Scientific Isolation?

The Consequences of Trump's China Initiative on Chinese Research [*]

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Abstract

The 2018 China Initiative by the Trump administration complicated procedures and reduced funding for US-China research collaborations. Using Scopus data, we analyze its impact on Chinese research. We find that the China Initiative significantly lowered the average quality of both the publications and the co-authors of Chinese researchers with prior US collaborations compared to Chinese researchers with prior European collaborations. Thus, we estimate that the China Initiative reduced yearly citations for affected Chinese researchers by 6 percent. The effect was stronger for high-productivity Chinese researchers in US-dominated fields, especially when their US co-authors played a leading role. JEL Codes: I23, O3, O31.

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I. Introduction

Since Deng Xiaoping initiated the liberalization of its economy in the early 1980s, China has experienced one of the most impressive economic growth takeoffs in recent history. Until recently, the Chinese growth has largely been of a "catch-up" nature, relying primarily on very high capital investment rates and on technological imitation facilitated by foreign direct investment and by China joining the World Trade Organization in 2001. However, this phase of imitation is increasingly giving way to a more independent model of innovation, with China emerging as a major power. Han, Jiang and Mei (2020) find that the yearly number of Chinese patents registered by the Chinese National Intellectual Property Administration (CNIPA) has caught up with – and even overtaken – the number of US patents registered by the United States Patent and Trademark Office. Based on patent data, Bergeaud and Verluise (2022) conclude China is close to becoming a leader in frontier technologies such as blockchain, computer vision, and 5G.

Similarly, Figure I provides evidence of the Chinese catch-up in science. The flow of Chinese scientific publications in the top five percent of most-cited journals in each field, as recorded in the Scopus database, now exceeds that of the US. The graph also depicts a strong international dependence. In addition to total publications in such journals by each country, it plots the total number of Chinese publications in the top five percent most cited journals that do not involve co-authors with current or previous US affiliations. Symmetrically, it plots the total number of US publications in the top five percent most cited journals that do not involve authors with a previous or current Chinese affiliation. The number of top "US-dependent" China papers currently represents about half of the total number of top Chinese publications, whereas "China-dependent" US top papers account for a third of all top US papers[1]. The role of such collaborations raises a crucial question: To what extent does the Chinese research hinge on U.S. partnerships?

This paper seeks to answer that question by leveraging the China Initiative as a quasi-natural experiment: namely, we analyze the effects of this exogenous shock to US collaborations on the volume and quality of Chinese research. The China Initiative was launched in November 2018 by Attorney General Jeff Sessions, who issued the statement: "Chinese economic espionage against the United States has been increasing – and it has been increasing rapidly. Enough is enough... We're not going to take it anymore. I have ordered the creation of a China Initiative led by Assistant Attorney General John Demers"[2]. The stated goal was to prevent Chinese economic espionage. Yet, only a small share of related judicial cases

[1]European publications in the top five percent most cited journals outnumber both Chinese and US publications. In Appendix A, we provide information on European dependency on China and the US. European papers in the top five percent most cited journals depend critically on the US but little on China.

[2]See Sessions (2018).

included charges of violating the Economic Espionage Act. Instead, many cases involve questions of "research integrity", mostly researchers failing to disclose all Chinese affiliations and sources of income while receiving US federal funding[3]. In practice, the China Initiative made administrative procedures more complicated, funding less accessible for collaborative projects between Chinese and US researchers, and it also led to the exclusion of targeted researchers from US institutions[4]. Survey evidence suggests the China Initiative has had a substantial chilling effect on US research collaborations with China[5]. Strictly speaking, the China Initiative was not the only policy move by the Trump administration to distance US research from China; in particular, three months before the China Initiative (CI) the Trump government initiated new NIH investigations also targeted at US-China research collaborations. Thus, what we shall refer to as the "China Initiative" shock in this paper, is a time dummy that covers all the new restrictions imposed by the Trump administration in 2018 on US-Chinese research collaborations. In early 2022, the US Department of Justice announced that it was ending the China Initiative.

The reduced scientific collaborations between US and Chinese researchers post-2018 are clearly visible in the aggregate data. Figure II depicts the evolution of the average share of US and European co-authors on papers published by Chinese authors. We first see that the share of European partnerships has been monotonically increasing since 2005. More interestingly, the share of US partnerships started rising more steeply but then declined sharply as of 2018, the year in which the China Initiative was implemented by the Trump administration[6].

The China Initiative arguably increased the cost for Chinese researchers to collaborate with US researchers, effectively reducing their set of possible co-authors. Without adaptation, it seems likely that this reduction would negatively impact their productivity. However, it could well be that they can perfectly and immediately compensate the loss of US co-authors. China's spectacular growth in scientific output implies that there are many available co-authors domestically, and there are of course also alternative co-authors in countries other than the US. In this case, their productivity would not fall and co-author quality would be constant. It is also of interest to study the dynamics of the productivity of affected researchers. Research projects take several years to complete, and for this reason, negative effects may appear with a lag. Similarly, finding new co-authors takes time, and for this reason, adaptation may also not occur instantly after the shock.

[3]See Guo, Aloe, and Hao (2021).

[4]See Schiavenza (2022).

[5]A survey of 1,949 researchers at US top universities in 2021 found that 16 percent of US scientists who had conducted research involving China over the past 3 years prematurely or unexpectedly ended or suspended research collaborations with scientists in China. The top reason (given by 61.2 percent of respondents) was that scientists wanted to distance themselves from collaborators in China due to the China Initiative (Lee and Li (2021)).

[6]In Appendix A, in order to check whether the lost collaborations are meaningful, we plot the trends in China-US and China-Europe collaborations, depending on the affiliation of the last author or the corresponding author of the paper.

To study these questions, we use information about Chinese publications, Chinese authors, and their foreign co-authors (especially from the US and Europe) from Scopus, the Elsevier database founded in 1996. Scopus has collected data covering 43,132 academic journals, 78 million publications, and 16 million authors. For each publication in this dataset, information is provided on the current and past academic affiliations of its authors, their current and past co-authors and their affiliations, and the various sources of funding including individual research grants.

In order to identify the causal effect of the China Initiative on Chinese researchers, we construct a treatment group and a control group. The treatment group comprises active Chinese researchers in the Scopus database with a high collaboration intensity with US co-authors, as well as no European co-author. Conversely, the control group encompasses active Chinese researchers with a high collaboration intensity with European co-authors, as well as no US co-author. The control group is meant to capture the situation where, *ceteris paribus*, the treated Chinese researcher would not be subject to the China Initiative. We estimate effects on the treated authors using a difference-in-differences design with the doubly-robust estimation method, as defined by Callaway and Sant'Anna (2020).

Our main findings can be summarized as follows. We first document the effect of the US decoupling shown in Figure II on our sample of treated Chinese authors. We show that the number of publications by treated Chinese researchers involving a US co-author decreases markedly, compared to publications by control Chinese researchers involving a European co-author. The effect is even more striking when focusing attention on publications in top 5 percent journals.

This negative direct impact of the Initiative on the quality of publications by treated authors could be countered if US co-authors were replaced by equally good co-authors from other countries. However, this is not the case. We find a decline in the average quality of co-authors of treated Chinese researchers following the enforcement of the Initiative. The quality of co-authors is itself a good predictor for future citations, both at the article level and at the author level. Since we have a relatively short time horizon, the H-index is an alternative proxy for paper quality to citations. However, we also investigate quality measures directly, see the following paragraph.

We finally turn to our main outcome: scientific productivity. We find a small negative effect of the China Initiative on the number of publications by Chinese researchers in the treatment group. More importantly, we find a strongly negative and significant trend break in the quality of publications by treated researchers following the implementation of the China Initiative, which is reflected both in the negative trend break in the citation count to publications by treated Chinese authors, and in the negative trend break in the number of publications by treated Chinese authors in top 5 percent journals, compared to the citation count and top 5 percent publications of control Chinese authors. In terms of magnitude, we estimate that the treated authors experience a drop in citations of 6 percent and publications in top journals of around 9 percent of their pre-period levels. We also investigate three potential sources of heterogeneity of the effect of the China Initiative. We find that the negative impact of the China Initiative is strongest (i) for those Chinese researchers in the treatment group with the highest research performance, (ii) who were publishing in US-dominated fields prior to the shock, and (iii) whose US-coauthors performed a more prominent role, as indicated by the order of these coauthors in their joint publications.

How valuable are US coauthors on average to Chinese scientists? Consider a scenario in which a Chinese author loses a US coauthor on a paper with four authors. What impact does this loss have on the author's total yearly productivity? One natural benchmark is that the loss is proportional to the US coauthor's share - that is, one-quarter of a paper. If a US coauthor can be easily replaced, the productivity loss might be smaller. Conversely, if the US coauthor provides crucial, irreplaceable input to the project — or the shock is magnified by difficulties in collaborating with other US researchers—the effect could be even larger than one full paper. We investigate this by comparing the estimated drop in US-coauthored top journal papers to that in all papers. We find that the estimated total effect is four times greater than proportional to the US coauthor share in the lost top journal publications. In fact, the total effect is comparable in magnitude to that of each US coauthor being pivotal to writing each joint paper.

This relationship between the shock to US-China coauthored papers and the total productivity loss to Chinese researchers provides a useful framework for understanding the aggregate effects of the China Initiative. Using a back-of-the-envelope calculation, we estimate that the observed decline in US-coauthored papers after 2018 would correspond to an aggregate decline of approximately 20 percent in top-journal publications by Chinese researchers. This implies that without the China Initiative, the number of top-journal publications by Chinese researchers in 2021 shown in Figure 1 would equal that of European researchers, at around 72,000 instead of 60,000. Average Chinese publications are much less exposed to the shock to US-collaborations than top-journal publications. Our back-of-the-envelope calculation shows that lost US-collaborations post 2018 only resulted in a 4-percent loss in the total number of publications by Chinese authors.

Although the policy resulted in a significant decline in the quality of publications by affected Chinese researchers, the aggregate effect on Chinese research output remains relatively modest. While the China Initiative may create a dent in the curve of Chinese top journal publications, the underlying positive trend shown in Figure 1 is unchanged. This resilience reflects China's transformation into a self-sustaining research hub. The vast domestic research ecosystem, bolstered by state support and a rapidly growing pool of highly trained scientists, has reduced China's vulnerability to external shocks. We find that US co-authors play a crucial role, particularly for researchers in US-dominated fields or those with strong publication records. However, the share of Chinese research directly impacted by the policy is relatively small, limiting its overall effect on national scientific output.

Existing research shows that US science was also negatively affected by the China Initiative. Our estimates of the effects per affected Chinese researcher are similar in magnitude to those found by Jia et al. (2024) for affected US researchers in the life sciences. However, the effects are likely larger on the Chinese side as significantly fewer US researchers than Chinese researchers were affected by the shock. In 2018, our data show that 146,000 Chinese researchers collaborated with US researchers, compared to 99,000 US researchers who collaborated with Chinese researchers.

Our paper relates to several strands of literature. First is the literature on imitation versus innovation-led growth and the middle-income trap, (e.g. see Acemoglu, Aghion and Zilibotti (2006); Acemoglu and Robinson (2012)) with its focus on the Chinese catch-up (e.g. see Zilibotti (2017); Acemoglu, Yang and Zhou (2021); Qiu, Steinwender and Azoulay (2022)[7]; Bergeaud and Verluise (2022); Roland (2023)). We contribute to this literature by looking at frontier Chinese research and the extent to which it suffered from the curtailing of Chinese-US collaborations following the China Initiative[8].

Second, our paper relates to a recent literature on US-Chinese research collaborations. The link between the rise of China and the creation of a potent US-China network of researchers has been documented by Veugelers (2010) in the early stages of the catch-up. Veugelers (2017) also stresses the impact of US connections in Chinese research and the lack of importance of European connections right before the China Initiative. More recently, Han, Jiang and Mei (2020) provide evidence of a reduction in the scientific "decoupling" between China and the US, i.e. a decrease in the extent to which US patents cite Chinese patents and vice versa. They also show that the degree of Chinese scientific dependence upon the US – namely the extent to which Chinese patents cite US patents more than US patents cite Chinese patents – has increased and then decreased over the past two decades. We contribute to this literature by estimating how reliant Chinese research is on US collaborations, despite its remarkable catching up[9].

A third strand of literature focuses more specifically on the China Initiative. As explained by Schi-

[7] Qiu, Steinwender and Azoulay (2022) argue that US researchers do not build as readily on the work of Chinese researchers compared to the work of scientists from developed countries.

[8] Acemoglu, Yang and Zhou (2021) look at the extent to which Chinese researchers redirect their research towards the research themes of newly appointed research directors when the latter are Communist Party members. Both their analysis and ours point to the importance of freedom in fundamental research: presumably, both political appointments of new research directors and the curtailing of US collaborations imply a reduction in Chinese researchers' freedom. For an excellent discussion of potential institutional barriers to innovation in China, see Roland (2023).

[9] Other papers in this literature include Cao et al. (2020) who argue that research collaborations between the US and China have strengthened, and Lee (2022) who argues that these collaborations have persisted despite the American sanctions.

avenza (2022) and by Gilbert and Kozlov (2022), a large fraction of the US research community has fought against its implementation and then advocated its abolition. That the Initiative has made collaborations between US and Chinese researchers more difficult has already been hinted at, e.g. by Lee (2022). More systematically, Jia et al. (2022) estimates the impact of the China Initiative shock on US-based researchers in the field of life sciences. They find that the research productivity of US-based scientists with prior co-authorship with Chinese researchers has significantly decreased following the shock. We contribute to this literature by looking at the impact of the China Initiative on the productivity of Chinese researchers, with results that mirror Jia et al. (2022) regarding the impact of the shock on US-based researchers. A closely related paper is Li and Wang (2024) that uses a design that is similar to ours but that differs in a few key aspects; see Appendix A.1. This study also concludes that Chinese researchers who collaborated with US researchers were negatively affected, but their estimated effect is considerably smaller than our estimated effect. Another related study is Flynn et al. (2024) with results that are complementary to ours. It finds that the China Initiative reduced the enrollment of Chinese graduate students in US universities PhD programs, that Chinese authors reduced their citation of US authors, while US authors did not reduce their citation of Chinese authors, and that Chinese authors who cite US authors and those who cite UK authors had a similar productivity trend after 2018.

Our paper also relates closely to a fourth branch of literature investigating the effect of political tensions on research output, particularly to a growing historical literature investigating the effect on research of conflicts, migrations, physical and human capital loss (e.g. see Waldinger (2012); Moser et al. (2014); Waldinger (2016)). Our work is more closely related to Kung and Wang (2021) who investigate the effect of the Cultural Revolution on researchers in Hong Kong, and to Iaria et al. (2018) who analyze the research impact of losing access to the international knowledge frontier, albeit in a very different setting from ours. We contribute to this literature by looking at the microeconomic impact on the volume and quality of the research output of losing access to high level collaborations with top researchers worldwide.

Fifth, this work relates to the recent literature on innovation and networks (e.g. see Azoulay, Graff Zivin and Wang (2010); Jaravel, Petkova and Bell (2018); Akcigit et al. (2018); and Aghion et al. (2023)). Closely related to our analysis are the Azoulay and Jaravel papers: they look at the effect of losing a star co-author on subsequent patented innovation. Similarly, we look at the effects on future research performance for Chinese researchers of the restrictions in US collaboration brought about by the China Initiative. Contrary to the two aforementioned papers, our analysis does not focus on the loss of a single co-author, but on the loss of the opportunity to access a large set of potential US co-authors, both at the time of the shock and in subsequent years.

The remaining part of the paper is organized as follows. Section 2 presents the data sample, our main variables, and our empirical methodology. Section 3 presents our results. Finally, Section 4 presents extensions and aggregate results, and Section 5 concludes.

II. Data and Methodology

II.A. The Scopus database

Our main source of information on the scientific production of Chinese researchers and their co-authors is the Scopus bibliometric database. Released by Elsevier in 2004, to date, the Scopus database covers 43,132 scientific journals, 78 million publications, and 16 million authors. Scopus comprises several data subsets, and the three datasets that are most directly relevant for us are: (i) the article-level dataset which includes information about the names of the authors of each article, their affiliations, the journal of publication, the article's citations, its All Science Journal Classification (ASJC) codes, and its related subject areas; (ii) the author-level dataset which informs us about the authors' latest affiliation(s) and about their main research areas; (iii) the journal-level dataset which includes their CiteScore metrics of journal quality per ASJC[10]. Scopus presents a lower data quality in social sciences. Hence, in our analysis, we only include authors who are not in these sciences. For similar reasons, we also remove authors entering Scopus before 1999.

This database covers a wider range of fields and a higher number of journals than Web of Science (Mongeon and Paul-Hus (2016)), and a better coverage of Chinese scientific articles than other bibliometric data sources such as Web of Science and PubMed in most academic fields (Baas et al. (2020); Singh et al. (2021)). Although other databases such as Microsoft Academic or Dimensions may include publications that are not reported by Scopus, the Scopus database does a better job at providing citation links between publications and other types of qualitative information on articles and authors (Visser, van Eck and Waltman (2021)).

II.B. Main outcomes

We consider two sets of outcome variables. First, outcome variables that reflect the productivity of Chinese researchers. Second, outcome variables which capture the evolution of co-authorship of treatment versus control Chinese researchers.

[10]The CiteScore index is computed as follows: for each journal, Scopus computes the ratio of the number of citations sent to articles published in this journal for the past four years to the number of published documents in Scopus over the same period (Klavans and Boyack (2017)).

We measure research productivity by the number and quality of publications at the author-year level. We count the total number of publications by researcher and year and call this variable *Publications*. We then count subsets of these total publications where we have indications of a larger author role in the publication or a high-impact publication. The variable TopJournal represents the number of publications in the top 5 percent most cited journals within an academic subject (e.g., medicine, chemistry). Following Scopus's *Citescore* metrics, in order to assess the real-time quality of the journal, we smooth the number of citations per paper over a four-year window around the current year [11]. The variable *TopCited* is the number of publications that are among the top 1 percent most cited papers by academic subject and year. Finally, we count the total number of citations of all papers published by the researcher in a year and call this variable *Citations*. For some robustness checks, we split the number of citations by the region of affiliation of citing authors and restrict attention to citations received within five or ten years after publication to limit the scope for truncation bias. While restricting the analysis to the citations received within one year does not yield results due to noise, we make the case in Appendix C.9 that the truncation bias does not drive our estimates. We also consider to this effect our results on the effect of the shock on the *TopCited* variable, which is also a citations-based metrics that is unaffected by construction by this truncation-bias. All the above variables are winsorized at the 97.5 percent level, in the distribution of all articles in Scopus, prior to selecting the sample. As measures of collaboration with different regions[12], we also compute the number of the above productivity measures (publications, etc.), weighted by the share of co-authors on each paper with affiliation in the US, Europe, or China[13].

We next turn to measures of the evolution of co-authors networks. Thus, we first compute the set of co-authors of a Chinese author in any given year. Then, we decompose the set of co-authors into new, short-term, and long-term co-authors. A new co-author in a given year is a co-author with whom the Chinese researcher has never collaborated before. Short-term co-authors are co-authors during a period between 1 and 5 years. Long-term co-authors are co-authors over more than five years in a row. We create indicator variables for having a new co-author ($NewCoauth$), a new short-term co-author ($STCoauth$)), and a new long-term co-author ($LTCoauth$). To measure co-authoring across regions, we break up these numbers according to the co-authors' region of origin: the US, Europe, or China.

Finally, we construct a measure of the quality of co-authors. We compute co-authors' H-Indexes[14] in

[11] By definition, the set of top 5 percent journals is thus allowed to change over our period of analysis, though it remains quite stable due to the use of time windows and our relatively short period of analysis.

[12] Our definition of Europe includes the 27 countries of the European Union, the United Kingdom, Switzerland, Norway, and Iceland.

[13] For example, if one Chinese author paper has one paper with 1/4 of co-authors from the US and another with 2/4 of co-authors from the US, then we count this as this co-author having a sum of 3/4 papers co-authored with US. We compute the equivalent sums for all of the above productivity measures.

[14] The H-index of an author is equal to h if the author has h publications with at least h citations each.

any given year based on information available by the end of the year[15]. This allows us to focus on the "real-time H-Index", which measures the *observed* quality of co-authors at the time of publishing. This variable is called $CoauthorHindex$.

II.C. Other variables

We collect a set of individual-level control variables, based on outcomes 2008-2012, in the vector X_i. In our empirical analysis, these variables are used both to compute the propensity-score weights and to control for differential trends in outcomes, for example, allowing research output to grow more quickly in certain research field and for junior researchers. The variables are intended to capture researcher cohort, field, productivity, and dependence on the US and Europe. For each author i, the variables in X_i include the year of the earliest publication in Scopus, the total number of publications and publications in the top five percent in the period 2008-2012, the number of citations received during that period, on all papers and on papers published with a US co-author (European co-author for the control), the H-index of the author at the end of the period, the number and average H-index of her co-authors during the period, her C-index of dependence on the US (Europe for the control; see Section 2.4). We also include indicator variables for field and domain of publication as defined by Scopus[16]. Finally, we include indicator variables for publishing in a subject in which the share of citations from articles published in the top five percent most cited journals from respectively US and European publications is above the median, as well as the average "topic prominence" for publications of the author during 2008-2012[17].

The last set of outcome measures pertains to the basic versus applied nature of the research carried out by the Chinese author. We measure basicness of research with the probability of publishing and the total number of the author's publications in basic journals according to the CHI Research Index[18]. We also decompose these basicness measures according to co-authors' countries of affiliation.

[15]For instance, if a paper published in 2010 receives a citation in 2018, this citation does not contribute to H-Index for the year 2010. However, it contributes to it for all years after 2018.

[16]The composition of our data constrains us to restrain our analysis to three of the five main subjects (physical, life, and health sciences) and exclude multidisciplinary and humanities publications. This limitation leads us to consider 16 fields of research (agricultural science, biochemistry, chemical engineering, chemistry, computer science, earth sciences, energy, engineering, environmental science, immunology, material science, mathematics, medicine, neurology, pharmacy, physics – dentistry is excluded due to scarcity of researchers in this field in the sample). Due to overlap between fields, we include in the regression an indicator variable at the author level for each of the three fields in which an author publishes the most during the selection period. The main domain of an author is however not prone to this issue, so we only use one per author.

[17]The topics themselves are defined using the citation network between articles, and the prominence measure is a combination of citations in recent years, the CiteScore metric, average number of authors, average age of references, and Scopus views (Klavans and Boyack (2017)).

[18]This is the same metric that is used in Murray et al. (2016).

II.D. Sample and treatment

We now describe our sample and definition of treated and control authors. Within the whole set of authors in the Scopus database, we identify the subset of Chinese researchers that were active before the shock. For any such researcher, we have access to information about her whole publication history as reported by Scopus and the affiliation reported in each publication. From this we derive: (i) the year in which the author's name appears for the first time; (ii) the author's main subject(s) as reflected by her publications; (iii) the author's past and current countries of affiliation[19]. We use the years from 2008 to 2012 as a selection period to define our sample of treated and control authors. Our regression analysis of the effects of the China Initiative zooms in on the period 2013-2021. We do not consider a researcher's production during the latter period in the selection process, in order to avoid selection on outcomes (as detailed in Appendix A.1).

In order to precisely identify our set of treated and control researchers, we use four selection criteria, that we call *affiliation*, *descent*, *dependence*, and *no-spillover*. We select researchers who had a Chinese affiliation until 2012 for at least two years and remained affiliated in China until 2014 (the *affiliation* criterion). Among these authors, we keep those who have a name indicating Chinese descent (the *descent* criterion). There are 333,173 such authors in Scopus.

Our main treatment group consists of Chinese researchers in that subgroup who show "high dependence" on US and have no European co-authors. The main control group consists of Chinese researchers within that same subgroup who show "high dependence" on European and have no US co-author. We measure dependence of researcher i upon her co-authors from region g by a collaboration index, C_i^g, defined as the citations-weighted average share of US or European co-authors on papers written by this author. Let ω_{il} be paper l's share of the total number of citations of papers published by researcher i during the selection period and let σ_l^g be the share of the authors on paper l that are from country group g. The collaboration index is defined as:

$$C_i^g = \sum_{l \in A_{i,T}} \omega_{il} \sigma_l^g, \quad g \in \{US, Europe\} \tag{1}$$

where A_i is the set of papers published by researcher i during the selection period [20]. Chinese authors with a US co-author dependency index C_i^{US} (respectively with a Europe-dependency index C_i^{Europe}) above

[19] We use an algorithm to interpolate a researcher's country of affiliation in the years for which she did not publish between two publications; See Appendix B.1.

[20] The average value for US co-author dependence is 0.030, to be compared with 0.017 for the average value for European co-author dependence.

the 90$^{\text{th}}$ percentile over the period 2008-2012 belong to the treatment group (respectively to the control group). We call this the *dependence* criterion. We exclude from each of these two groups individuals with co-authors in the other region (the *no-spillover* criterion). At the end, this selection process within the set of Chinese authors yields 23,662 treated authors and 17,858 control authors[21]. Note that researchers are excluded from the sample both if they are not sufficiently dependent on either the US or Europe or if they are dependent on both. Authors in the latter group are on average ranked higher than the sample authors, in terms of number of publications and H-index, while those in the former group are ranked lower[22].

When we study the effect on US collaborations, we have to carefully select the control outcome. The China Initiative directly affected the collaboration of Chinese authors with US co-authors. Our treatment group comprises Chinese researchers who relied heavily on US co-authors in the selection period, while our control group relied heavily on European co-authors in that period. In these regressions, for both groups, we use as outcome the continued collaboration with the region that they used to rely on in the selection period. When we estimate the effect of the China Initiative on the collaboration with US co-authors for the treated researchers, we hence use the collaboration with European co-authors as the comparison outcome for the control researchers. The identifying assumption is that had it not been for the China Initiative, the continued collaboration of the control authors with European co-authors would have had parallel trends with the treated authors' continued collaboration with US co-authors.

II.E. Balance and descriptive statistics

Our definition of treated and control researchers is motivated by the similar levels and paths of research productivity for the groups during the selection period 2008-2012. On average, research productivity remains similar across these groups during the period 2013-2017, both with regard to the total number of publications and the H-index, as shown in Figure III. In addition, treated and control Chinese researchers do not display systematic differences in seniority or in fields of study, two potential reasons for differential trends in publications and citations between the two groups.

Yet, a more careful analysis shows that other covariates are not balanced across treatment and control in the selection period, notably the quality of co-authors and the number of publications with co-authors from the dependency country (see Figure C.1.1 in the Appendix). However, after weighting observations

[21] After the first selection on the sample, we reach a sample of 26,856 treated authors and 20,408 control authors. Due to the fact that Scopus presents a lower data quality in social sciences, we only include authors who are not in these sciences. For the sake of comparability, we also remove authors entering Scopus before 1999.

[22] This group of researchers dependent neither on the US nor on Europe includes researchers highly dependent on domestic partnerships.

by propensity scores, very few absolute standardized mean differences between the treatment and control groups are greater than 0.1, and all are below 0.25. Moreover, the Kolmogorov-Smirnov statistic testing for differences in the empirical cumulative distribution is below 0.05 after matching, for all variables except co-author quality, which is included in the controls.

We also provide descriptive statistics for all of the regression outcomes during the pre-shock period in Table I. On average, sample authors publish 3.3 publications per year and 0.22 publications in top journals. Note that sample authors have a 94 percent chance to gain a new co-author, which shows that they are very active in updating their network. We also provide more descriptive statistics on individual-level characteristics in Table C.1.1 and Table C.1.2 of the Appendix.

III. Empirical Strategy and Results

III.A. Empirical strategy

To test our hypotheses, we use a difference-in-differences design. Our sample consists of our treatment and control authors for the years 2013 to 2021. We will investigate whether treatment and control authors had different trends in their outcomes than control authors after 2018, the year the China Initiative was launched. Our studied outcomes will be different variables of interest for each author i in year t (e.g. number of publications, citations, or co-author quality).

We obtain difference-in-differences and event-study estimates using the doubly-robust differences-in-differences (DRDID) estimation method, as defined by Callaway and Sant'Anna (2020). This estimator differences out the author fixed effects and studies within-author changes in outcomes between each year and the last year before the China initiative was implemented. The estimator allows the untreated outcome *trends* to depend linearly on the pre-determined characteristics in X_i, for example allowing researchers in different fields to have different trends. The estimator also uses propensity score weighting. It uses X_i to model both the trend in the outcome and the propensity score and is consistent if either (but not necessarily both) are correctly specified. It relies on the conditional parallel-trends assumption that treated and control authors with the same X_i have the same expected evolution of their untreated outcome. Although this is our main specification, we also show results from a model relying on unconditional parallel-trends in the appendix. The model requires specifying a period before which the treatment (the China Initiative) was not anticipated. We assume that this was not anticipated before the election of Donald Trump in 2016. More details of the estimator is in Appendix.

We next present our main findings. We proceed in several steps. We first analyze how the China Initiative affects US collaborations for treated Chinese researchers. We estimate the impact of the shock on US co-authorships by the fall in the number and quality of papers co-authored with US researchers. We then investigate the extent to which treated Chinese researchers compensated for the loss of US co-authorships by increasing their collaboration with authors outside of the US, to compensate their loss. To directly evaluate whether these authors were able to compensate the loss of US co-authors by other equally productive co-authors, we look at the effect of the shock on the average co-author quality, measured by co-author H-index. Finally, we turn to our main outcome variable: research productivity. We measure research productivity by the number of published papers, the number of citations of these papers, and the number of publications in top journals. Finally, we discuss the robustness of our main results and explore potential sources of heterogeneity in the effects of the China Initiative shock. We then examine its impact on research direction and the broader implications for aggregate effects at the national level.

III.B. The shock to US research partnerships

We now document and quantify the China Initiative shock on US collaborations for treated Chinese authors. Figure II displays the aggregate drop in the share of Chinese publications that were co-authored with US researchers, compared to that co-authored with Europeans. We now estimate the corresponding effects at the individual researcher level. In particular, we compare the evolution of the US collaborations of treated Chinese authors with that of European collaborations for control Chinese authors.

We first present evidence using event-study graphs. The upper left graph of Figure IV shows that US authors write markedly fewer articles with the treated Chinese authors after the shock, compared to the evolution of the European co-authorship of control Chinese researchers. The top right graph of Figure IV shows that the number of publications by treated authors in top journals with US co-authors also declines sharply after the shock, compared to the number of publications in top 5 percent journals by Chinese control authors with European co-authors. The perhaps clearest effect is found for citations of papers with US co-authors, see the bottom graph.

Table II summarizes our findings as to the average treatment effects of the shock on publication outcomes with US co-authors for treated Chinese researchers. We find significantly negative effects of the shock on the number of: (i) publications; (ii) publications in top journals; and (iii) citations, for the treated and with a European co-author for Chinese researchers in the control group. For top journal publications and citations, this effect represents about 14 percent of the mean of the variable prior to the shock, and around 7 percent of the pre-period mean for publications. These proportions are large, yet considerably smaller than the aggregate shock to US-China collaborations shown in Figure II, which is around twice as high relative to its pre-period level. This indicates that although the treated authors had a considerable share of their research exposed to US collaborations, the share of these collaborations that were lost was smaller than average. A possible reason is that a significant share of the US-China decoupling occurred through a drop in new collaborations, while the treated authors had more long-term collaborations and were able to retain these. This is explored in the following section.

III.C. Co-author network adaptation

We now investigate whether the treated Chinese authors are able to mitigate the negative effects of the lost US collaborations by finding new co-authors. The left panel of Figure V resounds the results from the previous section by showing that there is a decline in the probability of having a new US co-author for treated authors after 2018. At the same time, there is no change in the probability of having a new co-author for treated Chinese authors compared to control Chinese authors after the shock; see the right panel. Hence the decline in new US co-authors for Chinese researchers in the treatment group is compensated by a rise in new co-authorships for those same Chinese researchers outside of the US.[23]

Table III summarizes our findings regarding the effects of the China Initiative on the reallocation of Chinese researchers' co-authors. The first three columns show the shock to the treated authors' network of US co-authors. There are significant and negative effects on the probability for treated authors to publish with new US co-authors as well as short-term US co-authors[24]. On average, the China Initiative reduces the probability for a treated Chinese researcher of publishing with a new and short-term co-author in the US by 1.8 percentage points. This corresponds to a 7 percent drop compared to the pre-shock mean (0.245). This is partly offset by an increased probability of co-authoring with a long-term US co-author of 1.5 percentage points, indicating that Chinese researchers became more prone to maintain their research collaborations with long-term US co-authors. However, the precedent section also shows that they are less likely to publish with US coauthors altogether including in high quality journals. Therefore, we can rule out a positive effect of re-centering their network toward long-term coauthors had a positive impact. For the event-study graphs of effects on short- and long-term co-authors, see Figure C.2.1 and Figure C.2.2, respectively.

Columns (5)-(8) show a lack of significant effects on having a new, short-term, or long-term co-author of any nationality for the treated authors. Hence, the shocks to the co-author network shown in columns (1)-(3) have all been compensated with co-authors from countries other than the US. Taken together the results in this section point to a reallocation of co-authorship for treated Chinese researchers away from

[23] In section C.12, we analyze the direction of these collaborations. We reject the hypothesis according to which the authors compensate their lost US partnerships with more China-only partnerships.

[24] I.e., who had already been in their network for a short period

US co-authors towards co-authors from elsewhere. Within the set of US co-authors, the results indicate a shift from new and short-term to long-term US co-authors.

The next question is if the co-authors that replaced the US co-authors are of similar quality. We investigate this by studying the effect on the average H-index of the treated researchers. Column (8) shows a significant negative effect of the China Initiative on the average H-index of the treated authors' co-authors. While it may take more time to find new co-authors, the event study graph shows no evidence of their closing of the gap during our sample period (see Figure C.2.3 in the Appendix). We see this as direct evidence that the treated authors were not able to compensate the lost US collaborations with non-US co-authors of equal quality.

Note that the quality of co-authors is a good predictor for future citations, both at article level and at author level. In Table C.2.1 we regress citations within five years and citations within ten years on the current quality of co-authors measured by their average H-Index, and we indeed see positive and highly significant correlations between the average quality of co-authors and future citations. This suggests that the China Initiative lowered the quality of the treated researchers' scientific output. We now study this directly.

III.D. Scientific productivity

We finally turn to the effects of the China Initiative on scientific productivity of the treated authors, measured by their number of publications, citations, and publications in top journals. Figure VI shows the effect of the policy on the number of publications and on citations in an event-study graph. We find a small negative effect on the number of publications by treated authors compared to control authors, only significant at the 10 percent level. In contrast, we find evidence of a strong decline in the citation count to publications by treated authors compared to those of control authors. If anything, the effect is increasing over time, indicating that the loss induced by the shock is not temporary. This latter effect does not simply reflect a decline in citations from the US. Indeed, citations to treated researchers by other Chinese authors are shown to decline as well (see Figure C.6.2 in the Appendix). We provide further evidence of a decline in the quality of publications by treated researchers following the shock by looking at publications in top journals. The top right graph of Figure VI shows a decline in the number of publications by treated Chinese researchers compared to control researchers in top 5 percent journals. In the appendix, we provide event-study evidence that the number of papers by treated authors which are among the top 1 percent most cited papers in a given year, also drops starkly following the shock (see Figure C.3.1 in the Appendix).

Table IV reports the Average Treatment on the Treated (ATT) of the China Initiative on the amount and quality of publications by treated Chinese researchers on average over the whole analysis period. The table shows significantly negative effects on : (i) publications, although not strongly significant; (ii) publications in top five percent journals; (iii) number of papers published that fall into the top 1 percent of most cited papers of the year; (v) citations; (vi) citations received from publications with at least one Chinese author; (vii) average H-index of co-authors of treated researchers at the time of publication.

Together, these results confirm our findings in the event studies depicted in Figure VI, of a negative effect of the US policy on the volume and more importantly quality of subsequent research by treated Chinese authors. The effect on publications is of moderate size; it represents around 1 percent of the mean. There is on average a decline in citations of the order of 4 citations to all publications in a given year for the treated authors; this corresponds to about 6 percent of the average before the shock. Similarly, we find a decline of around 9 percent of the pre-shock mean value of the number of publications in the top 5 percent journals.

Note that the total effects of the China Initiative on treated Chinese authors in Table IV are generally larger than the direct loss due to falling US collaborations shown in Table II. The dependent variables in Table II are publications, top journal publications, etc., weighted by the US co-author shares on each paper for the treated authors. We hence measure the shock as proportional to the US co-author shares. If a treated author loses a paper with a US co-author share of 1/2, then this will be registered as a drop of 1/2 in the dependent variable in column (1) of Table II. However, the effect of losing half of the co-authors on a paper that are Americans could be larger or smaller than proportional to their co-author share, for example, if their participation is necessary for the successful completion of the project. In fact, we find that it is substantially higher. For example, the shock to US co-authored papers in top 5 percent journals is -0.004 while the total fall in published papers in these journals is -0.016. This indicates that the impact of the shock is four times larger than the shock measured as US co-author share, even after adaptation of the co-author network. The same is true for publications (by a factor of 3.7) and citations (3.4). In fact, the total effect is quite similar in magnitude to that of the shock to collaborations, measured as if each US co-author was pivotal to writing the paper.

III.E. Robustness

This section explores several alternative specifications and identification concerns. Each issue is discussed more at length in the appendix.

Sample selection: We check that our results are robust to alternative ways of selecting our sample; For details, see Appendix C.5. First, we change only the threshold in the *dependence* criterion. We now include in the treatment group all Chinese researchers with at least one US co-author, while our control group comprises all Chinese researchers with at least one European co-author. All the other selection criteria remain unchanged. Table C.5.2 in the Appendix shows no major change in the results when using this selection process, aside from the loss of significance on the effect of small magnitude on publications. We also explore changing the *affiliation* criterion to exclude from the sample authors who have a double affiliation with the US (in addition to the Chinese affiliation). However, this yields very similar estimates.

Home bias: Another possible concern is that US researchers are more likely to cite other US researchers and that many of the top journals are based in the US. Hence, the results could indicate a decoupling of Chinese treated authors from US citations and journals, and not necessarily reflect a fall in quality or impact in other regions. For citations, Qiu, Steinwender and Azoulay (2022) show that Chinese papers are under-cited in the US (possibly creating a negative bias), but also strongly over-cited in China (possibly creating a positive bias). In order to address these concerns, we computed estimates of the effect of the China Initiative on citations, splitting them by affiliation country of authors of the citing paper. Table C.6.1 shows that the citations of treated authors are decreasing post-2018 for all regions aside from Europe. In particular, the decline also appears in citations from China, in spite of the home bias, and from outside the rest of the world (outside the US, Europe, and China), in which we do not expect preferential treatment. As mentioned previously, the event-study graph of the effect on citations from China is shown in Figure C.6.2. Hence, the fall in quality after 2018 is not driven by a home bias in US citations. Regarding top journal publications, European publications account for more than half of all top 5 percent sources and become dominant after 2015, according to Scopus's CiteScore metric, and as shown in the left-hand panel of Figure C.6.1 in Appendix C.6. If we expect treated researchers to keep seeking publication in top-ranked sources, then these researchers could choose to submit to European journals.

Cross-group spillovers: A consequence of the China Initiative could be that Chinese authors in our sample move from US to Chinese co-authors. This type of reallocation is not a threat to our identification strategy unless treated authors increase their partnerships with Chinese authors who are in the control group. However, Figure C.7.1 in Appendix C.7 shows that while the number of papers published separately by authors of both treated and control authors is rising, this is not the case for papers authored by both a treated researcher and a control researcher. The number of such papers shows a slow decline after the selection period, and its trend does not seem to be affected by the China Initiative. Hence we find no trace of this type of spillover. Another (milder) threat to our identification strategy would occur if the treated authors started collaborating more frequently with European co-authors of the control group. In this case, there would be a negative effect of the shock on the control group, leading us to underestimate the true effect of the China Initiative. We investigate whether the treated author starts collaborating more with the control authors' European co-authors post-2018 and find that this is not the case, see Figure C.7.2.

Publication lags: Since research projects may take several years to complete, one may reasonably wonder how a recent shock like the China Initiative could have had an impact on the quality and direction of Chinese research that could be already detected in our data. As discussed in Appendix C.8, the following considerations help address this timing concern. First, the China Initiative is likely to have interrupted research projects with US co-authors which were close to completion, thereby affecting the volume and quality of Chinese publications. Second, the vast majority of Chinese authors in our sample produce at least one publication per year on average. The average time an author takes before publishing again after a given publication year amounts to 1.3 years, with a median of 1 year. Third, publication lags vary across projects and fields, and some publication lags are obviously substantially shorter than the mean. For example, surveying 3500 scientists of different fields, Huisman and Smits (2017) find that the average review duration for accepted papers across all fields is 17 weeks, ranging from a minimum of 12 weeks in medicine to a maximum of 25 weeks in economics and business. Excluding social sciences, the average duration of the peer-review process in all fields is 22 weeks. In all fields aside from Psychology, around 80 percent of all papers are published within six months after submission. Overall, the frequency of publications by researchers in the sample is sufficiently high that the shock caused by the China Initiative could have shown an impact after only one year.

Citations and data truncation: Total citations received by papers that a researcher publishes in a given year are one of our main measures of publication quality. However, the citations for papers of different qualities may have different time profiles, making the time of measurement important for the measured quality difference. In Appendix C.9, we perform several transformations to our measure of citations and show that our results and interpretations are constant through the different specifications. First, we only consider citations received within 10, 5, and 1 year(s) of publication. The only one that yields no significant negative result (of a magnitude of around 4 percent of the average value in the pre-shock period) is the 1-year metrics; see table Table C.9.1. We surmise that this is due to noise and the monthly timing of publication (a paper will not receive the same amount of citations if it was published in January or December of the same year). Second, we consider two normalizations: subtracting the mean and dividing the difference by the standard error of the yearly distribution, or simply dividing by the mean. Both devices allow us to compare how papers rank within their publication cohort, which in turn helps us deal with the truncation issue. Both results are also in line with the results on unprocessed citations in terms of sign. The result for the first normalization has a far larger magnitude. This could be due to the timing issue mentioned above. Finally, we also use the Field-weighted impact citation metrics provided by Scopus. The result is unchanged with a magnitude of around 4.8 percent.

Placebo: We perform a placebo test where we take 2010 instead of 2018 as the alternative year of shock. As shown in Figure C.10.1 for the volume of publications and for our two main measures of publication quality, we observe no trend breaks in these outcome variables for treated researchers. In Table C.10.1 in Appendix C.10, we show the results of the ATT values for the main outcome variables, estimated on a sample selected in the period 2001-2005 of a placebo shock happening in 2010. Although there is a positive effect on the number of publications in the top 5 percent of journals, this does not appear to be due to a trend break in 2010 based on the propensity score weighting, as can be seen in Panel (b) and (c) of Figure C.10.1. If anything, we find that treated authors in the placebo sample tend to deepen their links with the US compared to control authors after 2010, especially when looking at high-ranked publications.

Unconditional parallel trends: Appendix Figure C.11.1 provides the event study graphs for the regressions on productivity outcomes not conditioning on the controls in X_i. Without controls, the parallel trends assumption is frequently rejected in the pre-period, mainly because the estimated unconditional effects vary more from year to year than the corresponding conditional effects. Hence, it is likely that controls are necessary for the parallel trends assumption to hold in the post-period. At the same time, there is no significant negative trend in the pre-period that can explain the negative development in the post-period. The average difference between the pre- and post-period is similar to that in our main specification.

III.F. Heterogeneity

Having measured the average effects, we turn to heterogeneous effects by researcher quality, field and US-coauthor role in the collaboration. Finding equally good co-authors is likely more difficult for top Chinese researchers, and for researchers who work on topics that are dominated by US researchers. Top Chinese researchers are more likely to collaborate with top US co-authors because top co-authors are few and in high demand. In contrast, less productive treated authors may even benefit from the resulting co-author reallocation, if the highly productive treated authors are forced to collaborate with them instead of highly productive US co-authors. For this reason, it seems likely that the most productive treated authors are most negatively affected while the least productive treated authors are less affected, and may even be positively affected. Researchers in fields with a large US dominance may also be more severely affected, since there are fewer non-US co-authors to switch to in these fields after the shock. Finally, the Chinese researcher may be differentially affected if their US coauthors perform a leading role in their collaborative projects, as indicated by their position in the author order. We now investigate these two types of heterogeneity.

III.F.1. *Productivity levels*

In order to factor in heterogeneity based on performance, we run the same regressions as in Section 3.4, but separately for different categories of Chinese researchers. We break our sample of Chinese researchers into subsamples, where each subsample corresponds to a different tercile in the distribution of citations per author during the selection period, 2008-2012[25]. The results, broken up by pre-period citation terciles, are shown in Table V. The first three columns show that the negative shock to US collaborations was most severe for treated researchers in the highest tercile. The following table shows the effect on total publications, total publications in top 5 percent most cited journals, and total citations. For all three outcomes, the magnitude of the estimated effect is increasing in citation tercile, although most clearly so for total publications and citations. The effect on publications represents 4% of the pre-shock average for middle tercile scientists, compared to 7% for top tercile scientists. Even more strikingly, the point estimate for the drop in citations for top tercile researchers, 15.9, is almost five times higher than the point estimate for middle tercile researchers at 3.3, even though the former receive only slightly under 2.5 times the number of citations of the latter per year during the pre-period (118.4 for the top tercile and 51.8 for the middle tercile). Columns (4)-(6) show that we find no significantly negative effect on the volume of publications by the lowest tercile of Chinese researchers in the treatment group compared to those in the control group, whereas the publications of the middle and top tercile Chinese researchers in the treatment group appear to drop significantly compared to those of middle and top tercile Chinese researchers in the control group. Furthermore, the effect of the China Initiative on the number of publications in top 5 percent journals by top and middle tercile Chinese researchers in the treatment group, compared to the control group, is significantly negative and of larger magnitude than its overall effect on the number of publications in top 5 percent journals by the overall population of treated Chinese researchers.

III.F.2. *Fields and US dominance*

Here we look at how the effects of the China Initiative on the performance of Chinese researchers in the treatment group vary with the researchers' main fields of publication. More specifically, Figure VII shows the average aggregate ATT coefficients on the number of publications (left panel) and on the number of publications in the top 5 percent of journals (right panel) computed for treated Chinese researchers in each field separately, to identify which fields have been most notably affected by the US policy. The

[25] We use citations received up to 2012 rather than citations received for papers in 2008-2012. This allows us to not divide the authors according to later outcomes, but rather on real-time measures of their perceived quality.

top panel of Figure VII shows that treated Chinese researchers whose number of publications has been most significantly negatively affected by the China Initiative are those whose main publication fields are physics, especially materials science and energy, and chemistry, particularly in pharmacology and chemical engineering. The bottom panel shows that when it comes to publications in top journals, researchers in most fields have been negatively affected by the Initiative, but the effect is stronger for researchers whose main area of publication is physics, chemistry, and life sciences (especially in pharmaceuticals and in biochemistry). Interestingly, Figure VII also shows a monotonic relationship between the degree of US dominance in the corresponding main field of publication and the magnitude of the negative effect of the China Initiative both on treated Chinese researchers' publications overall and in top journals. It is in those fields in which US authors claim a higher share of total citations to papers in top 5 percent journals, that treated Chinese researchers' citations are more negatively affected by the shock. This correlation between US dominance and the negative shock on outcomes could explain why reallocation towards non-US co-authors does not mitigate the negative effects for treated authors: the subset of the group that is the most affected is the one that does not have other options than the US for co-authors of high quality.

Finally, Figure C.13.2 and Figure C.13.3 show that, whenever significant, the effects of the shock respectively on the publications and on the publications in top journals of treated Chinese researchers in each field are driven by researchers in the top half of the distribution of citations in the selection period. Another possible explanation for the difference in the shock's impact between natural sciences and life sciences is that during COVID US-Chinese collaborations were relatively more encouraged in life sciences than in natural sciences. The drastic productivity shock in medical fields also explains why standard errors are higher for life sciences. Although this would explain why we find very little effect for the field of medicine, the ordering between fields in natural sciences remains correlated with US dominance. Finally, there is no ex-ante reason why scientists of the control group should be affected differently from scientists in the treated group; to the extent that the COVID shock to publications affected both groups similarly, presumably it generated no systematic bias in our estimates.

III.F.3. US-coauthor Role

We next study heterogeneous effects on the treated Chinese researchers based on the role of their US coauthors. Borrowing insights from existing literature in scientometric studies, we use author order as an indicator of contribution type. Author order serves as a well-established signal of contribution types across many scientific fields. In most STEM fields, first authors typically lead the research execution and writing, last authors provide strategic guidance and resources as senior investigators, and middle authors usually play supporting roles. This convention is particularly strong in biomedicine and life sciences, chemistry, and engineering, and its validity as a measure of author contribution has been empirically validated, making it an effective proxy for identifying different forms of collaborative dependencies.[26] Following this convention, we infer the type of contributions of US (EU) coauthors by their position in the author sequence of the joint publications and then measure, at the individual researcher level, the extent to which these coauthors primarily act as first author, middle author, or last author during the pre-selection period. To ensure reliable classification, we exclude mathematics, computer science, and physics, where alphabetical ordering is a common practice.

We first describe the role that US-coauthors perform across all US-China collaborative research papers. In 2017, US researchers were middle authors in around half of all US-China collaborations in our data (see Figure C.13.6). In the remaining half of the collaborations, US authors held the more prominent positions of first or last authors. Papers in which US authors occupied prominent positions receive more citations and are more likely to be published in top journals, in particular, this holds for the 24% of US-China collaborations where US authors were both first and last authors. Over time, the share of collaborative projects where Chinese authors were first or last authors have been steadily increasing. The likely implication is that Chinese authors are increasingly taking the lead in joint research projects, both in terms of conceiving the idea, executing the research, and providing guidance and material resources.

We next categorize our sample of treated and control Chinese authors based on whether they rely primarily on US (EU) coauthors acting as first author, middle authors or last authors (for details, see Appendix C.13). In this sample, 45% of researchers primarily depend on US (EU) last authors, 40% on middle authors, and 15% on first authors, roughly consistent with the pattern at the aggregate level. We then split the sample by coauthor dependency type to estimate the heterogeneous effects separately for each subgroup. While these subgroups differ in their baseline characteristics such as seniority, productivity, and field composition, the treated and control researchers within each subgroup show similar pre-selection period characteristics (Table C.1.3). The balance in observable characteristics, combined with parallel pre-trends shown in the event study graphs (Figure C.13.5), suggests that our estimated differential effects are not driven by systematic differences in career trajectories across subgroups.

Table VI presents the heterogeneous treatment effects across different dependency types. Our analysis

[26] With some exceptions in mathematics, computer science and high energy physics where alphabetical ordering is common (L. Waltman, "An Empirical Analysis of the Use of Alphabetical Authorship in Scientific Publishing," Journal of Informetrics, vol. 6, no.4, pp. 700–711, Oct. 2012, doi: 10.1016/j.joi.2012.07.008). Sauermann and Haeussler (2017) shows that author order strongly correlates with actual contribution levels even when compared to detailed contribution statements (Sauermann, H., Haeussler, C. (2017). Authorship and contribution disclosures. Science advances, 3(11), DOI: 10.1126/sciadv.1700404.). To address potential bias from fields using alphabetical ordering, we conduct robustness checks by excluding mathematics and computer science publications. Our results remain qualitatively similar. See Appendix Table X.

reveals that the negative impact of the China Initiative primarily affects researchers who depend on US last authors, and to some extent first authors, while those dependent on middle authors show minimal changes. For number of publications, researchers dependent on US first authors experience a reduction of 0.35 papers, while those dependent on US last authors see a decline of 0.25 papers. In contrast, researchers primarily dependent on middle authors show no change in publication output. The impact on research quality is significant only for Chinese authors collaborating with US last authors. For this group, citation counts drop by 7.1 for and publications in top journals by 0.055 publications, representing a 23% decline from their pre-shock mean.

This approach enables us to uncover an interesting pattern: Chinese researchers who depended on US. collaborators in primary contributor positions (first or last authors) experienced larger declines in their research output compared to those who typically worked with US. researchers in supporting roles. In addition, those who relied on US last authors experienced substantially larger reductions in high-impact research, measured by citations and publications in top journals.

IV. Discussion

In this section, we discuss extensions of the paper to the effect of the China Initiative on the direction of research for affected researchers, and the size of its aggregate effect on Chinese research.

IV.A. What is the effect of the China Initiative on the direction of research?

The China Initiative may also impact the direction of Chinese research. In this section, we analyze the extent to which the China Initiative affected Chinese researchers' choice between more fundamental and more applied research.

We mentioned in the introduction recent work by Liu and Ma (2021) pointing at a positive effect of deglobalization on the basicness of innovation. It could also be the case that, following the China Initiative, treated Chinese researchers would decide to rely more on local research inputs which in turn should encourage more basic research in China. But it may also be the case that, facing restricted access to high-quality US co-authors, treated Chinese researchers would focus primarily on replicating or adapting existing ideas and findings, thereby producing more applied research.

We now look at whether the China Initiative affects the basic versus applied nature, henceforth the degree of "basicness", of treated authors' research. Our primary measure of research basicness is the *CHI Index*, developed by CHI Research and used for instance by Lim (2004) and Murray et al. (2016). This index assigns to each journal a value of basicness of research, from 1 to 4, in which 1 corresponds to the highest degree of applied science and 4 to the highest degree of fundamental research. We match the journals that are assigned a value in the CHI index scale to their identifier in Scopus. Then, we count the number of times an author published an article in a given year in a journal identified by CHI as being fundamental. We also consider an indicator variable equal to one whenever she published any such article at all during the year. Results are reported in Table D.0.1. We find no change in the overall number of basic publications by treated authors compared to control authors after the shock. However, we see a decline in the probability of publishing in a basic journal for treated authors, both globally and *with US co-authors* after the shock, compared to the evolution of the number of basic publications by control Chinese authors with European co-authors, significant at the 10% level. The effect for publications with US co-authors is of the same magnitude as the total effect. This suggests that the reduced ability of treated researchers to pursue basic research could come from their diminishing collaborations with US co-authors and has not been fully compensated by increasing their reliance on collaborations with non-US co-authors for basic research. Additional results on research direction are available in Appendix D.

IV.B. Aggregate effects

This section discusses the aggregate implications of our estimates and relates these to descriptive evidence. To assess the aggregate scientific output of China and the US, we attribute each nation's contribution to a paper based on the proportion of affiliated researchers listed as authors, following metrics such as Nature's key index of national scientific output. While there could be positive spillovers of international collaboration, we focus only on the direct effect of the Initiative.

In our above analysis, we find that the China Initiative reduced the number of citations by 3.9 per year in our sample of 23,662 treated researchers. In total, this amounts to a fall by 92,329 citations per year. Between 2013 and 2017, the total number of citations to papers published by authors with affiliations in China grew from 5.4 million to 6.64 million citations. The effect is around 1.4 percent of total citations in 2017 or one-third of the average annual citation growth between 2013 and 2017. A similar computation shows that the number of papers published in top 5 percent journals fell by 355, which is around 1 percent of China's total yearly output of such papers in 2017[27].

However, our estimates capture only the effect on the treatment group, comprised of the 5 percent Chinese researchers with highest dependency on US co-authors in the pre-period and with no collaboration with European researchers. Of course, other Chinese researchers were also affected, although we cannot

[27] When we compute the total effect in terms of citations, we count the citations once per author, even if several treated Chinese researchers collaborate on the same paper. In this case, the citations received by this paper appear several times in our regression. This makes the total effect (92,329) relatively high, compared to the total number of citations (6.6 million) that is computed using author shares, where a paper's citations are split between countries proportional to the share of authors of the paper who are affiliated to each country.

measure this using our design. Most of these other researchers collaborated less with US co-authors and hence were less exposed to the shock. Others were equally exposed to the shock but were excluded because they were also collaborating with Europeans.

We can use the size of the aggregate shock to China/US collaborations to make a back-of-the-envelope calculation of the total effect on China's scientific output. In 2017, US-collaborations accounted for 3.5 percent of all Chinese authors' publications. By 2021, this had fallen to 2.4 percent. In comparison, European collaborations accounted for 2.4 percent of Chinese publications in both years. Hence, the US collaboration share fell by 1.1 percentage points while the European collaboration share remained constant over this time period.

For the treated researchers, the total estimated negative effect on the number of publications was 3.7 times larger than the shock to US-collaborations. If this ratio were to apply to other Chinese authors, then an aggregate 1.1 percent drop would result in a drop in total publications by 4.1 percent. Moreover, if all US collaborations with Chinese researchers ceased entirely, the resulting decline in total Chinese scientific citations would be an additional 8.9 percent. Hence, the aggregate effect on Chinese research output is relatively modest.

The picture is slightly different if we focus in on higher quality research, captured by citations and publications in top journals. In 2017, US-collaborations accounted for 7 percent of all Chinese authors' citations. By 2021, this had fallen to 4 percent. In comparison, European collaborations accounted for 4 percent of Chinese citations in both years. Hence, the US collaboration share fell by 3 percentage points while the European collaboration share remained constant over this time period. For the treated researchers, the total effect on citations was 3.7 times larger than that to citations to US-collaboration papers. If this ratio were to apply to other Chinese authors, then an aggregate 3 percent drop would result in a drop in total citations by 10.2 percent. Moreover, if all US collaborations with Chinese researchers ceased entirely, the resulting decline in total Chinese scientific citations would be an additional 13.6 percent.

Chinese publications in top journals are even more exposed to US collaborations. In 2017, US-collaborations accounted for 12 percent of all Chinese authors' top-journal publications. By 2021, this ratio had fallen to 7 percent. In comparison, European collaborations accounted to 6 percent of Chinese top-journal publications in both years. Hence, the US collaboration share fell by 5 percentage points while the European collaboration share remained constant. According to our back-of-the-envelope calculations, a 5 percent drop in US (author-share weighted) collaborations would lead to a 20 percent drop in total top-journal publications. This implies that without the China Initiative, the number of top journal publications by Chinese researchers in 2021 would equal that of European researchers, at around 72,000 instead of 60,000.

Although the policy resulted in a significant decline in the quality of publications by affected Chinese researchers, the aggregate effect on Chinese research output remains relatively modest. While the China Initiative can create a dent in the curve of Chinese top journal publications, the underlying positive trend shown in Figure 1 remains unchanged. We find that US co-authors play a crucial role, particularly for researchers in US-dominated fields or those with strong publication records. However, the share of Chinese research directly impacted by the policy is relatively small, limiting its overall effect on national scientific output.

Our estimates of the effects per affected Chinese researcher are similar in magnitude to those found by Jia et al. (2024) for affected U.S. researchers in the life sciences. These estimates are not directly comparable, however, as the U.S. effects pertain only to life sciences, and our heterogeneity analysis reveals considerable variation across fields. Nonetheless, the combined findings suggest that the China Initiative had detrimental effects on researchers from both countries.

While the estimated effects per researcher are similar in China and the U.S., both the number of affected researchers and the share of research exposed to the shock are higher in China, as Figure I shows. Given that the volume of scientific output of the U.S. and China was roughly equal by 2018, and considering that the loss of collaborative U.S.-China papers due to the China Initiative negatively impacts both countries, why is China more exposed? The reason is that the Chinese share of the collaborative papers exceeds that of the US. For example, in the pre-shock period, only about half of these collaborative papers included more than one U.S. coauthor, whereas roughly three-quarters had multiple Chinese coauthors. Consequently, the aggregate scientific output exposed to the shock was 50 percent higher for China than for the U.S. in 2018.

Similarly, significantly fewer U.S. researchers than Chinese researchers were affected by the shock. In 2018, our data show that 146,000 Chinese researchers had some collaboration with U.S. researchers, compared to 99,000 U.S. researchers who collaborated with Chinese researchers. In other words, collaboration was more concentrated on the U.S. side than on the Chinese side, with a relatively small group of U.S. researchers collaborating extensively with many Chinese authors.

In sum, our findings, along with those of Jia et al., demonstrate that the China Initiative had significant negative effects on aggregate scientific output in both the U.S. and China. With a larger share of Chinese research exposed to the shock, the impact in China is likely greater. However, this policy produced no winners; it diminished the output of Chinese science, U.S. science, and, most notably, science as a whole.

V. Conclusion

In recent years, China's influence across various research domains has surged, solidifying its academic prominence globally to the extent that Chinese researchers can no longer be overlooked. In this paper, we provide insights into the extent to which Chinese innovation relies on foreign collaborations, particularly with the United States. To achieve this, we use the Scopus database to track the productivity of researchers. We consider the China Initiative policy as a quasi-natural experiment to analyze how this shock affected the volume, quality, and direction of Chinese research. We first show that Chinese researchers with prior US collaborations reallocated away from US researchers after the shock.We also see that this reallocation does not allow them to find co-authors of the same quality as their previous US co-authors. We believe that this is the reason why we find a negative effect of the Initiative on the average quality of both the publications of Chinese researchers with prior US collaborations, whereas US researchers with prior China collaborations do not appear to be affected. Moreover, we observe that this negative effect is stronger for Chinese researchers with higher research productivity and/or who work on US-dominated fields prior to the shock. The lack of reallocation towards China or the rest of the world suggests that the main beneficiary of the policy might have been Europe.

Our analysis can be extended in several interesting directions. One direction would be to consider other dimensions of heterogeneity among Chinese researchers, for example, the extent to which they work on research topics that meet the strategic priority of the Chinese government: our conjecture is that the negative effect of the China Initiative on the quality of subsequent publications should be less pronounced for Chinese researchers who work on topics that are considered as priorities by the Chinese government, e.g. digital and face recognition, biotechnologies, and energy transition. The use of textual information could also provide more detailed information as to the exact role of China and US-based researchers in common research projects. Furthermore, we focused on active researchers, but we leave to future research the subject of the long-term effects of the China Initiative on researchers entering academia, in particular PhD students. A second avenue for future research would be to investigate further the role of freedom and the mobility of Chinese researchers as determinants of the quality, nature, and direction of Chinese research: in particular, can Chinese research lead to Kuhnian discoveries and become truly frontier in the absence of both freedom at home and the ability to initiate collaborations with researchers abroad? A third avenue is to bridge the gap between the Scopus information on publications and the existing patenting information (see Bergeaud and Verluise (2022)) to better predict the technological fields where China is more likely to achieve frontier. These and other extensions of the analysis in this paper are left for future research.

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VI. Tables

Table I
Summary Statistics for Estimation Sample

Variable	N	Mean	SD	Min	Max
Panel 1: Productivity					
Publications	369567	3.3	4.7	0	259
TopJournal	369567	0.22	0.79	0	48
LastAuthor	369567	0.79	2	0	127
Citations	369567	53	115	0	5226
Panel 1b: With collaboration country					
Publications	369567	0.23	0.76	0	27
TopJournal	369567	0.032	0.21	0	13
LastAuthor	369567	0.053	0.47	0	52
Citations	369567	6	29	0	2828
Panel 2: Co-author network					
NewCoauth	261531	0.94	0.23	0	1
STCoauth	261531	0.86	0.35	0	1
LTCoauth	261531	0.64	0.48	0	1
Panel 2b: With collaboration country					
NewCoauth	261531	0.23	0.42	0	1
STCoauth	261531	0.21	0.4	0	1
LTCoauth	261531	0.12	0.32	0	1

Notes: This table summarizes the main outcome variables in the sample, conditional on publishing during the year of observation for panel 2. Collaboration country is the US for treated researchers and Europe for control reseachers.

Table II
US Collaboration Shock of Treated Chinese Authors (ATT)

	With US co-authors		
	(1)	(2)	(3)
Dep. Var.	Publications	TopJournal	Citations
ATT	-0.020***	-0.004***	-1.142***
	(0.006)	(0.001)	(0.162)
Mean.Dep.Var.Pre	0.254	0.035	8.294
Pvalue.PreTrend	0.570	0.811	0.074
N.authors	41063	41063	41063
N.obs	369567	369567	369567
Controls	Yes	Yes	Yes

Note: results are from DRDID regression, for each outcome for the whole sample and conditioning on having published during the year of observation. The dependent variables include the number of publications with US-based co-authors (column (1)), the number of publications on top 5% journals (within subject) with US-based co-authors (column (2)), and the number of citations with US-based co-authors (column (3)). Control variables account for the author's publication characteristics overall and by category of co-author during 2008-2012, including number of publications, number of accumulated citations, number of top publications, co-author dependency, as well as number of co-authors, characteristics of the fields and topics of interest of the author. Standard errors (SE) are clustered by author. In parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table III
Co-Author Network: Shock and Adaptation (ATT)

	US co-authors							
	NewCoauth	STCoauth	LTCoauth	co-authorHindex	NewCoauth	STCoauth	LTCoauth	co-authorHindex
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATT	-0.019***	-0.020***	0.015***	-1.169	0.003	-0.002	-0.001	-0.412**
	(0.007)	(0.006)	(0.006)	(0.990)	(0.003)	(0.006)	(0.007)	(0.178)
Mean.Dep.Var.Pre	0.243	0.250	0.101	16.895	0.943	0.887	0.570	14.904
Pvalue.PreTrend	0.313	0.890	0.024	0.128	0.490	0.805	0.876	0.153
N.authors	41017	41017	41017	25941	41017	41017	41017	39256
N.obs	261531	261531	261531	88766	261531	261531	261531	249535
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: results are from DRDID regression, for each outcome relating to any type of co-author or only US co-authors for the treated and European co-authors for the control. The unit of observation is author by year and the sample period is from 2013-2021. The dependent variable is the probability of publishing with a new co-author (columns (1,4)), the probability of publishing with a current short-term co-author, i.e. 1 and 5 years, (columns (2,5)), the probability of publishing with a current long-term co-author, i.e. > 5 years (columns (3,6)). Control variables account for author's publication characteristics overall and by category of co-author during 2008-2012, including number of publications, number of accumulated citations, number of top publications, co-author dependency, as well as number of co-authors, characteristics of the fields and topics of interest of the author. Standard errors (SE) are clustered by author. In parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table IV
Scientific Productivity (ATT)

Dep. Var.	(1) Publications	(2) TopJournal	(3) TopCited	(4) Citations	(5) CitationsChina	(6) co-authorHindex
ATT	-0.074**	-0.016***	-0.006***	-3.862***	-3.728***	-0.412**
	(0.036)	(0.006)	(0.002)	(0.771)	(0.940)	(0.178)
Mean.Dep.Var.Pre	3.061	0.179	0.043	63.597	76.230	14.904
Pvalue.PreTrend	0.967	0.379	0.802	0.006	0.226	0.153
N.authors	41063	41063	41063	41063	41063	39256
N.obs	369567	369567	369567	369567	369567	249535
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: results are from DRDID regression, for each outcome for the whole sample and conditioning on having published during the year of observation. The unit of observation is author by year and the sample period is from 2013-2021. The dependent variables include the number of publications (columns (1)-(2)), number of citations for publications from that year (columns (3)-(4)), rate of publications on top 5% journals (within subject) from that year (columns (5)-(6)), citations received from papers with at least one Chinese author (columns (7)), and the average H-index of co-authors at time of publication (column (8)). Control variables account for author's publication characteristics overall and by category of co-author during 2008-2012, including number of publications, number of accumulated citations, number of top publications, co-author dependency, as well as number of co-authors, characteristics of the fields and topics of interest of the author. Standard errors (SE) are clustered by author. In parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table V
Scientific Productivity - by Tercile of Author Pre-Period Citations (ATT)

	Publications						TopJournal			Citations		
	With US co-author											
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ATT	-0.004	-0.040***	-0.083**	-0.055	-0.115*	-0.358**	-0.017**	-0.041***	-0.053*	-2.024*	-3.270**	-15.892***
	(0.010)	(0.015)	(0.033)	(0.050)	(0.059)	(0.172)	(0.009)	(0.014)	(0.031)	(1.121)	(1.594)	(5.169)
Mean.Dep.Var.Pre	0.176	0.234	0.379	1.877	2.802	4.889	0.077	0.138	0.359	32.008	51.755	118.439
Pvalue.PreTrend	0.989	0.702	0.576	0.738	0.947	0.662	0.102	0.527	0.575	0.106	0.138	0.685
N.authors	14940	14407	11716	14940	14407	11716	14940	14407	11716	14940	14407	11716
N.obs	134460	129663	105444	134460	129663	105444	134460	129663	105444	134460	129663	105444
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: results are from DRDID regression by quantile, for each outcome for the whole sample and conditioning on having published during the year of observation. The unit of observation is author by year and the sample period is from 2013-2021. The dependent variable is the number publications with US-based co-authors for the treated and Europe-based co-authors for the control (column (1)-(3)), the total number of publications (column (4)-(6)), number of publications in top 5% journals (within subject) (columns (7)-(9)), total citations (column (10)-(12)). Control variables account for author's publication characteristics overall and by category of co-author during 2008-2012, including number of publications, number of accumulated citations, number of top publications, co-author dependency, as well as number of co-authors, characteristics of the fields and topics of interest of the author. Standard errors (SE) are clustered by author. In parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table VI Scientific Productivity - by Primary Role of US Coauthors

	Publications			Citations			TopJournal		
	First.Au	Last.Au	Middle.Au	First.Au	Last.Au	Middle.Au	First.Au	Last.Au	Middle.Au
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ATT	-0.354**	-0.251***	-0.026	-3.603	-7.126***	0.729	-0.003	-0.055***	0.009
SE	(0.149)	(0.068)	(0.065)	(3.252)	(1.880)	(1.668)	(0.026)	(0.014)	(0.013)
Mean.Dep.Var.Pre	4.344	3.688	2.964	85.097	84.396	63.605	0.209	0.236	0.169
Pvalue.PreTrend	0.267	0.506	0.490	0.691	0.014	0.809	0.712	0.005	0.625
N.authors	3072	11834	12484	3072	11834	12484	3072	11834	12484
N.obs	29088	112104	118260	29088	112104	118260	29088	112104	118260
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note:
We estimate doubly robust difference-in-differences models using annual publication data from 2013-2021. The sample consists of researchers across scientific fields, excluding Mathematics, Computer Science, and Physics. The dependent variable in columns 1-3 is the annual number of publications; in columns 4-6, the number of citations received; and in columns 7-9, the number of publications in journals ranked in the top 5 percent within their subject area. Controls include pre-period (2008-2012) research productivity and coauthorship networks, research field fixed effects, and Scopus entry cohort fixed effects. Standard errors are clustered at the author level. In parentheses: *** p<0.01, ** p<0.05, * p<0.1.

VII. Figures

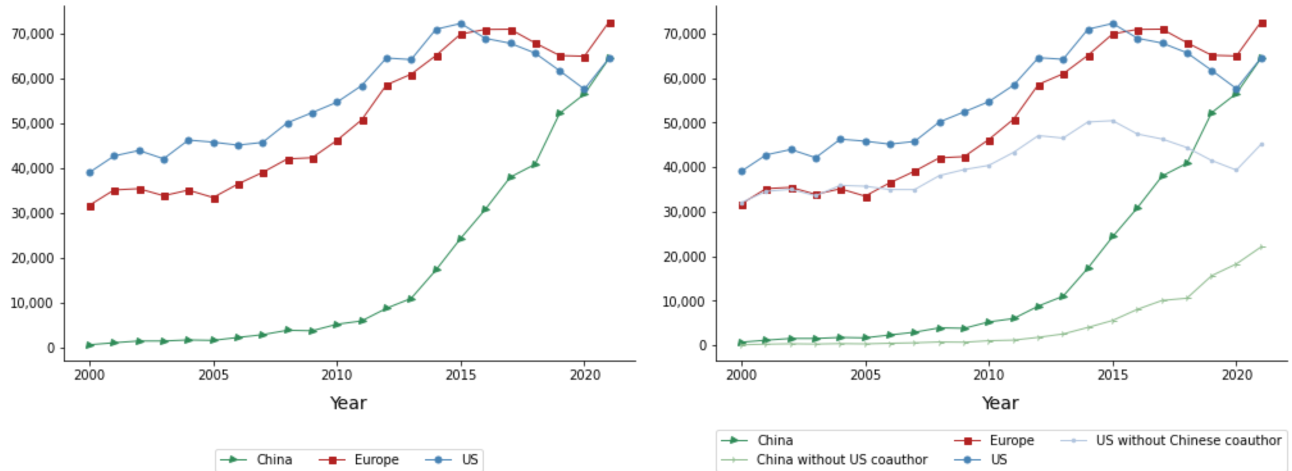


Figure I
Number of Publications in Top Journals by Country of Affiliation

Notes: This figure shows evidence of the Chinese growth in the number of scientific publications the top 5 percent most cited journals by field. The curve labelled with the mention *no US co-author* (*resp. no Chinese co-author*) accounts for publications without any US-affiliated (*resp.* China-affiliated) author or an author who has ever been affiliated to the United-States (*resp.* China).

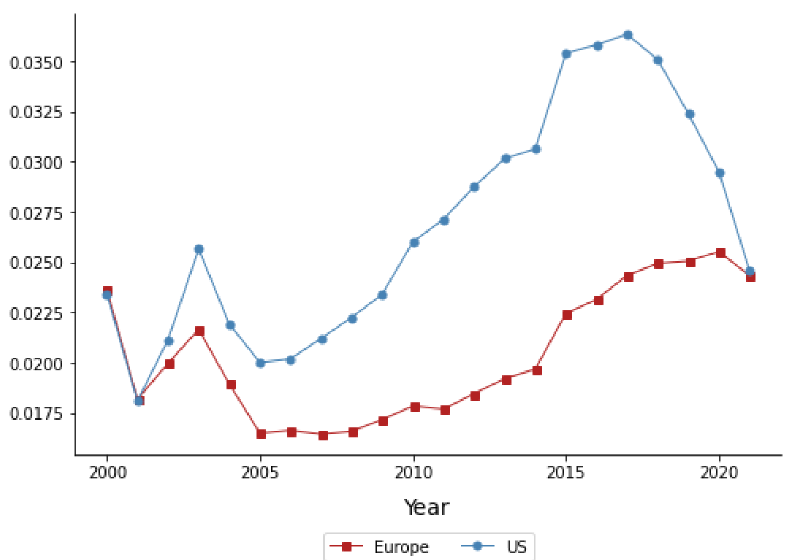


Figure II
Share of Collaborations of Chinese Authors with US and European Authors
in All Co-Authored Papers

Notes: This graph depicts the evolution of the average shares of European and US co-authors in publications with authors based in China.

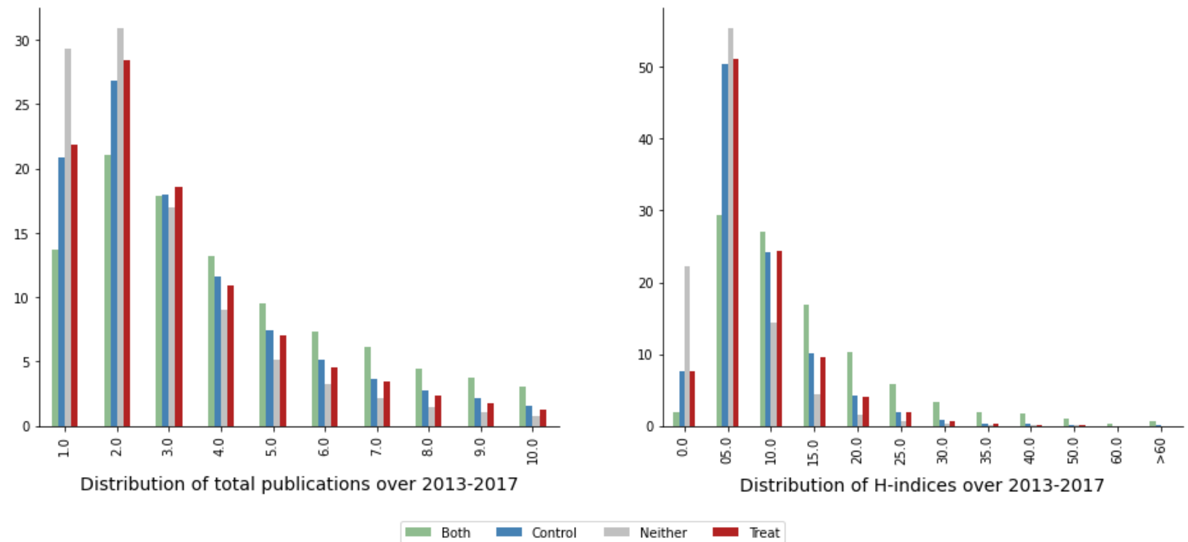


Figure III
Publications and H-Indices 2013-2017

Notes: This graph plots the distribution of publications (left) and of H-indices (right) during the period 2013-2017 for the set of researchers meeting the conditions to be kept as active researchers in China for the 2008-2012 period. The treated group and the control group are represented respectively in red and blue. The group of Chinese researchers who co-author both with European and US co-authors is represented in green. The group of Chinese researchers who co-author with neither European nor US researchers is plotted in grey.

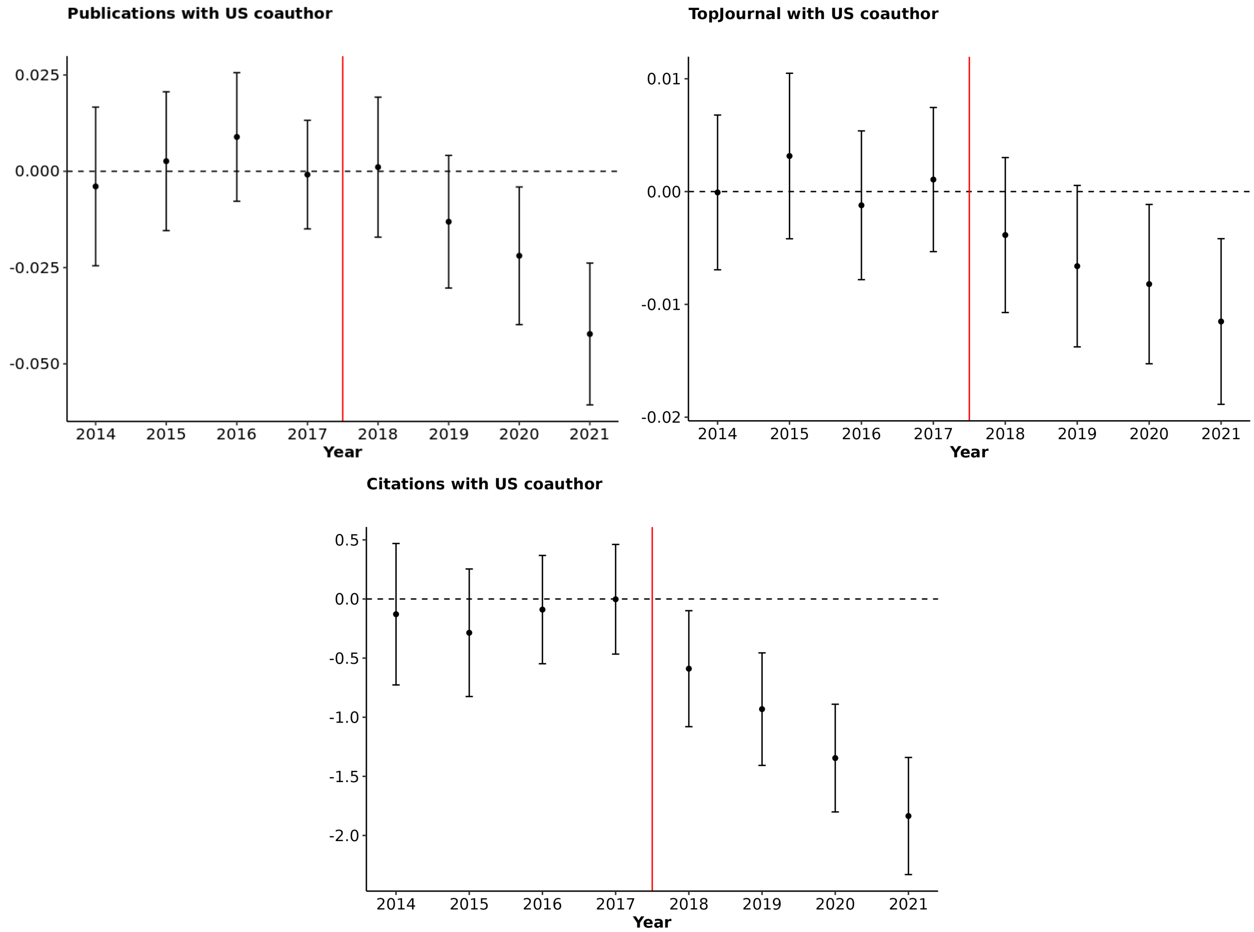


Figure IV
US Collaboration Shock of Treated Chinese Authors

Notes: The graph above reports regression estimates for the difference in number of publications by the treated with US co-authors and number of publications by the control with European co-authors for each year between 2013 and 2021. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), h-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the outcome variable.

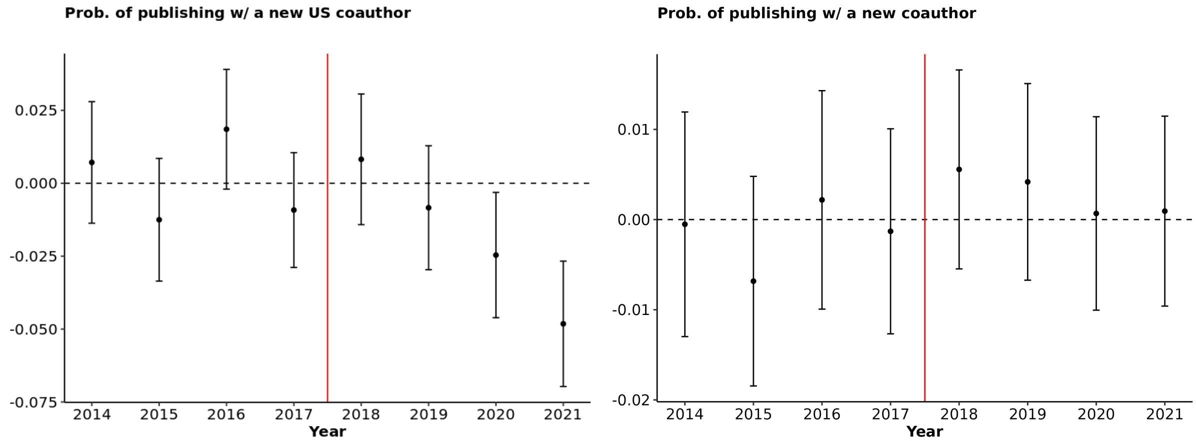


Figure V
Effect on Having a New Co-Author

Notes: The graphs above report regression estimates both for the difference in the probability of publishing with a new co-author (left) and publishing with a new US co-author for the treated and a new European co-author for the control (right) between the treated and the control group for each year between 2013 and 2021. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), h-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers.

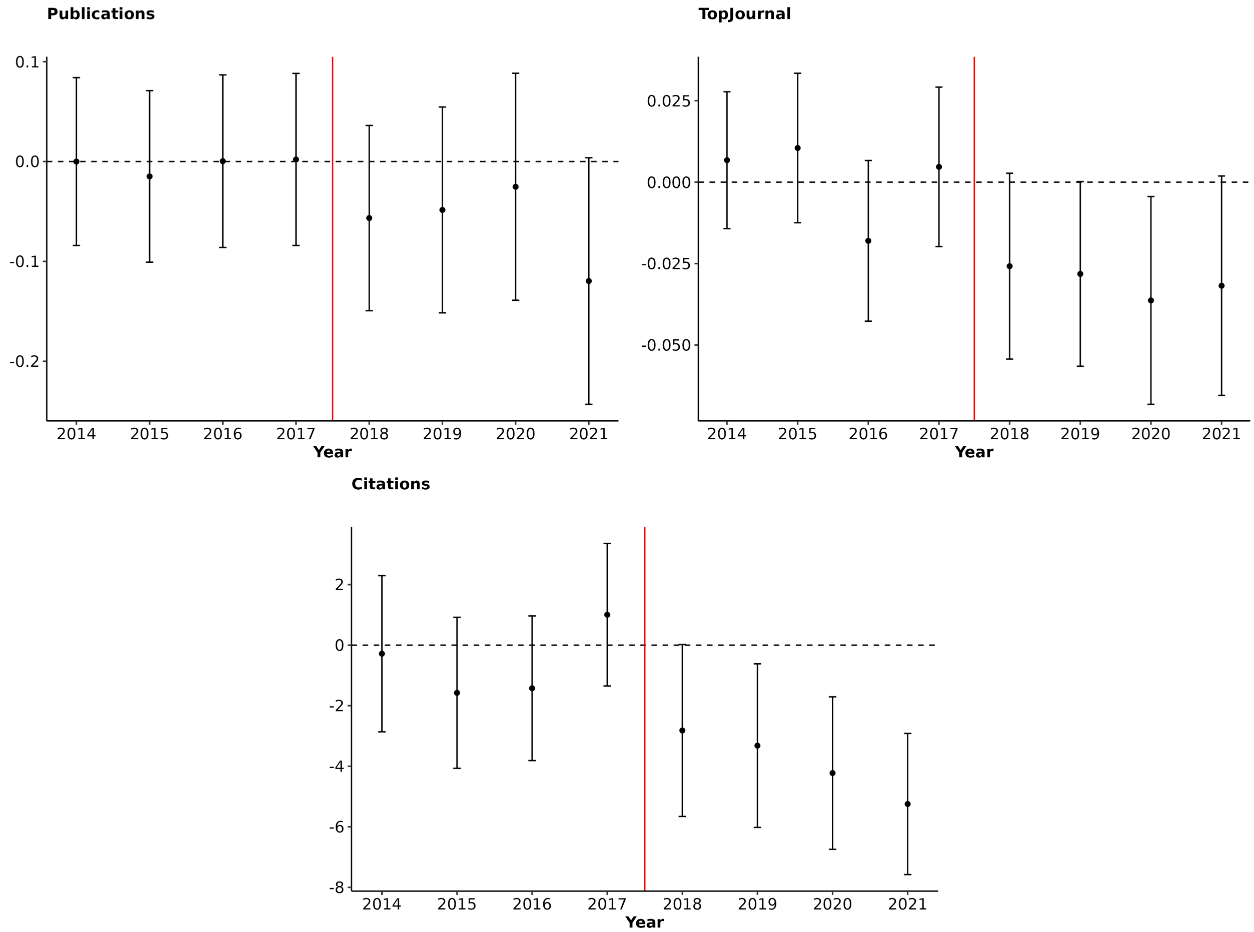


Figure VI
Scientific Productivity of Treated Chinese Authors

Notes: The graph above reports regression estimates for the difference in number of total publications and total citations between the treated and control group for each year between 2013 and 2021. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), h-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the outcome variable.

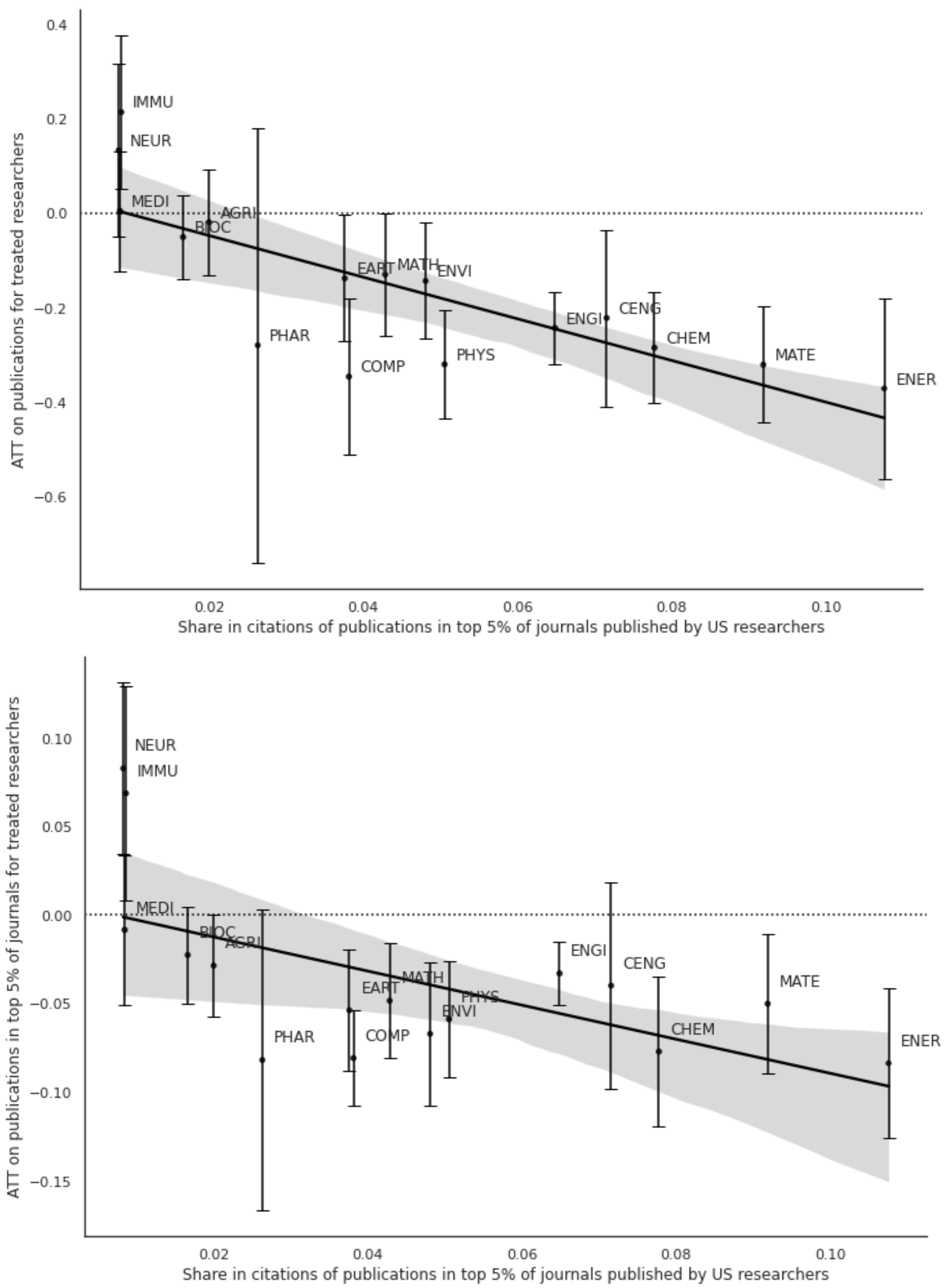


Figure VII

Effect of the China Initiative on Publications and Publications in Top 5 Percent Most Cited Journals: Effect by Field, Compared to US Dominance by Field

Notes: The graph above reports regression estimates for the difference in the total number of publications (left panel) and publications in the five percent most cited journals (right panel)for treated researchers writing in each field compared to their counterparts in the control group on average over the period 2018-2021 compared to the period 2013-2017. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), h-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the outcome variable. These estimates are plotted against the share of all citations to publications released between 2000 and 2012 in top 5 percent journals in that field that accrue to papers with at least one US author.

Appendix

A. Appendix to Section 1

Figure A.1 expands Figure I by also including the number of European publications in the top five percent most cited journals when removing publications by authors with current or past US and Chinese affiliations. The dependency of European researchers with regard to China is similar to that of US researchers with regard to China, although it appears to have increased less over time. Total European publications drop by three quarters when removing all papers by researchers with a past or present US affiliation. This dependency decreases over time but remains very high in 2020.

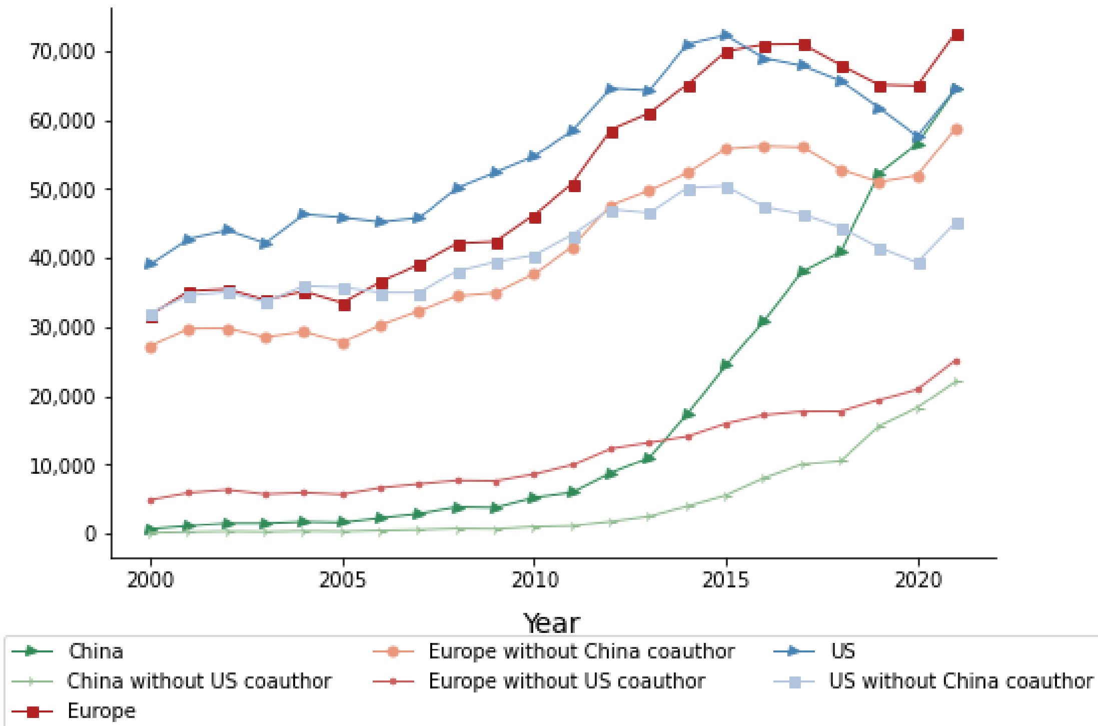
Figure A.2 allows us to better understand Figure II by plotting the total number of partnerships per year that features co-authors affiliated respectively only in the US and China and only Europe and China, by affiliation of the last author of a paper. In life sciences and natural sciences, the position of last authors usually goes to the principal investigator of a paper. While the number of China-Europe collaborations keeps increasing over the whole period, the number of China-US collaborations with a last author affiliated in either country stagnates and drops after 2018. The number of collaborations with a China-US last author drops as soon as 2018. It is not surprising that papers involving a US-based or China-US double affiliated last author decrease more strongly than those involving a Chinese last author: the China Initiative blocks US funding from going to some projects with Chinese collaborators, so that a US lab may not be funded to lead such a project. In both cases, the number of papers that are led by a scientist from neither group appears to be negligible compared to the rest.

Figure A.3 shows similar trends when sorting publications according to their corresponding authors instead. In this figure however, China-US publications with a US last author do not seem to suffer, which could hint at a possibility that it is harder for Chinese researchers to take part in collaborations in which they have the front role. China-US publications in which the corresponding author has a double affiliation decrease in the same way as those with a double-affiliated last author. Collaborations with a corresponding author affiliated in both countries seem to follow a similar pattern both for US-China and Europe-China collaborations.

Finally, Figure A.4 shows a mirror measures of the share of collaborations shown in Figure II. While the decrease in China-US partnerships as a share of US collaborations is not as large as this decrease as a share of collaborations, we can make the following remarks. The first is that the drop in Chinese collaborations is noticeable from the US side as well. The second is that Chinese international collaborations are rising much more steeply than US ones, and that the decrease in collaborations is therefore more striking for a country that asserts its global position in research than for a country that is already well connected.

Figure A.1

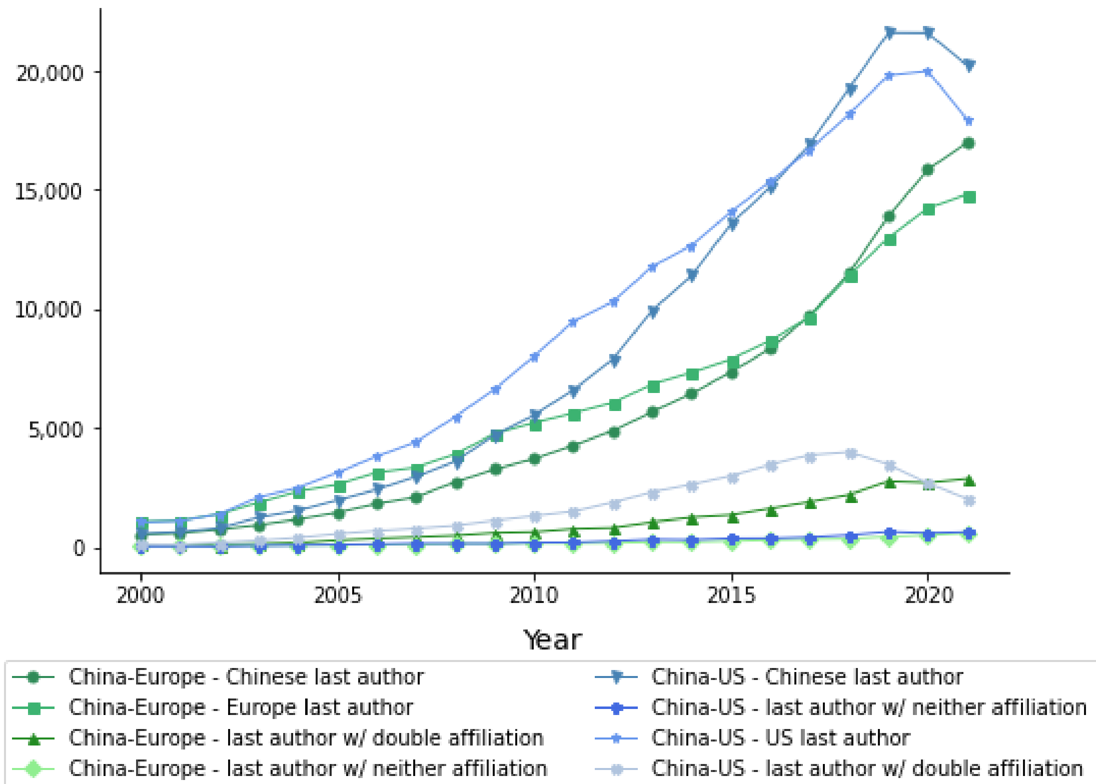
Number of Publications in Top Journals by Country Group/Region of Affiliation and by Type of Collaborations



Notes: This figure represents the number of publications in the top five percent most cited journals by country group. The curves labeled with the mention "without US co-author" (*resp.* "without China co-author") account for publications without any US-affiliated (*resp.* China-affiliated) author or an author who has ever been affiliated to the United-States (*resp.* China).

Figure A.2

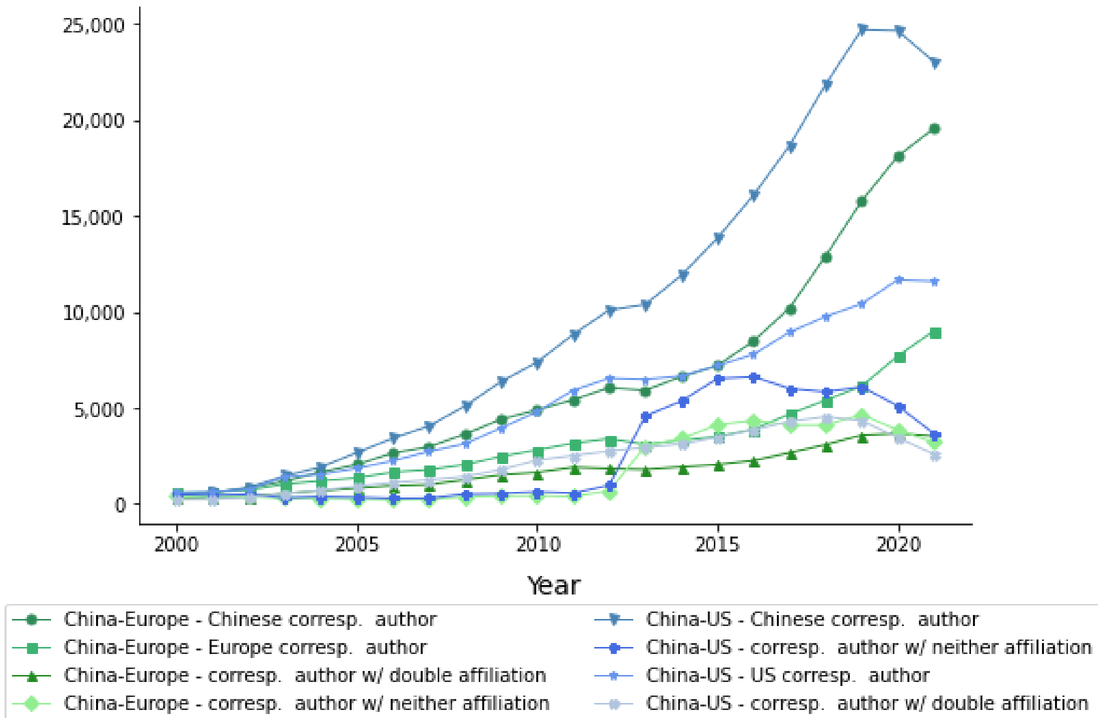
Number of Publications for China-US and China-Europe collaborations by affiliation of the last author



Notes: This figure represents the number of publications that respectively have at least one author affiliated both in China and Europe and none in the US, and at least one author affiliated both in China and in the US and none in Europe. Each group is divided according to whether the last author of the publication is affiliated in China, in Europe or the US, in both countries, or in neither of them.

Figure A.3

Number of Publications for China-US and China-Europe collaborations by affiliation of the corresponding author



Notes: This figure represents the number of publications that respectively have at least one author affiliated both in China and Europe and none in the US, and at least one author affiliated both in China and in the US and none in Europe. Each group is divided according to whether the corresponding author(s) of the publication is (are) affiliated in China, in Europe or the US, in both countries, or in neither of them.

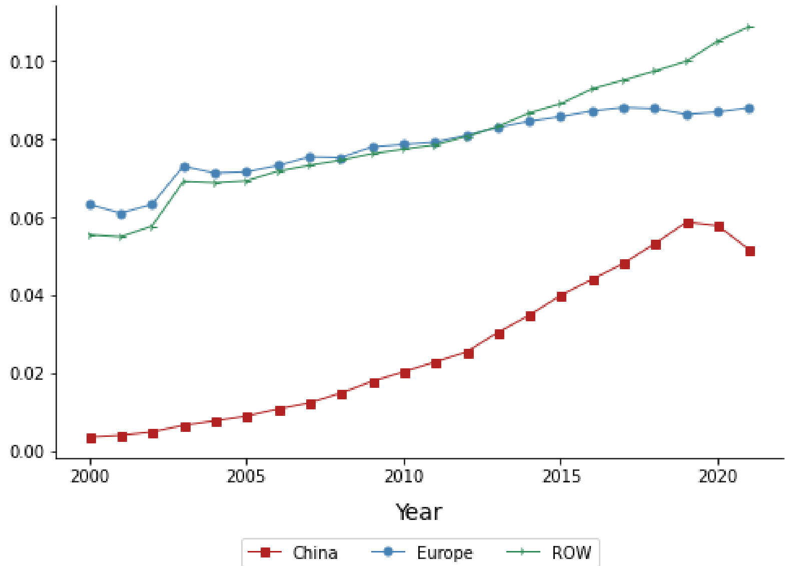


Figure A.4
Share of Collaborations of US Authors with China, Europe and Rest of the World in All Co-Authored Papers

Notes: This graph depicts the evolution of the average shares of European and US co-authors in publications with authors based in China.

A.1. Comparison of approach to that of Li and Wang (2024)

We now explain how our approach differs from that in Li and Wang (2024). The sample selection and definition of treatment and control is similar to ours, but differs in three key respects. First, the definition of treated and control authors is different. Their treatment group consists of researchers who collaborated with at least one U.S. researcher between 2010 and 2014. The control group consists of researchers who collaborated with a scientist from another country between 2010 and 2014, and who did not collaborate with a US scientist between 2010 and 2018. Hence, there is one selection criterion for the treatment group and two for the control group. This asymmetry implies that the most productive researchers, who collaborate with researchers from the US and other nations, are in the treatment group but excluded from the control group. Hence, there will be a considerable productivity gap between the two groups ex ante, in contrast to our selection criteria (see Figure 3). Note also that while the first criterion is applied until 2014, the second selection criterion for the control group only is applied through the pre-period and is dropped at the treatment year, 2018.

The other difference is that Li and Wang (2024) uses matching on the outcome variables (number paper, citation, novelty, etc.) in the pre-period 2015-2018. This is problematic, because conditioning on realized outcomes can distort the within-unit variation required for identification. The problem is better known when involving including a lagged dependent variable in a fixed effects regression, but applies equally when conditioning the sample, for example, via matching. This problem is particularly acute in short panels, such as ours, and when the matching is made asymmetrically around the treatment date (e.g. Chabé-Ferret, Sylvain, 2017).

To see why this is problematic, consider the following simple case. Suppose that treated authors always publish one paper per year, that control authors publish a paper with probability .5, and that treatment has no effect. Suppose that we select a sample of treatment and control authors who published one paper every year in the pre-period. This way, we select control authors who happened to be unusually productive in the pre-period and average treated authors. In this sample, there will be parallel trends in the pre-period by construction. When the control authors return to their normal expected productivity (0.5) post-treatment, then the difference (before-after) for the control authors will be 0.5. For treated authors, if the China Initiative has no effect, the differential (before-after) will be 0. Hence, the difference-in-difference estimator will show a positive treatment effect of 0.5 although the true effect is zero.

A third difference is that we allow for differential trends, by all our control variables in X_i, whereas Li and Wang (2024) only control linearly for the number of unique collaborators in the same institution and career age, denoted as $E_{i,t}$ and $H_{i,t}$, respectively.

B. Appendix to Section 3

Our definition of treated and control researchers uses information on researchers' affiliation locations and Chinese names. We now discuss how we measure these.

B.1. Researcher location

Due to the fact that we can only observe a researcher's affiliation during a year in which she publishes, we have to infer her affiliation in a year in which she does not publish from her publication pattern in the year in which she publishes. Based on the information about researchers' locations over their careers, we have built an algorithm that allows us to match a researcher to the place she is affiliated with. We interpolate researchers' places of residence based on their publication affiliations and estimate, for years in which they do not publish, their probability of residing in a given country. For example, if an author published with a Chinese affiliation in 2012 and a U.S. affiliation in 2015, we assign a 50 percent probability of residence in China for both 2013 and 2014. In our main analysis, we retain researchers with a probability of at least 50 percent of having still published in China before 2014. For our U.S. analysis, we include those with a probability of at least 50 percent of having still published in the U.S. before 2014.

B.2. Classification of Chinese names

In our main analysis and in Section 4.7, we use researchers' names to identify researchers with Chinese origins. The process of classification of surnames and first names follows several steps. First, for each name in the entire population of researchers in Scopus, we take the entire set of existing names and the affiliation country of each researcher who bears that name and compute the number of researchers who bear that name in each country or region. Then, we perform the following χ^2 tests for different combinations of countries/regions, namely China versus US, China versus the rest of the world [28], and US versus the rest of the world[29]:

- We test whether the last name is over-represented in the first country;
- We test whether the first name is over-represented in the first country;
- We test whether people with the same first name bear on average a last name that is over-represented in the first country;
- We test whether people with the same last name bear on average a first name that is over-represented in the first country;

The threshold that we picked is a χ^2 above 0.000001. In this case, out of the last 10 names that are considered over-represented, 7 appear to be Chinese. We then consider a researcher to have a Chinese name if her χ^2 is above the threshold for any of these measures compared to the US or the rest of the world. In our main sample for Chinese researchers, we further exclude authors who have a first name corresponding to the US, in order to exclude the possibility that they are US citizens who emigrated to China. Although this restriction could be contested since Chinese citizens could name their children with US first names, we argue that this restriction does not change our results as it only concerns 93 researchers.

[28] Excluding Macao, Singapore, Hong Kong, Korea, Vietnam and India due to the high number of people with Chinese names in these countries.

[29] Excluding most English-speaking countries and Central American countries.

B.3. The doubly robust estimator

This section describes the doubly robust estimator from Callaway and Sant'Anna (2020). Let $D = 1$ be a variable indicating treatment, and $p(X)$ denote the probability of being treated conditional on X. Let $\Delta Y_t = Y_t - Y_{pre-period}$ be the change in the outcome variable between the current year t and the pre-period, and let $\mu_{0,t}(X) = E\left(\Delta Y_t | X, D = 0\right)$ be the expected corresponding change in the outcome had the individual not been treated, conditional on X. The formula for estimating the coefficients displayed in our event-study graphs, β_t^{dr}, using this estimator is

$$\beta_t^{dr} = E\left[\left(\frac{D}{E[D]} - \frac{\frac{p(X)(1-D)}{(1-p(X))}}{E\left[\frac{p(X)(1-D)}{(1-p(X))}\right]}\right)(\Delta Y_t - \mu_{0,t}(X))\right]$$

The average treatment effect, β^{dr}, reported in our tables is the average value of the post-shock estimates of β_t^{dr}.

We estimate this model using the R-package `did`. It implements the following steps. First, propensity scores $\hat{p}(X_i)$ are computed by performing a logit regression of treatment status at the author level on the individual characteristics X_i discussed above. Then, the following procedure is implemented for each year t, both pre- and post-treatment. For any outcome variable y, we select the value for each individual both in the current year and for a past year. This past year is the last year prior to the current one which is in the pre-shock period. The difference between these values is called Δy_{it}. We do not include the years 2016 and 2017 in the pre-shock period for this computation, due to Donald Trump's election possibly allowing individuals to anticipate such kind of political change. That is, for all years after 2018, in our case, the past period consists of the year 2015.

Then, for the control group, we regress Δy_{it} on their covariates X_i. Using the estimates from this regression, we compute the predicted values, $\hat{m}_{it}(X_i)= X_i'\hat{\gamma}_t$, for Δy_{it} not only for the control group but also for the treated as if they were control authors. We then take the difference Δy_{it} - $\hat{m}_{it}(X_i)$. This is the outcome regression part of the doubly robust estimation procedure.

For the treated group, this value is then divided by the share of treated authors, and for the control, it is multiplied by the ratio of the author's $\frac{\hat{p}(X_i)}{1-\hat{p}(X_i)}$ to the average value of this inverse probability score in the control group. This is the inverse probability weighting part of the doubly-robust estimation procedure. We finally take the difference between the two values: this is the Average Treatment on the Treated (ATT) for a year[30]. To estimate the average ATT in the post-period, we simply take the average ATT over the post-shock period, as shown in Callaway and Sant'Anna (2020).

C. Appendix to Section 4

This subsection collects additional results and figures mentioned in the main text in Section 3.

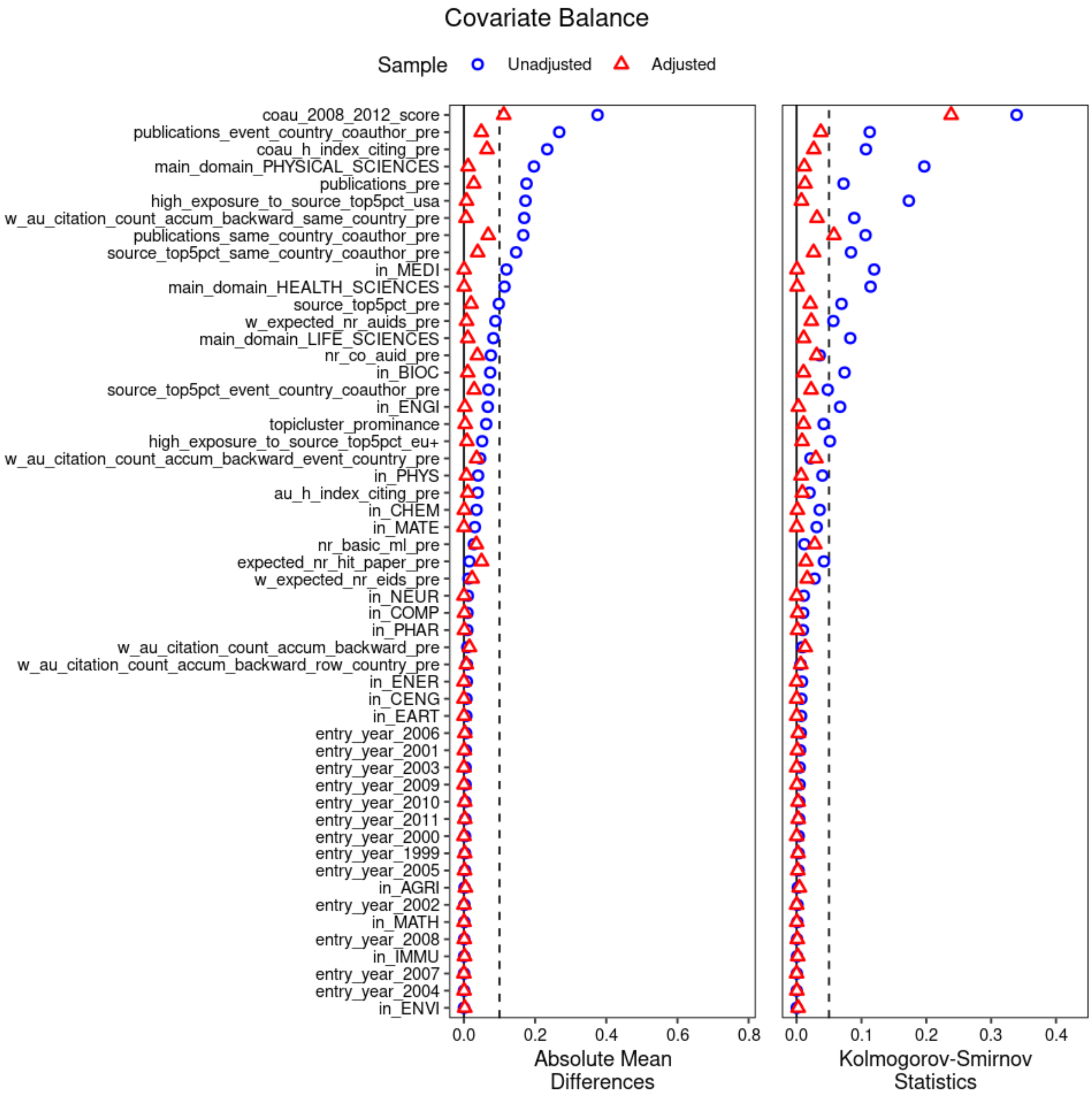
C.1. Sample balance

Figure C.1.1 shows that there are very few significant absolute mean differences between the treatment and control groups after weighting observations by propensity scores, and moreover the remaining differences are no longer significant when using Kolmogorov-Smirnov statistics. It also shows that treated and control Chinese researchers do not display systematic differences in seniority or in fields of study, two potential reasons for differential trends in publications and citations between the two groups.

[30] The effect is not an Average Treatment Effect (ATE) due to the fact that it is computed using the propensity scores and is conditional on the covariates; we cannot compute an ATE as we would need to include all control authors with the same weight.

Figure C.1.1

Differences based on Observables between the Treated and the Control, after and before Weighting: Absolute Mean Differences and Kolmogorov-Smirnov Statistics



Notes: The graph above depicts absolute mean differences (left) and Kolmogorov-Smirnov statistics (right) for the differences between the unweighted sample (red) and the weighted sample (blue). The variables included are publications, publications with the US and Europe respectively for the treated and the control, and citations in the pre-period (respectively *publications_pre*, *publications_same_country_pre* and *citations_pre*), as well as the interaction of seniority represented by the year of first publication on Scopus and main domain of study (variables *y_x_dom*). We can see that the weighted sample features almost no differences in the latter.

For further information on sample balance, Table C.1.1 shows the distribution of authors in the sample across years of first publication in Scopus and scientific fields identified by Scopus. Table C.1.2 shows descriptive statistics for selection-period characteristics.

Table C.1.1
Summary Statistics - Individual Level

Variable	Control Group N	Percent	Treated Group N	Percent	Test
First year of publication in Scopus:	17631		23432		X2= 26.199**
... 1999	447	3%	534	2%	
... 2000	515	3%	617	3%	
... 2001	755	4%	880	4%	
... 2002	879	5%	1138	5%	
... 2003	1054	6%	1517	6%	
... 2004	1294	7%	1734	7%	
... 2005	1591	9%	2199	9%	
... 2006	1755	10%	2192	9%	
... 2007	1766	10%	2347	10%	
... 2008	2139	12%	2806	12%	
... 2009	2160	12%	2963	13%	
... 2010	1992	11%	2716	12%	
... 2011	1284	7%	1789	8%	
Main domain of study:	17631		23432		X2= 1586.199***
... Health sciences	2412	14%	5850	25%	
... Life sciences	3003	17%	5881	25%	
... Physical sciences	12216	69%	11701	50%	

Statistical significance markers: * p<0.1; ** p<0.05; *** p<0.01

Notes: This table summarizes the distribution of our sample in their main discrete individual characteristics accounting for sample attrition.

Table C.1.2
Summary Statistics - Individual Level - Controls

Variable	Control Group N	Mean	SD	Treated Group N	Mean	SD	Test
Publications (2008-2012)	17608	12	10	23409	10	9.1	F= 260.702***
Total citations (2008-2012)	17608	242	354	23409	257	360	F= 18.745***
Share of publications in top 5% cited journals (2008-2012)	17608	0.45	1.6	23409	0.68	2.3	F= 127.668***

Statistical significance markers: * p<0.1; ** p<0.05; *** p<0.01

Notes: This table summarizes the values of the main controls used for pre-period characteristics in the regressions.

C.1.i. By Coauthor Role

Table C.1.3 Sample Balance by Coauthor Role

	First Author (N=3232)			Last Author (N=12456)			Middle Author (N=13140)		
	Mean			Mean			Mean		
	Control	Treated	SMD	Control	Treated	SMD	Control	Treated	SMD
Author Age	9.499	9.386	0.019	7.25	7.163	0.019	7.967	7.828	0.03
Publications	15.428	16.486	-0.075	10.224	10.853	-0.067	12.933	13.023	-0.008
Citations	147.786	122.305	0.1	75.433	74.234	0.008	117.29	95.303	0.106
Subject Composition									
AGRI	0.073	0.073	-0.001	0.1	0.096	0.012	0.082	0.07	0.041
BIOC	0.088	0.053	0.124	0.151	0.108	0.118	0.109	0.051	0.186
CENG	0.013	0.018	-0.04	0.006	0.013	-0.09	0.013	0.02	-0.064
CHEM	0.047	0.106	-0.28	0.06	0.102	-0.176	0.12	0.151	-0.095
EART	0.117	0.116	0.003	0.076	0.085	-0.034	0.043	0.043	0.001
ENER	0.015	0.024	-0.073	0.007	0.015	-0.091	0.009	0.025	-0.164
ENGI	0.29	0.377	-0.191	0.129	0.18	-0.153	0.213	0.306	-0.228
ENVI	0.062	0.039	0.094	0.054	0.044	0.041	0.043	0.049	-0.028
IMMU	0.006	0.01	-0.054	0.025	0.037	-0.079	0.016	0.011	0.04
MATE	0.051	0.075	-0.105	0.025	0.061	-0.235	0.059	0.08	-0.092
MEDI	0.193	0.088	0.266	0.312	0.207	0.227	0.247	0.165	0.191
NEUR	0.017	0.008	0.07	0.022	0.015	0.043	0.016	0.007	0.071
PHAR	0.028	0.013	0.088	0.034	0.035	-0.003	0.03	0.021	0.051

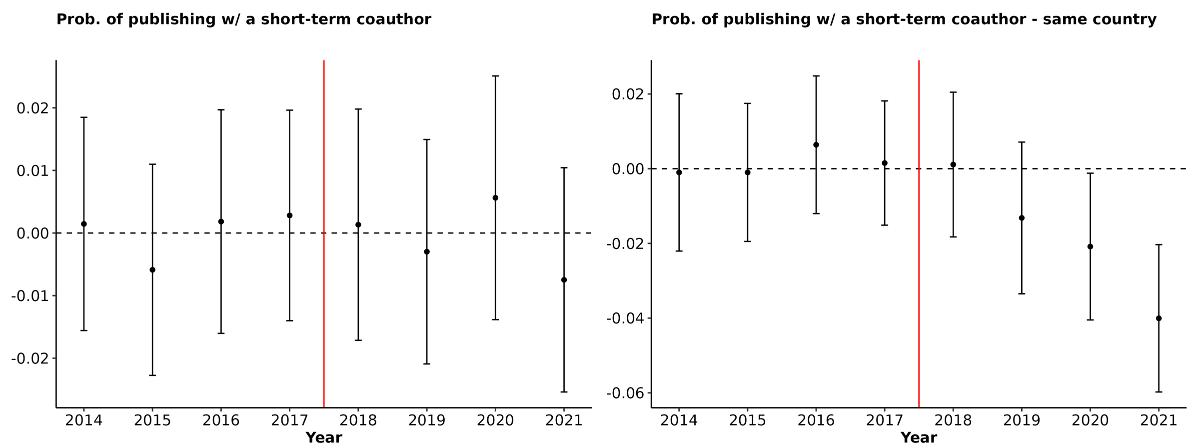
Note:
The sample consists of researchers across scientific fields, excluding Mathematics, Computer Science, and Physics. Author age refers to an author's scopus age till 2012, publications refer to the total number of publications during 2008-2012, and Citations refer to the total number citations an author has received by the end of 2012. The SMD (standardized mean difference) computes the difference in mean between the treated and the control for each subsample and then divide the difference by the standardized deviation of the whole subsample.

C.2. Co-author networks

Event-study graphs, short- and long-term co-authors: The event-study graphs of effects on short- and long-term co-authors are shown in Figure C.2.1 and Figure C.2.2, respectively. The corresponding graph for co-author H-indexes is shown in Figure C.2.3.

Figure C.2.1

Effect on Having a Short-Term Co-Author: Global and US Compared to Control with Europe



Notes: The graphs above report regression estimates both for the difference in the probability of publishing with a short-term co-author (left) and publishing with a short-term US co-author for the treated and a short-term European co-author for the control (right) between the treated and the control group for each year between 2013 and 2021 (short-term meaning a co-author that the author had for between 1 and 5 years). Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), H-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers.

Importance of co-author quality: We argue that the main mechanism for the drop in overall quality of treated researchers is the impossibility of reallocating towards high-quality co-authors outside of US academia. Table C.2.1 provides evidence at the article level that the average H-index of authors of a paper is a strong predictor of citations received in the five and ten years after publications. *Event study graphs*: In order to assess the presence of parallel trends, we provide in addition to the estimated p-value of the parallel trends the event study graphs for the regressions that we include in the paper.

C.3. Additional results

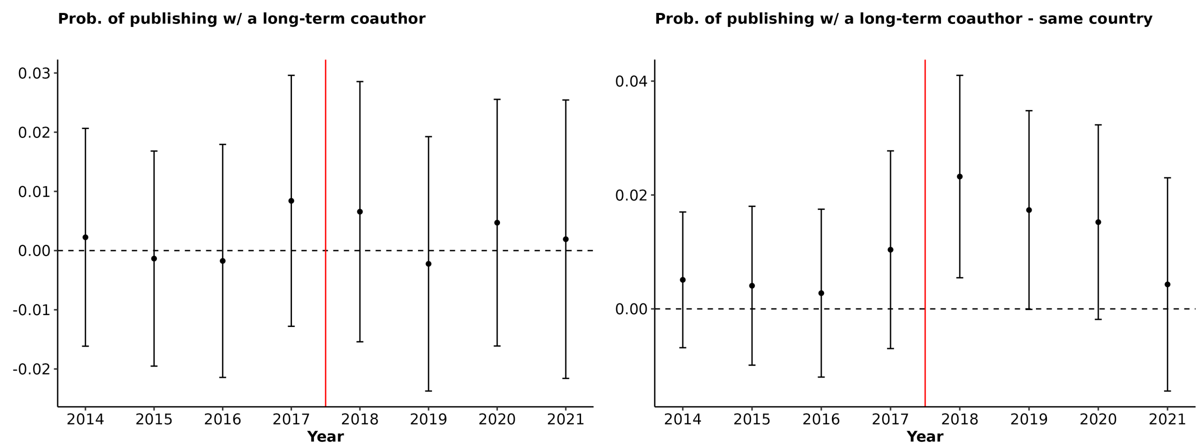
The event-study graph of the effect of the China Initiative on the number of papers in the top 1 percent cited papers is shown in Figure C.3.1.

C.4. Journal and co-author quality metrics

Here, we extend our event study analysis to using alternative specifications of the number of publications in top 5 percent journals, namely using the CiteScore metrics instead of our own and using a threshold of 10 percent rather than 5 percent.

Figure C.2.2

Effect on Having a Long-Term Co-Author: Global and US Compared to Control with Europe



Notes: The graphs above report regression estimates both for the difference in the probability of publishing with a long-term co-author (left) and publishing with a long-term US co-author for the treated and a long-term European co-author for the control (right) between the treated and the control group for each year between 2013 and 2021 (long-term meaning a co-author that the author had for over 5 years). Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), H-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers.

Table C.2.1

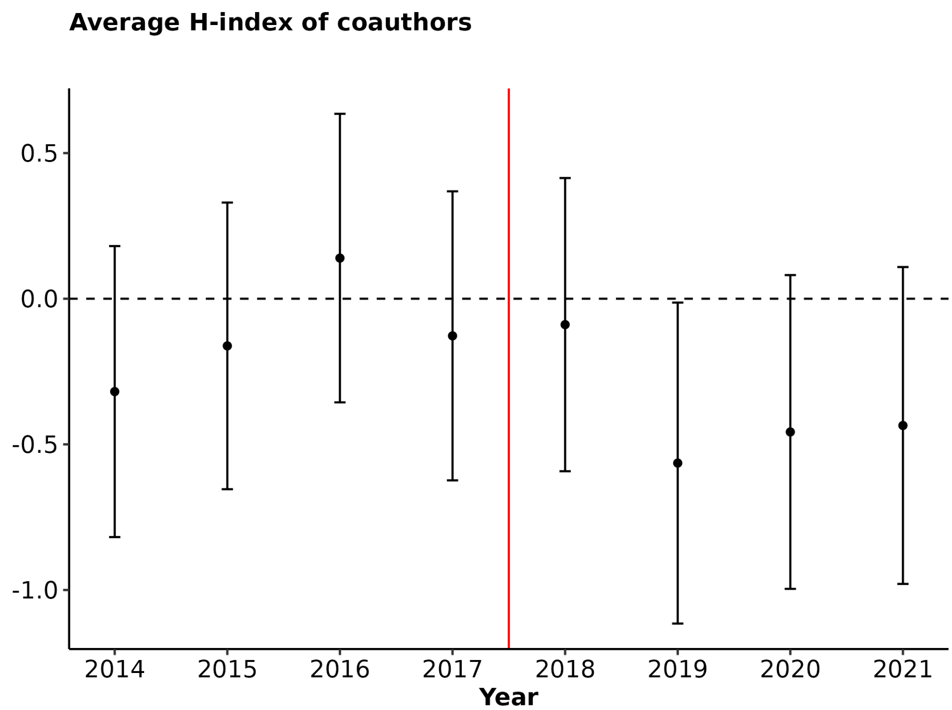
Predictions of the Number of Citations (5 and 10 Years Windows)
Using the Average H-Index of Co-Authors (Paper Level)

Dependent Variables:	Citations (5 years post. publication)	Citations (10 years post. publication)
Model:	(1)	(2)
Variables		
Average H-index of co-authors	1.088***	1.508***
	(0.0808)	(0.1150)
Fit statistics		
Observations	1,391,945	1,391,945
R^2	0.04256	0.04849
Adjusted R^2	0.04250	0.04843

Clustered (year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

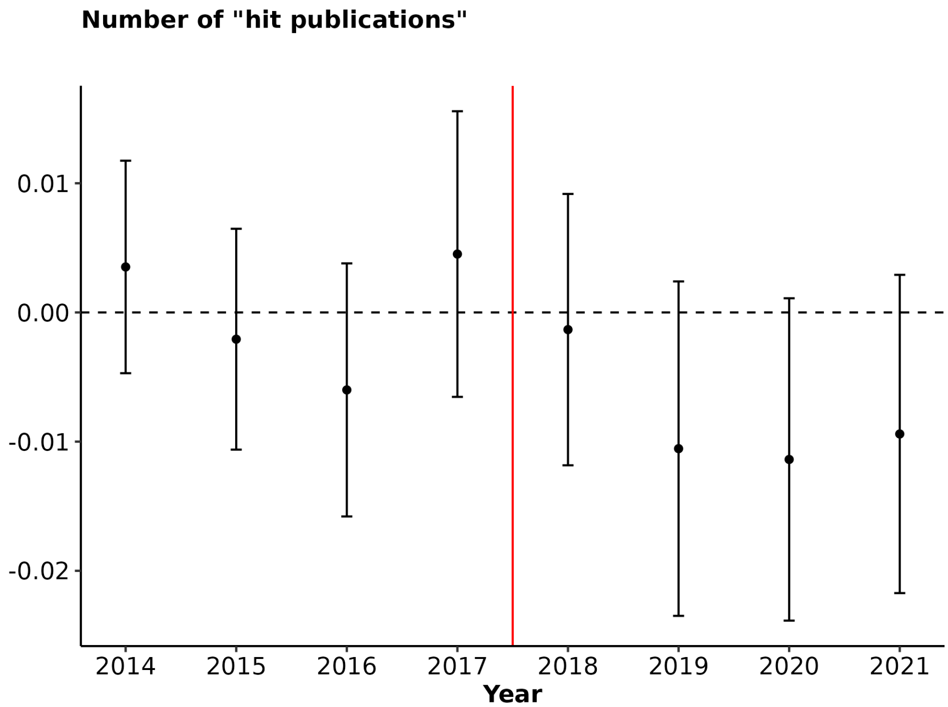
Notes: The table above reports estimates for a fixed-effects regression of the citations received in the next 5 and 10 years by a paper based on the average H-index of its authors. The fixed effects include time and main domain of study (life, health, physical sciences).

Figure C.2.3
Effect on Average Real-Time H-Index of Co-Authors



Notes: The graph above reports regression estimates for the difference in average H-index of co-authors between the treated and control group for each year between 2013 and 2021, based on information available at the year this measure is calculated. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), H-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the outcome variable.

Figure C.3.1
Effect of the China Initiative on the Number of Papers in the Top 1 Percent Cited Papers



Notes: The graph above reports regression estimates for the difference in number of papers in the top 1 percent most cited papers of the year between the treated and control group for each year between 2013 and 2021. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), H-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the outcome variable.

Table C.4.1
ATT for Alternative Outcome Variables

	TopJournal (CiteScore)		TopJournal (10% threshold)		co-authorHindex (normalised by seniority)	
		with US		with US		with US
	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-0.010	-0.006***	-0.045**	-0.016***	-0.022***	-0.060**
	(0.013)	(0.002)	(0.021)	(0.004)	(0.007)	(0.029)
Mean.Dep.Var.Pre	0.449	0.077	0.823	0.131	1.201	2.206
Pvalue.PreTrend	0.680	0.621	0.227	0.106	0.258	0.349
N.authors	41063	41063	41063	41063	39256	25941
N.obs	369567	369567	369567	369567	249535	88766
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note:results are from DRDID regression. The unit of observation is author by year and the sample period is from 2013-2021. The dependent variable is the number of publications on top 5% journals according to citescore, total and with a US co-author for the treated and European co-author for the control (columns (1)-(2)), number of publications on top 10% journals, total and with a US co-author for the treated and European co-author for the control (columns (3)-(4)), and age-normalized H index of co-authors, overall and only US co-authors for the treated and European co-authors for the control ((5)-(6)). Control variables account for author's publication characteristics overall and by category of co-author during 2008-2012, including number of publications, number of accumulated citations, number of top publications, co-author dependency, as well as number of co-authors, characteristics of the fields and topics of interest of the author. Standard errors (SE) are clustered by author. In parentheses: *** p< 0.01, ** p< 0.05, * p< 0.1.

We also show that using a seniority-adjusted H-index (dividing the value by seniority in Scopus) for co-authors to avoid lifecycle effects on their H-index as provided does not change our result. Table C.4.1 summarizes the ATT for these variables on average over the period.

C.5. Sample selection

China-US double affiliates: Our main sample includes authors who have Chinese names and who are considered to be residents in China in the selection period, but who also appear to have a double affiliation with the US (i.e. they keep publishing also with a US affiliation until 2014). The question of whether to include them hinges on whether we count them as sources of Chinese science or not. We perform the same analysis as above on the same sample, with one added restriction: removing researchers who could be considered as affiliated to the US as described above. Table C.5.1 shows that our main results hold when removing these researchers, with point estimates that are not statistically significantly different from the ones that we find when including these authors. The magnitudes of the point estimates are slightly smaller, which could be due to these authors being more strongly affected than the non-double affiliates. However, we can also notice that the p-value for the pre-trend in publications with same country co-authors is smaller for this subsample (0.038) compared to the main sample (0.481). This is probably due to the fact that these Chinese-US-affiliated researchers have Chinese-Europe-affiliated counterparts in the control group, which argues in favor of keeping them in the sample.

Lower collaboration threshold: We reproduce our estimations on a sample that no longer uses our C-index measure to select the treated and control groups. Results are displayed in Table C.5.2. We start from the same population of Chinese researchers as before, keeping the same criteria of *affiliation*, *descent*, and *no-spillover*. In this new sample, we change the criterion *dependence* in the following way: we consider as treated authors the ones who have published with a US co-author at least once during the selection period and never with a European co-author during the selection period. Conversely, control authors have published at least once with a European co-author and never with a US co-author during

Table C.5.1

Average Treatment on the Treated (ATT) for Publications-Related Performances of Researchers (without Double-Affiliates)

	Publications		Citations		TopJournal		TopCited	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATT	-0.060**	-0.109***	-4.687***	-6.408***	-0.017**	-0.033***	-0.006**	-0.014***
	(0.031)	(0.038)	(1.068)	(1.332)	(0.009)	(0.012)	(0.003)	(0.005)
Mean.Dep.Var.Pre	3.087	3.087	95.938	95.938	0.262	0.262	0.065	0.065
Pvalue.PreTrend	0.987	0.975	0.145	0.062	0.233	0.152	0.886	0.963
N.authors	38229	38229	38172	38172	38172	38172	38172	38172
N.obs	344061	344061	244113	244113	244113	244113	244113	244113
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cond. on publishing		Yes		Yes		Yes		Yes

Note: results are from DRDID regression, for each outcome for the whole sample and conditioning on having published during the year of observation. The unit of observation is author by year and the sample period is from 2013-2021. The dependent variable is the number of publications (columns (1)-(2)),number of citations for publications from that year (columns (3)-(4)), rate of publications on top 5 % journals (within subject) from that year (columns (5)-(6)), citations received from papers with at least of Chinese author (columns (7)-(8)). Control variables account for author's publication characteristics overall and by category of co-author during 2008-2012, including number of publications, number of accumulated citations, number of top publications, co-author dependency, as well as number of co-authors, characteristics of the fields and topics of interest of the author. Standard errors (SE) are clustered by author. In parentheses: *** p<0.01, ** p<0.05, * p<0.1.

the selection period. This allows us to keep more lower-quality authors who are also less dependent on the US or Europe and therefore less affected by the China Initiative. However, most of our results hold. In particular, the drop in the quality of publications of treated authors compared to control authors remains. Treated Chinese authors also publish fewer papers both overall and in top journals with US co-authors compared to what control Chinese authors publish with European co-authors.

C.6. Home bias

We next discuss concerns arising since many top journals are US-based and since citations exhibit a home bias.

C.6.i. Journals

The vast majority of journals in the top 5 percent of the distribution of citations per paper in the database for a given year and field are published in the US. One could argue that the observed effects of the China Initiative shock on treated Chinese researchers are mechanical: if an author publishes less with US co-authors, she will have fewer publications in US journals, including top ones.

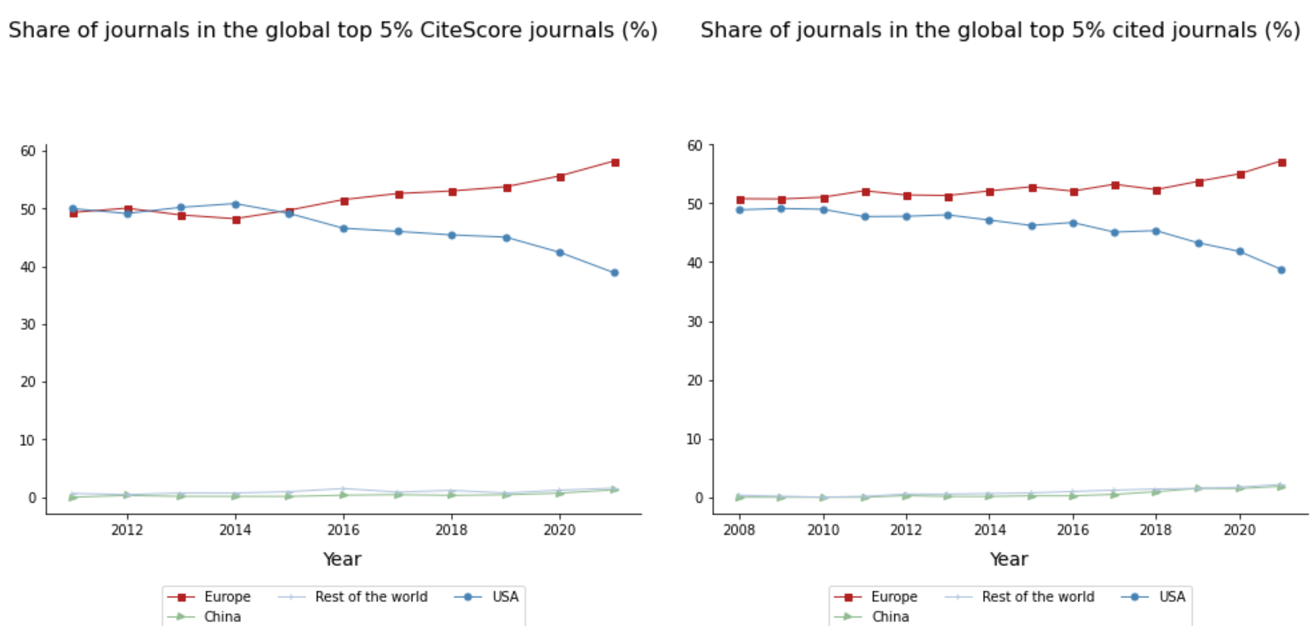
However, according to Scopus's CiteScore metric, and as shown in the left-hand panel of Figure C.6.1, US-based journals are only dominant during the first third of the period of analysis. European publications account for more than half of all top 5 percent sources and become dominant after 2015. Although our metrics are constructed at a higher level (field instead of ASJC code) than Citescore, the magnitude and trends are quite similar. As shown on the right-hand panel of Figure C.6.1, the European share is slightly higher than the US even at the start of the period while the US share decreases as steadily as when using CiteScore. If we expect treated researchers to keep seeking publication in top-ranked sources, then these researchers could choose to submit to European journals.

Table C.5.2
ATT for Main Outcomes - Alternative Sample (Simple Selection)

				w/ US co-author			w/ US co-author	
	Publications	Citations	TopJournal	Publications	TopJournal	NewCoauth		co-authorHindex
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATT	-0.053	-3.741***	-0.036***	-0.015**	-0.004**	0.004	-0.014***	-0.386**
	(0.032)	(1.035)	(0.011)	(0.006)	(0.002)	(0.003)	(0.005)	(0.175)
Mean.Dep.Var.Pre	3.007	91.136	0.237	0.358	0.072	0.945	0.214	14.928
Pvalue.PreTrend	0.112	0.209	0.045	0.095	0.002	0.043	0.246	0.161
N.authors	47242	47186	47186	47242	47186	47186	47186	39623
N.obs	425178	300196	300196	425178	300196	300196	300196	251553
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cond. on publishing								Yes

Notes: Results are from DRDID regression, for each outcome relating to any type of co-author or only US co-authors for the treated and European co-authors for the control. The unit of observation is author by year and the sample period is from 2013-2021. The dependent variable is the total number of publications (1), citations (2), publications in top 5% journals (3), publications (4) and publications in top 5% journals (5) with US co-authors for the treated and European co-authors for the controls, probability of publishing with a new co-author (6) and with a new US co-author for the treated and new European co-author for the control (7), and average H-index of co-authors (8). Control variables account for author's publication characteristics overall and by category of co-author during 2008-2012, including number of publications, number of accumulated citations, number of top publications, co-author dependency, as well as number of co-authors, characteristics of the fields and topics of interest of the author. Standard errors (SE) are clustered by author. In parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Figure C.6.1
Share of All Journals in the Top 5 Percent of Journals by Publication Region (%)



Notes: The graph above represents the share of all sources of publications per region of publication that are in the top 5 percent of the distribution of citations received over a rolling window of 4 years, within their academic field.

Table C.6.1
ATT on Citations by Region of Affiliation of Authors of the Citing Papers

	citations	citations w/o China	citations (China)	citations (US)	citations (Europe)	citations (RoW)
	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-5.269***	-2.496***	-5.511***	-2.298***	-0.020	-2.356***
	(1.161)	(0.609)	(1.523)	(0.279)	(0.404)	(0.647)
Mean.Dep.Var.Pre	98.809	44.536	119.885	18.483	26.296	50.992
Pvalue.PreTrend	0.063	0.007	0.714	0.000	0.997	0.102
N.authors	39799	39799	39799	39799	39799	39799
N.obs	255653	255653	255653	255653	255653	255653
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cond. on publishing	Yes	Yes	Yes	Yes	Yes	Yes

Notes : Results are from DRDID regression, for each outcome relating to any type of co-author. The unit of observation is author by year and the sample period is from 2013-2021. The ouctome variable is the total number of citations received from this region, for respectively the whole world (1), the whole world excluding China (2), China (3), the US (4), Europe (5), and the rest of the world (6). Control variables account for author's publication characteristics overall and by category of co-author during 2008-2012, including number of publications, number of accumulated citations, number of top publications, co-author dependency, as well as number of co-authors, characteristics of the fields and topics of interest of the author. Standard errors (SE) are clustered by author. In parentheses: *** p<0.01, ** p<0.05, * p<0.1.

C.6.ii. Citations

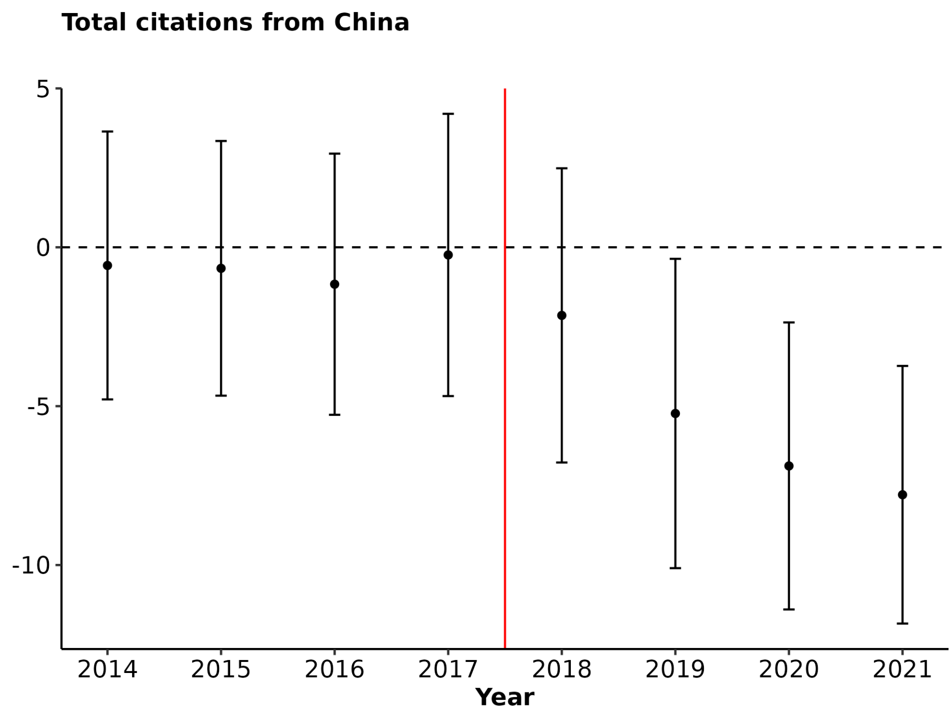
A related concern arises because there is a geographical component to citations. Qiu, Steinwender and Azoulay (2022) show that Chinese papers are under-cited in the US and that the probable explanation is a lack of ability to spread the information about their research through a research network. Therefore, the decline in collaboration with the US could lead to a mechanical decrease in citations. On the other hand, Chinese research has the largest home bias of all the countries they analyze. Indeed, the authors find that the share of home citations by Chinese researchers largely surpasses the real weight of Chinese research in Chemistry. Therefore, a drop in US citations of Chinese research after the China Initiative could be compensated by Chinese home citations. This home bias could come into play to lower the expected effect on citations of the China Initiative.

In order to address these concerns, we computed estimates of the effect of the China Initiative on citations, splitting them by affiliation country of authors of the citing paper. Table C.6.1 shows that the citations are decreasing for all regions aside from Europe. In order to subtract the home bias from the estimate, we use citations from all countries but China. These citations decline by 2.5, about 5 percent of the mean. The pre-trend from this regression is however very significant. When we focus on citations from the USA, we find a very strong effect of -12 percent. This figure probably captures — at least partly — the mechanical decrease stemming from the mechanism described by Qiu, Steinwender and Azoulay (2022). Due to the high pre-trend for these metrics, it is hard to quantify how much.

Nevertheless, the decline also appears in citations from China in spite of the home bias and from the rest of the world, in which we do not expect preferential treatment. These effects represent around 4 percent of the mean per year on average, about the same as the effect on total citations. Furthermore, the pre-trend completely disappears. This is also shown in Figure C.6.2 of the corresponding event-study graph of the effect on citations from China. This implies that the decrease that we observe in citations does not only reflect the decrease in awareness of Chinese research in the US but also a decrease in quality or, at least, in influence of research by treated authors, in China and the rest of the world.

w

Figure C.6.2
Effect on Number of Total Citations from Chinese Papers

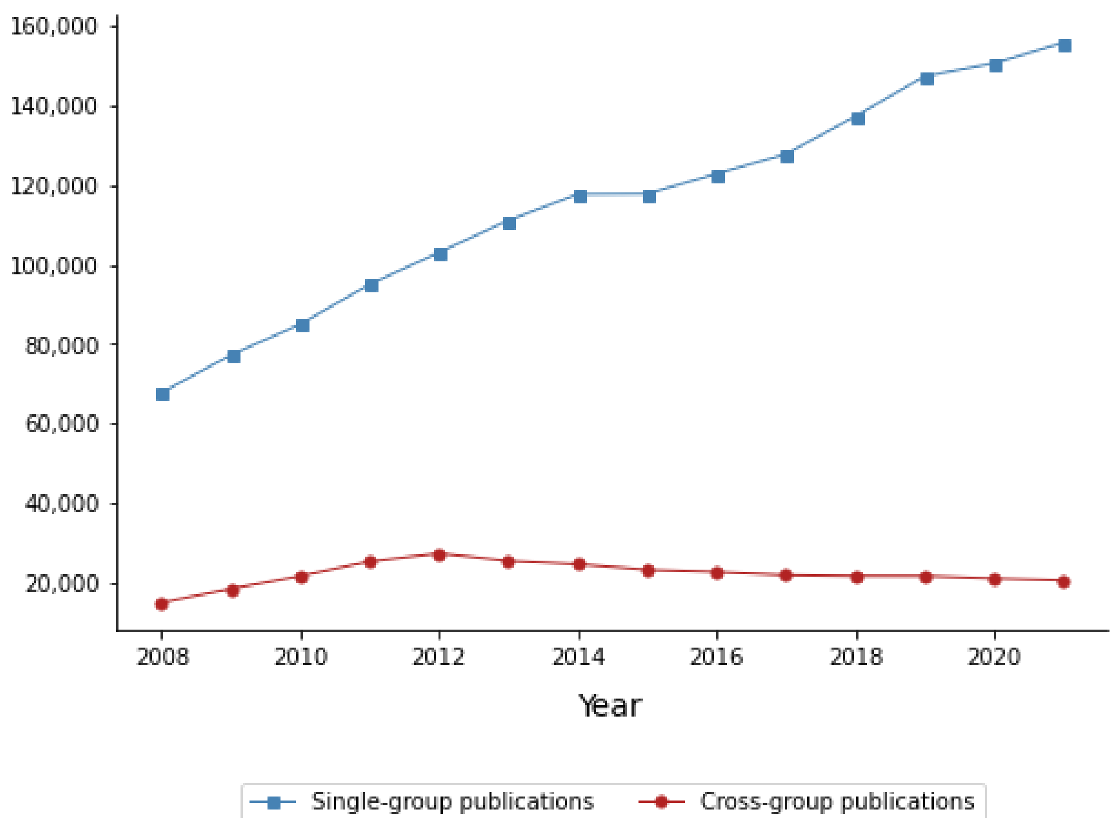


Notes: The graph above reports regression estimates for the difference in number of citations received from papers published by authors with a Chinese affiliation between the treated and control group for each year between 2013 and 2021. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), H-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the outcome variable.

C.7. Cross-group Spillovers

A consequence of the China Initiative could be that Chinese authors in our sample move from US to Chinese co-authorship. This type of reallocation is not a threat to our identification strategy unless treated authors increase their partnerships with Chinese authors who are in the control group. Given that control Chinese authors are comparable to treated authors, and that both work with international researchers, an increase in collaborations between the two could be a viable option for the treated authors, in order to replace US co-authors. However, Figure C.7.1 shows that while the number of papers published separately by authors of both groups is rising, this is not the case for papers authored by both a treated researcher and a control researcher. The number of such papers shows a slow decline after the selection period, and its trend does not seem to be affected by the China Initiative

Figure C.7.1
Single- and Cross-Group Publications between 2008 and 2021



Notes: The graph above report represents the share of publications by researchers of the sample that are co-authored respectively by at least one co-author of each group (blue) and by no authors of the same group (red).

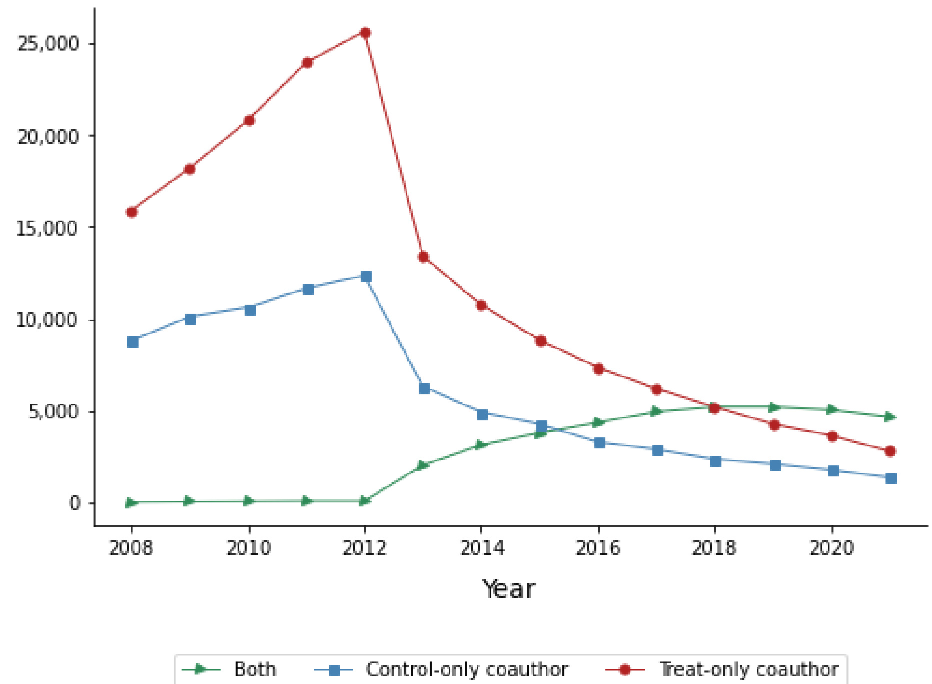
Another (milder) threat to our identification strategy would occur if instead of turning to control group authors, the treated group started collaborating more frequently with European co-authors of the treated group. In this case, there would be a negative effect of the shock on the treated group, leading us to underestimate the true effect of the China Initiative. We consider US co-authors of the treated Chinese researchers and European co-authors of control Chinese researchers during the selection period

2008-2012[31]. How many US co-authors in the former set keep co-authoring only with treated Chinese authors? How many European co-authors in the latter set keep co-authoring only with control Chinese researchers? How many US and European researchers start co-authoring with both treatment and control Chinese researchers? Figure C.7.2 shows the evolution of the number of co-authors in each category. If treated Chinese authors were co-authoring more with long-term co-authors of Chinese authors in the control group, we would observe a trend break at the moment of the China Initiative in the "Both" and the "Control-only co-author" lines; this does not appear to be the case.

[31]Due to attrition of the sample of co-authors, if we condition on being a co-author before 2018, the change in trend that we want to check for is going to be partly absorbed by a mechanical drop in the number of co-authors.

Figure C.7.2

Number of US and European Co-Authors from the Selection Period, who Continue to Collaborate with Treated/Control/Both Groups



Notes: The graph represents the number of active US and European co-authors of the sample during the selection period (2008-2012) each year by each of the following categories: has only published with treated authors (red), has only published with control authors (blue), has published with both (green).

C.8. Publication lags

Research projects, especially those that are most impactful, can take years before completion. Thus, one may reasonably wonder how a recent shock like the China Initiative could have had an impact on the quality and direction of Chinese research that could have already been detected in our data. However, the following considerations help address this timing concern. First, the China Initiative is likely to have interrupted research projects with US co-authors which were close to completion, thereby affecting the volume and quality of Chinese publications[32]. Second, the vast majority of Chinese authors in our sample produce at least one publication per year on average. Note first that peer review processes differ widely across disciplines and can be quite short in some fields. Surveying 3500 scientists of different fields, Huisman and Smits (2017) find that the average review duration for accepted papers across all fields is 17 weeks, ranging from a minimum of 12 weeks in medicine to a maximum of 25 weeks in economics and business. Excluding social sciences, the average duration of the peer-review process in all fields is of 22 weeks. In all fields aside from Psychology, around 80 percent of all papers are published within six months after submission. Table C.8.1 provides statistics on the research productivity of Chinese authors in our sample. On average, the time an author takes before publishing again after a given publication year amounts to 1.3 years, with a median of 1 year. A treated researcher (resp. control) publishes with

[32] Aghion et al. (2019) show that more earmarks to US states from the Senate's Appropriation committee, has a positive effect of university patents after only one year, presumably for the same reason: the resulting additional funding to research and development, helps complete innovative projects already started.

a US co-author (resp. European) every two years on average. The same observation can be made when looking at publications by the two groups in the top 1 percent cited papers and top 5 percent of journals. Overall, the frequency of publications by researchers in the sample is sufficiently high that the shock caused by the China Initiative could have shown an impact after only one year. This observed frequency of publications is consistent with the view that researchers in our sample pursue several ongoing projects at the same time. Each project may take more than one year to be completed, yet it is quite realistic that the China Initiative shock did affect the flow of (high-quality) publications with US co-authors.

We also show that treated Chinese authors have fewer new and short-term co-authors from the US compared to control Chinese authors and their European co-authors following the shock. Furthermore, they are more likely to publish with a long-term US co-author in the years right before the shock. This in turn might be explained by the fact that treated Chinese researchers anticipated the shock and therefore decided to give priority to completing their long-term projects with their existing US co-authors, at the expense of projects with more recent co-authors. Due to the China Initiative, they are also unable to find new co-authors of the same quality outside of the US, which explains why co-author quality remains low instead of reverting to the pre-shock level.

Table C.8.1

Descriptive Statistics - Average Years between Two Years of Publication, per Author in the Sample - 1999-2017

Statistic	Min	Median	Mean	St. Dev.	Max
Average time between publications	1.000	1.200	1.332	0.446	9.000
Average time between publications with same country co-author	1.000	1.571	2.030	1.328	12.000
Average time between publications with Chinese co-author	1.000	1.214	1.373	0.517	12.000
Average time between publications in top 5% most cited journals	1.000	2.000	2.387	1.785	17.000
Average time between top 1% cited publications	1.000	2.000	2.559	1.954	15.000

C.9. Citation analysis and data truncation

Total citations received by papers that a researcher publishes in a given year are one of our main measures of publication quality. However, the estimate obtained on this measure could be biased due to the shape of the distribution of citations received over time per paper. Because the number of citations accumulated over time typically increases non-linearly, the difference in citations for papers of different qualities increases over time. Unfortunately, controlling for year fixed effects is not enough to take this non-linear shape into account as we are estimating the effect of the China Initiative parametrically as a constant per year. As a consequence, there could be a bias in the estimated effect. (Note that our alternative measures of quality, based on journal quality, do not suffer from this type of bias.)

Consider the comparison between a treated Chinese author and a control Chinese author. Before the shock, the two authors publish papers of the same quality. After the shock, the control author keeps publishing papers of the same quality whereas the treated author publishes papers of lower quality. If we compare the citations received by the new papers produced by the two authors respectively, early after the shock, we shall observe a *smaller* difference than that between the citations received for the same papers later in time. By the same token, more recent papers suffer from the so-called truncation bias in citations.

In other words, the difference in citations between the two papers increases over time. If it is measured later, for the same quality and the same shock, the observed effect is larger. Given that over the years, we see less and less of the actual distribution of citations for papers of the treated and the control, we could expect to underestimate the shock in absolute value as we move further away from 2018.

This truncation bias in patenting has been well identified, see for example Hall, Jaffe and Trajtenberg (2001) and Hall, Jaffe and Trajtenberg (2005). And the bias that truncation induces in the distribution of citations received over time due to the skewness of that distribution[33] is known, not only to economists but also in scientometrics[34].

Yet, Figure C.9.1 shows that at the paper level, the linear approximation is not unrealistic for citations received in the first 10 years upon publication of the paper for papers published between 2000 and 2010. This is also the case for authors of the sample, who receive more citations on average than the majority of Scopus authors. We can see that after 6 years, the difference between these better-cited authors and the majority starts to increase, but not exponentially.

In accordance with the literature, and in order to remove this potential bias, we perform several transformations to our measure of citations and show that our results and interpretations are constant through the different specifications. We summarize the different variable transformations in table Table C.9.1.

The first transformation that we apply is truncation. We only consider citations received during a given period. This will eliminate part of the bias, even though recent papers' citation record will be "more truncated" than the rest (for instance, we will only observe citations in 2021 and 2022 for a paper published in 2021, while we will observe citations from 2017 to 2022 for a 2017 paper). However, this counteracts a part of the bias. We select citations received within 10, 5, and 1 year(s) of publication. The only one that yields no significant negative result (of a magnitude of around 4 percent of the average value in the pre-shock period) is the 1-year metrics. We surmise that this is due to noise and the monthly timing of publication (a paper will not receive the same amount of citations if it was published in January or December of the same year).

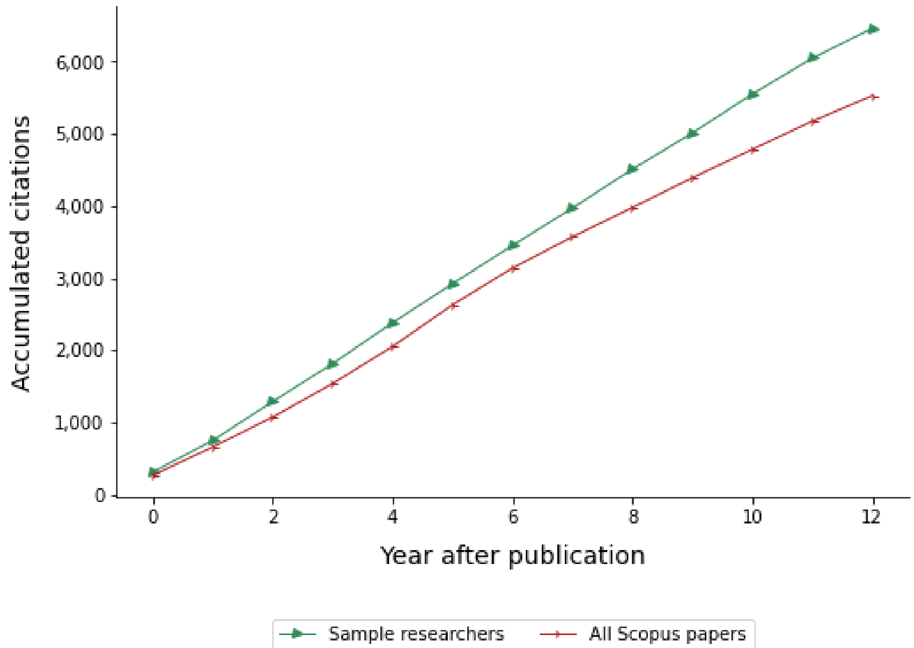
The second type of transformation we apply to the metrics is normalization at the level of all papers (not only those of sample authors) for a given year. We consider two normalizations: subtracting the

[33] Redner (1998) approximates the tail of the distribution with a power law, Lehmann, Lautrup and Jackson (2003) find that either a power-law or stretched exponential fit the data, Vieira and Gomes (2010) find that a double exponential-Poisson law fits best the empirical distribution.

[34] Hassan et al. (2017) use the hit rate of papers, Kaur, Radicchi and Menczer (2013) cite a variety of field/year normalizations.

Figure C.9.1

Average Citations Received per Year after Publication
for Articles Published between 2000 and 2010



Notes: The graph above reports the number of citations received for papers published between 2000 and 2010, respectively for all papers in Scopus and papers published by authors of the sample. Our calculation includes zeros for years in which a paper has received no citations.

Table C.9.1
ATT on Different Metrics of Citations

	Citations	Citations (10y)	Citations (5y)	Citations (1y)	Citations (Norm.)	Citations/Average	FWCI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ATT	-3.862***	-0.755***	-0.521***	-0.046	-0.089***	-0.220***	-0.170***
	(0.783)	(0.201)	(0.155)	(0.039)	(0.029)	(0.067)	(0.055)
Mean.Dep.Var.Pre	63.597	16.665	12.624	2.336	0.601	4.074	3.541
Pvalue.PreTrend	0.006	0.010	0.053	0.005	0.312	0.200	0.012
N.authors	41063	41063	41063	41063	41063	41063	41063
N.obs	369567	369567	369567	369567	369567	369567	369567
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes : Results are from DRDID regression, for each outcome relating to any type of co-author or only US co-authors for the treated and European co-authors for the control. The unit of observation is author by year and the sample period is from 2013-2021. The dependent variable is the total number of citations (1), citations received within 10, 5 and 1 years after publication ((2)-(4)), citations demeaned and divided by the standard error of the distribution of citations to publications from the same year (6), citations divided by the average number of citations to papers published the same year (7), and field-weighted-impact citations (based on 4 years calculations). Control variables account for author's publication characteristics overall and by category of co-author during 2008-2012, including number of publications, number of accumulated citations, number of top publications, co-author dependency, as well as number of co-authors, characteristics of the fields and topics of interest of the author. Standard errors (SE) are clustered by author. In parentheses: *** p< 0.01, ** p< 0.05, * p< 0.1.

mean and dividing the difference by the standard error of the yearly distribution, or simply dividing by the mean. Both devices allow us to compare how papers rank within their publication cohort, which in turn helps us deal with the truncation issue. Both results are also in line with the results on unprocessed citations in terms of sign. The result for the first normalization has a far larger magnitude. This could be due to the underestimation issue mentioned above. Finally, we also use the Field-weighted impact citation metrics provided by Scopus. The result is unchanged with a magnitude of around 4.8 percent.

C.10. Placebo test

Table C.10.1 presents results from using the years 2001-2005 as the placebo pre-shock period, and 2010 as the placebo shock year, otherwise using the same methodology as in our core analysis. We see no significant effect of the placebo shock on the volume and quality of publications by "treated" Chinese researchers. Figure C.10.1 displays the event study graphs for the three main outcomes.

Table C.10.1
ATT for Main Outcomes - Placebo Sample

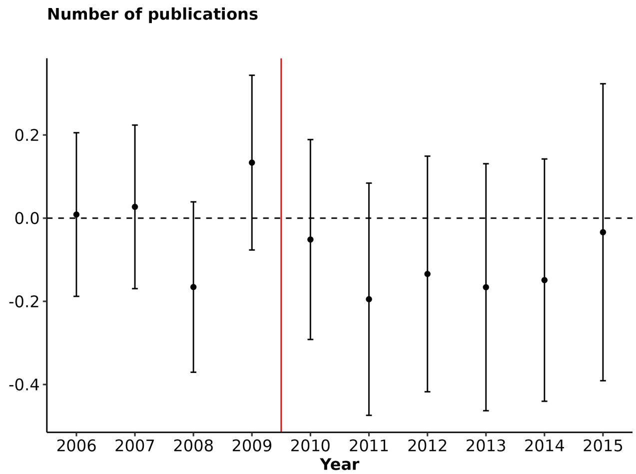
	Publications		Citations		TopJournals		CitationsChina	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATT	-0.066	-0.127	-3.411	-6.483	0.026	0.026	1.546	-3.652
	(0.091)	(0.140)	(3.981)	(4.915)	(0.022)	(0.022)	(4.447)	(8.348)
Mean.Dep.Var.Pre	4.115	4.115	119.601	119.601	0.136	0.136	117.750	117.750
Pvalue.PreTrend	0.094	0.217	0.284	0.118	0.036	0.036	0.702	0.992
N.authors	8589	8573	8573	8573	8573	8573	8573	8573
N.obs	94479	79636	79636	79636	79636	79636	79636	79636
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cond. on publishing		Yes		Yes		Yes		Yes

Note:results are from DRDID regression, using year 2010 as the year of a placebo shock, for each outcome for the whole sample and conditioning on having published during the year of observation. The unit of observation is author by year and the sample period is from 2013-2021. The dependent variable is the number of publications (columns (1)-(2)),number of citations for publications from that year (columns (3)-(4)), rate of publications on top 5% journals (within subject) from that year (columns (5)-(6)), citations received from papers with at least of Chinese author (columns (7)-(8)). Control variables account for author's publication characteristics overall and by category of co-author during 2001-2005, including number of publications, number of accumulated citations, number of top publications, co-author dependency, as well as number of co-authors, characteristics of the fields and topics of interest of the author. Standard errors (SE) are clustered by author. In parentheses: *** p<0.01, ** p<0.05, * p<0.1.

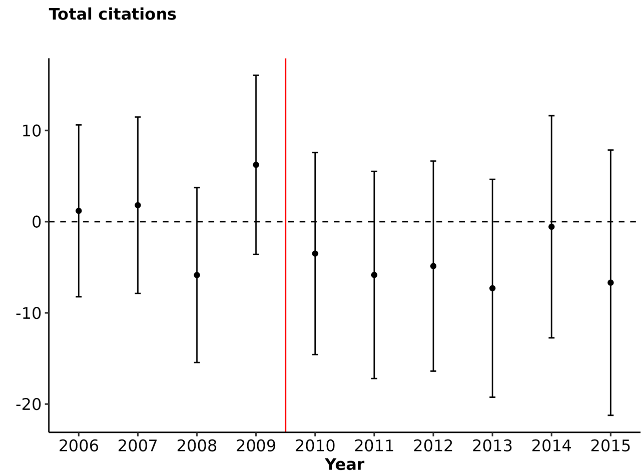
Figure C.10.1

ATT on Total Publication (a), Total Number of Citations (b), and Publications in Top 5 Percent of Journals (c) for a Placebo Shock in 2010

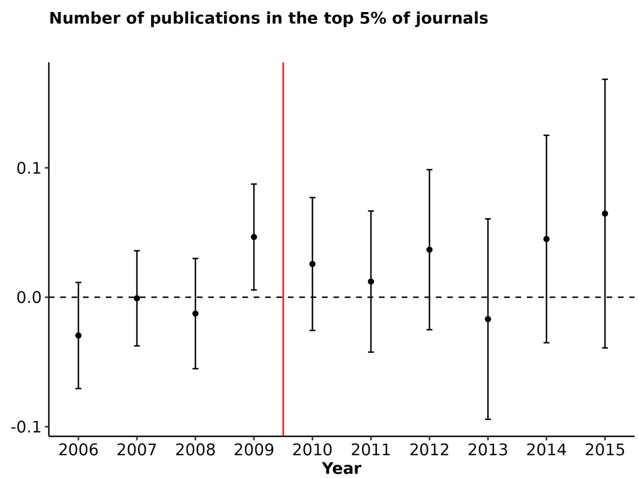
(a)



(b)



(c)

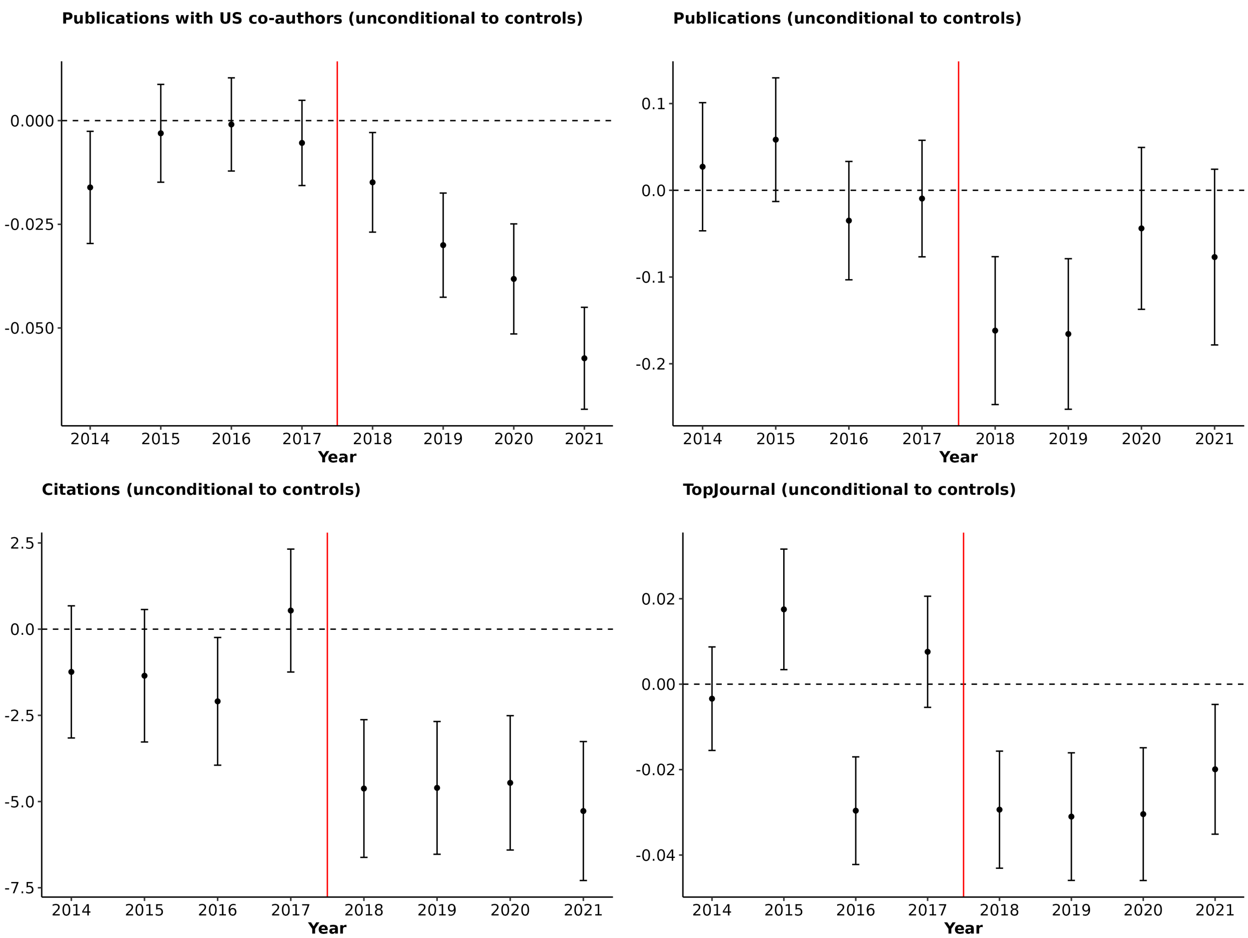


Notes: The graph above reports regression estimates for the difference in the different outcomes between the placebo-treated and control group for each year between 2001 and 2015, for a placebo shock happening in 2010. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), H-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the outcome variable.

C.11. Unconditional parallel trends

Figure C.11.1 provides the event study graphs for the regressions on productivity outcomes in which the parallel trends assumptions is unconditional on controls. We can see that the controls appear to be necessary for the parallel trends assumption to hold, mainly because the estimated unconditional effects vary more from year to year. At the same time, there is no significant negative trend in the pre-period that can explain the negative development in the post-period. The average difference between the pre- and post-period is similar to that in our main specification.

Figure C.11.1
Effect on Productivity of Treated Researchers



Notes: The graph above reports regression estimates for each year between 2013 and 2021, for the following outcomes: the difference in publications with US co-authors for treated Chinese authors and European co-authors for control Chinese authors (top-left), the difference in total publications between treated and control authors (top-right), the difference in total citations between treated and control authors (bottom-left) and the difference in publications in the top 5% most cited journals between treated and control authors (bottom-right). Those estimates are obtained with the method of Callaway and Sant'Anna (2020), without using any controls. The years 2016 and 2017 are considered a period of potential anticipation. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the outcome variable.

C.12. Co-author Reallocation

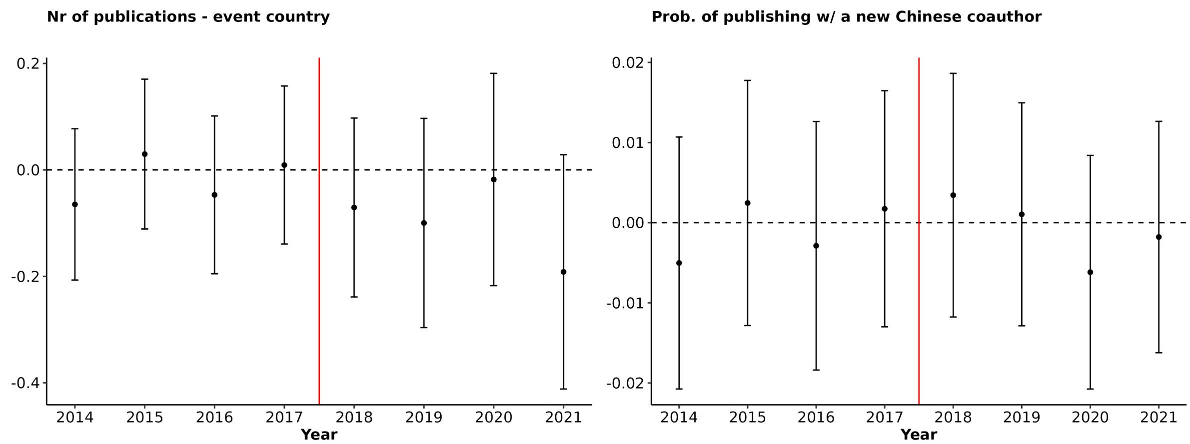
This subsection discusses co-author reallocation. We find that the treated authors reduce their new collaborations with US researchers. We now investigate how they reallocate collaborations with researchers from other countries. We cannot easily use our research design to estimate whether treated authors, who publish with US authors in the pre-period, publish more with European co-authors as a result of the China Initiative. The reason is that the symmetric outcome from the control authors, who publish with Europeans in the pre-period, is whether they publish more with US authors in the post-period. However, control Chinese authors are presumably also hindered in their ability to collaborate with US researchers following the shock. Hence, the symmetric outcome is also affected by the China Initiative and cannot be used as control outcome.

However, publications of Chinese researchers with co-authors from countries or regions outside the US and Europe are not subject to this bias. Figure C.12.1 shows evidence that there is no reallocation towards Chinese co-authors, be it in number of publications or in the probability of adding a new Chinese co-author. Moreover, Figure C.12.2 shows that there is a marginally significant negative effect of the China Initiative shock on the reallocation towards the rest of the world. Similarly, Table C.12.1 reports the estimate for the ATT on publications in top 5 percent cited journals with co-authors from China and the rest of the world. The estimates are negative, and the effect is significant for publications in top 5 percent cited journals with co-authors from the rest of the world.

The result shows that treated authors were not able to reallocate towards regions outside the US and Europe. Perhaps they were able to reallocate towards European co-authors, which we cannot test using our design. However, as we show in Section 4, this does not compensate for the loss in paper quality due to the loss of US co-authors. It is an open question why the loss of US co-authors may cause a loss of collaborations also with researchers from other countries. A potential explanation is that the lost projects involving US co-authors also meant that the treated authors lost co-authorship ties with researchers from other regions. More generally, losing ties to US researchers could imply reduced access to resources of these researchers, including their co-authorship networks.

Figure C.12.1

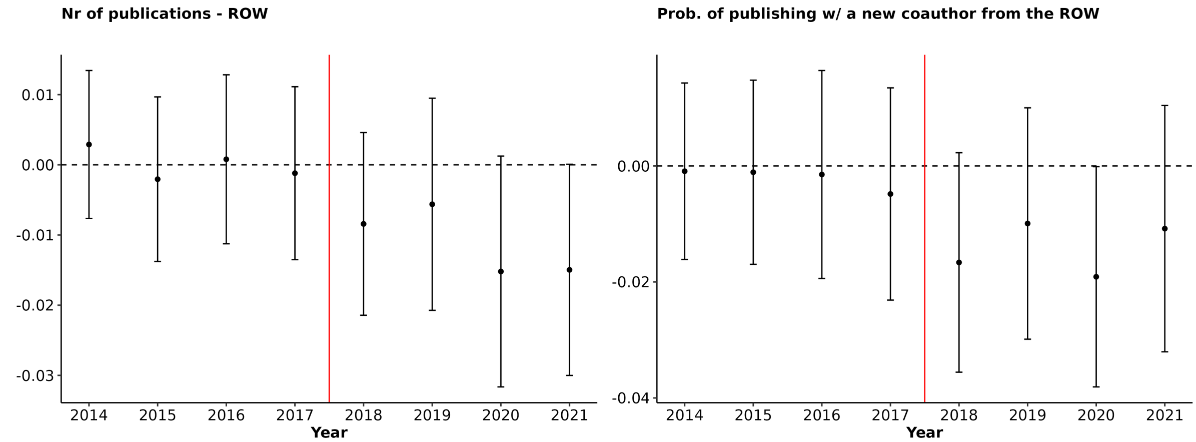
Effect on Reallocation to Chinese Co-Authors: Number of Publications and Having a New Chinese Co-Author



Notes: The graphs above report regression estimates both for the difference in the number of publications with a Chinese co-author (left) and in the probability of publishing with a new Chinese co-author (right) between the treated and the control group for each year between 2013 and 2021. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received and H-index of researchers and their co-authors in the selection period (total, with US co-authors for the treated and European for the control, with Chinese and rest of the world co-authors), first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and expected progression of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the number of publications.

Figure C.12.2

Effect on Reallocation to ROW Co-Authors: Number of Publications and Having a New ROW Co-Author



Notes: The graphs above report regression estimates both for the difference in the number of publications with a co-author from the rest of the world(left) and in the probability of publishing with a new co-author from the rest of the world(right) between the treated and the control group for each year between 2013 and 2021. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received and H-index of researchers and their co-authors in the selection period (total, with US co-authors for the treated and European for the control, with Chinese and rest of the world co-authors), first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and expected progression of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the number of publications.

Table C.12.1

ATT on Publications and Top Publications by Place of Affiliation of Co-Author

	with coau from China	with coau from ROW	with coau from China	with coau from ROW
	publications	publications	nr_source_top5pct	nr_source_top5pct
	(1)	(2)	(3)	(4)
ATT	-0.065**	-0.004*	-0.009*	-0.000*
	(0.030)	(0.002)	(0.005)	(0.000)
Mean.Dep.Var.Pre	2.737	0.074	0.134	0.010
Pvalue.PreTrend	0.858	0.741	0.139	0.726
N.authors	41063	41063	41063	41063
N.obs	369567	369567	369567	369567
Controls	Yes	Yes	Yes	Yes

Notes : Results are from DRDID regression, for each outcome relating to any type of co-author or only US co-authors for the treated and European co-authors for the control. The unit of observation is author by year and the sample period is from 2013-2021. The dependent variables are respectively the number of publications with Chinese co-authors (1), with co-authors from the rest of the world, i.e. not the US, Europe or China (2), and publications in top 5% cited journals with Chinese co-authors (3) and rest of the world co-authors (4). Control variables account for author's publication characteristics overall and by category of co-author during 2008-2012, including number of publications, number of accumulated citations, number of top publications, co-author dependency, as well as number of co-authors, characteristics of the fields and topics of interest of the author. Standard errors (SE) are clustered by author. In parentheses: *** p<0.01, ** p<0.05, * p<0.1.

C.13. Heterogeneity

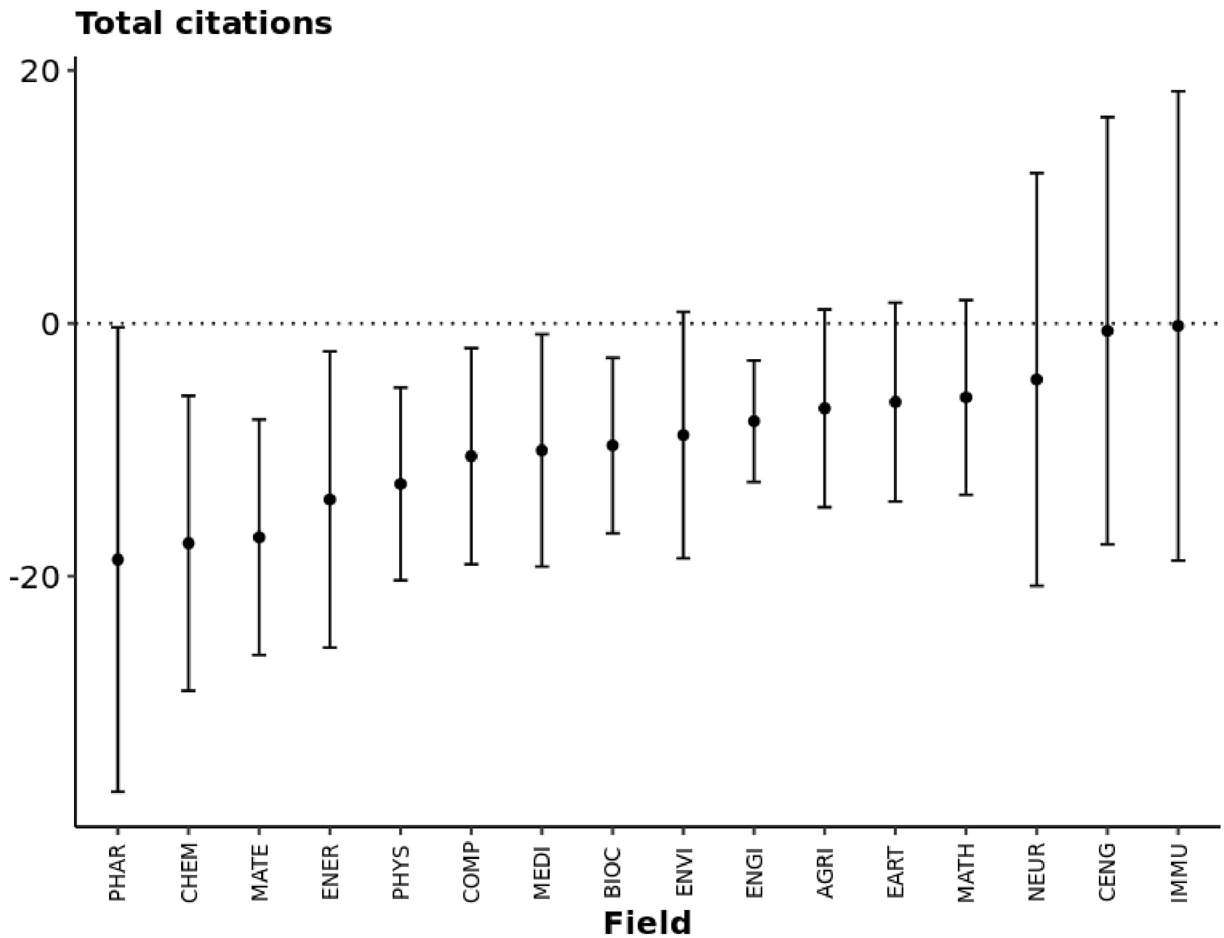
Additional results by field: Figure C.13.1 complements Figure VII by showing that our results also hold on total citations received by researchers publishing in a given field. Figure C.13.2 and Figure C.13.3 further show that within each field, the effect is driven by the top quantile, proving that the heterogeneity that we observe based on citations received in the selection period is not driven by field composition in these quantiles. Figure C.13.4 presents the results shown in Figure VII using a different ordering. The effects on total and top journal publications are ordered by European dominance in each fields. A slight negative correlation between the size of the ATT and European dominance in each field is observed, though it is less pronounced than the correlation we present in our primary analysis.

Heterogeneity by US-coauthor role: We categorize each treated Chinese author based on whether they rely primarily on US (EU) coauthors acting as first author, middle authors or last authors. We categorize dependency types in two steps. First, we compute a role-specific C-index for each individual that captures the contribution by US (EU) authors in each role :

$$C_i^k = \sum_{l \in A_i} \omega_{il} \sigma_l^k, \quad k \in \{first, mid, last\} \tag{2}$$

Where the notation follows that of equation 1, except that σ_l^k is now a dummy that indicates the presence of coauthor of role k from the collaboration country. Second, we assign each researcher to their primary dependency type based on which role-specific C-index has the highest value.

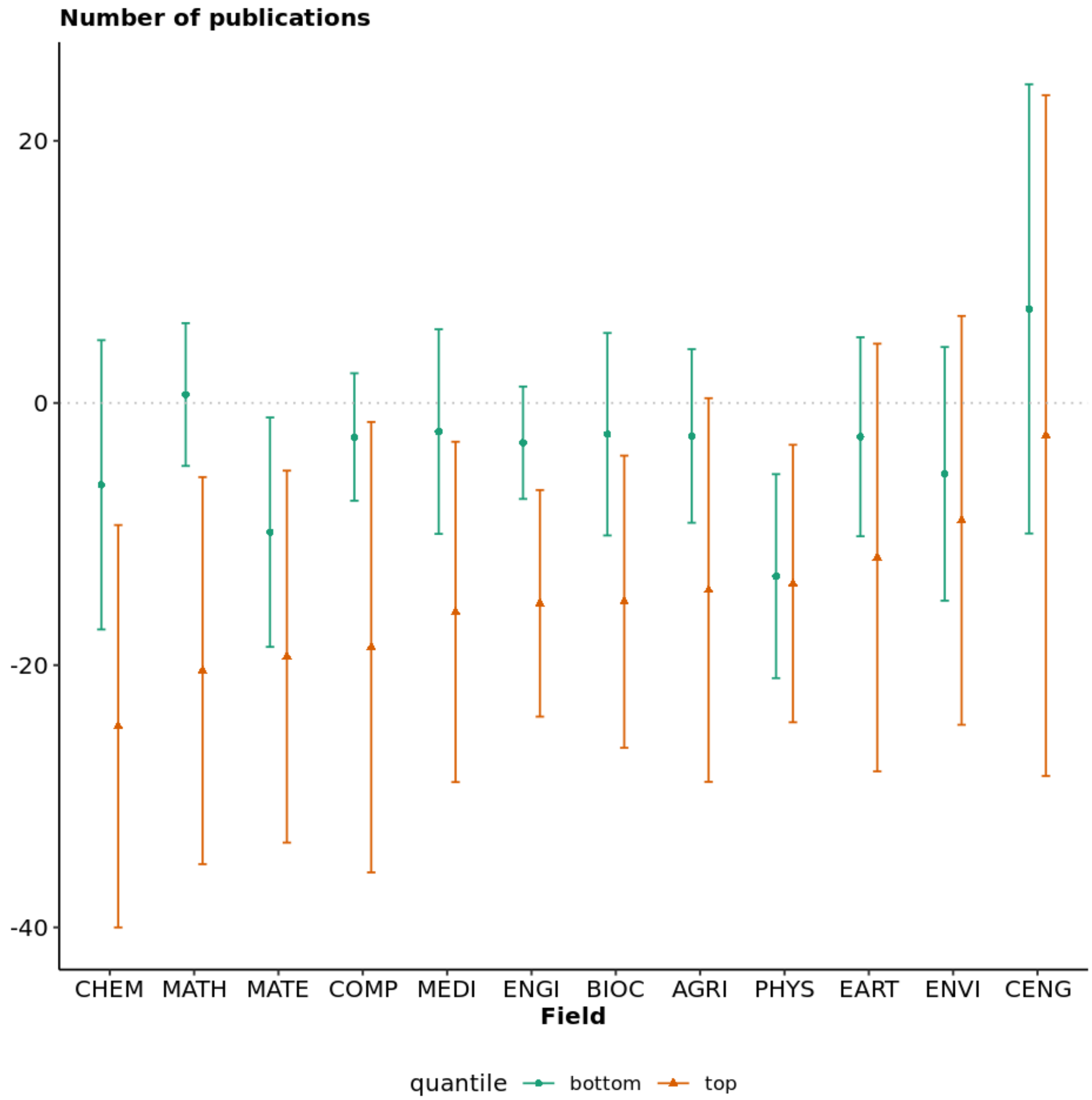
Figure C.13.1
Effect of the China Initiative on Citations: Effect by Field



Notes: The graph above reports regression estimates for the difference in the total number of citations for treated researchers writing in each field compared to their counterparts in the control group on average over the period 2018-2021 compared to the period 2013-2017. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), H-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the outcome variable.

Figure C.13.2

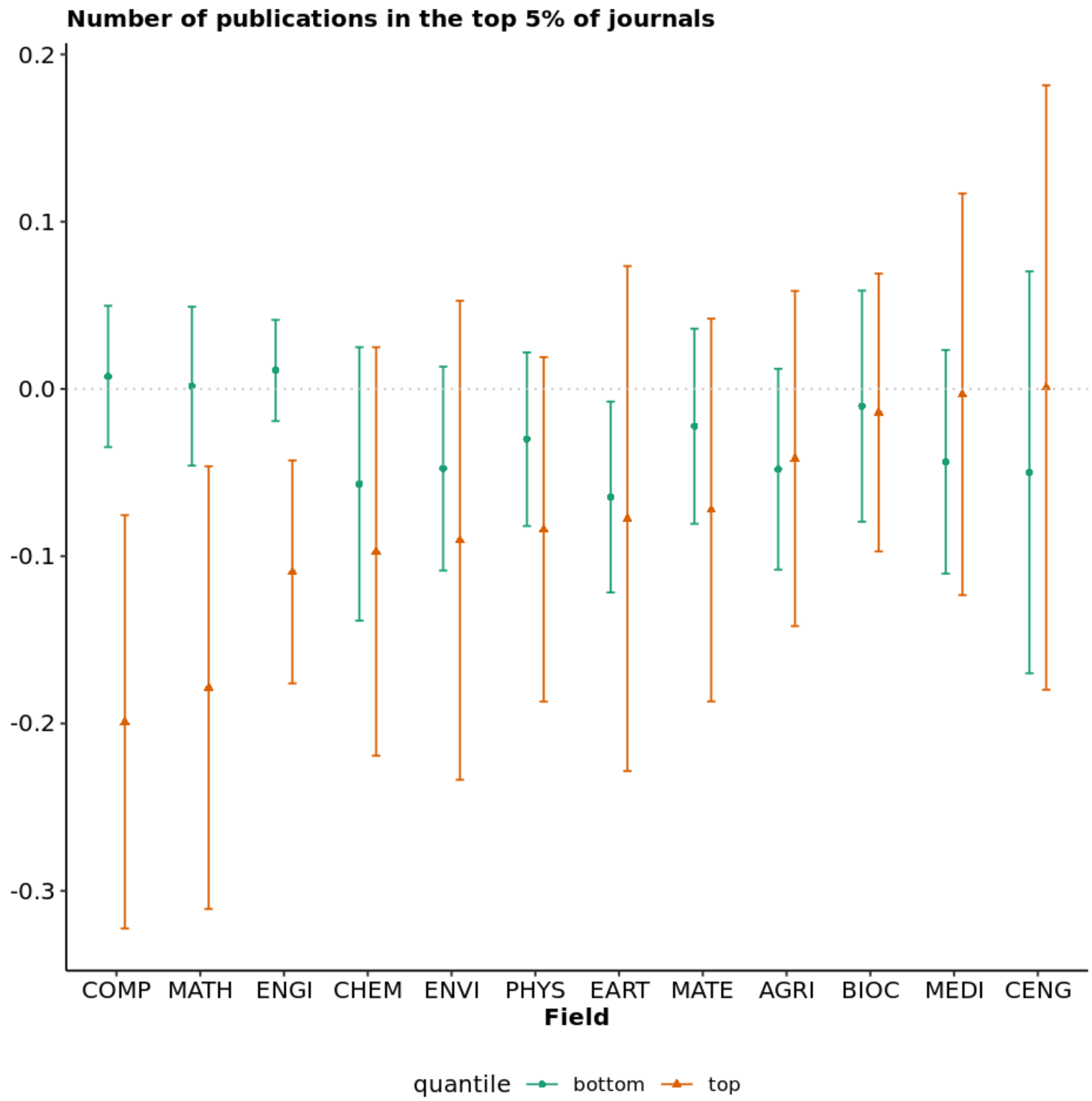
Effect of the China Initiative on Publications: Effect by Field and Quantile



Notes: The graph above reports regression estimates for the difference in the total number of publications for treated researchers writing in each field compared to their counterparts in the control group on average over the period 2018-2021 compared to the period 2013-2017. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), H-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the outcome variable.

Figure C.13.3

Effect of the China Initiative on Publications in Top Journals:
Effect by Field and Quantile



Notes: The graph above reports regression estimates for the difference in the total number of publications in the top 5 percent of journals for treated researchers writing in each field compared to their counterparts in the control group on average over the period 2018-2021 compared to the period 2013-2017. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), H-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the outcome variable.

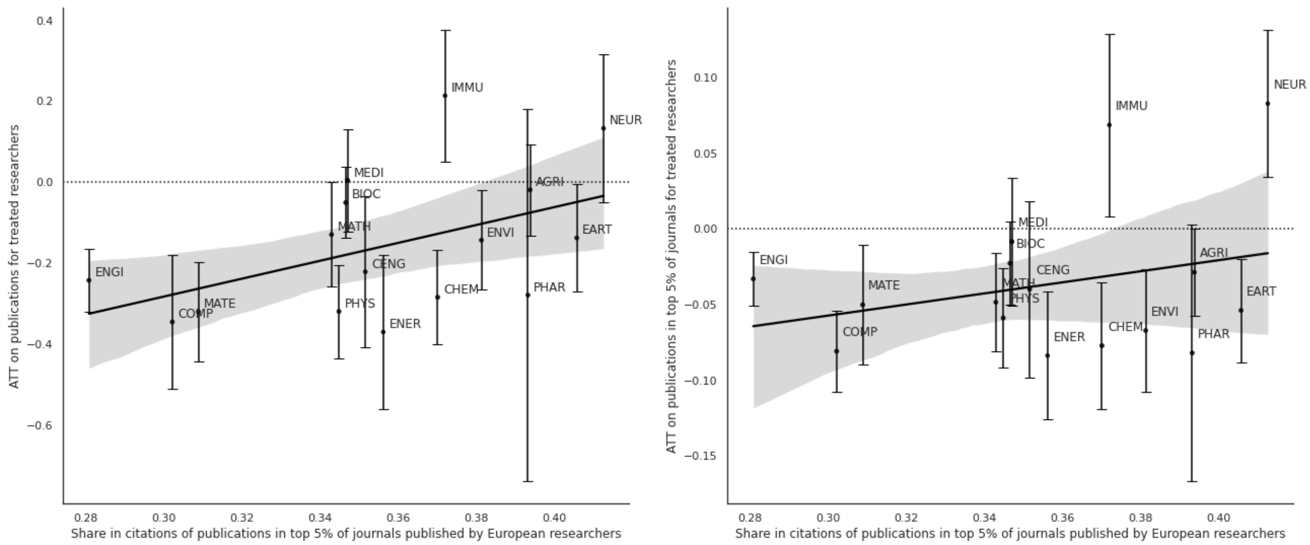


Figure C.13.4

Effect of the China Initiative on Publications and Publications in Top 5 Percent Most Cited Journals: Effect by Field, Compared to European Dominance by Field

Notes: The graph above reports regression estimates for the difference in the total number of publications (left panel) and publications in the five percent most cited journals (right panel)for treated researchers writing in each field compared to their counterparts in the control group on average over the period 2018-2021 compared to the period 2013-2017. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), h-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers. The dataset is winsorized at the top and bottom of the distribution at the 2.5 percent level for the outcome variable. These estimates are plotted against the share of all citations to publications released between 2000 and 2012 in top 5 percent journals in that field that accrue to papers with at least one Europe-based author.

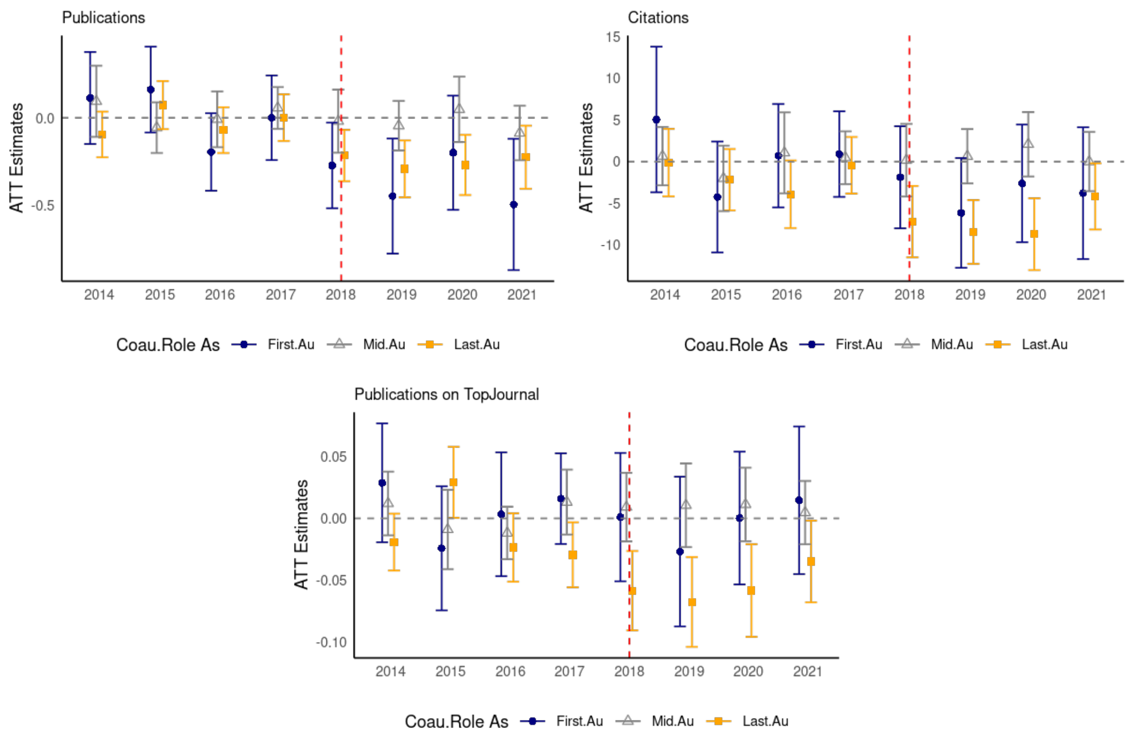


Figure C.13.5
Effect on Productivity by Coauthor Role

Notes: The graph above presents event study results corresponding to Table VI For each outcome measure, we divide the sample into three subgroups based on the primary US-coauthor role documented during 2008-2012. Using the Doubly Robust Difference-in-Differences (DR-DID) method, we estimate the dynamic effects for each subgroup over the period 2014-2021.

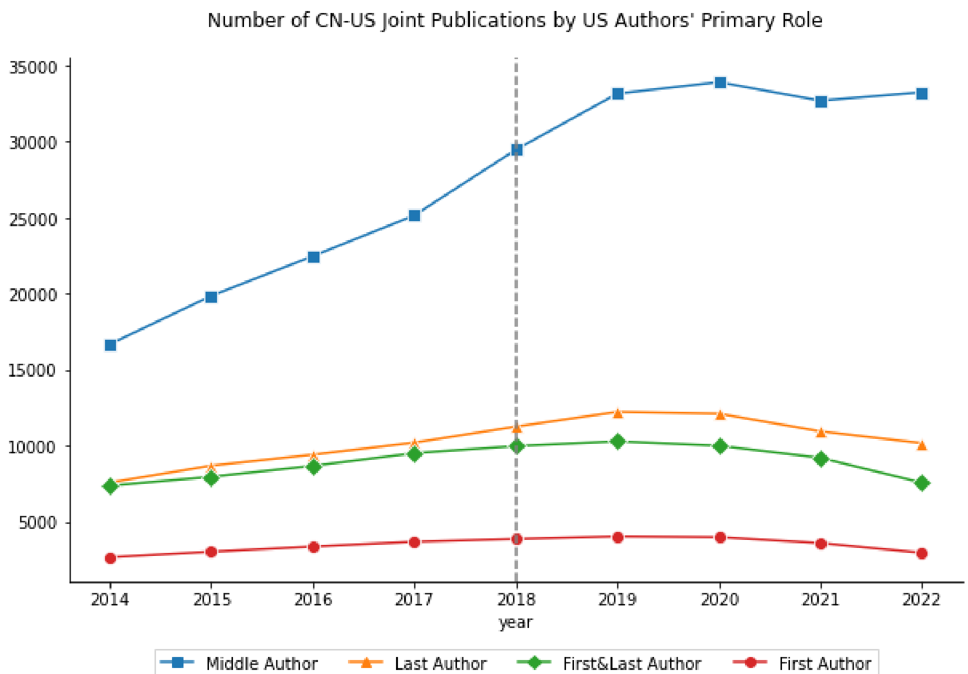


Figure C.13.6
Number of CN-US Joint Publications by US Author's Primary Role

Notes: This graph uses the complete set of research collaborations between Chinese and U.S. researchers as documented in the Scopus database. For each publication, U.S. author contributions are classified into four mutually exclusive categories based on authorship position: (1) first author - U.S. researcher as first but not last author; (2) last author only - U.S. researcher as last but not first author; (3) first and last author - U.S. researchers in both first and last positions; and (4) middle author - U.S. researchers only in middle positions.

D. Appendix to Section 5

In this Subsection, we assess the effect of the China Initiative on the direction of Chinese research and in particular in the decision to research applied or fundamental subjects. This Subsection relates the role of openness and freedom in basic research (Aghion, Dewatripont and Stein (2008)).

Recent work by Liu and Ma (2021) points at a positive effect of deglobalization on the basicness of innovation. It could also be the case that, following the China Initiative, treated Chinese researchers would decide to rely more on local research inputs which in turn should encourage more basic research in China. But it may also be the case that, facing restricted access to high-quality US co-authors, treated Chinese researchers would focus primarily on replicating or adapting existing ideas and findings, thereby producing more applied research. Here we look at the extent to which the China Initiative shock would affect the basicness of research by treated Chinese authors. Our primary measure of research basicness is the CHI Index, developed by CHI Research and used for instance by Lim (2004) and Murray et al. (2016). This index assigns to each journal a value of basicness of research, from 1 to 4, in which 1 corresponds to the highest degree of applied science and 4 to the highest degree of fundamental research. We match the journals that are assigned a value in the CHI index scale to their identifier in Scopus. Then, we count the number of times an author published an article in a given year in a journal identified by CHI as being fundamental, and we also consider an indicator equal to one whenever she published any such article at all during the year. Main results regarding research directions are displayed in Table D.0.1. We find no change in the overall number of basic publications by treated Chinese authors compared to control Chinese authors after the shock. However, we see a decline in the probability of publishing in a basic journal for treated Chinese authors, both globally and with US co-authors after the shock, compared to the evolution of the the probability of publishing in a basic journal by control Chinese authors, both globally and with European co-authors. This effect is however only significant at the 10% level.

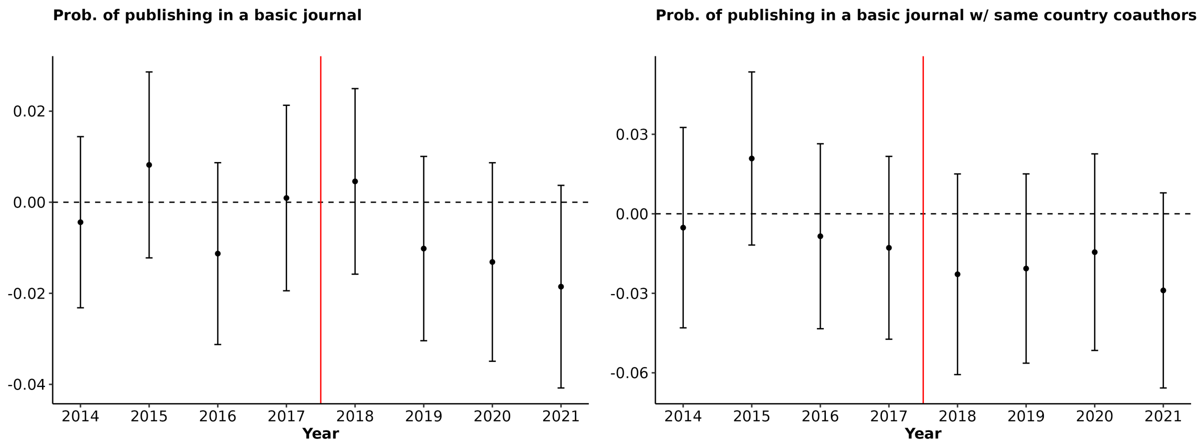
Table D.0.1
Average Treatment on the Treated (ATT) on Research Direction-Related Outcomes

			with US co-authors	
	any basic publication	basic publications	any basic publication	basic publications
	(1)	(2)	(3)	(4)
ATT	-0.011*	-0.010	-0.019*	-0.003
	(0.006)	(0.018)	(0.010)	(0.014)
Mean.Dep.Var.Pre	0.249	0.745	0.142	0.293
Pvalue.PreTrend	0.492	0.883	0.541	0.901
N.authors	41017	33681	27005	18925
N.obs	261531	153082	92185	47713
Controls	Yes	Yes	Yes	Yes

Notes: Results are from DRDID regression, for each outcome relating to any type of co-author or only US co-authors for the treated and European co-authors for the control. The unit of observation is author by year and the sample period is from 2013-2021. The dependent variable is the probability of publishing in a journal classified as basic by CHI research (columns (1) and (3)), the number of publications in such journals (columns (2) and (4)). Control variables account for author's publication characteristics overall and by category of co-author during 2008-2012, including number of publications, number of accumulated citations, number of top publications, co-author dependency, as well as number of co-authors, characteristics of the fields and topics of interest of the author. Standard errors (SE) are clustered by author. In parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Figure D.1

Effect on Probability of Publishing in a Basic Journal:
Global and US Compared to Control with Europe



Notes: The graphs above report regression estimates both for the difference in the probability of publishing in a journal flagged as basic by CHI research (left) and of doing so with a US co-author for the treated and a European co-author for the control (right) between the treated and the control group for each year between 2013 and 2021. Those estimates are obtained with the method of Callaway and Sant'Anna (2020). Propensity scores are computed using publications, publications in the top journals, citations received in the selection period (total and with US co-authors for the treated and European for the control), H-index of researchers and their co-authors in the selection period, first year of publication on Scopus, dependency on co-authors, number of co-authors in the selection period, main fields of activity, exposure to US or European dominance and the Scopus metrics of prominence of topics of interest of researchers.