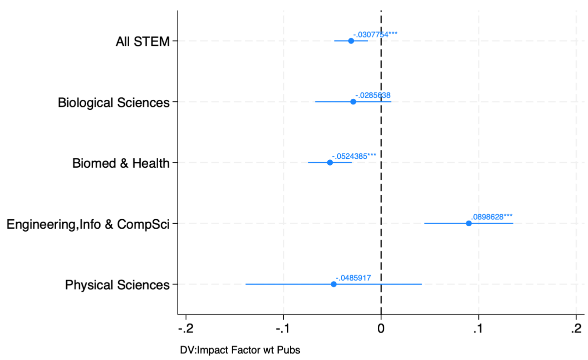
Figure 11: Coefficient Plots for Productivity Change among U.S.-based Researchers, by Researcher's Modal Field



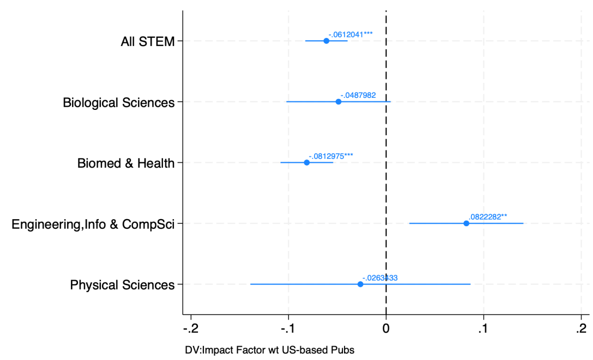
(a) DV: Pubs



(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	129,223				

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	76,102				

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	7.57	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	852,906				

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.	(4) Enrolls in U.S.	(5) Enrolls in U.S.
Treatment = ethnically Chinese=1	0.0323***	-0.0198***	-0.0238***	0.0250***	
	(0.00466)	(0.00376)	(0.00483)	(0.00510)	
Treatment = ethnically Chinese=1 × Post-2016=1	-0.0348***	0.00924**	0.0218***	-0.0309***	
	(0.00782)	(0.00404)	(0.00670)	(0.00803)	
Treatment = ethnically Chinese in top quality decile=1					0.132***
					(0.0101)
Treatment = ethnically Chinese in top quality decile=1 × Post-2016=1					-0.0583***
					(0.0170)
Field FE	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y
Prior Country FE	Y	Y	Y	Y	Y
Prior University Rank FE	N	N	N	Y	N
Model	OLS	OLS	OLS	OLS	OLS
Mean DV	0.239	0.0910	0.169	0.265	0.265
Observations	129204	129204	129204	92069	92069

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	0.129***			
	(0.0131)			
Treatment = ethnically Chinese from China=1 × Post-2016=1	-0.0364***			
	(0.0103)			
Treatment = ethnically Chinese not from China=1		0.0185***		
		(0.00468)		
Treatment = ethnically Chinese not from China=1 × Post-2016=1		-0.0227**		
		(0.00884)		
Treatment = ethnically Chinese from U.S.=1			0.00172	
			(0.00674)	
Treatment = ethnically Chinese from U.S.=1 × Post-2016=1			-0.00843	
			(0.0138)	
Treatment = ethnically Chinese not from U.S.=1				0.0465***
				(0.00536)
Treatment = ethnically Chinese not from U.S.=1 × Post-2016=1				-0.0374***
				(0.00876)
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	129204	129204	129204	129204

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 (3) and (4) are statistically different at the 10% level, p = 0.093. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

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 clustering at the field level. The dependent variable is in the column heading. The analysis sample is citation shares to U.S. and U.K. papers among Chinese publications. The analysis period is 2011-2019, where the post treatment period is 2016-2019. "Treated" refers to citation shares to U.S. papers, with those to U.K. papers 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	-0.000167	0.000216	-0.000112	-0.000182
× Post-2016=1	(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

	Extensive Margin		Intensive Margin			
	(1) Pubs	(2) U.S. Pubs	(3) Pubs	(4) U.S. Pubs	(5) IF wted Pubs	(6) IF wted U.S. Pubs
Predom. Cite US=1	0.079	0.115*				
	(0.049)	(0.062)				
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	N	N	Y	Y	Y	Y
Year FE	N	N	Y	Y	Y	Y
Model	Cox	Cox	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y	Y
Mean DV	2,018.594	2,018.200	3.298	1.120	6.891	2.667
Observations	9,566	9,566	54,276	48,408	54,276	48,408

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 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. Column (1) and (2) report the estimated coefficients from a Cox proportional hazards model. The failure event in this analysis is defined as stopping publication. The analytical sample is the matched CEM sample. Column (3)-(6) reports the estimated coefficients from Poisson model. The regression is weighted by the CEM matching weight. Intensive margin specifications also include the treatment indicator, 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	-0.130***	-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	2.955	3.134	3.635	3.154
Observations	54,276	5,347	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	-0.169**	0.008	-0.051	0.190**
	(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	0.895	1.091	1.327	1.485
Observations	48,408	4,913	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	-0.120***	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	6.891	6.322	6.662	7.397	6.489
Observations	54,276	5,347	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	-0.145*	0.024	-0.078	0.214**
	(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	2.667	2.067	2.663	3.112	3.292
Observations	48,408	4,913	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

	Extensive Margin		Intensive Margin			
	(1) Pubs	(2) U.S. Pubs	(3) Pubs	(4) U.S. Pubs	(5) IF wted Pubs	(6) IF wted U.S. Pubs
Ethnic CN=1	0.071***	0.060***				
	(0.008)	(0.007)				
Ethnic CN=1 × Post-2016=1			-0.020***	-0.054***	-0.031***	-0.061***
			(0.007)	(0.008)	(0.009)	(0.011)
Indiv FE	N	N	Y	Y	Y	Y
Year FE	N	N	Y	Y	Y	Y
Model	Cox	Cox	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y	Y	Y
Mean DV	4.732	4.466	2.664	1.626	7.884	5.278
Observations	231,264	231,264	646,581	615,559	646,581	615,559

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. 'Ethnic CN' refers the treatment group: being ethnically Chinese, as identified by name. The control group is non-ethnically Chinese researchers. Column (1) and (2) report the estimated coefficients from a Cox proportional hazards model. The failure event in this analysis is defined as stopping publication. The analytical sample is the matched CEM sample. Column (3)-(6) reports the estimated coefficients from Poisson model. The regression is weighted by the CEM matching weight. Intensive margin specifications also include the treatment indicator, 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	2.664	1.962	3.027	2.254	2.421
Observations	646,581	81,939	439,273	58,566	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	-0.054***	-0.078***	-0.068***	0.088***	-0.044
	(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	1.626	1.105	1.921	1.171	1.554
Observations	615,559	76,921	425,839	52,457	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***	-0.029	-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	7.884	6.627	9.316	5.235	6.358
Observations	646,581	81,939	439,273	58,566	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	-0.061***	-0.049*	-0.081***	0.082***	-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	5.278	3.855	6.494	2.962	4.133
Observations	615,559	76,921	425,839	52,457	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 15 million CVs. We restricted to individuals reporting complete educational backgrounds, which amounts to 1.8 million CVs. An individual has a complete educational background if each of their education spells includes both start and end dates. We further restricted to those who graduated from STEM[32] programs, inferring academic fields from reported department names (Section A.4). This leaves 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 determined which degrees were terminal based on which began last for a given individual. Next, we discarded individuals a lacking terminal degree at the doctoral level, individuals who did not claim at least one degree pursued prior to their doctorate, and individuals for whom the terminal degree was not unique. 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. In addition, we proxied the quality of each student's prior degree institution using 2023 research rankings from SCIMago. This amounts to 129,223 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 unique 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 (after 2005) and beginning a post-graduation job (after 2008).

[32]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).

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 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	129,223
Ph.D. last year	2,017.22	2.89	2,008	2,015	2,017	2,019	2,033	129,223
Treatment = ethnically Chinese	0.16	0.37	0	0	0	0	1	129,223
Origins								
Prior degree in U.S.	0.18	0.38	0	0	0	0	1	129,223
Prior degree in China	0.11	0.32	0	0	0	0	1	129,223
Prior degree in India	0.10	0.30	0	0	0	0	1	129,223
Prior degree in U.K.	0.07	0.26	0	0	0	0	1	129,223
Prior degree in Brazil	0.05	0.22	0	0	0	0	1	129,223
Destinations								
Enrolls in U.S. university	0.24	0.43	0	0	0	0	1	129,223
Enrolls in U.K. university	0.09	0.29	0	0	0	0	1	129,223
Enrolls in Chinese university	0.07	0.25	0	0	0	0	1	129,223
Enrolls in Indian university	0.08	0.27	0	0	0	0	1	129,223
Enrolls in Brazilian university	0.04	0.20	0	0	0	0	1	129,223
Enrolls in non-U.S. anglo. university	0.17	0.37	0	0	0	0	1	129,223
Research fields								
Science & Engineering program	0.79	0.41	0	1	1	1	1	129,223
Medicine/Health program	0.21	0.41	0	0	0	0	1	129,223

Notes: This table provides summary statistics for the Doctoral Student dataset. The unit of observation is an individual student enrolling in a doctoral 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	0.14	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: This table provides summary statistics for the U.S. Graduates data set. 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: This table provides summary statistics for researchers whose first publication in Dimensions was after 2008. We observe that researchers with ORCID profiles have generally stronger research attributes.

Table A4: Comparison of Researchers in Dimensions With and Without ORCID iDs, Ethnically Chinese vs. Non-Ethnically Chinese

	Non-ORCID, non-eth. CN 8,121,699 (67.9%)	Non-ORCID, eth. CN 2,004,004 (16.7%)	ORCID, non-eth. CN 1,597,553 (13.3%)	ORCID, eth. CN 244,340 (2.0%)
Years active after 2008	2.703	2.865	5.497	6.045
Publications (lifetime)	4.829	5.641	14.752	18.941
Pre-2016 publications	1.798	1.812	3.004	3.513
Post-2016 publications	3.028	3.828	11.742	15.424
SJR-weighted publications (lifetime)	9.784	12.566	32.683	48.726
Pre-2016 SJR-weighted publications	3.667	3.708	6.600	8.279
Post-2016 SJR-weighted publications	6.117	8.858	26.084	40.447
# of grants (lifetime)	0.073	0.060	0.246	0.296
# of research organizations (lifetime)	1.019	1.296	2.082	2.454
STEM field	0.721	0.894	0.797	0.938
HASS field	0.119	0.029	0.177	0.058
Missing field	0.160	0.077	0.026	0.004
Missing publications	0.078	0.073	0.009	0.004
Has ORCID	0.000	0.000	1.000	1.000
Ethnically CN	0.000	1.000	0.000	1.000

Notes: This table provides summary statistics for researchers whose first publication in Dimensions was after 2008. In this table, an ethnically Chinese researcher is one whose last name in Dimensions is among China's top 150 most frequent surnames.

A.2 Knowledge Flows Dataset

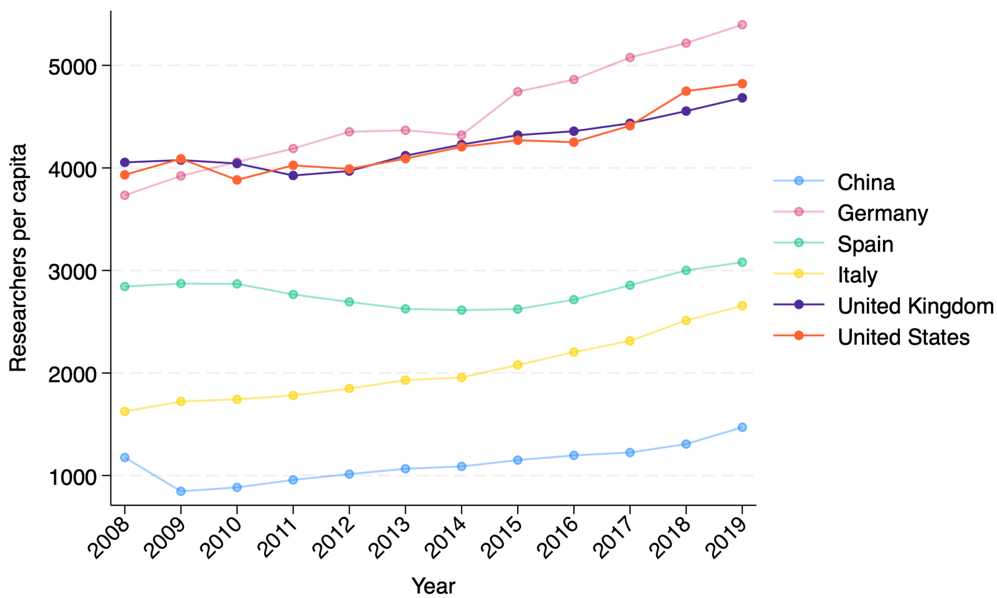
Dimensions from Digital Science provides the bibliometric data we use to examine the impact of U.S.-China tensions on scientific knowledge flows. The Dimensions data covers over 1.8 billion citations connecting over 140 million publications, providing a comprehensive and global view of the academic citation landscape (Thelwall, 2018; Singh et al., 2021).[33] 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 publications 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 papers 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 written by Chinese research teams and 2,847,700 publications written by 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 (citing) publication, we identify the (cited) papers on its reference list. For each cited paper, we assign an origin based on the affiliation address

[33] More information about the Dimensions database can be found in Hook, Porter and Herzog (2018); Herzog, Hook and Konkiel (2020).

Figure A1: Per Capita Researchers Across Countries

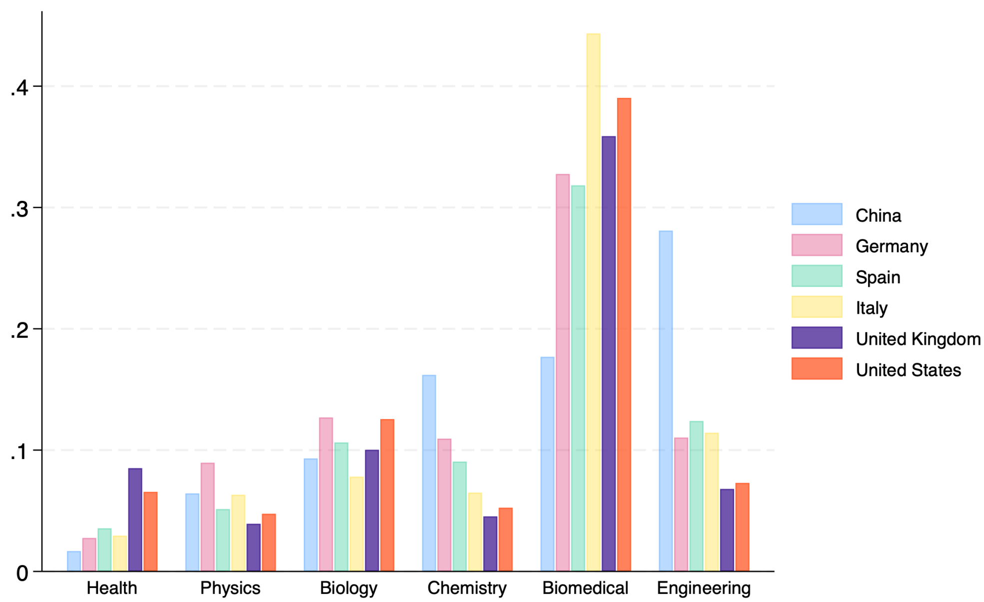


Notes: This plot presents the number of researchers per capita for various countries between 2008 and 2019. The data is sourced from the World Bank via the UNESCO Institute for Statistics (UIS). We observe that the U.S. and the U.K. exhibit both similar levels and similar trends.

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 assigned to that country published within five years of the citing publication. 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 their 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.

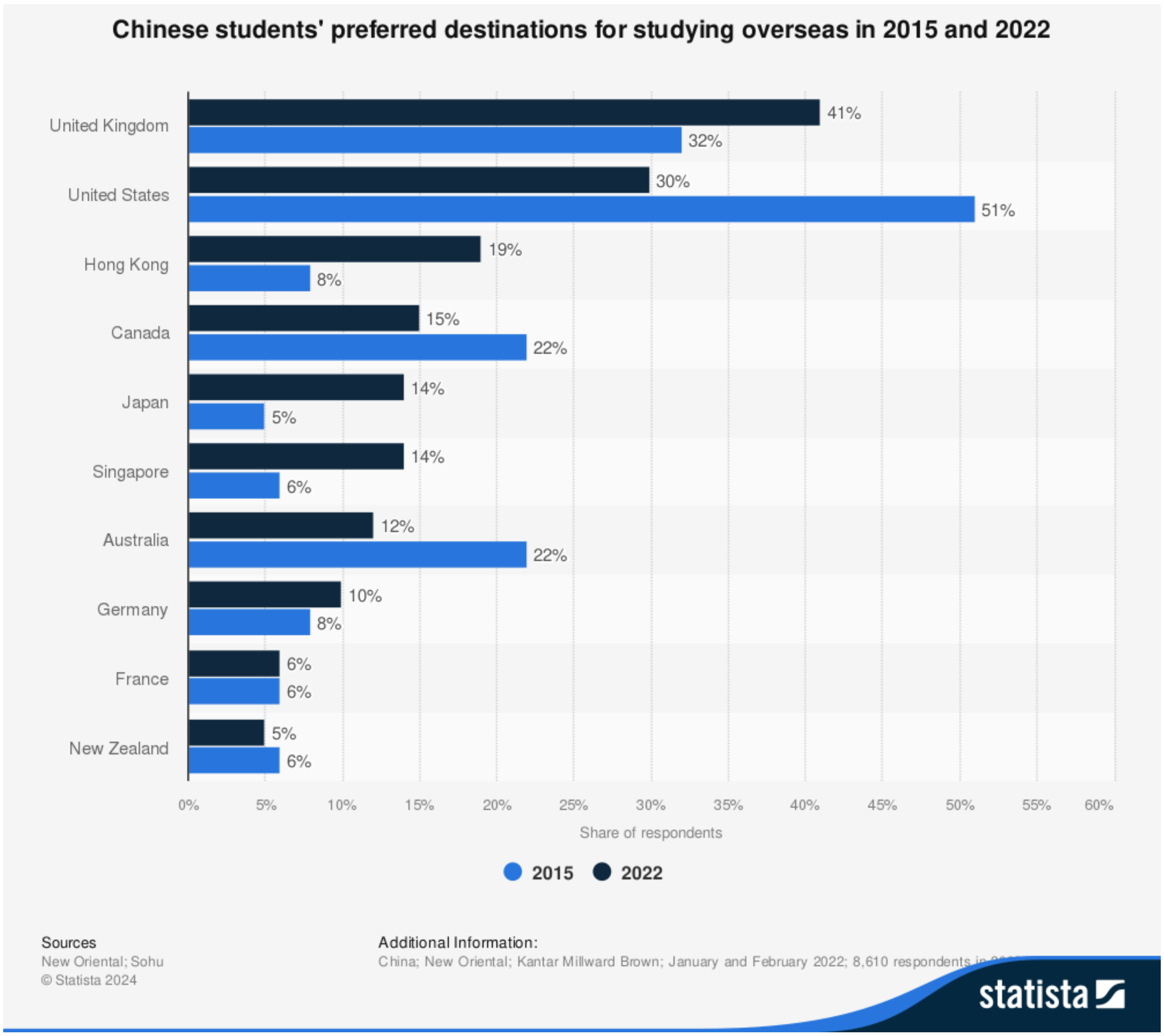
In analyzing knowledge flows between the U.S. and China, we make comparisons with U.K. researchers and U.K.-produced research. We believe that these comparisons can serve as useful counterfactual trends for a variety of reasons. First, researchers per capita tracks similarly for the U.S. and the U.K., as shown in Figure A1. Second, as shown in Figure A2, U.S. and U.K. researchers have similar distributions across scientific fields of their impact-factor-weighted publications. Lastly, the U.S. and U.K. are top destinations for Chinese students, as shown in Figure A3.

Figure A2: Fraction of Countries' Impact-Factor-Weighted Publications Belonging to Fields (2008-2015)



Notes: This plot graphs the fraction of countries' impact-factor-weighted publications belonging to each of the selected STEM fields. Publications are 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.

Figure A3: Statista: Chinese Students' Preferred Destinations for Studying Overseas in 2015 and 2022



Notes: This figure graphs the results of a survey gathering destination country preferences for (nationally) Chinese students studying abroad. In both 2015 and 2022, the U.K. and the U.S. were the top two preferred destinations.

In Table A5, 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 references to U.S.-produced papers or references to U.K.-produced papers. These citation shares come from the publications of Chinese research teams.

Table A5: 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: This table provides summary statistics for the Publication-Citation Shares data set. The unit of observation is a publication-citation share to U.S.- or U.K.-produced papers. Citing publications belong to STEM fields and are written by Chinese research teams.

In Table A6, 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 papers.

Table A6: 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: This table provides summary statistics for the U.S.-U.K. Publications dataset. The unit of observation is a publication authored by a U.S. or U.K. research team. The sample includes only publications associated with STEM fields. Publications with no citations are discarded.

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 factors of the publishing journals.

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 papers from the U.S. and are below the 25th percentile for their field for their citation share to papers 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. science 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 [34]. The descriptive statistics of the matching covariates are shown in Table A7. The CEM algorithm matched 11,975 individuals, out of which 5,982 who predominately cite scientific papers from the U.S. and 5,993 who predominately cite papers from the U.K. We use matching weights generated

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

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 A7. In addition, we show summary statistics on the publications of these groups in Table A8.

Table A7: China-based Researcher Panel Descriptive Statistics: CEM Matching Variables

	(1) All	(2) Matched	(3) Matched-Treated	(4) Matched-Untreated
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)	(3.449)	(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	0.657	0.657	0.657
	(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	2.405	2.391	2.418
	(5.120)	(1.546)	(1.552)	(1.539)
Growth Rate of IF-wt Pubs 2008-2012	0.0114	0.0300	0.0284	0.0316
	(0.254)	(0.248)	(0.253)	(0.244)
Num Impact Factor Weighted Pubs	9.680	4.605	4.402	4.807
	(13.20)	(3.457)	(3.332)	(3.567)
Observations	132,272	11,977	5,994	5,983

Notes: Standard deviation in parentheses.

Table A8: China-based Researcher Panel Descriptive Statistics: Outcome Variables

	(1) All	(2) Matched	(3) Matched-Treated	(4) Matched-Untreated
Num Pubs	4.481	2.405	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	4.402	4.807
	(13.20)	(3.457)	(3.332)	(3.567)
Impact Factor Weighted US-based Pubs	3.315	1.582	1.277	1.889
	(6.058)	(2.123)	(1.787)	(2.373)
Observations	132,272	11,977	5,994	5,983

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 A9 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 A9. In addition, we show summary statistics on the publications of these groups in Table A10.

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

	(1) All	(2) Matched	(3) Matched-Treated	(4) Matched-Untreated
Num Pubs in 2008-2012	9.604	4.055	3.898	4.750
	(16.44)	(5.253)	(5.092)	(5.867)
Career Age	10.53	4.490	4.353	5.096
	(9.885)	(4.374)	(4.224)	(4.939)
Num Active Years in 2008-2012	2.921	2.070	2.020	2.290
	(1.509)	(1.250)	(1.224)	(1.335)
1[University]	0.445	0.431	0.422	0.469
	(0.497)	(0.495)	(0.494)	(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	0.247	0.593
	(11.66)	(1.540)	(1.325)	(2.236)
(mean) subj_code	34.99	33.86	33.74	34.41
	(5.591)	(4.443)	(4.310)	(4.956)
1[Have Foreign Address]	0.242	0.0282	0.0235	0.0493
	(0.428)	(0.166)	(0.151)	(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	-0.00390	-0.00231	-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	-0.0136	-0.0183
	(0.540)	(0.524)	(0.522)	(0.535)
Num Impact Factor Weighted Pubs	8.589	4.712	4.557	5.399
	(15.96)	(5.137)	(4.982)	(5.721)
Growth Rate of Num CN Collab 2008-2012	0.0157	0.00410	0.00201	0.0122
	(0.246)	(0.143)	(0.0964)	(0.254)
Num Chinese Collaborator	0.287	0.0552	0.0189	0.216
	(1.990)	(0.557)	(0.283)	(1.140)
Growth Rate of Num Collab 2008-2012	0.0347	0.0333	0.0336	0.0324
	(0.562)	(0.539)	(0.544)	(0.519)
Num Collaborator	12.66	7.888	7.696	8.743
	(17.97)	(6.756)	(6.571)	(7.464)
Observations	675,195	231,264	188,755	42,509

Notes: Standard deviation in parentheses.

Table A10: U.S.-based Researcher Panel Descriptive Statistics: Outcome Variables

	(1) All	(2) Matched	(3) Matched-Treated	(4) Matched-Untreated
Num Pubs in 2008-2012	9.604	4.055	3.898	4.750
	(16.44)	(5.253)	(5.092)	(5.867)
Career Age	10.53	4.490	4.353	5.096
	(9.885)	(4.374)	(4.224)	(4.939)
Num Active Years in 2008-2012	2.921	2.070	2.020	2.290
	(1.509)	(1.250)	(1.224)	(1.335)
1[University]	0.445	0.431	0.422	0.469
	(0.497)	(0.495)	(0.494)	(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	0.247	0.593
	(11.66)	(1.540)	(1.325)	(2.236)
(mean) subj_code	34.99	33.86	33.74	34.41
	(5.591)	(4.443)	(4.310)	(4.956)
1[Have Foreign Address]	0.242	0.0282	0.0235	0.0493
	(0.428)	(0.166)	(0.151)	(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	-0.00390	-0.00231	-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	-0.0136	-0.0183
	(0.540)	(0.524)	(0.522)	(0.535)
Num Impact Factor Weighted Pubs	8.589	4.712	4.557	5.399
	(15.96)	(5.137)	(4.982)	(5.721)
Growth Rate of Num CN Collab 2008-2012	0.0157	0.00410	0.00201	0.0122
	(0.246)	(0.143)	(0.0964)	(0.254)
Num Chinese Collaborator	0.287	0.0552	0.0189	0.216
	(1.990)	(0.557)	(0.283)	(1.140)
Growth Rate of Num Collab 2008-2012	0.0347	0.0333	0.0336	0.0324
	(0.562)	(0.539)	(0.544)	(0.519)
Num Collaborator	12.66	7.888	7.696	8.743
	(17.97)	(6.756)	(6.571)	(7.464)
Observations	675,195	231,264	188,755	42,509

Notes: Standard deviation in parentheses.

A.4 Ethnicity & Field Imputation

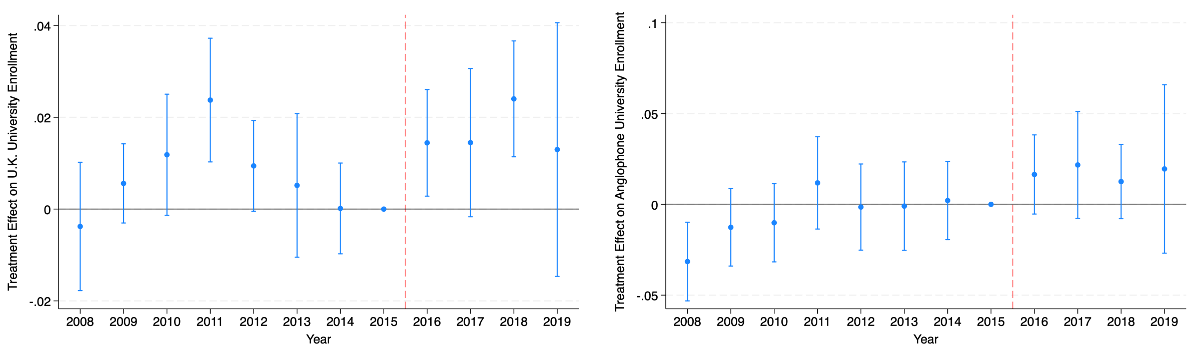
This paper uses measures of ethnicity and scientific field distilled from self-reported names and departments, respectively. To impute ethnicity, we employ the Python package *ethnicseer* using individuals' full names. We use *ethnicseer* specifically because it can classify ethnicity with the granularity 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. First, 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 A4(a) and A4(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 A4: Event Studies for Propensity to Enroll in English Speaking Alternative Universities



(a) Enrolls in U.K. University **(b)** Enrolls in Non-U.S. Anglophone Univ.

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 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	0.0323***	0.0326***	0.0327***	0.0331***
	(0.00466)	(0.00469)	(0.00439)	(0.00497)
Treatment = ethnically Chinese=1 × Post-2016=1	-0.0348***	-0.0348***	-0.0342***	-0.0379***
	(0.00782)	(0.00786)	(0.00778)	(0.00810)
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	129204	131132	121902	91940

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 doctoral students. 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 A5(a) we visualize the possibility of a parallel trends violation using the Stata *pretrends* package based on the work of Roth (2022). Second, in Figure A5(b), we run the HonestDiD estimation procedure for sensitivity analysis based on Rambachan and Roth (2023). Finally, in Figure A5(c), we run a permutation test.

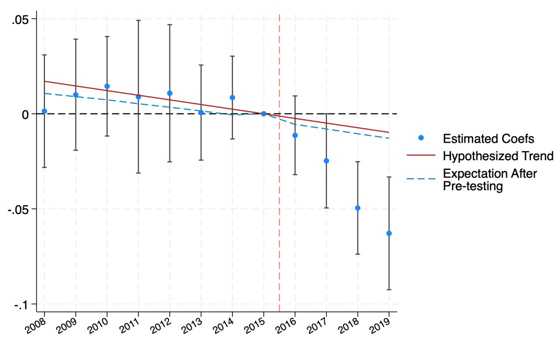
Table A12: Main Treatment Effects on Enrollment among Ethnically Chinese Researchers Restricted to CN, IR, IN, and KR

	(1) Enrolls in U.S.	(2) Enrolls in U.S.
Treatment = ethnically Chinese=1	0.0970***	0.138***
	(0.0129)	(0.00660)
Treatment = ethnically Chinese=1 × Post-2016=1	-0.0542***	-0.0578***
	(0.00991)	(0.0102)
Field FE	Y	Y
Cohort FE	Y	Y
Prior Country FE	Y	N
Model	OLS	OLS
Sample	CN, IR, IN, KR Only	CN, IR, IN, KR Only
Mean DV	0.155	0.155
Obs	33929	33929

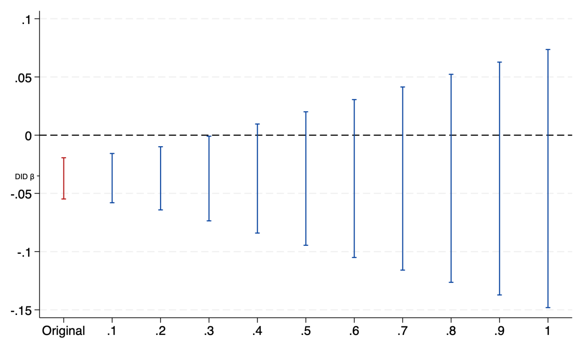
Notes: Standard errors clustered at the field-year level in parentheses. The dependent variable is in the column heading. The analysis sample is all global doctoral students whose prior degree is from either India, South Korea, Iran, or China. The analysis period is 2008-2019, where the post treatment period is 2016-2019. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A5: Parallel Trends Tests for Enrollment in U.S. Doctoral Programs Results

(a) *pretrends* Test



(b) *honestdid* Test



(c) *ritest* Test

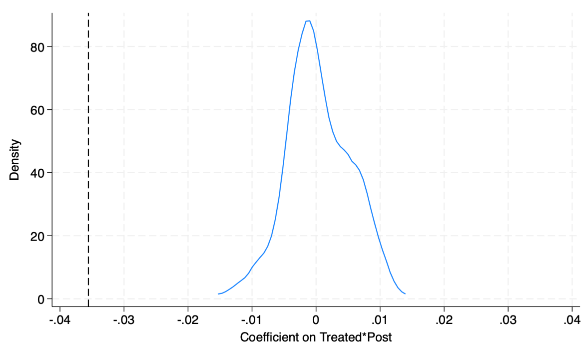
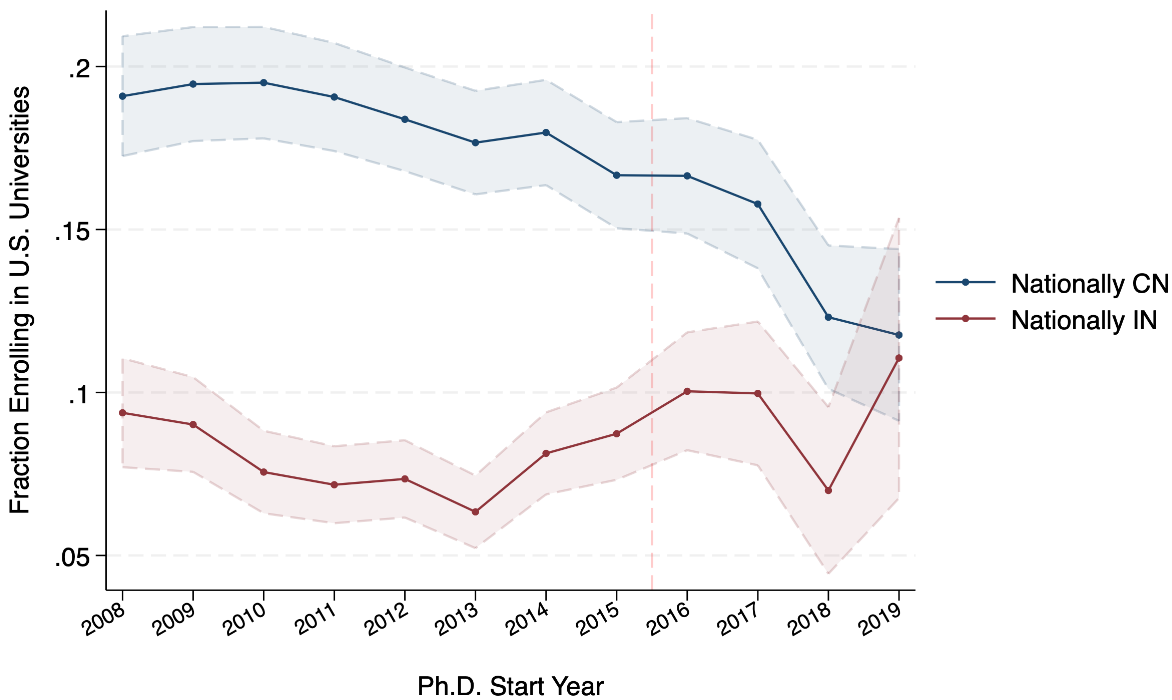
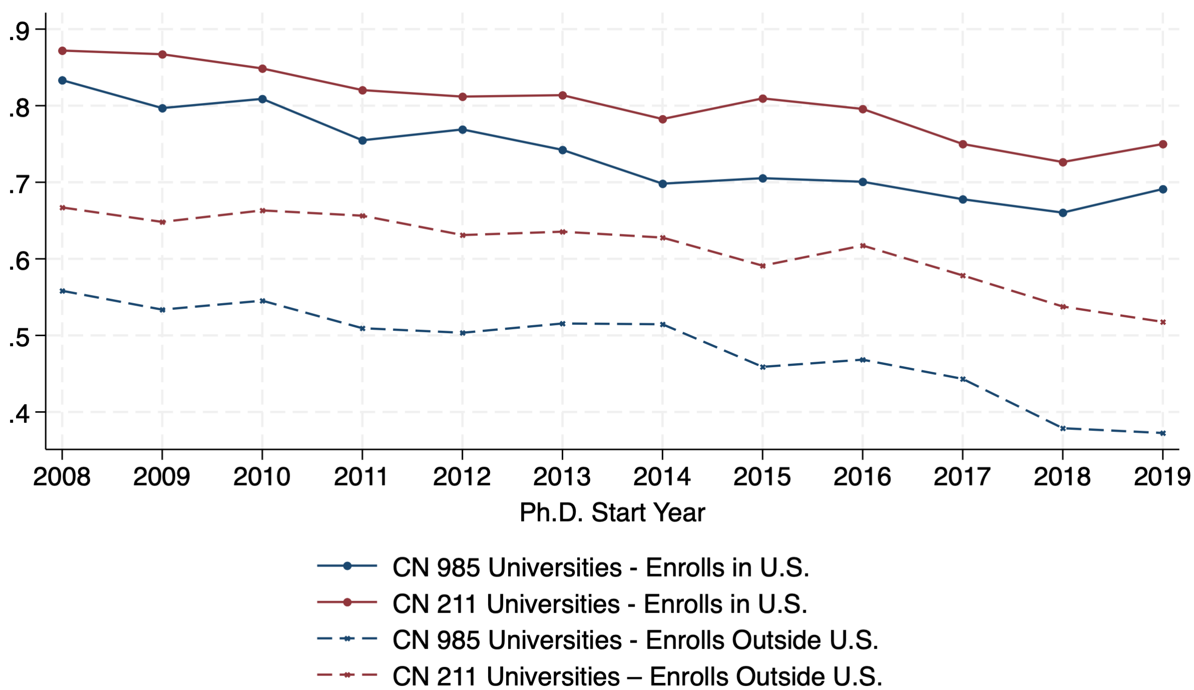


Figure A6: Raw Fraction of New Doctoral Students Enrolling in U.S. By Nationality



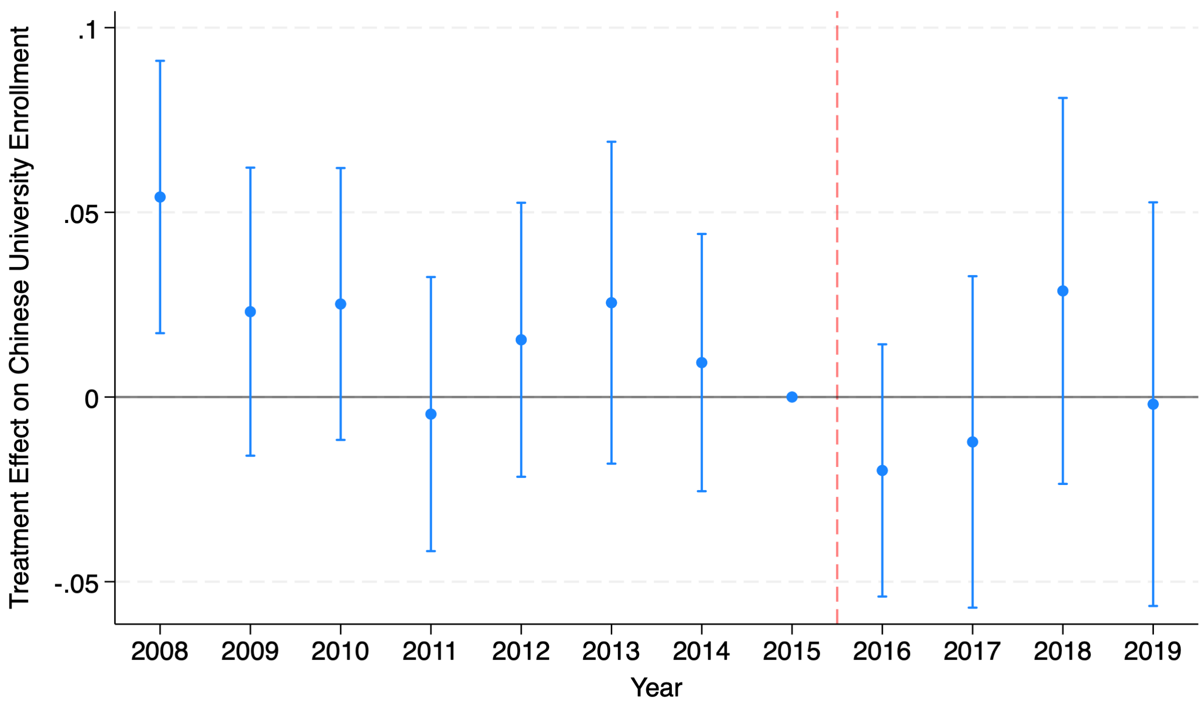
Notes: This figure plots the raw fraction of new doctoral students enrolling in U.S. universities by nationality. We infer the nationality of an incoming doctoral student based on the country of their prior degree. We include plots for nationally Chinese and nationally Indian doctoral students.

Figure A7: Fraction of Nationally Chinese Doctoral Students Coming From Top Chinese Universities



Notes: This figure plots the raw fraction of new doctoral students from China whose prior degree was at a top Chinese university, split by whether or not they enrolled in a U.S. doctoral program. A doctoral student comes from a top Chinese university if their prior degree university is associated with China's "985" or "211" education projects. We observe the fraction of Chinese doctoral students with these credentials to be falling over time.

Figure A8: Event Study for Propensity to Enroll in a Chinese University



Notes: This plot reports event-study coefficients from a regression predicting enrollment in a Chinese 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.

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 A9(a) and A9(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, 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 A10 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 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.

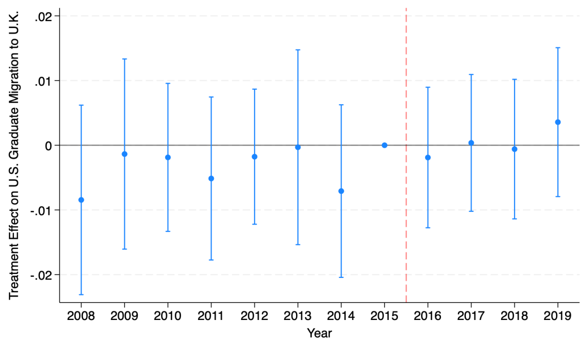
Table A13: Main Treatment Effects on Mobility among Ethnically Chinese U.S. Graduates (Ph.D. Only)

	(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 × Post-2016=1	-0.0304***	0.00396	0.00820*
	(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

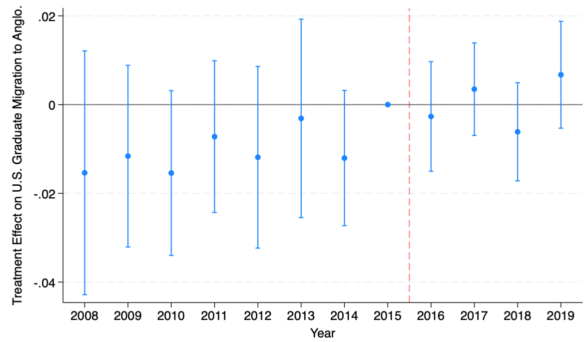
Notes: Robust standard errors in parentheses without clustering. The dependent variable is in the column heading. The analysis sample is all jobs taken after 2008 by U.S. graduates earning degrees after 2005. The analysis period is 2008-2019, where the post treatment period is 2016-2019. * $p < 0.10$,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

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 A9: Event Studies for Likelihood of Migration to English Speaking Alternative Employers



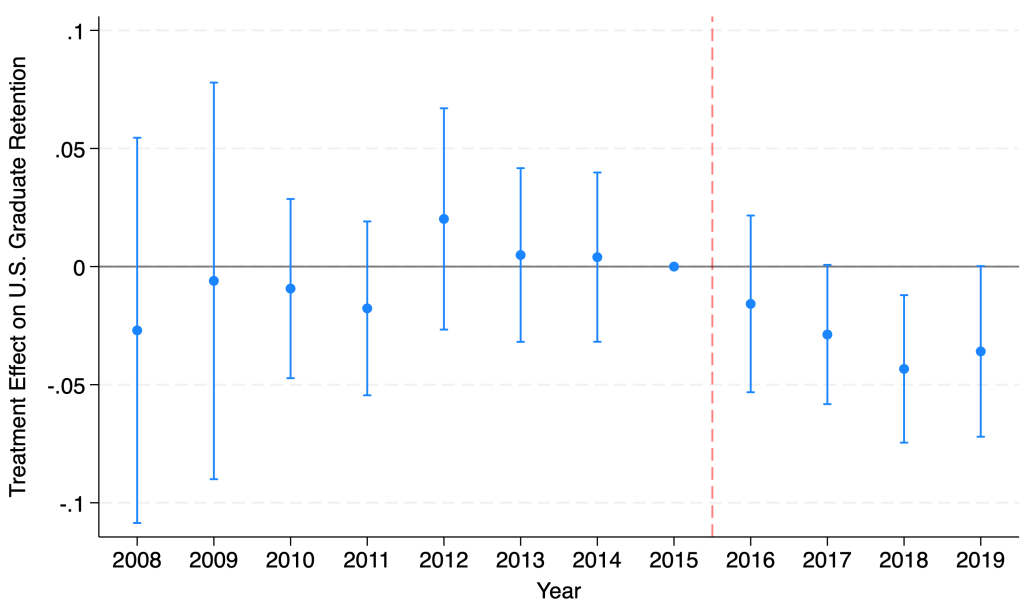
(a) Job at U.K. Employer



(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.

Figure A10: 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.

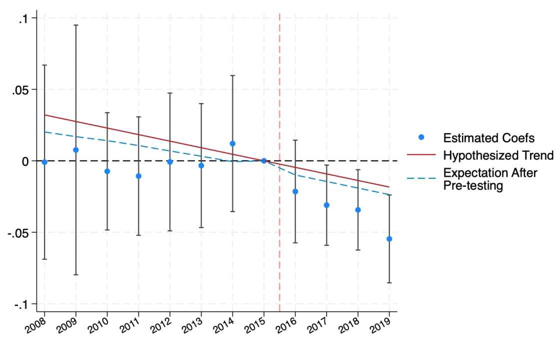
Table A14: Main Treatment Effects on Mobility among Ethnically Chinese U.S. Graduates with Lag Sensitivity

	(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

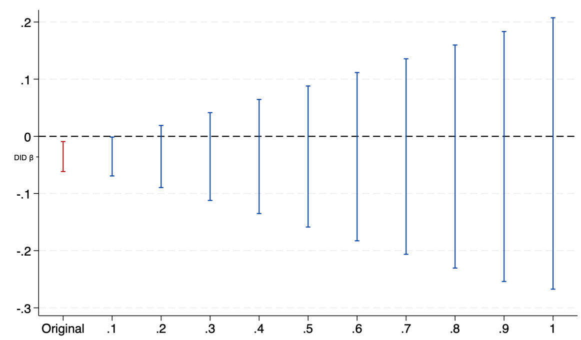
Notes: Standard errors clustered at the field-year level in parentheses. The dependent variable is in the column heading. The analysis sample is all jobs taken after 2008 by U.S. graduates earning degrees after 2005. Each column varies the maximum number of years permitted between a researcher's job 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 A11(a) we visualize the possibility of a parallel trends violation using the Stata *pretrends* package based on the work of Roth (2022). Second, in Figure A11(b), we run the HonestDiD estimation procedure for sensitivity analysis based on Rambachan and Roth (2023). Finally, in Figure A11(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

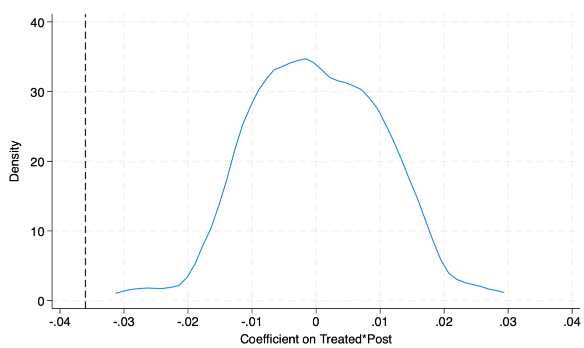
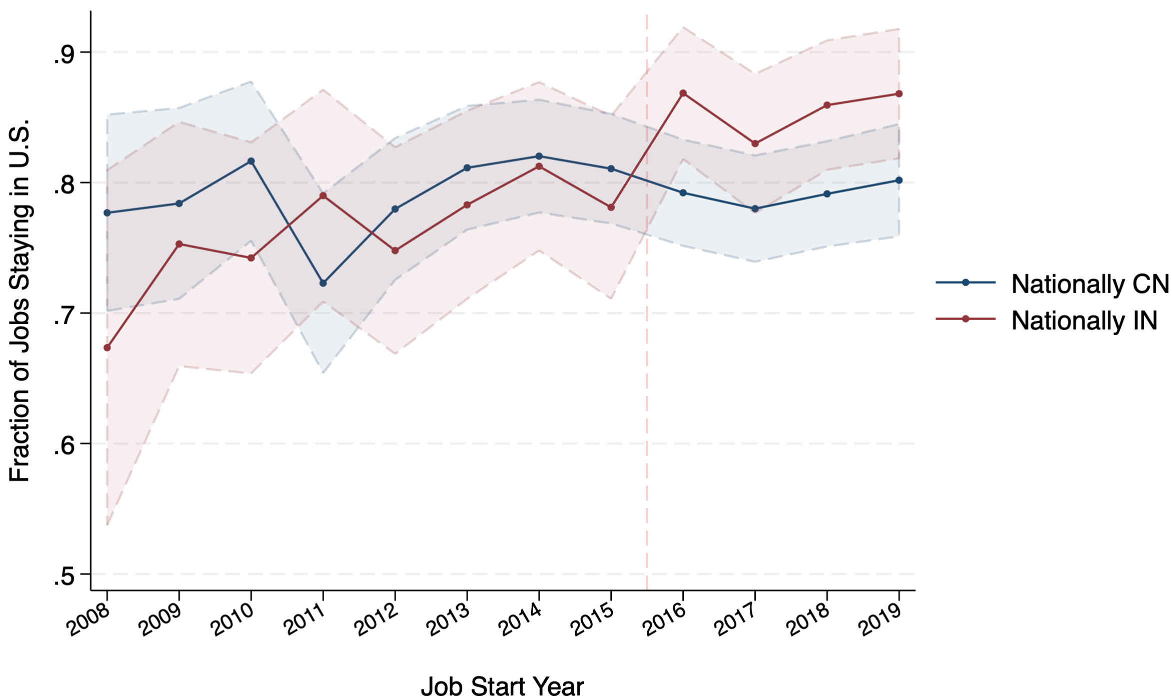


Figure A12: Raw Fraction of Post-Graduation Jobs Staying in U.S. By Graduate Nationality



Notes: This figure plots the raw fraction of post-graduation jobs taken with U.S. employers by the graduate's nationality. We infer the nationality of a U.S. graduate based on the location of their prior degree institution. We include plots for nationally Chinese and nationally Indian U.S. graduates.

D Additional Knowledge Flows Results and Robustness Checks for Chinese Researchers Building on Science Produced in the 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 references on Chinese publications that cite U.S. papers relative to U.K. papers. Figure A13(a) uses a dependent variable limited to recent papers, which are defined as papers produced within five years of the citing publication. Figure A13(b) uses a dependent variable limited to frontier papers, defined as top-cited papers in a scientific field. Finally, Figure A13(c) shows the results with a dependent variable limited to both recent and frontier papers. All of the figures show a distinctive trend break at the 2016.

We conduct a series of additional analyses and demonstrate the robustness of our findings. First, in Table A15, we highlight that our results regarding citations to frontier research are not driven by the cutoff point at which we define a paper as being at the frontier. In this table, we repeat our analysis for frontier research with a threshold of the paper being in the top 3% or 5% of papers in its field's citation distribution. The results are fairly similar across these specifications.

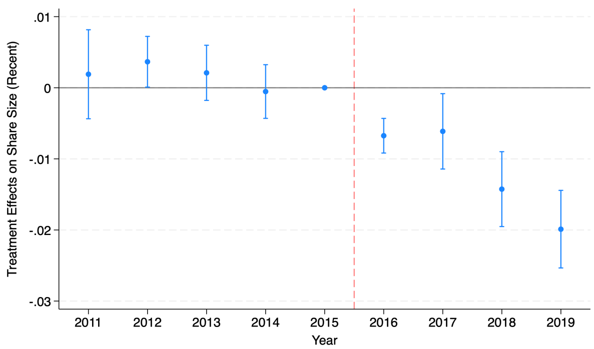
Table A15: Main Treatment Effects on Knowledge Flows among Chinese Publications (Other Frontier Thresholds)

	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

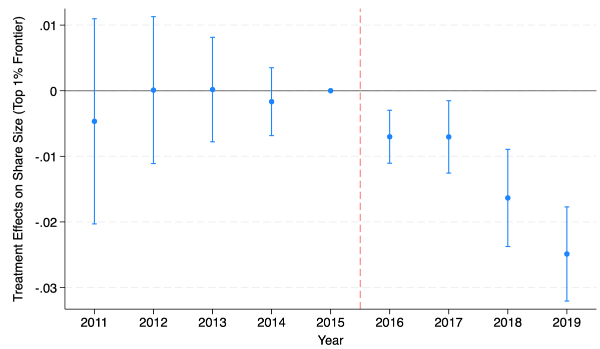
Notes: Robust standard errors in parentheses with standard errors clustered at the field level. The dependent variable is in the column heading. The analysis sample is citations shares to U.S. or U.K. papers among Chinese publications. The analysis period is 2011-2019, where the post treatment period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

In Table A16, we address the possibility that specific fields of Chinese science have significantly different changes in relative quality during the window of our analysis, and that these changes drive our results instead of tensions between the U.S. and China. The difference-in-difference estimates remain largely unchanged.

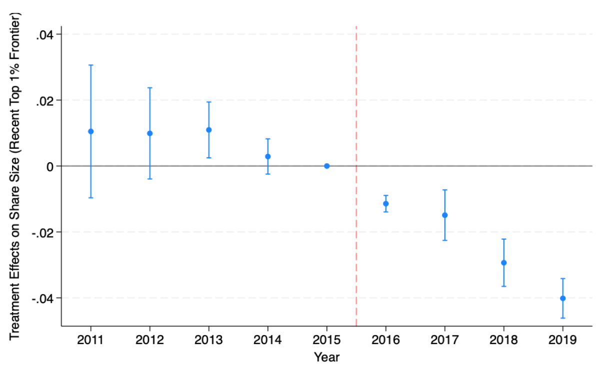
Figure A13: Event-Study Plots for Chinese Researchers Building on U.S. Science



(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 citation shares on Chinese publications. The treated group is citation shares to U.S. papers, and the control group is citation shares to U.K. papers. The regressions include fixed effects for the citing publication. Standard errors are clustered at the field level.

Table A16: Main Treatment Effects on Knowledge Flows among Chinese Publications (Field Time Trends)

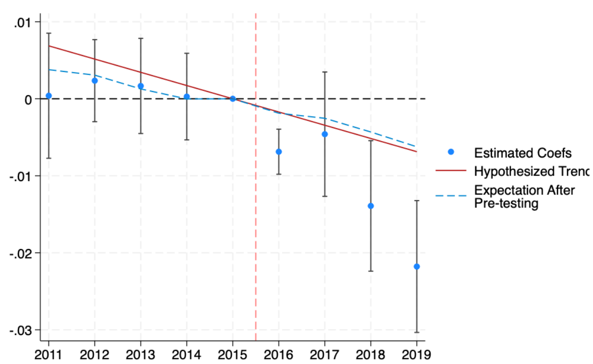
	DV: Share Size			
	(1) Raw	(2) Recent	(3) Frontier	(4) Recent Frontier
Treated = citing U.S.=1	0.182***	0.125***	0.281***	0.247***
	(0.0137)	(0.0150)	(0.0186)	(0.0231)
Post-2016=1	-0.00853***	-0.00682***	-0.00611***	-0.00718***
	(0.00129)	(0.00141)	(0.000875)	(0.00141)
Treated = citing U.S.=1	-0.0138***	-0.0140***	-0.0142***	-0.0321***
$\times$ Post-2016=1	(0.00438)	(0.00256)	(0.00514)	(0.00553)
Field-Time Trends	Y	Y	Y	Y
Model	OLS	OLS	OLS	OLS
Mean DV	0.126	0.0853	0.193	0.162
Observations	4237614	4042500	3332908	2303014

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 citation shares to U.S. or U.K. papers among Chinese publications. The analysis period is 2011-2019, where the post treatment period is 2016-2019. 'Treated' refers to citation shares to U.S. papers, with those to U.K. papers serving as the control group. * p < 0.10, ** p < 0.05, *** p < 0.01.

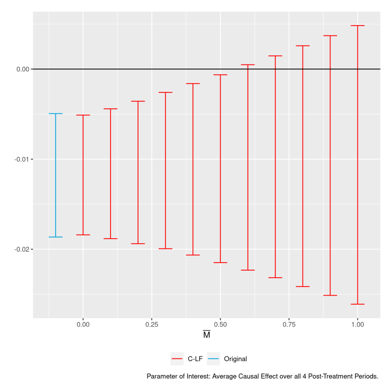
Given that we implement a difference-in-differences empirical approach, we run additional analyses to test our estimates robustness to the possibility of non-parallel trends. We do this using three methods. First, in Figure A14(a) we visualize the possibility of a parallel trends violation using the Stata *pretrends* package based on the work of Roth (2022). Second, in Figure A14(b), we run the HonestDiD estimation procedure for sensitivity analysis based on Rambachan and Roth (2023). Finally, in Figure A14(c), we run a permutation test.

Figure A14: Parallel Trends Tests for Chinese Reliance on U.S. Science Results

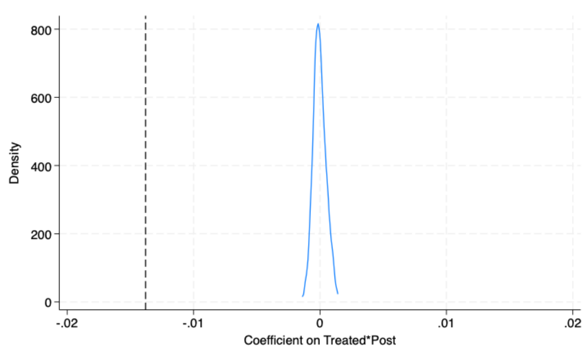
(a) *pretrends* Test



(b) *honestdid* Test



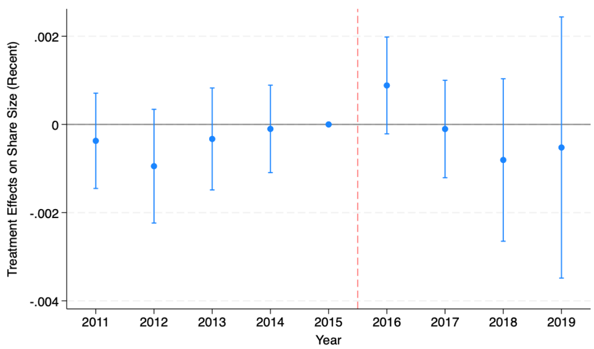
(c) *ritest* Test



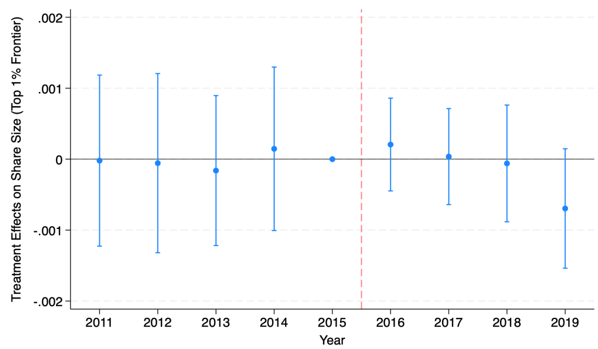
E Additional Knowledge Flows Results and Robustness Checks for U.S. Researchers Building on Science Produced in China

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 references to China-produced papers when comparing publications by U.S. versus U.K. research teams. Figure A15(a) uses a dependent variable limited to recent papers, which are defined as papers produced within five years of the citing publication. Figure A15(b) uses a dependent variable limited to frontier papers, defined as top-cited papers in their scientific field. Finally, Figure A15(c) shows the results with a dependent variable limited to both recent and frontier papers. All of the figures show relatively flat plots across years.

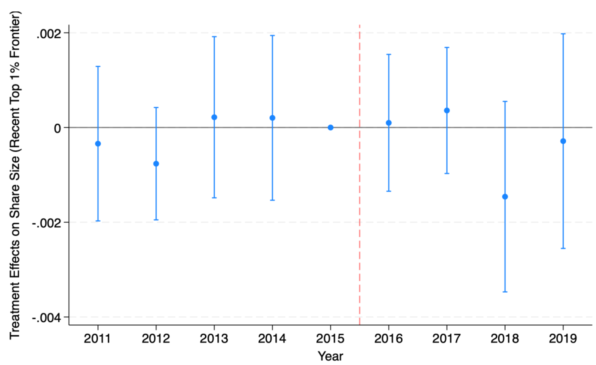
Figure A15: Event-Study Plots for U.S. Researchers Building on Chinese Science



(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 to Chinese papers among U.S. and U.K. publications. The treated group is U.S. publications, and the control group is U.K. publications. The regressions include fixed effects for publication year and research field. Standard errors are clustered at the field level.

F Additional Productivity Results and Robustness Checks for China-based Researchers

We report the Kaplan-Meier survival curve from the Cox Proportional Hazard Model below in Figure A16.

We report the heterogeneity by field analysis of each STEM field below in Figure A17 and Table A17.

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 the robustness of our findings when varying the definition of the treatment and control. We begin by running our main specification but change the citation share thresholds at which we define a Chinese researcher to be reliant on U.S.- or U.K.-produced research. Table A18 shows the results for the thresholds of 75%, 50%, and 90%. Each of these results show not statistically significant effects on productivity.

We also 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 A19, 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 A18. 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.

Table A19: 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 × 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Main Treatment Effects on Productivity among China-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) Math	(7) Physics
Predom. Cite US=1 × Post-2016=1	-0.061	-0.130***	-0.006	0.014	-0.057*	0.062	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	2.955	3.134	3.337	3.635	2.552	3.154
Observations	4,698	5,347	17,982	5,401	16,541	1,449	2,858

	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	-0.097	-0.169**	0.008	-0.078	-0.051	0.079	0.190**
	(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	0.895	1.091	0.883	1.327	1.010	1.485
Observations	3,952	4,913	16,843	4,571	14,264	1,360	2,505

	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	-0.042	-0.120***	0.031	0.006	-0.044	0.082	0.185***
	(0.054)	(0.043)	(0.033)	(0.061)	(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	7.298	6.322	6.662	7.015	7.397	4.872	6.489
Observations	4,698	5,347	17,982	5,401	16,541	1,449	2,858

	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	-0.060	-0.145*	0.024	-0.184	-0.078	0.055	0.214**
	(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	2.050	2.067	2.663	2.275	3.112	2.055	3.292
Observations	3,952	4,913	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 A18: Main Treatment Effects on Productivity among China-based Researchers, By Different Threshold Definitions of Reliance

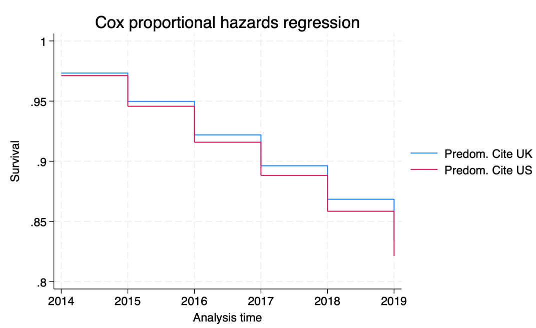
	Treatment: Cite Share to US above 75pctile			
	(1)	(2)	(3)	(4)
	Pubs	US Pubs	IF wt Pubs	IF wt US Pubs
Predom. Cite US (>75pct)=1 × post=1	-0.024	-0.003	-0.005	-0.005
	(0.016)	(0.027)	(0.018)	(0.032)
Indiv FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y
Mean DV	3.298	1.120	6.891	2.667
Observations	54,276	48,408	54,276	48,408

	Treatment: Cite Share to US above 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	10.920	3.961
Observations	307,392	286,009	307,392	286,009

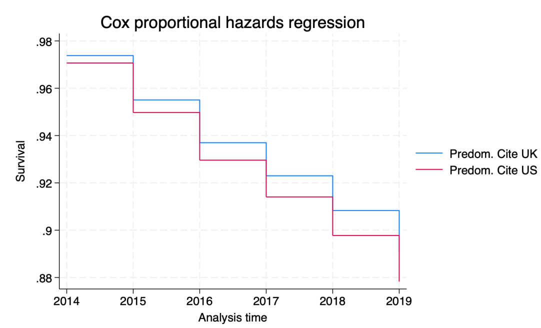
	Treatment: Cite Share to US above 90pctile			
	(1)	(2)	(3)	(4)
	Pubs	US Pubs	IF wt Pubs	IF wt US Pubs
Predom. Cite US (>90pct)=1 × post=1	0.035	0.070	0.056	0.068
	(0.042)	(0.074)	(0.047)	(0.082)
Indiv FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Model	Poisson	Poisson	Poisson	Poisson
CEM	Y	Y	Y	Y
Mean DV	2.682	0.907	5.223	2.022
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 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 A16: Kaplan-Meier Survival Curve among China-based Researchers



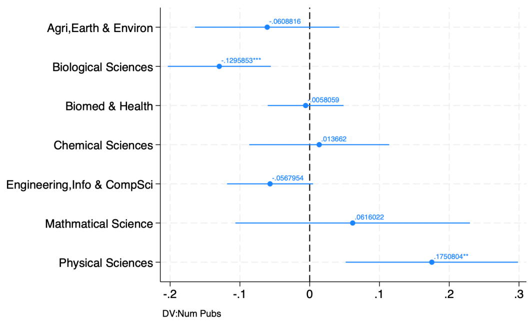
(a) DV:Pubs



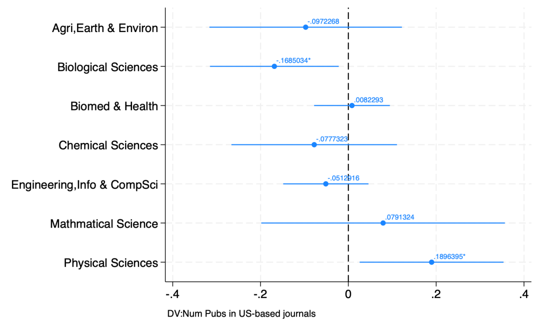
(b) DV: U.S. Pubs

Notes: The Kaplan-Meier curves display the estimated survival probability over time. The failure event is stop publishing anywhere in the world in Panel (a), and stop publishing in U.S.-based journals in Panel (b).

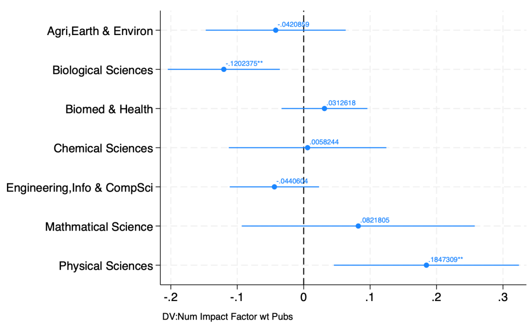
Figure A17: Coefficient Plots for Productivity Change among China-based Researchers, by Researcher's modal field



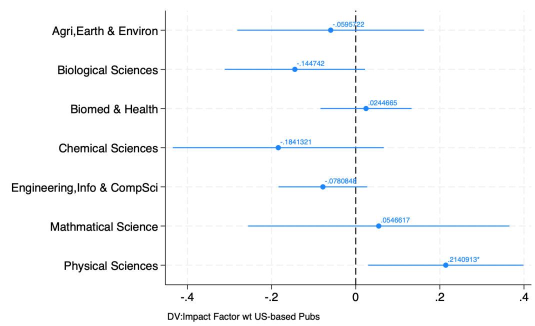
(a) DV: Pubs



(b) DV: U.S. Pubs



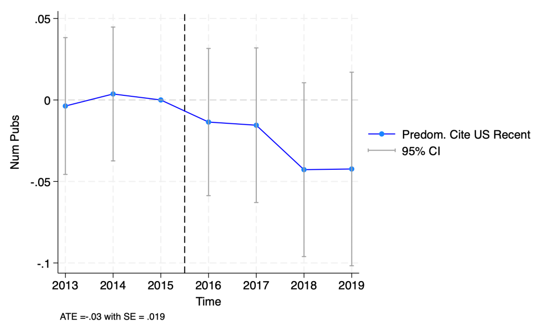
(c) DV: IF wt Pubs



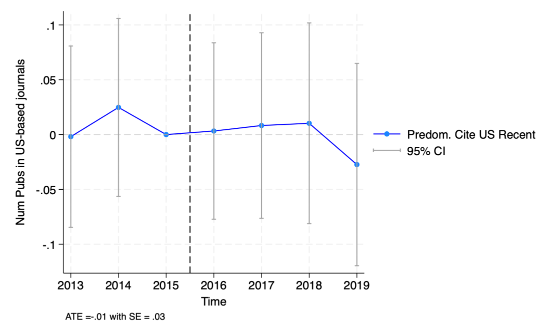
(d) DV: IF wt U.S. Pubs

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

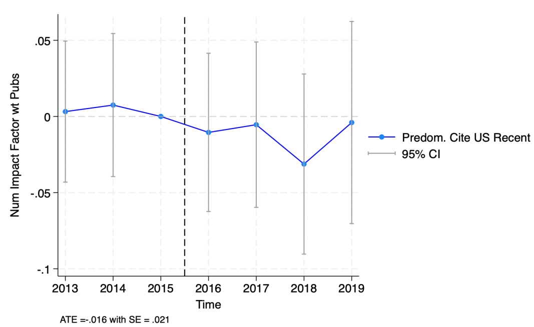
Figure A18: Productivity Change among Chinese Researchers, using recent citation share to define treatment



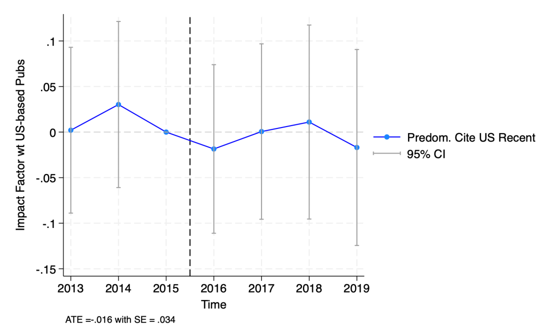
(a) DV: Num Pubs



(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 the subfigure title. The treated group is the China-based researchers predominately citing U.S. papers, as defined by recent citation share, and the control group is the China-based researchers predominately citing U.K. papers. 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.-based Researchers

We report the Kaplan-Meier survival curve from the Cox Proportional Hazard Model below in Figure A19

We report the heterogeneity by field analysis for each STEM field below in Figure A20 and TableA20.

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 A21 shows the results of the permutation test, while Figure A22 shows the results of HonestDiD.

Table A20: 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	2.354	1.962	3.027	2.167	2.254	1.794	2.421
Observations	24,210	81,939	439,273	27,037	58,566	3,309	12,247

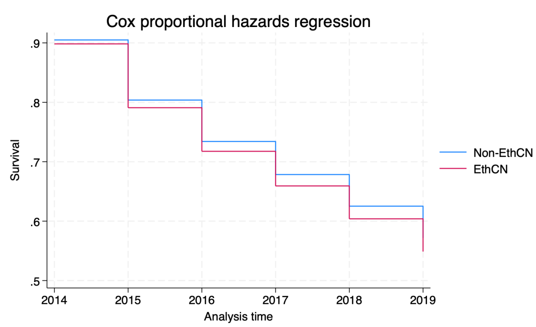
	DV:Num Pubs in US-based journals						
	(1) Agri, Earth & Environment	(2) Biological Sciences	(3) Biomed. & Health	(4) Chemical Sciences	(5) Engineering Info & CompSci	(6) Mathmatical Sciences	(7) Physical Sciences
Ethnic CN=1 × Post-2016=1	-0.108**	-0.078***	-0.068***	0.032	0.088***	-0.019	-0.044
	(0.044)	(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	1.299	1.105	1.921	1.188	1.171	0.897	1.554
Observations	21,947	76,921	425,839	24,624	52,457	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	0.030	-0.029	-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	4.852	6.627	9.316	6.048	5.235	3.974	6.358
Observations	24,210	81,939	439,273	27,037	58,566	3,309	12,247

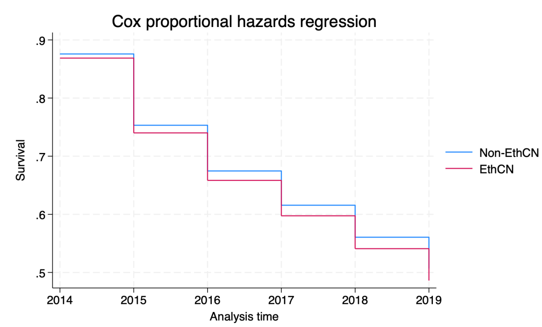
	DV:Impact Factor wt US-based Pubs						
	(1) Agri, Earth & Environment	(2) Biological Sciences	(3) Biomed. & Health	(4) Chemical Sciences	(5) Engineering Info & CompSci	(6) Mathmatical Sciences	(7) Physical Sciences
Ethnic CN=1 × Post-2016=1	-0.048	-0.049*	-0.081***	0.057	0.082***	-0.004	-0.026
	(0.047)	(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	2.795	3.855	6.494	3.827	2.962	2.197	4.133
Observations	21,947	76,921	425,839	24,624	52,457	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 A19: Kaplan-Meier Survival Curve among U.S.-based Researchers



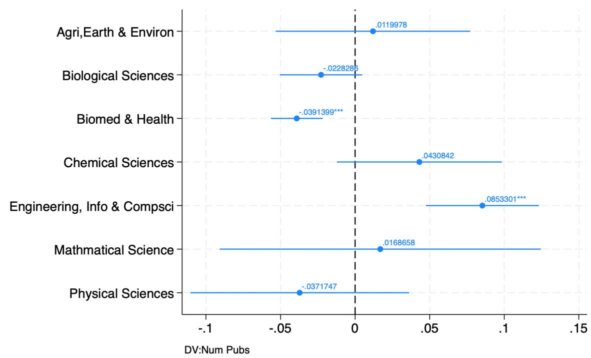
(a) DV: Pubs



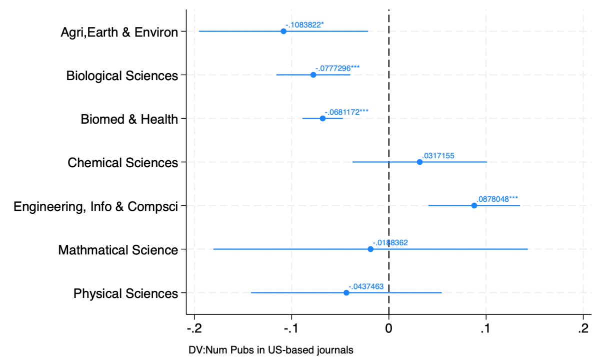
(b) DV: U.S. Pubs

Notes: The Kaplan-Meier curves display the estimated survival probability over time. The failure event is stop publishing anywhere in the world in Panel (a), and stop publishing in U.S.-based journals in Panel (b).

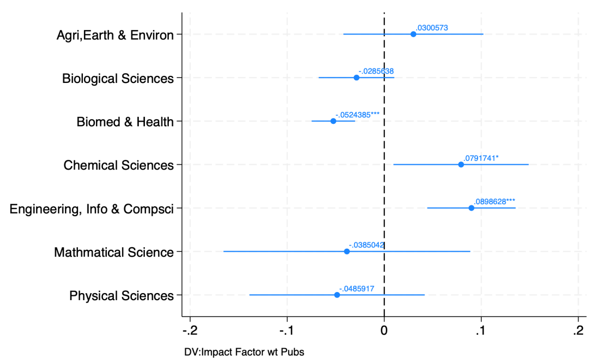
Figure A20: Coefficient Plots for Productivity Change among U.S.-based Researchers, by Researcher's modal field



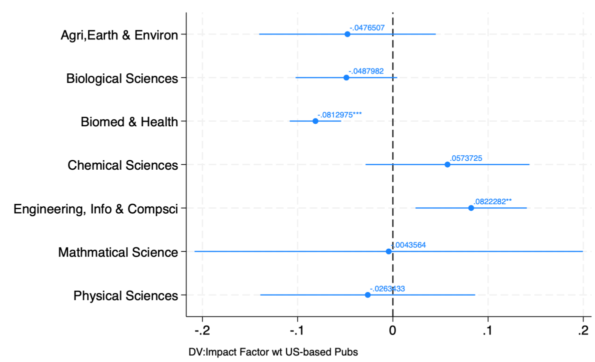
(a) DV: Pubs



(b) DV: U.S. Pubs



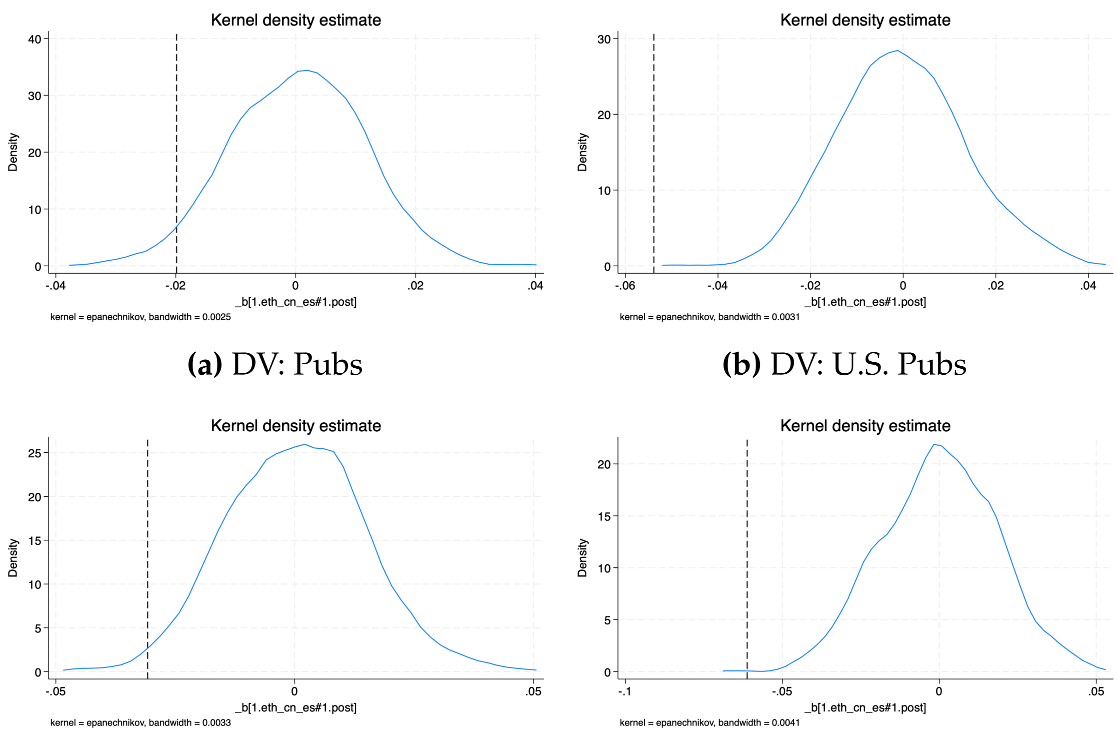
(c) DV: IF wt Pubs



(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.

Figure A21: *ritest* Robustness Check for Productivity Change among U.S.-based Researchers



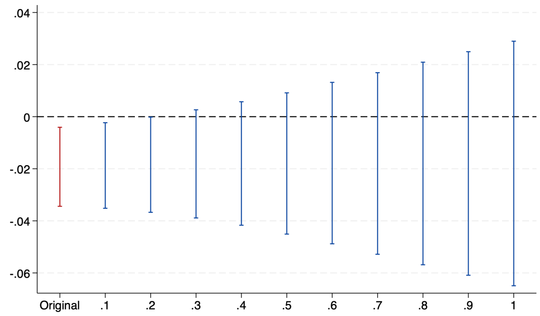
(a) DV: Pubs

(b) DV: U.S. Pubs

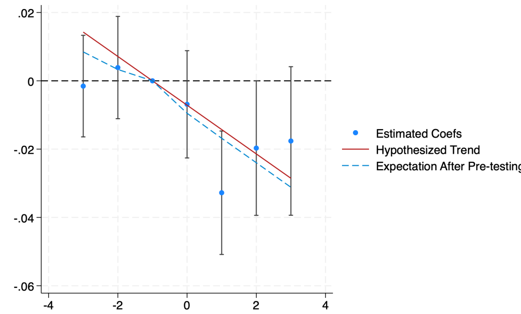
(c) DV: IF wt Pubs

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

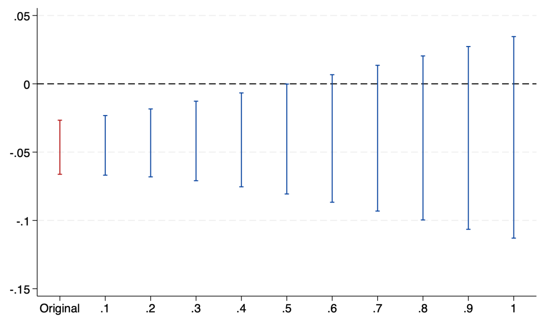
Figure A22: *honestdid* Robustness Check for Productivity Change among U.S.-based Researchers



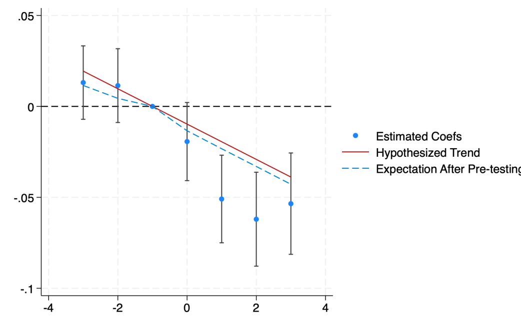
(a) DV: Pubs



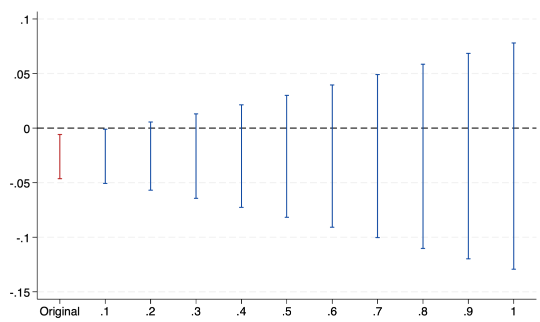
(b) DV: Pubs



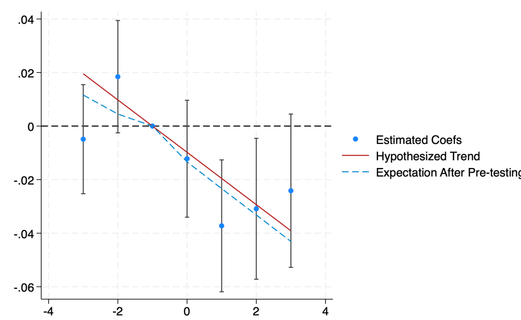
(c) DV: US Pubs



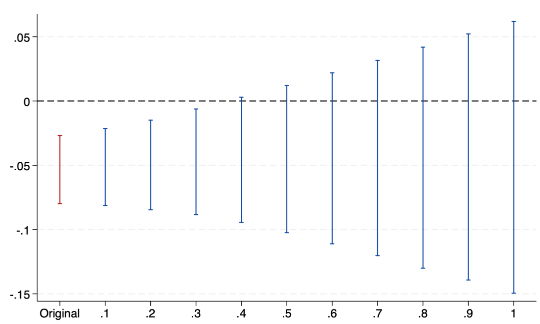
(d) DV: U.S. Pubs



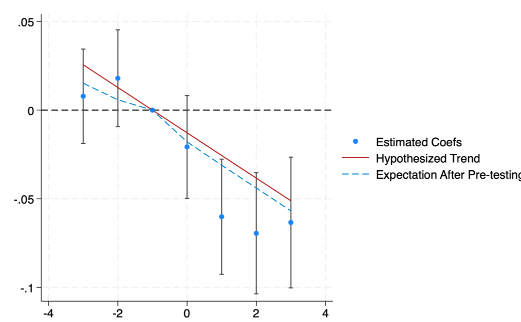
(e) DV: IF wt Pubs



(f) DV: IF wt Pubs



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



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