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The Rise of China and the Global Production of Scientific Knowledge*

Hyejin Ku[†] Tianrui Mu[‡]

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Abstract: This paper examines how China's growing research capabilities impact global research universities across scientific fields. Using bibliometric data from 1980 to 2020, we assess the effects of the "China shock" on high-impact publications, novel concepts, and citation patterns. Our analysis reveals a positive net effect in Chemistry and Engineering & Materials Science (EMS), but a negative effect in Clinical & Life Sciences (CLS). In other fields, the effects are mostly positive but imprecise. We highlight the coexistence of competition and spillover effects, with their relative strength shaped by field characteristics, such as expansion potential and the quality of China's research.

Keywords: China shock in science, knowledge production, ideas, competition, spillovers

JEL codes: J24, I23, O31

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1. Introduction

In January 2025, DeepSeek, a Chinese AI startup, made global waves with the release of a groundbreaking, highly cost-efficient AI model (*The Economist*, 2025; *The New York Times*, 2025). Yet, China's rapid rise as a technological powerhouse extends far beyond artificial intelligence. In terms of both total and high-impact science and technology publications, China has outpaced traditional research leaders such as the UK, Japan, Germany, and France, and by 2020, stands on equal footing with the United States (see **Figure 1**).[1] In a related shift, while only six Chinese universities were ranked among the top 40 academic institutions in the inaugural 2016 Nature Index, by 2024, nearly half of these top institutions are based in China (see **Table A1**).[2] This rapid advancement in China's scientific and technological capabilities is truly remarkable, with its research expected to continue expanding in the foreseeable future.

Against this backdrop, an important question arises: How does China's growing presence in the global scientific arena impact research productivity worldwide? Will China's expanding research capacity crowd out research outside its borders, or will the increasing stock of knowledge produced in China spur new ideas and innovations among scientists globally? This paper addresses this critical question by studying the impact of China's rise in science (or

[1] In the Web of Science data underlying this figure, publications are attributed to countries based on the institutional affiliations of the authors rather than their nationalities. For example, a publication by a Chinese researcher based at MIT is counted as a US output. If a publication is co-authored by two scientists—one affiliated with Peking University and the other with Stanford—it is counted toward both China's and the United States' publication outputs. See Xie and Freeman (2020) on the scientific contribution of Chinese diaspora researchers—those born in China and working abroad.

[2] The Nature Index is an open database that tracks author affiliations and institutional collaborations. It monitors contributions to research articles published in top-tier natural-science and health-science journals, selected for their reputation by an independent group of researchers. Active researchers in the natural and health sciences choose journals included in the Nature Index. These researchers identify journals where they would prefer to publish their best work, without relying on traditional metrics like the Journal Impact Factor. The list of journals was last updated in 2023 to include health sciences publications, aiming to represent the leading journals in the field. It's important to note that the Nature Index tracks only a small proportion of all research articles, focusing solely on the natural and health sciences. Various factors, including the size and research specialization of institutions, influence their output. The Nature Index provides two key metrics: Count and Share. The Count metric gives one point for an institution or region if any of its authors are involved in an article, regardless of co-authors' affiliations. The Share metric is a fractional count reflecting the proportion of authors from each institution or region on an article. This method treats all authors as equal contributors, with the total Share for an article being 1.0.

the "China shock" in science) on the research performance of global research universities (by field) outside mainland China (or "China" hereafter), using extensive bibliometric data spanning four decades, from 1980 to 2020. We focus on the period between 1995 and 2020 as the phase of China's take-off, while using 1980–1995 for placebo analysis.[3] Our analysis encompasses all science and technology fields available in the Web of Science (WoS), excluding the social sciences and humanities.[4]

There are at least two major challenges in isolating the causal impact of the China shock on scientific research at universities outside of China. First, since, in modern times (1995–2020), as opposed to historical contexts (e.g., 1900–1930, as in Iaria et al., 2018), researchers worldwide have easy access to the latest knowledge through electronic journals and platforms like the Web of Science and Google Scholar, it is unclear who is affected versus unaffected by the China shock. Second, easily conceivable measures of exposure to China (e.g., research collaboration with Chinese institutions, the influx of Chinese students and scholars, etc.) are likely to be endogenous to each university-field's research potential.[5]

To address this, we propose a novel shift-share research design, operationalized within the "idea space" (see the seminal work by Azoulay et al. (2010) for this concept). Specifically, we assess the exposure of different universities within each field (e.g., MIT-Chemistry or UC Berkeley-Chemistry) to varying levels of the China shock, defined based on the topic-specific growth of China's research capacity from 1995 to 2020, and the initial (e.g., 1990–1995) topic composition of research at each university-field.[6] To implement this, we use new data from Web of Science InCites (hereafter "InCites"), which classifies a near-universe of WoS

[3] As shown in **Figure 1**, China's research output was negligible until it began to increase in the late 1990s, which justifies our choice of the main analysis window between 1995 and 2020.
[4] In social sciences and humanities, there has been little progress in China's research output as measured by WoS and outputs are less comparable across countries.
[5] For studies documenting the causal effect of Chinese graduate students on individual faculty members, see, for example, Gaulé and Piacentini (2013) and Borjas et al. (2018).
[6] In our baseline, we use 1990–1995 to measure the topic composition of "initial" research at each university-field. Our results are robust to alternative choices for the initial period, such as 1980–1985, 1985–1990, or 1980–1995.

documents published since 1980 into clusters or topics based on their citing and cited relationships.[7]

In our baseline analysis, we focus on the growth of high-impact (top 10% cited among articles within the same field and published in the same year) publications at each university-field (or "department" hereafter) from 1995 to 2020 as the primary outcome. Our findings reveal that exposure to China has a positive net effect on the research output of universities outside mainland China in Chemistry and Engineering & Materials Science (EMS), while the effect is negative in Clinical & Life Sciences (CLS). Specifically, a one standard deviation (SD) increase in exposure to China between 1995 and 2020 leads to a 27% higher growth in high-impact output in Chemistry, a 36% higher growth in EMS, and an 8% lower growth in CLS. In other fields, the estimates are imprecise and statistically indistinguishable from zero, although the signs of the effects are mostly positive. Our results remain robust to different measures of exposure to the China shock, exclusion of departments that dominate any particular topic, and an alternative analysis window (1995–2015 instead of 1995–2020 to avoid interference from the 2018 China Initiative).[8]

We also explore alternative outcome measures. Specifically, our results remain consistent when using the total number of publications (regardless of citation percentiles) or the number of publications in a predetermined set of high-quality journals as the outcome variable, rather than the number of top 10% cited publications used in our baseline analysis. In addition, we examine the production of novel concepts, measured by the emergence of new bigrams in titles—terms that did not appear in prior research within the same field over the

[7] InCites' classification is available at the macro, meso (within macro), and micro (within meso) topic levels. A macro topic corresponds to a broad scientific field, such as Chemistry or Mathematics. **Table A2** shows examples of meso topics within Chemistry from the InCites 2023 Citation Topics schema. In constructing university-by-field exposure to the China shock using the shift-share approach, we focus on meso topics within fields. For robustness, we also present results using micro topics to construct our shift-share variable.
[8] The 2018 China Initiative, launched by the US Department of Justice under the Trump administration, aimed to address national security concerns related to Chinese technological and intellectual property theft. The initiative had significant implications for US–China academic relations (see Jia et al., 2024; Aghion et al., 2023).

previous ten years—following text analysis methods similar to those used by Iaria et al. (2018) and Bloom et al. (2024). We find that departments more exposed to the China shock generate more novel concepts in Chemistry and EMS, but fewer in CLS, consistent with our findings on high-impact publications.

One might suspect that the positive net effects observed in Chemistry and EMS are driven by increased collaboration with China—such as coauthorship with China-based researchers or greater reliance on Chinese funding—in departments more exposed to China compared to those less exposed. However, our main results remain invariant when we restrict the analysis to departmental publications that do not involve China-based coauthors or Chinese funding. If increased collaboration is not the explanation, then what accounts for the divergent research trajectories of departments that were more versus less exposed to the China shock?

Conceptually, the entry of new players into the global scientific arena can generate two opposing effects. On the one hand, the influx of scientists may create a competition or congestion effect, reducing the marginal product of existing researchers (see Borjas and Doran, 2015a, 2015b). On the other hand, more researchers can stimulate new ideas and generate a spillover effect (see Romer, 1986, 1990; Lucas, 1988; Jones, 1995). Although it is not possible to separately identify these two effects, the estimated net effects suggest that spillover effects dominate in Chemistry and EMS, while competition effects prevail in CLS. In other fields, the two opposing forces seem to largely offset each other. If competition effects were the sole driver, the net effects would be negative across all fields, but this is not what we observe, pointing to the presence of spillover effects in this context.

To provide more concrete evidence of the spillover effects, we utilize data from OpenAlex (Priem et al., 2022) and obtain the reference lists for each publication from the departments in our sample.[9] For each item on the reference list, we determine whether it constitutes "Chinese" research, defined as a publication involving at least one author affiliated with mainland China-based institutions. Consistent with the presence of spillover effects, we find that, for most fields, departments more exposed to the China shock are more likely to cite Chinese research compared to departments less exposed. When examining heterogeneity, we observe little difference in effects between US and non-US departments or between high- and low-tier departments in most fields. This suggests that weaker departments are more susceptible to both the negative competition effects and the positive spillover effects associated with greater exposure to the China shock. Consistent with this, in CLS—the field where the net effects are negative—we find that the negative impact of exposure to China is more pronounced in non-US departments and lower-ranked departments.

Overall, two key findings emerge from our analysis. First, China's increasing research capacity generates spillover effects in addition to the congestion effects typically expected for incumbents. These spillover effects can be substantial. For example, in Chemistry, the estimates show that departments exposed to a one SD higher level of the China shock experience a 28 percentage point (or 27%) higher growth in high-impact (top 10% cited) publications between 1995 and 2020. Given the 1995 mean of 34 papers per department in Chemistry, this corresponds to an additional 9.5 publications. If each top 10% cited publication is valued at $274,000 (the typical size of an NSF standard grant in Chemistry), the effects translate to approximately $2.6 million in additional funding for the affected department. These are the net effects (i.e., spillover minus competition), providing a lower bound for the spillover effects.

Second, the relative strength of spillover and competition effects varies significantly across fields. A key advantage of our approach is that it enables us to compare the net effects

[9] OpenAlex is an open-access bibliographic catalog that includes scientific papers, authors, and institutions. It was launched in January 2022 by OurResearch as a successor to the discontinued Microsoft Academic Graph. OpenAlex serves as a free alternative to commercial platforms like Clarivate's Web of Science and Elsevier's Scopus.

of the China shock across different scientific fields within a common framework—using the same dataset, time periods, and identification strategy. As a result, the differential net effects documented here should be attributed to the characteristics of each field, rather than to differences in datasets, time periods, or research designs. Specifically, Chemistry and EMS likely possess characteristics that generate relatively large spillover effects, which outweigh the competition effects. In contrast, CLS likely has features that produce weak spillover effects in comparison to congestion effects.

To shed light on the heterogeneous net effects of the China shock across scientific fields, we draw on a simple theoretical framework from Borjas and Doran (2015a), in which two key parameters govern the strength of competition and spillover effects. Guided by this model, we map eight scientific fields into a two-dimensional space. The first dimension captures congestion forces, proxied by the share of experimental or empirical (as opposed to theoretical) research in a random sample of abstracts, classified using GPT-4 mini predictions. Fields with a higher share of experimental or empirical research are assumed to have greater scope for expansion and to experience lower levels of congestion. The second dimension reflects factors that are *a priori* conducive to spillover effects, such as China's relative position to the research frontier—proxied by the China–US ratio of top 1% cited publications from 1995 to 2020—and a more egalitarian field hierarchy, proxied by the inverse of the P90–P50 ratio of high-impact publications among departments from 1990 to 1995. We find that Chemistry and EMS are characterized by both a larger scope for expansion and stronger Chinese research. Mathematics also demonstrates strong Chinese research capacity but is subject to greater congestion. In CLS, although expansion potential is comparable to that in Chemistry and EMS, the quality of Chinese research is notably lower. Chemistry and EMS further distinguish themselves through more egalitarian institutional hierarchies.

Overall, our analysis highlights that the effects of China's rise in science on the research performance of global universities (outside mainland China) are neither universally positive nor negative. Due to the simultaneous presence of competition and spillover effects, the net impact of exposure to China is nonnegative across most fields, with the exception of Clinical & Life Sciences (CLS). Moreover, in fields less prone to congestion, the entry of a major new player can generate positive net effects—particularly when that player conducts cutting-edge research and the field exhibits relatively flat institutional hierarchies. Notably, these effects emerge even though our analysis focuses exclusively on universities located outside mainland China, and exposure to the China shock is measured in terms of intellectual proximity (idea space) rather than geographic proximity. This underscores that scientists worldwide are subject to the congestion and spillover effects of China's expanding research capacity, regardless of whether they engage directly with Chinese researchers.

We relate to several strands of the literature. First, we contribute to the growing body of research on China's rise in science and technology (Xie et al., 2014; Veugelers, 2017; Xie and Freeman, 2019, 2020; Bergeaud and Verluise, 2022; Beraja et al., 2023a, 2023b; Aghion et al., 2023; Jia et al., 2024; Lerner et al., 2024a; Qiu et al., 2025). Specifically, we provide novel causal evidence on how China's expanding research capacity has affected universities outside mainland China over a 25-year period (1995–2020). Our findings show that the scientific impact of China's rise is more nuanced than its well-documented effect on import competition (see, e.g., Autor et al., 2013; Dauth et al., 2014).

Second, we build on the empirical literature on knowledge production, particularly studies examining how the entry or exit of researchers affects the productivity of incumbents (Waldinger, 2010, 2012; Azoulay et al., 2010, 2019a; Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Borjas and Doran, 2012; Moser et al., 2014; Ganguli, 2015). These studies typically exploit exogenous events—such as immigration flows or the deaths of prominent scientists—that alter the local scientific environment, often within a single discipline. Our study differs in two key ways. First, the China shock we examine operates in the idea space rather than physical space, meaning the competition and spillover effects we observe arise through intellectual proximity rather than co-location or direct competition for positions and funding. Second, we apply a unified empirical framework across multiple scientific fields, allowing for cross-field comparisons of net effects. This approach reveals the coexistence of congestion effects (Borjas and Doran, 2015a, 2015b) and spillover effects (Romer, 1986, 1990; Lucas, 1988; Jones, 1995) within the idea space, with their relative magnitudes varying by discipline.

Lastly, we contribute to the literature on the science of sciences (Jones, 2009; Kantor and Whalley, 2014, 2023; Li, 2017; Hvide and Jones, 2018; Iaria et al., 2018; Jaravel et al., 2018; Azoulay et al., 2019b; Bloom et al., 2020; Iaria et al., 2022; Babina et al., 2023; Hill and Stein, 2025a, 2025b; Hager et al., 2024; Lerner et al., 2024b). This literature examines factors shaping the production of knowledge and the careers of scientists, including access to frontier research, institutional incentives, and funding structures. We highlight the rapid and largely unanticipated expansion of China's research capacity as a previously underexplored force influencing global scientific productivity. As China continues to invest heavily in science and technology, the competition and spillover dynamics we document will likely remain important in shaping the global landscape of research.

2. Background and Data

2.1 China's Rise as a New Scientific Powerhouse

Following the end of the Cultural Revolution in 1976, Chinese academia began to develop steadily throughout the late 1970s and 1980s. Since the 1990s, the Chinese government has introduced several policies that have significantly enhanced the country's research capabilities.

Notably, Project 211, launched in 1995, and Project 985, initiated in 1998, provided substantial funding to elite universities across mainland China. Additionally, programs such as the Changjiang Scholars Program (launched in 1998) and the Thousand Talents Plan (introduced in 2008) were established to attract overseas Chinese and international scholars through financial and honorific incentives (see Ash et al. 2022; Shi et al. 2023).

Alongside these initiatives, China has experienced a dramatic expansion in higher education since 1999 (Che and Zhang 2018). By 2018, the number of science and engineering doctoral degrees awarded in China was approaching that of the United States (National Science Board 2022). This rapid growth in the STEM-educated workforce, coupled with substantial government investment in science and technology, has likely driven China's impressive rise as a scientific superpower. As illustrated in **Figure 1**, by the late 2000s, China had surpassed traditional research leaders such as the United Kingdom, Germany, Japan, and France in both total research output and top 10% cited science and technology publications.

2.2 Classifying Scientific Publications into Topics at Scale

Our research design exploits differential exposure to the China shock across university-by-fields, based on the topic composition of their initial (i.e., before China's rise) publications, combined with China's topic-specific growth between 1995 and 2020. To this end, we utilize "Citation Topics" data provided by Clarivate's InCites, a platform that enables citation-based evaluation of all documents in the Web of Science (WoS).[10] Citation Topics are generated algorithmically using a Leiden-type community detection algorithm (Traag et al., 2019), which clusters documents based on their cited and citing relationships. This method covers all WoS documents from 1980 to the present, with each document assigned to a single topic. The clustering algorithm ensures minimum cluster sizes and incorporates cited relationships from

[10] Clarivate owns both the Web of Science and InCites, as well as other data products.

pre-1980 documents. Clarivate updates the clustering annually as new documents are added to WoS. For our analysis, we use the 2023 version of the Citation Topics schema.[11]

Citation Topics are organized into three hierarchical levels: macro, meso, and micro clusters. A micro cluster is a subfield within a meso cluster, and a meso cluster is a subfield within a macro cluster. There are ten macro clusters (referred to as "fields"): (1) Clinical & Life Sciences (CLS); (2) Chemistry; (3) Agriculture, Environment & Ecology (AEE); (4) Electrical Engineering, Electronics & Computer Science (EE&CS); (5) Physics; (6) Social Sciences; (7) Engineering & Materials Science (EMS); (8) Earth Sciences (Earth); (9) Mathematics; and (10) Arts & Humanities. We focus on the eight science and technology fields, excluding (6) Social Sciences and (10) Arts & Humanities, as China's progress in these areas has been minimal according to WoS data, and research outputs in these fields are less comparable across countries.

For example, in the field of mathematics, our dataset contains 64 micro topics, which closely aligns with the 63 subfields (or topics) identified by Borjas and Doran (2012), where topics were manually assigned by editors of *Mathematical Reviews*. In contrast, our approach employs algorithmic clustering at scale, analyzing millions of articles in the Web of Science. In our baseline analysis, we use meso topics to construct our shift-share measure, and for robustness, we also utilize micro topics.

For certain analyses involving text content or citation patterns, we combine article-level data from InCites with data from OpenAlex (Priem et al., 2022), which provides abstract text and citation networks at the article level. Specifically, we use InCites article-level data from 1980 to 2020 (last updated on August 25, 2023) for the eight fields under study. To this data, we merge in article-level information from OpenAlex (last updated on October 31, 2024), using digital object identifiers (DOIs).

[11] Further details on Citation Topics are available here: https://incites.zendesk.com/hc/en-gb/articles/22514077746961-Citation-Topics#h_01HPJ0TQ344Z3EDDSBGFJZEWZ2.

2.3 World's Top Research Universities

Our sample focuses on the top 200 universities (outside mainland China) in each field, based on the number of high-impact (top 10% cited) publications from 1990 to 1995. We restrict our attention to university-fields that had a continuous presence in the international research arena prior to China's rise in research capacity, by requiring non-zero high-impact publications (top 10% cited) in 1980, 1985, 1990, and 1995. This requirement ensures the inclusion of departments with an established research track record before the China shock while leading to different sample sizes across fields—for example, 199 departments in Chemistry and 148 in Mathematics. [12] For simplicity, we refer to a university-by-field combination as a "department."[13] We then follow these departments over the period 1995–2020 for our main analysis, while using 1980–1995 for placebo analysis.

Table 1 presents summary statistics by field. Panel A shows the number of meso topics available within each field. Panel B displays the variation in our measure of exposure to China (defined in Section 3). Panel C summarizes the number of high-impact publications (top 10% cited within field and publication year) at the department level, reporting levels in 1995 and 2020, as well as the changes over this period.

Between 1995 and 2020, the number of high-impact publications increases across all fields, though to varying degrees. In Chemistry, for instance, the average department produced 33 such publications in 1995, rising to 63 by 2020. In Mathematics, the number grows from 9 in 1995 to 12 in 2020, albeit at a more modest rate. This suggests that the absolute number of publications increased across all fields. Whether these publications translate into valuable knowledge is a separate question, beyond the scope of this paper. We treat publication counts as one metric to compare departmental performance.

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[12] Our results remain robust when equalizing sample sizes across fields.

[13] Strictly speaking, however, these are not the same as administrative units within universities, as researchers in a given field, such as chemistry, may belong to multiple administrative units within the same institution.

Given this general expansion in publication output, we isolate both congestion and spillover effects through a relative comparison of departments that were more versus less exposed to the China shock, using a difference-in-differences framework. Congestion effects are reflected in the slower growth of more exposed departments relative to less exposed ones, even if the more exposed departments still exhibit positive absolute growth.

In Panel D, we report alternative measures of research performance. Panel E presents the share of output that either involves China-based co-authors or is (co-)funded by China-based funding agencies, reported for 1995 and 2020, respectively.

3. Empirical Framework

3.1 Identification Strategy

We are interested in understanding how differential exposure to China's rise affects the growth of each department's research output over the period from 1995 to 2020. We expose different departments to varying degrees of the China shock in science using a shift-share design. Our department-level specification is analogous to the city-level analysis in Card (2001), where city-level growth in outcomes is related to predicted immigrant inflows in a shift-share framework. Setting $t = 2020$ and $t - 1 = 1995$, we estimate the following equation:

$$\Delta y_i = \alpha + \beta \Delta c_i + \gamma \boldsymbol{X}_i + \lambda W_i + e_i, \quad (1)$$

where $\Delta y_i \equiv \frac{y_{it} - y_{it-1}}{y_{it-1}}$, the growth of department i's output between $t - 1$ and t. For department i's output in t, we use the number of high-quality publications, defined as those in the top 10% most cited (within field and publication year). We also consider alternative measures of research performance, including publications in a predetermined set of high-impact journals that do not rely on citation percentiles. Additionally, we examine the count of novel concepts—measured as the appearance of new bigrams—in department i's publications, as a complementary indicator of research performance.

Our main explanatory variable, department i's exposure to China's rise between $t-1$ and t, is defined as follows:

$$\Delta c_i = \sum_p s_{ip} \frac{y_{pt}^{cn} - y_{pt-1}^{cn}}{y_{pt-1}^{w}}, \quad (2)$$

where $s_{ip} \equiv \frac{y_{ipt_0}}{y_{it_0}}$, measuring the share of department i's initial total output (y_{it_0}) that is on topic p (y_{ipt_0}). For the initial period t_0, we use 1990–1995 in our baseline analysis but also test for robustness using earlier periods such as 1980–1985, 1985–1990, and 1980–1995. The variables y_{pt}^{cn} and y_{pt-1}^{cn} indicate China's total output in topic p in periods t and $t-1$, respectively. We express the change in China's output in that topic as a share of the topic's initial size, scaling it by y_{pt-1}^{w}, the worldwide output in that topic in period $t-1$. In practice, we compute Δc_{it} using a leave-one-out approach, such that y_{pt}^{cn}, y_{pt-1}^{cn}, and y_{pt-1}^{w} exclude any publications involving department i.

The vector $\boldsymbol{X}_i$ captures department i's initial (1990–1995) characteristics, including the institution's ranking within the field (represented by dummies for five tiers) and its geographic location (grouped into the US, UK, East Asia including Japan, Western Europe excluding the UK, and other regions). This allows us to compare departments that were similarly ranked and located in the same geographic areas—groups that, in the absence of the China shock, would be expected to follow similar growth trajectories. In addition, we control for the share of department i's initial (1990–1995) output that involved a China-based coauthor, as well as the share of all coauthors' surnames that are ethnically Chinese among all 1990–1995 publications from department i.[14] These controls account for the possibility that departments with stronger

[14] To identify ethnic Chinese researchers, we use the methodology outlined by Xie and Freeman (2020). We retrieve the 100 most common surnames in mainland China (which account for over 80% of the population) from China's Ministry of Public Security, converting these surnames to Pinyin (the Romanization of Chinese characters), and then match these names with surnames in each department's publications between 1990–1995 found in the Web of Science.

initial ties to China-based institutions or ethnic Chinese coauthors may have followed different growth paths between 1995 and 2020.

In addition, equation (1) accounts for the fact that some topics within a field are generally expanding, while others may exhibit slower growth. If a department happens to specialize in high-growth topics—regardless of its exposure to China's rise—its output would naturally follow a higher growth trajectory. To address this potential confounder, we adopt the following approach: for each topic p, using data from 1980 to 1995 (i.e., prior to our main analysis window), we estimate the following model:

$$lny_{pt} = a + \delta_p t + u_{pt}. \quad (3)$$

Here, the estimate $\widehat{\delta_p}$ reflects the historical growth rate of each topic, which may serve as a predictor of its future growth trajectory.[15] For each department, we take the weighted average of $\widehat{\delta_p}$ using its initial topic shares such that:

$$W_i = \sum_p s_{ip}\widehat{\delta_p}. \quad (4)$$

To account for the effects of departments' exposure to generally fast- (versus slow-) growing topics, we condition on W_i in equation (1). Our results are robust to using quintiles of W_i in place of the continuous measure.

The parameter of interest is β, which shows the effect of a percentage point higher exposure to China's rise on the growth of a department's own output between 1995 and 2020. Our identifying assumption is that conditional on $\boldsymbol{X}_i$ and W_i, there is no correlation between Δc_i and e_i in equation (1); that is, $cov[\Delta c_i, e_i] = 0$.

In light of recent developments in shift-share research designs (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022), we argue that, in this context, the source of the identifying

[15] The above equation yields an average R-squared of 0.778 across all topics in our sample. Naturally, one could fit a higher-order polynomial in t instead of a linear model to further improve explanatory power.

assumption lies in the exogeneity of the "shares"; that is, $cov[s_{ip}, e_i] = 0$ (see equations (1) and (2)). We focus on departments that are well-established, defined as those with non-zero high-impact publications in 1980, 1985, 1990, and 1995. The composition of research topics in these departments was largely determined prior to China's entry into the global scientific arena. Among similarly ranked departments located in the same region and tier, and with comparable initial links to China-based institutions or ethnic Chinese researchers (as captured by the covariates in $\boldsymbol{X}_i$), topic specialization of each department is unlikely to reflect differences in their future growth potential.

This assumption is further reinforced by the inclusion of W_i (see equation (4)), which accounts for departments' differential growth potential arising from initial topic composition—specifically, exposure to topics that were projected to experience high (versus low) growth. In contrast, it is more difficult, in this context, to justify an argument based on the exogeneity of the "shifts," since China's investment and growth in particular topics may have been influenced by the perceived potential of the foreign departments specializing in those topics. Following the guidance of Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2025), we conduct a series of empirical tests to evaluate the plausibility of our "exogenous shares" assumption; see Section 4.2 for details.

3.2 Illustration of Empirical Strategy

In equation (2), variation in Δc_i arises from two primary sources. The first is the topic-specific growth of China's output over time, measured relative to the initial size of each topic. To illustrate the sources of variation in the China shock, we use Chemistry as an example. Panel A of **Figure 2** displays the growth of China's output in each meso topic within Chemistry between 1995 and 2020. Topics are arranged in ascending order based on China's topic-specific growth during this period. Accordingly, the rightmost topics on the horizontal axis represent those in which China experienced the most significant growth—referred to here as "China topics." For comparison, we overlay the same figure with topic-specific predicted growth (see equations (3) and (4)). Importantly, the topics in which China saw the highest growth are not necessarily those that would have grown faster in the absence of China's rise. This distinction underscores the additional variation contributed by China's differential engagement across research areas.

The second source of variation is the initial composition of topics across different departments. For instance, Panel B of **Figure 2** illustrates the differences in topic shares between the University of California, Los Angeles (UCLA) and the University of Texas at Austin (UT Austin) within Chemistry, where topics are ordered from low to high growth of China's research. Although both institutions were similarly ranked during 1990–1995, UT Austin specialized more in topics that would experience faster growth in China between 1995 and 2020, making it more exposed to the China shock than UCLA.

Continuing with Chemistry as an example, we illustrate our identification strategy in **Figure 3**. In Panel A, the y-axis depicts the growth in each department's output between 1995 and 2020, while the x-axis captures exposure to China over the same period. A positive relationship emerges between the long-run change in departmental output and the long-run change in exposure to China. Panel B uses the same x-axis but shifts the y-axis to show output growth between 1980 and 1995. As the figure indicates, departments that would later experience greater exposure to China did not exhibit systematically different growth trajectories during the pre-shock period. Below, we systematically examine this relationship across all fields.

4. China's Rise in Science and Global Knowledge Production

4.1 The Net Impact of Exposure to China

In **Table 2**, we present estimates of equation (1), using high-impact (top 10% cited) publications as the baseline measure of research performance. Panel A shows the simple correlation between the growth in the department's output and its exposure to the China shock between 1995 and 2020. Panel B controls for university tier FE (five tiers within fields) and country group FE (US, UK, East Asia including Japan, Western Europe excluding the UK, and other). To the specification in Panel B, Panel C additionally includes departments' initial links to China, measured by the share of their publications from 1990-95 that include any China-based coauthors and the share of Chinese surnames among all authors appearing in the department's publications from 1990-95, the latter being used as a proxy for the concentration of ethnic Chinese faculty, students, or coauthors. Lastly, Panel D builds on Panel C, and it further conditions on W_i, the projected growth rate of each topic weighted by the department's initial topic shares. We therefore account for the fact that some departments will grow faster than others simply because their initial specialization in topics that are generally expanding, for reasons unrelated to China's rise.

Exposure to China in **Table 2** is standardized so all coefficients show the effect of a one SD increase. For most fields, estimates are imprecisely estimated, except for CLS, Chemistry, and EMS. Focusing on Panel D, column 2, we find that a one SD increase in exposure to China leads to a 28 pp (27%) increase in the growth of high-impact output in Chemistry. The same exposure leads to a 64 pp (36%) increase in the growth of own output in EMS (column 6). In contrast, the effect is negative in CLS, where one SD increase in exposure to China decreases own output by 35 pp (8%).

Alternative Measures of Research Performance. Our baseline measure of research performance is the count of high-impact (top 10% cited) publications. The top x% status is determined by comparing articles published in the same field and year. Therefore, departments that are more or less exposed to the China shock face, *ex ante*, the same opportunities and constraints in reaching the top x% citation threshold with their publications. However, one potential concern is that publications from departments more exposed to the China shock might attract more citations than others despite being of the "same quality."[16]

To alleviate this concern, we consider alternative outcome measures that capture research performance and find results broadly consistent with our baseline. In Panel A of **Table 3**, we repeat the specification from Panel D of **Table 2** (our baseline). In Panel B, we use the total count of publications, irrespective of their citation percentiles. Since departments' high-impact publications tend to go hand in hand with their overall output, the results remain similar.

In Panel C, we predefine a set of "high-impact" journals within each field as those with a Category Normalized Citation Impact (CNCI) above a certain threshold. We use an admittedly arbitrary threshold of the top 20% in CNCI among all journals within a field to yield a publication count roughly comparable to that in our baseline, though alternative thresholds are possible. We then count the number of publications appearing in this predetermined set of high-impact journals—similar in spirit to the Nature Index—regardless of individual citation performance. Again, the results remain stable.

Lastly, in Panel D, we count the number of "novel concepts" produced by each department. Using titles of all papers published by each department, we identify the appearance of new bigrams—defined as two-word phrases not seen in prior research within the same field over the preceding ten years. This approach follows text analysis methods similar to those used

[16] Measuring a publication's "true" merit independently of citations is a challenging task, and addressing that question is beyond the scope of this paper.

by Iaria et al. (2018) and Bloom et al. (2024).[17] We find that departments more exposed to the China shock generate more novel concepts in Chemistry and EMS, but fewer in CLS—consistent with our findings on high-impact publications.

4.2 Assessing the Plausibility of Exogenous Shares

We maintain that the identifying assumption in our research design—specifically, that $cov[\Delta c_i, e_i] = 0$—is valid due to the exogeneity of the "shares," i.e., $cov\left[s_{ip}, e_i\right] = 0$. Following the guidelines proposed by Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2025), we present two sets of diagnostic tests to support this assumption.

First, we identify the five topics within each field with the largest Rotemberg weights (Goldsmith-Pinkham et al., 2020), as these are most influential in determining the variation in our exposure measure. For each of these topics, we regress its share in each department's initial output (from 1990 to 1995) on a set of department characteristics, $\mathbf{\Omega}_i$, that could plausibly predict future output growth. Specifically, $\mathbf{\Omega}_i$ includes university tier (five groups), country group (with the US as the reference category), the proportion of the department's initial output co-authored with researchers based in China, and the share of authors with Chinese surnames in the department's initial publications. The results are reported in Appendix B (**Tables B1–B8**), with one table per field. Overall, the explanatory power of these characteristics for initial topic shares is modest, lending support to our identifying assumption of exogenous shares (Goldsmith-Pinkham et al., 2020).

[17] Within each field, we pool all publication titles from 1995 to 2020, along with those from the preceding 10 years. We tokenize the titles into individual words and remove stop words, using the NLTK stop word list, single-letter words, possessive endings (e.g., "'s"), and the top 10,000 most frequent words in Wikipedia up to 2007 (Goldhahn et al., 2012). The remaining words are stemmed using the Snowball stemmer, and we construct bigrams—defined as consecutive word pairs—from the processed text. For each publication title in year t, we compare its bigrams against the full set of bigrams that appeared in the field between $t - 10$ and $t - 1$. Bigrams that have never appeared in that window are labeled as novel bigrams. We count the number of novel bigrams per publication and aggregate these counts to the department-year level.

Second, we examine pre-trends in outcomes relative to exposure. We calculate the five-year growth rate in each department's research output (measured by top 10% cited publications) for successive five-year periods—1980–85, 1985–90, 1990–95, …, 2015–20—and regress these growth rates on the initial topic shares (for the five high-weight topics) as well as on the main exposure measure. As shown in **Figures B1–B8**, we find little difference in output trends between departments with high versus low shares of the key topics, or with high versus low exposure to the China shock.

4.3 Robustness Checks

To ensure that the net effects isolated above are indeed attributable to exposure to the China shock in science, we perform a series of robustness checks outlined below.

Shares from earlier periods. We investigate whether our results are sensitive to different methods of constructing exposure to China, as shown in **Table A3**. Panel A replicates our baseline results from Panel D of **Table 2**, using the topic compositions of each department's publications from 1990 to 1995 to define exposure to China, as specified in equation (2). Panels B through D explore alternative time windows for measuring departments' topic shares—specifically, 1980–1985, 1985–1990, and 1980–1995, respectively. Although the estimates become less precise when using older topic shares (see Borusyak et al., 2025), the overall patterns remain consistent with our baseline findings.

Micro- instead of meso-level topics. As mentioned in Section 2, the InCites data provide topic clustering of Web of Science publications at the macro, meso, and micro levels. The macro level corresponds to broad disciplines—such as Chemistry and Mathematics—which we refer to interchangeably as "fields." In constructing university-by-field exposure to the China shock using a shift-share design (see equation (2)), we use meso-level topics within fields in our baseline specification. Assigning shocks based on meso topics offers sufficient variation while also allowing for interactions across micro topics within the same meso category. This approach is therefore more flexible than assigning shocks based on micro topics. Nonetheless, for robustness, we also construct the shift-share variable using micro-level topics. As shown in **Table A4** the results remain consistent with our baseline when using micro topics instead of meso topics to define exposure.

China Initiative. Our analysis focuses on the period from 1995 to 2020, which we interpret as the era of China's research takeoff. One potential concern is that the effects we attribute to the China shock may be confounded by the 2018 China Initiative. Introduced by the Trump administration, the China Initiative aimed to address national security concerns related to Chinese technological and intellectual property theft. Existing studies show that the initiative negatively affected both US and Chinese scientists.[18]

To avoid potential confounding from the China Initiative, we repeat our analysis using a restricted window of 1995–2015, defining both exposure to the China shock and research outcomes within this period. As shown in **Table A5**, the results remain largely consistent with our baseline, suggesting that our findings are not driven by the later effects of the China Initiative.

Dominant players. In our shift-share variable in equation (2), the "shift" term reflects China's growth in a given topic, normalized by the size of that topic worldwide. Although our

[18] Using PubMed data from 2010 to 2021 in biomedical and life sciences, Jia et al. (2024) find that the initiative reduced research productivity among U.S. scientists collaborating with Chinese counterparts, relative to those working with researchers from other countries. Similarly, using Scopus data from 2013 to 2021, Aghion et al. (2023) find that the initiative negatively impacted both the average quality of publications and the caliber of co-authors for Chinese researchers who were more reliant on US-based collaborators.

identification strategy does not rely on the "shift" being exogenous, a potential concern remains regarding reverse causality.

For example, consider a hypothetical scenario in which topic P within a field is a highly specialized area, studied almost exclusively at a single institution—say, MIT. Suppose that Chinese students train at MIT in this topic and subsequently return to China, where they contribute to building capacity in the same area. If MIT's early focus on topic P is the primary driver of China's later growth in that topic—rather than Chinese domestic policies or other idiosyncratic factors (see, e.g., Beraja et al. 2023a, 2023b)—then our framework would face a reverse causality issue. In this case, it's not that MIT's growth in topic P is driven by China, but rather that China's growth is linked to MIT's early specialization.

To address this concern, we exclude departments that account for a substantial share of worldwide output in any meso topic, as detailed in **Table 4**. Panel A replicates our baseline results (from Panel D of **Table 2**). Panels B and C exclude departments responsible for at least 5% of the world's total output in each meso topic, based on all publications and on top 10% cited publications, respectively. The results remain consistent with our baseline estimates, indicating that such reverse causality is unlikely to be driving our main findings.

Sample size. Despite applying the same criteria for constructing our sample (see Section 2), the number of observations varies across fields. To ensure that these differences are not driving the heterogeneous findings across fields, we impose a uniform sample size equal to that of the smallest field—EE&CS, with 121 departments—for all fields and repeat our main analysis. For example, in Chemistry, we select the top 121 departments out of the original 199.

As shown in **Table A6**, the positive net effects of exposure to China in Chemistry and EMS, as well as the negative effects in CLS, remain consistent when comparing the full sample (Panel A) to the restricted sample (Panel B). In Earth Sciences (column 7), the sign of the effect changes, suggesting some heterogeneity in the impact across stronger and weaker departments within that field. Overall, the cross-field pattern observed in our baseline analysis appears unlikely to be driven by differences in sample size.

4.4 Competition and Spillover Effects

One might suspect that the positive net effects observed in Chemistry and EMS are driven by increased collaboration with China—such as coauthorship with China-based researchers or greater reliance on Chinese funding—among departments more exposed to China compared to those less exposed. However, while there is a general upward trend in collaboration with China between 1995 and 2020, there is no systematic pattern in this increase (see Panel E of Table 1). Moreover, our main results remain robust when we restrict the analysis to departmental publications that do not involve China-based coauthors or Chinese funding (see Panels B and C of **Table 5**). In fact, for Physics, the positive net effect of exposure becomes both larger and statistically significant under these restrictions.

The continued positive net effects observed in Chemistry and EMS for research outputs that did not directly involve collaboration with China point to the presence of spillover effects in this context. If competition effects were the sole driver, we would expect to see negative net effects across all fields; however, this is not what we observe.

To provide more concrete evidence of spillover effects, we utilize data from OpenAlex and gather the reference lists for each publication from the departments in our sample. For each item on the reference list, we determine whether it constitutes "Chinese" research, defined as a publication involving at least one author affiliated with a mainland China-based institution. Consistent with the presence of spillover effects, we find that departments more exposed to the China shock are more likely to cite Chinese research compared to departments with lower exposure (see **Table 6**). In particular, Panel B of **Table 6** uses the growth in the share of each department's publications that cite any Chinese work as the dependent variable, while Panel C focuses on the share of Chinese work among all references in the department's publications. This pattern holds across most disciplines. These findings suggest that spillover effects dominate in Chemistry and EMS, while competition effects prevail in CLS. In other fields, the two opposing forces seem to largely offset each other.

The spillover effects can be substantial. For example, in Chemistry, our estimates show that departments exposed to one SD higher levels of the China shock experience a 28 percentage point (or 27%) higher growth in high-impact (top 10% cited) publications between 1995 and 2020. Given the 1995 mean of 34 papers per department in Chemistry, this corresponds to an additional 9.5 publications. If each top 10% cited publication is valued at $274,000 (the typical size of an NSF standard grant in Chemistry), the effects translate to approximately $2.6 million in additional funding for the affected departments. These are the net effects (i.e., spillover minus competition), providing a lower bound for the spillover effects.

When examining heterogeneity, we observe little difference in effects between US and non-US departments, or between high- and low-tier departments, in most fields (see **Table 7**). This suggests that weaker departments are more susceptible to both the negative competition effects and the positive spillover effects associated with greater exposure to the China shock. Consistent with this, in CLS—the field where the net effects are negative—we find that the negative impact of exposure to China is more pronounced in non-US departments and lower-ranked departments.

4.5 Topic-level Analysis

To isolate the causal effect of exposure to China, our analysis compares departments more versus less exposed to China's growing research capacity within a difference-in-differences

(DID) framework. As with any DID design, our approach captures the *relative* effect between more and less exposed departments.

Take, for example, the positive net effect observed in Chemistry. In absolute terms, it is possible that all departments experienced a decline in their own output due to China's rise, but more exposed departments saw a smaller decline. Conversely, it may be that all departments experienced output growth, with more exposed ones benefiting more. Therefore, the causal effect identified in this paper should be interpreted against the backdrop of such aggregate trends.

To shed light on the global trend, we conduct a topic-level analysis by estimating the following equation, analogous to equation (1):

$$\Delta lnY_p^w = \alpha_0 + \alpha_1 \Delta lnY_p^{cn} + \nu_p, \quad (5)$$

where ΔlnY_p^w is the change in the log of total global output in topic p between 1995 and 2020, and ΔlnY_p^{cn} is the corresponding change in the log of China's output. While this regression is not intended to establish causality, it serves as a useful benchmark against which to interpret our main results.

Table 8 presents the estimates of equation (5), pooling topics across all fields. Columns 1 and 2 use the growth in total global output, while Columns 3 and 4 focus on global output *excluding* publications involving China-based coauthors. Column 1 shows an elasticity of 0.421 between China's and the world's output. If the global number of publication "slots" were fixed, we would expect this estimate to be zero. Column 2 allows the coefficient to vary by field. In Column 3, when focusing on global output excluding China, the elasticity drops slightly to 0.401. Again, if global publication capacity were fixed, we would expect a negative coefficient here. Column 4 provides field-specific elasticities excluding China, showing smaller values in Mathematics and Earth Sciences, and larger values in Chemistry and EMS.

Overall, we find little evidence that China's growing publication output has displaced that of other countries. This suggests that global publication capacity is not fixed but has been expanding over time. This interpretation aligns with earlier evidence from Panel C of **Table 1**, which shows a substantial increase in the average number of publications between 1995 and 2020—across all fields, and even when restricted to high-impact publications.

5. Discussion

Our analysis shows that the net effect of exposure to China varies significantly across fields, due to two competing forces at play: congestion and spillover effects. The key question is what determines the relative strength of these two forces. To explore this, we build on the simple model of knowledge production proposed by Borjas and Doran (2015a), adapting the terminology to fit our framework. For simplicity, we illustrate the model using mathematics—as in Borjas and Doran (2015a)—but the logic of the model is more general and applies across fields.

5.1 Conceptual Framework

Consider a production function where "mathematical knowledge" (proxied by publications), Y, depends on the stock of ideas, A, the stock of resources K used as inputs (e.g., computing resources), and the stock of scientists L. Suppose that the production function is given by

$$Y = A^{\phi}\left(\alpha_K K^{\delta} + \alpha_L L^{\delta}\right)^{\frac{1}{\delta}}, \quad (6)$$

where ϕ is the "externalities" elasticity. The elasticity of substitution between labor and capital is $\sigma = \frac{1}{1-\delta}$. For simplicity, assume that $A = L$ (stock of ideas is proportional to the number of researchers). Then, the effects of a supply shock ($dlogL$)—in our context, the entry of China into the global scientific arena—on the marginal product of scientists can be expressed as:

$$dlogMP_L = \begin{cases} \left((\phi - s_K) + \dfrac{\delta s_L s_K}{\phi + s_L}\right) dlogL & \text{if } dlogK = 0, \\ \phi\, dlogL & \text{if } dlogK = dlogL, \end{cases} \quad (7)$$

where $dlogK = 0$ refers to the short run and $dlogK = dlogL$ the long run. In the expression above, $s_L = \alpha_L \frac{L^\delta}{Q^\delta}$, where $Q = \left(\alpha_K K^\delta + \alpha_L L^\delta\right)^{\frac{1}{\delta}}$ while $s_K = 1 - s_L$.

While the long-run effect (in which other inputs fully adjust) is always positive, the sign of the short-run effect depends on the parameters governing congestion and spillover effects. To shed light on the short-run effect, we define $\frac{dlogMP_L}{dlogL} \equiv f(\phi, \sigma)$ and examine how f varies as we change the parameters ϕ and σ. Following Borjas and Doran (2015a), we assume $\sigma = 1$, corresponding to the Cobb-Douglas case. Under this assumption, it is straightforward to show that that $\frac{\partial f}{\partial \phi} > 0$ and $\frac{\partial f}{\partial \sigma} > 0$. In other words, the impact of new entrants on incumbents' productivity increases when knowledge spillovers are more effective and when substitution between capital and labor inputs is more elastic.

5.2 Characterizing Different Scientific Fields

Building on the insights from the simple model above, we seek to better understand the heterogeneous net effects of the China shock across scientific fields. Specifically, we map eight fields into a two-dimensional space (**Figure 4**). The horizontal axis captures congestion forces, proxied by the share of experimental or empirical (as opposed to theoretical) research in a random sample of abstracts from the OpenAlex dataset, classified using GPT-4 mini predictions.[19] Fields with a higher share of experimental/empirical research are assumed to have greater scope for expansion and to experience lower levels of congestion.

[19] Specifically, we utilize GPT-4o mini and abstract text from OpenAlex. To reduce computational workload, we take a 1% random sample from the full matched dataset within each year and Micro topic between 1995 and 2020, and we drop publications whose abstracts are either empty or exceed 500 words (likely due to measurement errors in the OpenAlex data). For each of these publications, we ask GPT to analyze its abstract and provide a numerical score between 0 and 1, where 0 indicates "purely theoretical" and 1 indicates "purely empirical or experimental."

The vertical axis reflects factors that are, *a priori*, conducive to spillover effects. One such factor is China's relative position to the research frontier, proxied by the China–US ratio of top 1% cited publications from 1995 to 2020. We also consider several additional factors: a more egalitarian field hierarchy (measured by the inverse of the P90–P50 ratio of top 10% cited publications among departments in the sample from 1990–1995), median team size, and the prevalence of inter-institutional research collaboration (i.e., share of 1995–2020 publications in the field that involve at least two institutions).

We find that Chemistry and EMS (Engineering & Materials Science) are characterized by both a greater scope for expansion and stronger Chinese research (Panel A, **Figure 4**). Mathematics also demonstrates strong Chinese research capacity but faces higher levels of congestion. In contrast, while CLS (Clinical & Life Sciences) exhibits expansion potential comparable to Chemistry and EMS, the quality of Chinese research in this field is substantially lower. Chemistry and EMS further stand out for their more egalitarian institutional hierarchies (Panel B). Meanwhile, median team size and inter-institutional collaboration appear less predictive of field-level variation (Panels C and D). This is consistent with our earlier finding that direct collaboration with China is not the primary driver of the positive net effects observed in Chemistry and EMS. Rather, the spillover effects likely occur within the idea space.

While this exercise is based on a highly stylized model of knowledge production and relies on imperfect proxies for key parameters, it remains instructive for understanding the heterogeneous net effects of the China shock across scientific fields within this framework.

We then take the mean of all scores between 1995 and 2020 for each field as a field-level characteristic. We specifically use the model gpt-4o-mini-2024-07-18, and include only one abstract in each query to avoid arbitrary contextual comparisons with other abstracts. The following prompt precedes every abstract: "You are an expert at classifying academic research. You will be given a publication abstract. Return a numerical score between 0 and 1, where 0 means purely theoretical and 1 means purely empirical or experimental. Provide your response strictly in the specified format." The temperature is set to 0, and all other parameters are left at their default settings.

6. Conclusions

China’s rapid emergence as a scientific and technological superpower is one of the most transformative developments of recent decades. With significant growth in research capacity—particularly in high-impact publications—China has become a formidable player, challenging long-established leaders such as the US, UK, Japan, Germany, and France. We investigate how China’s rise has affected research productivity at universities outside mainland China, focusing on the period from 1995 to 2020, during which China’s research capacity expanded dramatically.

Our key contribution lies in its methodology, which leverages novel data that classifies millions of publications into fine-grained topics within each scientific field. We employ a shift-share design implemented in the “idea space,” exposing universities in various fields (e.g., MIT-Chemistry or UC Berkeley-Chemistry) to different levels of the China shock. These levels are based on the topic-specific growth of China’s research capacity over time, as well as the initial research composition at each university-field. This approach enables us to isolate the causal effects of China’s rise from other confounding factors and to compare net effects across scientific fields within a unified framework.

Our findings reveal that the effects of China’s rise in science on the research performance of global universities outside mainland China are neither universally positive nor negative. Instead, the net impact varies across scientific fields, driven by the interplay between competition and spillover effects. In fields such as Chemistry and Engineering & Materials Science (EMS)—where China’s research quality is relatively strong—we find evidence of positive net effects, suggesting that spillovers outweigh the negative effects of congestion. In contrast, in fields like Clinical & Life Sciences (CLS), where Chinese research remains less advanced, congestion effects dominate, presenting challenges for incumbent institutions.

As China continues to increase its investment in science and technology, driven by a growing pool of STEM-educated talent, the global research community should strive to leverage the benefits of an expanding knowledge base while mitigating the downsides of intensified competition and potential crowding out. This study offers a valuable foundation for future research into the broader implications of China's rise on global scientific and technological progress.

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Table 1. Summary statistics, 1995-2020

	CLS	Chemistry	AEE	EE&CS	Physics	EMS	Earth	Math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Number of topics							
Number of Meso topics	132	37	24	26	27	20	12	8
	Panel B. Exposure to China							
Exposure to China b/w 1995 and 2020	0.57	1.03	0.77	2.53	0.40	1.72	1.03	0.68
	(0.13)	(0.27)	(0.11)	(0.36)	(0.10)	(0.25)	(0.21)	(0.11)
	Panel C. High-impact (top 10% cited) output							
Top 10% cited output in 1995	137.72	33.78	28.10	16.85	43.81	13.68	12.57	9.72
	(142.84)	(24.42)	(21.19)	(16.24)	(37.46)	(9.66)	(11.74)	(7.98)
Top 10% cited output in 2020	655.20	63.80	80.50	79.48	133.04	30.57	51.45	12.52
	(601.34)	(53.61)	(59.15)	(59.88)	(103.29)	(25.94)	(39.49)	(10.53)
Growth rate of top 10% cited output b/w 1995 and 2020	4.35	1.05	2.21	5.61	2.43	1.79	4.82	0.70
	(2.88)	(1.45)	(2.04)	(6.53)	(1.77)	(2.49)	(5.60)	(1.50)
	Panel D. Alternative measures of research performance							
Growth rate of total output b/w 1995 and 2020	2.72	1.29	1.94	4.07	1.49	1.90	3.09	1.22
	(1.45)	(0.90)	(1.15)	(2.51)	(0.91)	(1.72)	(1.84)	(0.93)
Growth rate of output in high-impact journals b/w 1995 and 2020	3.24	2.53	3.41	5.66	3.23	2.85	5.11	1.53
	(1.93)	(1.80)	(2.10)	(3.65)	(2.05)	(2.38)	(7.09)	(1.74)
Growth rate of new bigrams in all publications b/w 1995 and 2020	2.00	1.10	1.61	3.56	2.35	1.76	3.91	1.46
	(1.21)	(0.82)	(1.02)	(2.28)	(1.47)	(1.51)	(2.80)	(1.35)

Table 1. Summary statistics, 1995-2020 (continued)

	Panel E. Collaboration with China							
Share of top 10% cited output collaborated with China in 1995	0.00	0.00	0.00	0.01	0.03	0.01	0.04	0.01
	(0.00)	(0.01)	(0.01)	(0.03)	(0.07)	(0.03)	(0.10)	(0.07)
Share of top 10% cited output collaborated with China in 2020	0.10	0.27	0.21	0.24	0.35	0.31	0.26	0.14
	(0.03)	(0.14)	(0.09)	(0.13)	(0.15)	(0.19)	(0.12)	(0.17)
Share of top 10% cited output funded by China in 1995	0.00	0.00	0.00	0.00	0.03	0.00	0.02	0.00
	(0.00)	(0.01)	(0.01)	(0.02)	(0.07)	(0.01)	(0.08)	(0.01)
Share of top 10% cited output funded by China in 2020	0.05	0.23	0.15	0.19	0.32	0.27	0.21	0.11
	(0.02)	(0.13)	(0.09)	(0.12)	(0.15)	(0.17)	(0.11)	(0.16)
N	199	199	195	121	196	157	167	148

Notes. Panel A reports the number of Meso topics in each field. Panel B reports the mean (SD) of exposure to China (as defined by equation (2)) between 1995 and 2020 by department. Panel C summarizes the number of high-impact publications (top 10% cited within field and publication year) at the department level, reporting levels in 1995 and 2020, as well as the growth rate over this period. Panel D reports growth rates of alternative outcome measures between 1995 and 2020. High-impact journals are top 20% journals with at least 30 publications in the field over 1995-2020, ranked by their Category Normalized Citation Impact (CNCI) over 1995-2020. New bigrams are bigrams in publication titles that did not appear in any prior title in the field over the previous 10 years. Panel E summarizes the number of high-impact publications collaborated with China. A publication is collaborated with China if it involves any co-author affiliated with a China-based institution. A publication is funded by China if it is (co-)funded by any China-based funding agency. Standard deviations are shown in parentheses. Data source: Web of Science InCites.

Table 2. Impact of exposure to China's rise in science

	Dependent variable: Growth rate of high-impact (top 10% cited) publications, 1995-2020							
	CLS	Chemistry	AEE	EE&CS	Physics	EMS	Earth	Math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. No control							
Exposure to CN	-0.398**	0.195*	0.277**	0.782	0.182	0.637***	0.433	0.206
	(0.162)	(0.116)	(0.138)	(0.982)	(0.159)	(0.190)	(0.476)	(0.138)
	Panel B. Tier and Country							
Exposure to CN	-0.333**	0.278**	0.079	0.906	0.204	0.649***	0.392	0.184
	(0.157)	(0.124)	(0.130)	(0.920)	(0.142)	(0.212)	(0.452)	(0.117)
	Panel C. Initial ties to China							
Exposure to CN	-0.340**	0.275**	0.130	0.917	0.205	0.640***	0.405	0.180
	(0.159)	(0.129)	(0.136)	(0.923)	(0.137)	(0.224)	(0.424)	(0.114)
	Panel D. Predicted global output growth							
Exposure to CN	-0.352**	0.282*	0.102	1.036	0.171	0.641***	0.189	0.141
	(0.161)	(0.149)	(0.144)	(0.962)	(0.148)	(0.225)	(0.758)	(0.116)
N	199	199	195	121	196	157	167	148

Notes. Each column reports estimates of equation (1) for departments' top 10% cited publication growth rate between 1995 and 2020 in the respective field. The main explanatory variable, "exposure to China", is standardized (i.e., mean 0 and standard deviation 1) within each field. Panel A has no controls. Panel B controls for tier FE and country FE. For tier FE, departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in the field. For country FE, there are five country groups: US, UK, East Asia, Western Europe (excluding UK), and others. Panel C additionally controls for initial ties to China and Chinese researchers. For each department, we compute the share of its initial (1990-1995) publications that involve at least one co-author affiliated with a China-based institution and the share of authors with Chinese surnames among all authors associated with its initial (1990-1995) publications. Panel D additionally controls for exposure to predicted global output growth. Exposure to predicted global output growth is based on projected global growth in publications in each topic between 1980 and 1995 weighted by initial topic shares. Robust standard errors are reported in parentheses. Data source: Web of Science InCites. *** p<.01, ** p<.05, and * p<.1.

Table 3. Alternative measures of research performance

	Dependent variable: Growth rate of various outcomes, 1995-2020							
	CLS	Chemistry	AEE	EE&CS	Physics	EMS	Earth	Math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Top 10% cited output							
Exposure to CN	-0.352**	0.282*	0.102	1.036	0.171	0.641***	0.189	0.141
	(0.161)	(0.149)	(0.144)	(0.962)	(0.148)	(0.225)	(0.758)	(0.116)
	Panel B. Total output							
Exposure to CN	-0.193**	0.232**	0.002	0.250	0.094	0.589***	0.111	-0.063
	(0.086)	(0.108)	(0.102)	(0.341)	(0.069)	(0.140)	(0.272)	(0.086)
	Panel C. Output in high-impact journals							
Exposure to CN	-0.204*	0.474**	-0.018	0.210	0.194	0.654***	-1.138	-0.185
	(0.108)	(0.216)	(0.159)	(0.442)	(0.187)	(0.187)	(1.776)	(0.149)
	Panel D. New bigrams							
Exposure to CN	-0.130*	0.201**	0.076	-0.114	0.040	0.350***	0.158	-0.091
	(0.070)	(0.097)	(0.107)	(0.300)	(0.155)	(0.111)	(0.437)	(0.119)
N	199	199	195	121	196	157	167	148
Tier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial ties to China	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted global output growth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Each column reports estimates of equation (1) for departments' growth rate of various outcomes between 1995 and 2020 in the respective field. The main explanatory variable, "exposure to China", is standardized (i.e., mean 0 and standard deviation 1) within each field. Panel A repeats our baseline (Panel D of Table 2) with top 10% cited publication growth rate as the outcome. Panel B reports results for total publication growth rate. Panels C reports results for growth rate of publications in top 20% journals, where journals with at least 30 publications in the field over 1995-2020 are ranked by their Category Normalized Citation Impact (CNCI) over 1995-2020. Panel D reports results for growth rates of new bigrams between 1995-2020, where we count bigrams in publication titles that did not appear in any prior title in the field over the previous 10 years. Robust standard errors are reported in parentheses. Data source: Web of Science InCites. *** p<.01, ** p<.05, and * p<.1.

Table 4. Robustness to excluding dominant institutions

	Dependent variable: Growth rate of high-impact (top 10% cited) publications, 1995-2020							
	CLS	Chemistry	AEE	EE&CS	Physics	EMS	Earth	Math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Baseline							
Exposure to CN	-0.352**	0.282*	0.102	1.036	0.171	0.641***	0.189	0.141
	(0.161)	(0.149)	(0.144)	(0.962)	(0.148)	(0.225)	(0.758)	(0.116)
N	199	199	195	121	196	157	167	148
	Panel B. Exclude if >5% of global output							
Exposure to CN	-0.353**	0.282*	0.102	1.036	0.101	0.641***	0.189	0.141
	(0.161)	(0.150)	(0.144)	(0.962)	(0.179)	(0.225)	(0.758)	(0.116)
N	198	198	195	121	189	157	167	148
	Panel C. Exclude if >5% of global top 10% cited output							
Exposure to CN	-0.316*	0.227	0.113	1.282	0.046	0.584**	0.183	0.139
	(0.185)	(0.158)	(0.145)	(1.064)	(0.161)	(0.239)	(0.768)	(0.120)
N	157	180	189	111	174	155	161	146
Tier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial ties to China	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted global output growth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Each column reports estimates of equation (1) for departments' top 10% cited publication growth rate between 1995 and 2020 in the respective field. The main explanatory variable, "exposure to China", is standardized (i.e., mean 0 and standard deviation 1) within each field. Panel A repeats our baseline (Panel D of Table 2). Panels B and C exclude departments with at least 5% of the world's output in each Meso topic, based on total and top 10% cited publications, respectively. Robust standard errors are reported in parentheses. Data source: Web of Science InCites. *** p<.01, ** p<.05, and * p<.1.

Table 5. Research output not involving China-based collaborators or Chinese funding

	Dependent variable: Growth rate of high-impact (top 10% cited) publications, 1995-2020							
	CLS	Chemistry	AEE	EE&CS	Physics	EMS	Earth	Math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Overall							
Exposure to CN	-0.352**	0.282*	0.102	1.036	0.171	0.641***	0.189	0.141
	(0.161)	(0.149)	(0.144)	(0.962)	(0.148)	(0.225)	(0.758)	(0.116)
	Panel B. Output without China-based collaborators							
Exposure to CN	-0.301**	0.234**	0.018	0.552	0.260**	0.555***	0.129	0.037
	(0.147)	(0.094)	(0.113)	(0.685)	(0.121)	(0.152)	(0.555)	(0.099)
	Panel C. Output without Chinese funding							
Exposure to CN	-0.333**	0.242**	0.023	0.601	0.256**	0.555***	0.150	0.059
	(0.153)	(0.102)	(0.123)	(0.728)	(0.125)	(0.162)	(0.585)	(0.094)
N	199	199	195	121	196	157	167	148
Tier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial ties to China	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted global output growth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Each column reports estimates of equation (1) between 1995 and 2020 in the respective field. The main explanatory variable, "exposure to China", is standardized (i.e., mean 0 and standard deviation 1) within each field. Panel A repeats our baseline (Panel D of Table 2) with top 10% cited publication growth rate as the outcome. Panel B reports results when restricting outcomes to each department's publications that do not involve any China-based coathors. Panel C shows results when outcomes to each department's publications that do not involve any funding from China-based funding agencies. Robust standard errors are reported in parentheses. Data source: Web of Science InCites. *** p<.01, ** p<.05, and * p<.1.

Table 6. References to Chinese research

	CLS	Chemistry	AEE	EE&CS	Physics	EMS	Earth	Math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Growth rate of top 10% cited publications, 1995-2020							
Exposure to CN	-0.352**	0.282*	0.102	1.036	0.171	0.641***	0.189	0.141
	(0.161)	(0.149)	(0.144)	(0.962)	(0.148)	(0.225)	(0.758)	(0.116)
	Panel B. Change in share of publications citing China, 1995-2020							
Exposure to CN	0.010**	0.015***	0.025***	0.013*	-0.006	0.013	0.020	0.032**
	(0.004)	(0.005)	(0.007)	(0.007)	(0.005)	(0.009)	(0.014)	(0.013)
Mean of Dep. Var.	0.527	0.784	0.637	0.611	0.689	0.680	0.637	0.325
	Panel C. Change in share of references including China, 1995-2020							
Exposure to CN	0.000	0.006*	0.006***	0.007***	-0.004*	0.003	0.002	0.006**
	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
Mean of Dep. Var.	0.042	0.118	0.057	0.086	0.078	0.113	0.068	0.029
N	199	199	195	121	196	157	167	148
Tier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial ties to China	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted global output growth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Each column reports estimates of equation (1) between 1995 and 2020 in the respective field. The main explanatory variable, "exposure to China", is standardized (i.e., mean 0 and standard deviation 1) within each field. Panel A repeats our baseline (Panel D of Table 2) with top 10% cited publication growth rate as the outcome. Panel B reports results for changes in the share of a department's publications that cite any publication involving a China-based institution. Panel C reports results for changes in the mean share of a department's publications' references involving a China-based institution. Robust standard errors are reported in parentheses. Data source: Web of Science InCites & OpenAlex. *** p<.01, ** p<.05, and * p<.1.

Table 7. Heterogeneity by university location and tier

	Dependent variable: Growth rate of high-impact (top 10% cited) publications, 1995-2020							
	CLS	Chemistry	AEE	EE&CS	Physics	EMS	Earth	Math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. US vs. non-US							
Exposure to CN × US	-0.104	0.172	0.099	-0.344	0.080	0.365	0.343	-0.072
	(0.118)	(0.212)	(0.202)	(0.402)	(0.267)	(0.276)	(0.805)	(0.141)
Exposure to CN × non-US	-0.929**	0.326*	0.104	2.435	0.225	0.928***	-0.578	0.315**
	(0.411)	(0.178)	(0.193)	(1.692)	(0.163)	(0.351)	(0.891)	(0.154)
p-value for difference	0.058	0.548	0.986	0.096	0.634	0.194	0.285	0.051
	Panel B. High vs. Low-tiers							
Exposure to CN × High tier	-0.076	0.354*	0.258	-0.088	0.252	0.362**	-0.146	0.058
	(0.223)	(0.211)	(0.222)	(0.618)	(0.177)	(0.171)	(0.534)	(0.098)
Exposure to CN × Low tier	-0.485**	0.228	0.037	1.676	0.121	0.858**	0.474	0.240
	(0.231)	(0.168)	(0.169)	(1.349)	(0.197)	(0.342)	(1.117)	(0.211)
p-value for difference	0.209	0.588	0.386	0.169	0.612	0.151	0.479	0.409
N	199	199	195	121	196	157	167	148
Tier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial ties to China	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted global output growth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

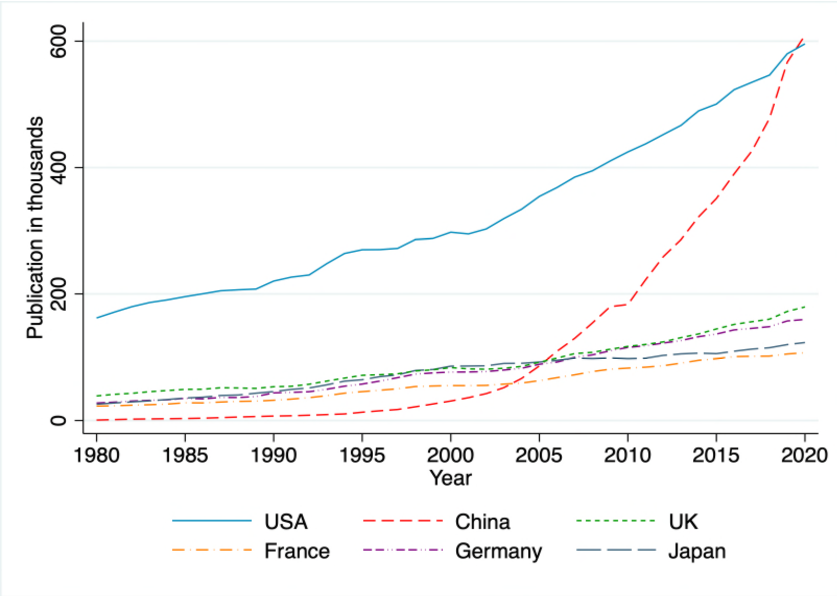
Notes. Each column reports estimates of a variant of equation (1) for departments' top 10% cited publication growth rate between 1995 and 2020 in the respective field. The main explanatory variable, "exposure to China", is standardized (i.e., mean 0 and standard deviation 1) within each field. Panel A reports results where exposure to China is interacted with a dummy indicating whether a department is US-based. Panel B reports results where exposure to China is interacted with a dummy indicating whether a department is in the High tier, where departments are divided into two equally sized tiers based on their top 10% cited publications between 1990 and 1995 in the field. Each panel reports two-sided p-values under the null hypothesis that the coefficients of the interaction terms are equal. Robust standard errors are reported in parentheses. Data source: Web of Science InCites. *** p<.01, ** p<.05, and * p<.1.

Table 8. Topic-level analysis

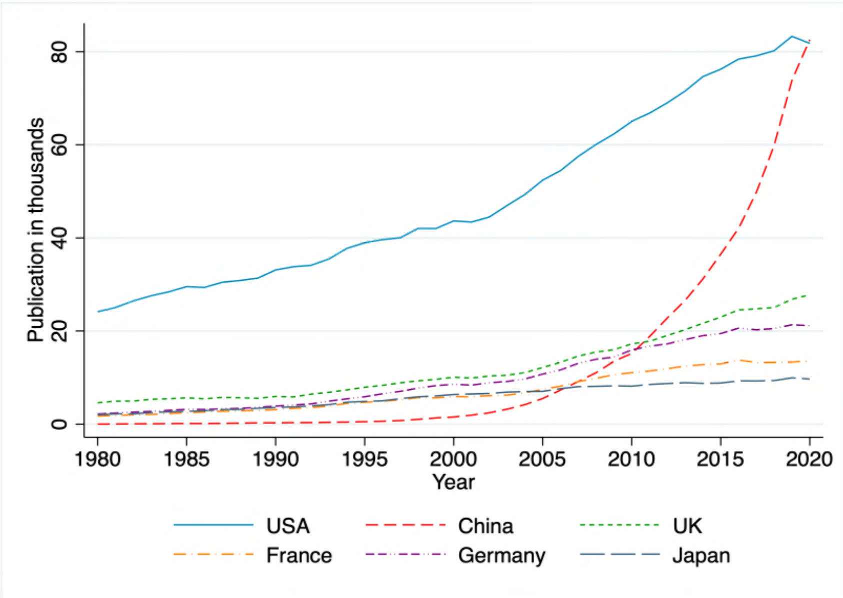
	Dependent variable: Change in log world's output 1995-2020			
	All publications		**Excluding China**	
	(1)	(2)	(3)	(4)
Change in log China's output: 1995-2020	0.421***		0.401***	
	(0.026)		(0.024)	
CLS × Change in log China's output: 1995-2020		0.374***		0.352***
		(0.043)		(0.046)
Chemistry × Change in log China's output: 1995-2020		0.648***		0.584***
		(0.082)		(0.073)
AEE × Change in log China's output: 1995-2020		0.348**		0.276*
		(0.138)		(0.147)
EE&CS × Change in log China's output: 1995-2020		0.547***		0.510***
		(0.056)		(0.055)
Physics × Change in log China's output: 1995-2020		0.379***		0.313***
		(0.056)		(0.058)
EMS × Change in log China's output: 1995-2020		0.565***		0.521***
		(0.044)		(0.054)
Earth × Change in log China's output: 1995-2020		0.302***		0.185
		(0.111)		(0.118)
Math × Change in log China's output: 1995-2020		0.543**		0.389
		(0.251)		(0.292)
N	273	273	273	273
Field FE	No	Yes	No	Yes

Notes. Each column reports estimates of equation (5) between 1995 and 2020. The sample pools Meso topics from all fields. Columns 1 and 2 report results for growth in total global output. Columns 3 and 4 report results for global output excluding publications involving any China-based institution. There are 13 Meso topics where China has zero publication in 1995, hence being out of the sample, including 10 in CLS, and one in Chemistry, EE&CS, and Physics, respectively. Robust standard errors are reported in parentheses. Data source: Web of Science InCites. *** p<.01, ** p<.05, and * p<.1.

Figure 1. China's rise in science



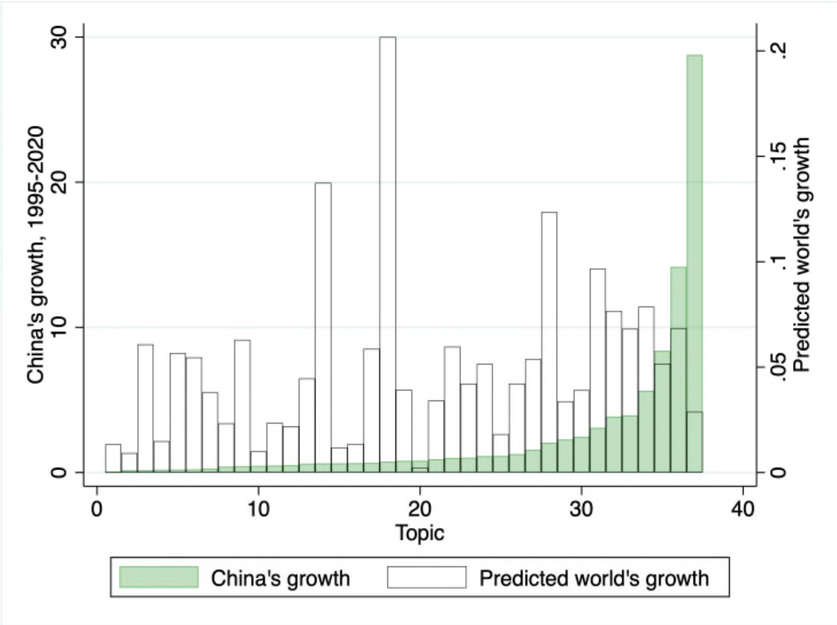
(A) Total publication



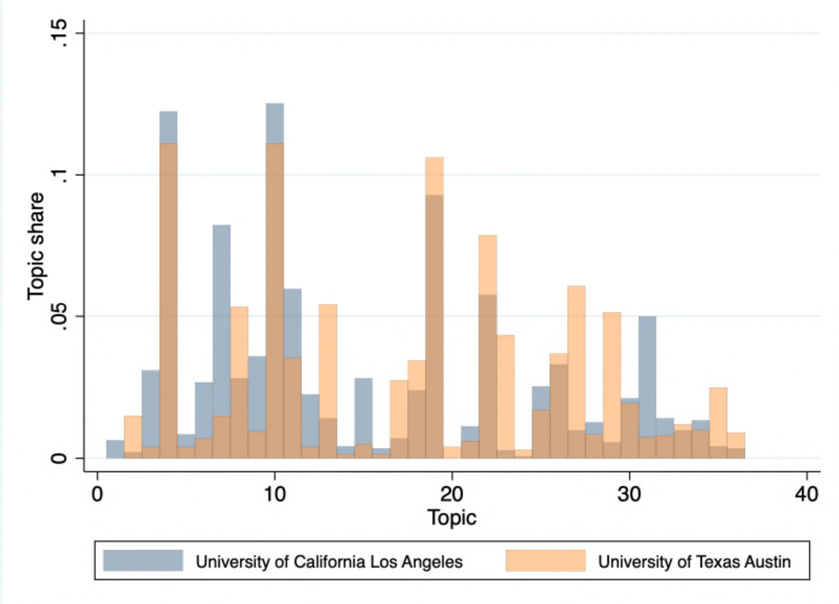
(B) Top 10% cited publication

Notes To count science and technology publications, we include all research areas in the Citation Topics schema except for Social Sciences and Arts & Humanities. Top 10% cited status is based on output of the same document type published in the same field and the same year. Data source: Web of Science InCites.

Figure 2. Sources of variation



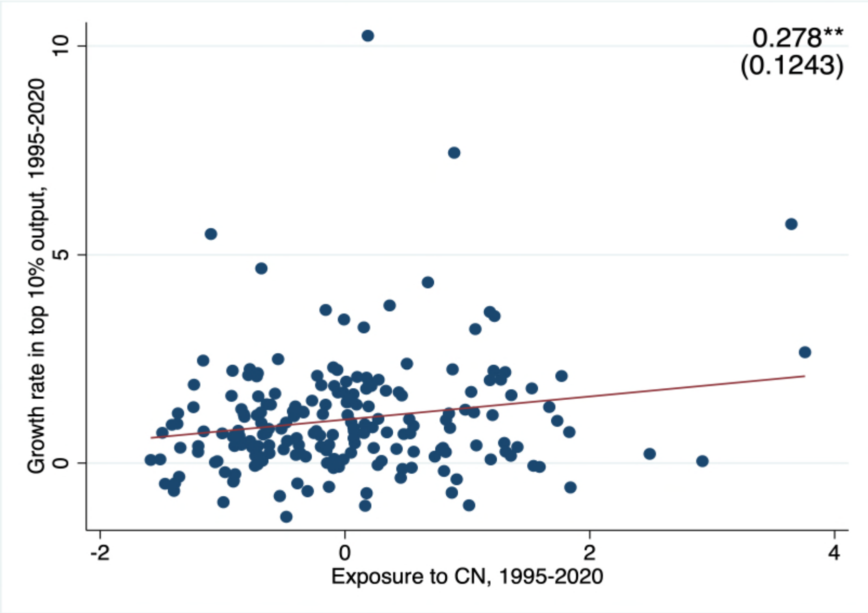
(A) China’s growth in different topics, 1995-2020



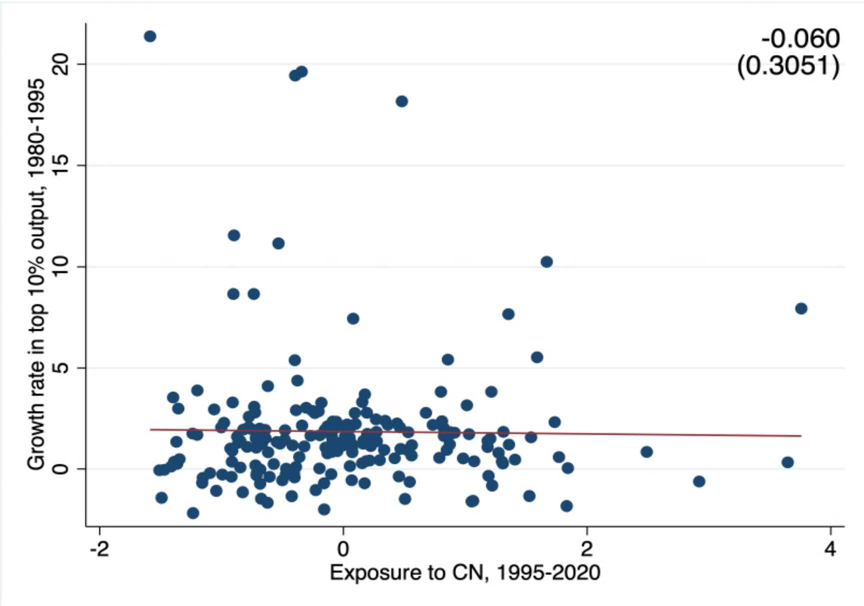
(B) Initial (1990-95) topic shares

Notes. For each topic in Chemistry, Panel A plots changes in China's share of the world's total output on the left vertical axis and predicted world’s growth based on equation (3) on the right vertical axis. Panel B plots topic distributions of the University of California Los Angeles and the University of Texas at Austin in Chemistry, where an institution's topic share is the fraction of its total publications in the field between 1990 and 1995 on the topic. On the horizontal axis, topics are arranged by changes in China’s share of world’s total output between 1995 and 2020 in the ascending order. Data source: Web of Science InCites.

Figure 3. Sketch of identification strategy



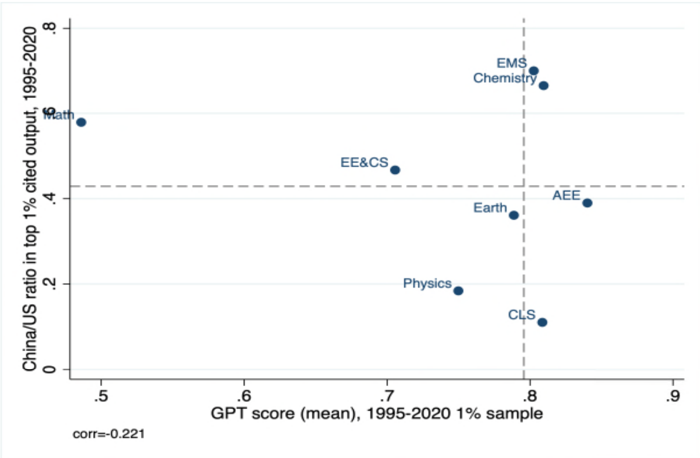
(A) Growth in output, 1995-2020



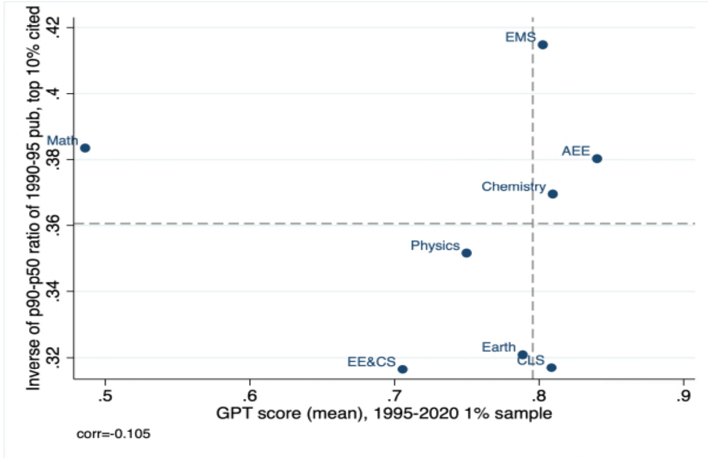
(B) Growth in output, 1980-1995

Notes. Panels A and B plot changes in a department's growth rate of top 10% cited publications in Chemistry between 1995 and 2020, and between 1980 and 1995, against changes in the department's exposure to China between 1995 and 2020, respectively. University tier FE and country-group FE are conditioned on (similar to Panel B of Table 2). Top 10% cited status is based on output of the same document type published in the same field and the same year. Each point represents a department. The slope of the linear fitted line is shown at the top right corner, with robust standard errors reported inside parentheses. N=199. Data source: Web of Science InCites.

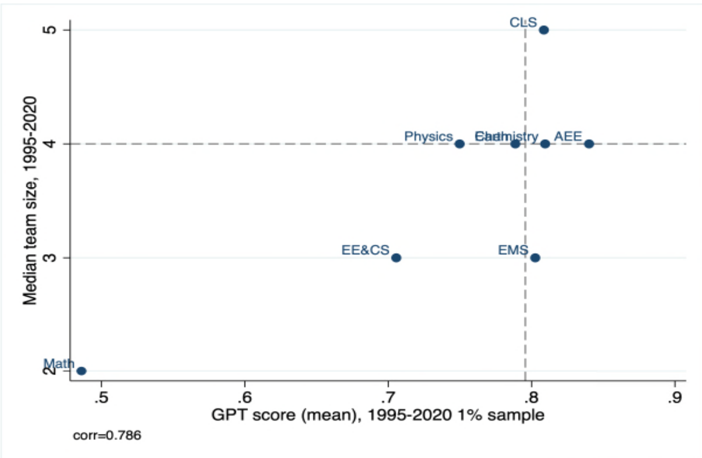
Figure 4. Characterizing scientific fields



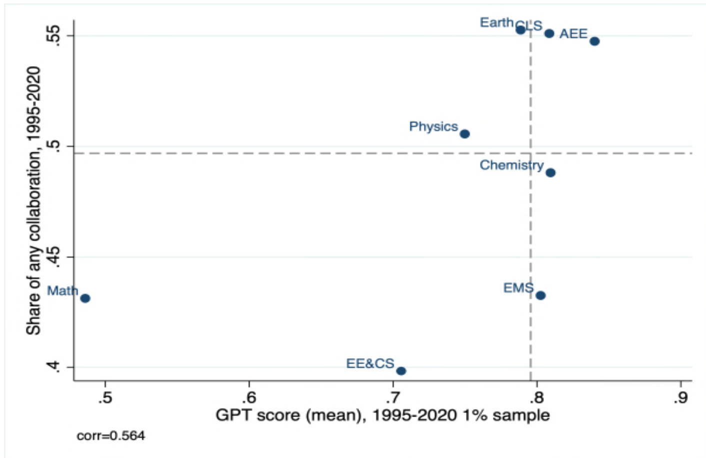
(A) China/US ratio in top 1% cited output, 1995-2020



(B) Inverse of p90-p50 ratio of 1990-95 pub, top 10% cited



(C) Median team size, 1995-2020



(D) Share of institutitional collaboration, 1995-2020

Notes. The horizontal axes show shares of experimental or empirical (as opposed to theoretical) research in a random 1% sample of abstracts from the OpenAlex dataset, classified using GPT-4 mini predictions. On the vertical axis, Panel A plots the China–US ratio of top 1% cited publications from 1995 to 2020, Panel B plots the inverse of p90-p50 ratio of departments' top 10% cited publications from 1990 to 1995 in the sample, Panel C plots the median team size of all publications from 1995 and 2020 in the sample, and Panel D plots share of publications that involve at least two institutions from 1995 and 2020. Data source: Web of Science InCites and OpenAlex.

Appendix A

Table A1. Nature Index

2016 Ranking			2024 Ranking		
Position	**Institution**	**Share**	**Position**	**Institution**	**Share**
1	Harvard University, US	881.95	1	Harvard University, US	1143.4
2	Stanford University, US	636.39	2	University of Chinese Academy of Sciences (UCAS), China	635.81
3	Massachusetts Institute of Technology (MIT), US	567.07	3	University of Science and Technology of China (USTC), China	631.2
4	The University of Tokyo (UTokyo), Japan	527.05	4	Peking University (PKU), China	617.17
5	University of Oxford, UK	438.51	5	Nanjing University (NJU), China	609.45
6	University of Cambridge, UK	432.89	6	Zhejiang University (ZJU), China	595.37
7	University of California, Berkeley (UC Berkeley), US	426.98	7	Tsinghua University, China	593.45
8	Swiss Federal Institute of Technology Zurich (ETH Zurich), Switzerland	377.17	8	Sun Yat-sen University (SYSU), China	492.47
9	Peking University (PKU), China	369.83	9	Shanghai Jiao Tong University (SJTU), China	488.94
10	University of Michigan (U-M), US	368.6	10	Massachusetts Institute of Technology (MIT), US	484.86
11	University of California, San Diego (UC San Diego), US	363.26	11	Stanford University, US	474.13
12	University of California, Los Angeles (UCLA), US	345.08	12	Fudan University, China	461.26
13	Yale University, US	338.19	13	Sichuan University (SCU), China	413.63
14	Columbia University in the City of New York (CU), US	325.93	14	The University of Tokyo (UTokyo), Japan	389.36
15	University of Toronto (U of T), Canada	325.16	15	University of Oxford, UK	388.35
16	University of Pennsylvania (Penn), US	312.66	16	University of Michigan (U-M), US	380.5
17	Kyoto University, Japan	311.72	17	University of Cambridge, UK	368.12
18	Northwestern University (NU), US	302.72	18	Swiss Federal Institute of Technology Zurich (ETH Zurich), Switzerland	346.26
19	University of Washington (UW), US	296.45	19	Yale University, US	342.16
20	Nanjing University (NJU), China	290.48	20	Nankai University (NKU), China	337.67
21	California Institute of Technology (Caltech), US	287.3	21	Wuhan University (WHU), China	334.72
22	University of Wisconsin-Madison (UW-Madison), US	281.45	22	University of Toronto (U of T), Canada	334.38
23	Tsinghua University, China	278.65	23	University of California, San Diego (UC San Diego), US	331.74
24	Cornell University, US	269.4	24	Columbia University in the City of New York (CU), US	330.31
25	The University of Texas at Austin (UT Austin), US	269.34	25	University of Pennsylvania (Penn), US	323.65
26	University of Illinois at Urbana-Champaign (UIUC), US	266.45	26	Cornell University, US	320.47
27	Johns Hopkins University (JHU), US	263.56	27	University of California, Los Angeles (UCLA), US	313.78
28	University of Science and Technology of China (USTC), China	261.4	28	Huazhong University of Science and Technology (HUST), China	312.65
29	Nanyang Technological University (NTU), Singapore	254.94	29	University of California, Berkeley (UC Berkeley), US	312.19
30	Princeton University, US	253.35	30	Shandong University (SDU), China	309.49
31	University of Minnesota (UMN), US	243.24	31	University of Washington (UW), US	295.93
32	Swiss Federal Institute of Technology Lausanne (EPFL), Switzerland	228.57	32	Northwestern University (NU), US	295.49
33	UCL, UK	224.28	33	Johns Hopkins University (JHU), US	294.65
34	Imperial College London (ICL), UK	222.98	34	Xiamen University (XMU), China	289.61
35	Zhejiang University (ZJU), China	222.73	35	Soochow University, China	289.15
31	University of Minnesota (UMN), US	243.24	31	University of Washington (UW), US	295.93
36	University of California, Santa Barbara (UCSB), US	216.45	36	Southern University of Science and Technology (SUSTech), China	279.54
37	Duke University, US	213.82	37	Jilin University (JLU), China	268.37
38	National University of Singapore (NUS), Singapore	213.03	38	National University of Singapore (NUS), Singapore	253.94
39	The University of Chicago (UChicago), US	211.71	39	Central South University (CSU), China	252.7
40	Fudan University, China	209.78	40	Washington University in St. Louis (WUSTL), US	251.01

Notes. The table shows the 2016 and 2024 Nature Index Research Leaders rankings of institutions based on fractional counts (Share) of publications in high-quality journals. The 2016 ranking is based on Nature Index data from 1 January 2015 to 31 December 2015. The 2024 ranking is based on Nature Index data from 1 January 2023 to 31 December 2023. China-based institutions are marked with a blue color. Data source: Nature Index Research Leaders.

Table A2. Example of Meso topics

Field	Topic
Chemistry	2.1 Synthesis
Chemistry	2.114 Organic Semiconductors
Chemistry	2.123 Protein Structure, Folding & Modelling
Chemistry	2.145 Biosensors
Chemistry	2.15 Physical Chemistry
Chemistry	2.160 Microfluidic Devices & Superhydrophobicity
Chemistry	2.165 Nanofibers, Scaffolds & Fabrication
Chemistry	2.166 Chromatography & Electrophoresis
Chemistry	2.167 Microelectromechanical Systems
Chemistry	2.170 Nucleic Acids Chemistry
Chemistry	2.176 Drug Delivery Chemistry
Chemistry	2.190 Surfactants, Lipid Bilayers & Antimicrobial Peptides
Chemistry	2.209 Spectrometry & Separation
Chemistry	2.210 Corrosion & Deposition Chemistry
Chemistry	2.211 Mass Spectrometry
Chemistry	2.22 Inorganic & Nuclear Chemistry
Chemistry	2.234 Photochemistry
Chemistry	2.241 Membrane Science
Chemistry	2.244 Chemometrics
Chemistry	2.259 Optical Chemistry
Chemistry	2.276 Metalloenzymes
Chemistry	2.282 Hydrogen Chemistry & Storage
Chemistry	2.296 Textile Chemistry
Chemistry	2.298 Perovskite Solar Cells
Chemistry	2.311 Nitroxides, Antioxidants & Free Radicals
Chemistry	2.326 Neutron Capture Therapy
Chemistry	2.39 Polymer Science
Chemistry	2.41 Catalysts
Chemistry	2.53 Polymers & Macromolecules
Chemistry	2.59 Pigments, Sensors & Probes
Chemistry	2.62 Electrochemistry
Chemistry	2.67 Nanoparticles
Chemistry	2.74 Photocatalysts
Chemistry	2.76 2D Materials
Chemistry	2.78 Photoluminescence
Chemistry	2.89 Ionic, Molecular & Complex Liquids
Chemistry	2.90 Water Treatment

Notes. This table presents a list of meso topics within Chemistry from the InCites 2023 Citation Topics schema.

Table A3. Robustness to exposure based on earlier topic shares

	Dependent variable: Growth rate of high-impact (top 10% cited) publications, 1995-2020							
	CLS	Chemistry	AEE	EE&CS	Physics	EMS	Earth	Math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Baseline							
Exposure to CN	-0.352**	0.282*	0.102	1.036	0.171	0.641***	0.189	0.141
	(0.161)	(0.149)	(0.144)	(0.962)	(0.148)	(0.225)	(0.758)	(0.116)
	Panel B. Exposure based on 1980-1985 topic shares							
Exposure to CN	-0.129	0.227*	-0.087	0.564	0.249	0.250	-0.234	0.139
	(0.095)	(0.128)	(0.166)	(1.105)	(0.182)	(0.232)	(1.457)	(0.118)
	Panel C. Exposure based on 1985-1990 topic shares							
Exposure to CN	-0.095	0.153	-0.044	1.124	0.006	0.482**	0.004	0.138
	(0.108)	(0.139)	(0.154)	(1.039)	(0.103)	(0.226)	(1.187)	(0.107)
	Panel D. Exposure based on 1980-1995 topic shares							
Exposure to CN	-0.342**	0.258*	0.012	1.166	0.158	0.542**	0.097	0.134
	(0.168)	(0.147)	(0.160)	(1.098)	(0.138)	(0.235)	(1.119)	(0.114)
N	199	199	195	121	196	157	167	148
Tier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial ties to China	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted global output growth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Each column reports estimates of equation (1) for departments' top 10% cited publication growth rate between 1995 and 2020 in the respective field. The main explanatory variable, "exposure to China", is standardized (i.e., mean 0 and standard deviation 1) within each field. Panel A repeats our baseline (Panel D of Table 2), using the topic compositions of each department's publications from 1990 to 1995 to define exposure to China, as specified in equation (2). Panels B through D explore alternative time windows for measuring departments' topic shares—specifically, 1980–1985, 1985–1990, and 1980–1995, respectively. Robust standard errors are reported in parentheses. Data source: Web of Science InCites. *** p<.01, ** p<.05, and * p<.1.

Table A4. Robustness to using micro (vs. meso) topics

	Dependent variable: Growth rate of high-impact (top 10% cited) publications, 1995-2020							
	CLS	Chemistry	AEE	EE&CS	Physics	EMS	Earth	Math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. No control							
Exposure to CN	-0.351**	0.168	0.273**	0.012	0.108	0.829***	0.298	0.009
	(0.149)	(0.108)	(0.137)	(0.433)	(0.155)	(0.219)	(0.391)	(0.139)
	Panel B. Tier and Country							
Exposure to CN	-0.155	0.218*	0.149	0.388	0.121	0.696***	0.130	0.004
	(0.144)	(0.114)	(0.132)	(0.503)	(0.147)	(0.235)	(0.404)	(0.116)
	Panel C. Initial ties to China							
Exposure to CN	-0.166	0.215*	0.167	0.554	0.125	0.715***	0.195	-0.003
	(0.145)	(0.119)	(0.132)	(0.581)	(0.144)	(0.234)	(0.378)	(0.113)
	Panel D. Predicted global output growth							
Exposure to CN	-0.149	0.200*	0.159	0.518	0.102	0.694***	-0.079	0.014
	(0.148)	(0.115)	(0.129)	(0.568)	(0.151)	(0.246)	(0.522)	(0.109)
N	199	199	195	121	196	157	167	148
Number of Micro topics	932	264	247	207	165	137	66	64

Notes. Each column reports estimates of equation (1) for departments' top 10% cited publication growth rate between 1995 and 2020 in the respective field. Exposure to China and predicted global output growth are constructed based on Micro instead of Meso topics. The main explanatory variable, "exposure to China", is standardized (i.e., mean 0 and standard deviation 1) within each field. Panel A has no controls. Panel B controls for tier FE and country FE. For tier FE, departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in the field. For country FE, there are five country groups: US, UK, East Asia, Western Europe (excluding UK), and others. Panel C additionally controls for initial ties to China and Chinese researchers. For each department, we compute the share of its initial (1990-1995) publications that involve at least one co-author affiliated with a China-based institution and the share of authors with Chinese surnames among all authors associated with its initial (1990-1995) publications. Panel D additionally controls for exposure to predicted global output growth. Exposure to predicted global output growth is based on projected global growth in publications in each topic between 1980 and 1995 weighted by initial topic shares. Robust standard errors are reported in parentheses. Data source: Web of Science InCites. *** p<.01, ** p<.05, and * p<.1.

Table A5. Restricting analysis window to 1995-2015

	Dependent variable: Growth rate of high-impact (top 10% cited) publications, 1995-2015							
	CLS	Chemistry	AEE	EE&CS	Physics	EMS	Earth	Math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. No control							
Exposure to CN	-0.452***	0.251**	0.190	0.865	0.135	0.574***	0.320	0.218
	(0.158)	(0.119)	(0.140)	(1.024)	(0.149)	(0.192)	(0.423)	(0.142)
	Panel B. Tier and Country							
Exposure to CN	-0.340**	0.334***	-0.035	1.041	0.177	0.531**	0.364	0.175
	(0.154)	(0.124)	(0.134)	(0.957)	(0.136)	(0.209)	(0.370)	(0.121)
	Panel C. Initial ties to China							
Exposure to CN	-0.334**	0.332***	0.007	1.029	0.182	0.527**	0.279	0.172
	(0.159)	(0.127)	(0.152)	(0.942)	(0.137)	(0.219)	(0.371)	(0.119)
	Panel D. Predicted global output growth							
Exposure to CN	-0.355**	0.371**	-0.029	1.107	0.138	0.540**	-0.397	0.126
	(0.160)	(0.148)	(0.157)	(0.963)	(0.152)	(0.223)	(1.084)	(0.130)
N	199	199	195	121	196	157	167	148

Notes. Each column reports estimates of equation (1) for departments' top 10% cited publication growth rate between 1995 and 2015 in the respective field. The dependent variable is growth rate of top 10% cited publications between 1995 and 2015 to avoid interference from the 2018 China Initiative. The main explanatory variable, "exposure to China", is standardized (i.e., mean 0 and standard deviation 1) within each field. Panel A has no controls. Panel B controls for tier FE and country FE. For tier FE, departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in the field. For country FE, there are five country groups: US, UK, East Asia, Western Europe (excluding UK), and other. Panel C additionally controls for initial ties to China and Chinese researchers. For each department, we compute the share of its initial (1990-1995) publications that involve at least one co-author affiliated with a China-based institution and the share of authors with Chinese surnames among all authors associated with its initial (1990-1995) publications. Panel D additionally controls for exposure to predicted global output growth in the specification in Panel B. Exposure to predicted global output growth is based on projected global growth in publications in each topic between 1980 and 1995 weighted by the initial topic share. Robust standard errors are reported in parentheses. Data source: Web of Science InCites. *** p<.01, ** p<.05, and * p<.1.

Table A6. Robustness to uniform sample size

	Dependent variable: Growth rate of high-impact (top 10% cited) publications, 1995-2020							
	CLS	Chemistry	AEE	EE&CS	Physics	EMS	Earth	Math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Baseline (T2 Panel D)							
Exposure to CN	-0.352**	0.282*	0.102	1.036	0.171	0.641***	0.189	0.141
	(0.161)	(0.149)	(0.144)	(0.962)	(0.148)	(0.225)	(0.758)	(0.116)
N	199	199	195	121	196	157	167	148
	Panel B. N=121							
Exposure to CN	-0.328	0.420*	0.199	1.036	0.344*	0.663***	-0.863*	0.158
	(0.216)	(0.212)	(0.207)	(0.962)	(0.176)	(0.186)	(0.485)	(0.109)
N	121	121	121	121	121	121	121	121
Tier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial ties to China	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predicted global output growth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Each column reports estimates of equation (1) for departments' top 10% cited publication growth rate between 1995 and 2020 in the respective field. The main explanatory variable, "exposure to China", is standardized (i.e., mean 0 and standard deviation 1) within each sample. Panel A repeats our baseline (Panel D of Table 2). Panel B repeats the baseline specification with uniform sample size across all fields, i.e. N=121. In each field, we rank departments by their top 10% cited publications between 1990 and 1995 in the field and take the top 121 departments. Robust standard errors are reported in parentheses. Data source: Web of Science InCites. *** p<.01, ** p<.05, and * p<.1.

Appendix B

Table B1. Relationship between topic shares and institution characteristics: CLS

	Dep. Var.: Topic share over 1990-1995					Dep. Var.: Exposure to CN
	1.196 Micro & Long Noncoding RNA	1.164 Endocrinology & Metabolism	1.66 HIV	1.21 Psychiatry	1.79 Molecular & Cell Biology - Physiology	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of collaboration with CN; 1990-1995	0.003	-0.513	1.568	0.202	-0.662	-2.180
	(0.010)	(0.340)	(1.191)	(0.441)	(0.438)	(5.808)
Share of Chinese surnames; 1990-1995	-0.003	0.047	0.052	-0.118	-0.016	-0.482
	(0.002)	(0.098)	(0.129)	(0.122)	(0.120)	(1.482)
4th tier	-0.000	-0.002	-0.001	0.001	0.004	0.002
	(0.000)	(0.002)	(0.002)	(0.002)	(0.003)	(0.033)
3rd tier	-0.000	0.003	0.004	0.000	0.004	-0.022
	(0.000)	(0.002)	(0.003)	(0.002)	(0.003)	(0.032)
2nd tier	-0.000	0.001	0.007	0.001	0.000	0.007
	(0.000)	(0.002)	(0.003)	(0.002)	(0.002)	(0.034)
1st tier	-0.000	-0.002	0.006	0.002	0.004	-0.007
	(0.000)	(0.002)	(0.003)	(0.003)	(0.002)	(0.031)
East Asia	-0.000	-0.002	-0.008	-0.020	0.014	0.038
	(0.000)	(0.003)	(0.004)	(0.003)	(0.004)	(0.057)
Europe	-0.000	0.001	-0.002	-0.010	-0.004	-0.000
	(0.000)	(0.003)	(0.004)	(0.003)	(0.003)	(0.039)
UK	-0.000	-0.002	-0.002	-0.004	-0.003	-0.075
	(0.000)	(0.003)	(0.004)	(0.004)	(0.003)	(0.036)
other	-0.000	0.002	-0.007	0.001	0.003	-0.018
	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)	(0.031)
Observations	199	199	199	199	199	199
R-squared	0.031	0.069	0.169	0.162	0.109	0.043

Notes. Each column reports regression results where we regress a department's initial (1990-1995) topic share or exposure to China on various department characteristics. Share of collaboration with China is the share of a department's initial (1990-1995) publications involving any co-author affiliated with a China-based institution. Share of Chinese surnames is the share of Chinese surnames among all authors associated with its initial (1990-1995) publications. Each tier (or country group) is represented by a dummy variable equal to one if an institution is in the tier (or country group). The 5th tier (the lowest tier) and the US are used as the reference groups for tiers and country groups, respectively. Departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in each field. Countries are divided into five groups: US, UK, East Asia, Western Europe (excluding UK), and Other. The five topics presented have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). Robust standard errors are reported in parentheses. Data source: Web of Science InCites.

Table B2. Relationship between topic shares and institution characteristics: Chemistry

	Dep. Var.: Topic share over 1990-1995					Dep. Var.: Exposure to CN
	2.62 Electrochemistry	2.74 Photocatalysts	2.123 Protein Structure, Folding & Modelling	2.298 Perovskite Solar Cells	2.1 Synthesis	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of collaboration with CN; 1990-1995	0.316	0.043	-1.100	-0.024	0.670	4.816
	(0.288)	(0.135)	(0.588)	(0.042)	(1.498)	(4.458)
Share of Chinese surnames; 1990-1995	0.073	-0.040	-0.192	-0.003	-0.538	0.608
	(0.052)	(0.024)	(0.164)	(0.005)	(0.357)	(1.005)
4th tier	0.000	0.003	-0.009	-0.001	0.006	-0.001
	(0.003)	(0.002)	(0.010)	(0.001)	(0.021)	(0.064)
3rd tier	-0.000	0.005	-0.010	-0.000	0.002	0.055
	(0.003)	(0.003)	(0.009)	(0.001)	(0.023)	(0.066)
2nd tier	-0.003	0.001	-0.008	-0.001	-0.018	-0.002
	(0.003)	(0.001)	(0.009)	(0.001)	(0.019)	(0.059)
1st tier	0.001	0.004	0.007	-0.001	-0.035	0.039
	(0.002)	(0.002)	(0.011)	(0.001)	(0.016)	(0.054)
East Asia	0.011	0.007	-0.046	0.005	0.031	0.421
	(0.004)	(0.003)	(0.014)	(0.002)	(0.028)	(0.081)
Europe	0.006	0.000	-0.034	0.001	0.005	0.076
	(0.004)	(0.003)	(0.015)	(0.001)	(0.030)	(0.085)
UK	0.001	-0.003	-0.014	-0.000	0.012	-0.069
	(0.004)	(0.003)	(0.022)	(0.000)	(0.029)	(0.086)
other	0.011	-0.001	-0.019	0.000	-0.007	0.129
	(0.004)	(0.002)	(0.010)	(0.000)	(0.022)	(0.075)
Observations	199	199	199	199	199	199
R-squared	0.133	0.077	0.155	0.234	0.116	0.152

Notes. Each column reports regression results where we regress a department's initial (1990-1995) topic share or exposure to China on various department characteristics. Share of collaboration with China is the share of a department's initial (1990-1995) publications involving any co-author affiliated with a China-based institution. Share of Chinese surnames is the share of Chinese surnames among all authors associated with its initial (1990-1995) publications. Each tier (or country group) is represented by a dummy variable equal to one if an institution is in the tier (or country group). The 5th tier (the lowest tier) and the US are used as the reference groups for tiers and country groups, respectively. Departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in each field. Countries are divided into five groups: US, UK, East Asia, Western Europe (excluding UK), and Other. The five topics presented have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). Robust standard errors are reported in parentheses. Data source: Web of Science InCites.

Table B3. Relationship between topic shares and institution characteristics: AEE

	Dep. Var.: Topic share over 1990-1995					**Dep. Var.: Exposure to CN**
	3.2 Marine Biology	3.35 Zoology & Animal Ecology	3.16 Phytochemicals	3.83 Bioengineering	3.85 Food Science & Technology	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of collaboration with CN; 1990-1995	0.329	-1.030	3.866	0.423	-0.169	5.468
	(1.513)	(0.870)	(1.257)	(0.588)	(0.443)	(1.890)
Share of Chinese surnames; 1990-1995	-2.093	-0.070	0.184	0.157	0.368	1.168
	(0.787)	(0.429)	(0.177)	(0.182)	(0.188)	(0.602)
4th tier	0.015	0.005	0.008	0.004	0.004	0.003
	(0.033)	(0.016)	(0.008)	(0.011)	(0.007)	(0.026)
3rd tier	-0.045	0.011	-0.015	-0.007	0.004	-0.024
	(0.030)	(0.015)	(0.008)	(0.008)	(0.007)	(0.021)
2nd tier	-0.019	0.012	-0.016	-0.011	0.006	-0.049
	(0.032)	(0.016)	(0.007)	(0.009)	(0.006)	(0.022)
1st tier	-0.071	-0.010	-0.014	-0.012	0.015	-0.003
	(0.030)	(0.016)	(0.006)	(0.008)	(0.006)	(0.022)
East Asia	-0.085	-0.066	0.045	-0.001	0.026	0.127
	(0.038)	(0.013)	(0.012)	(0.010)	(0.005)	(0.025)
Europe	-0.084	-0.041	0.028	0.017	0.018	0.121
	(0.036)	(0.017)	(0.007)	(0.009)	(0.006)	(0.022)
UK	-0.104	-0.009	0.024	0.002	0.036	0.086
	(0.035)	(0.020)	(0.009)	(0.008)	(0.012)	(0.028)
other	-0.029	-0.000	-0.000	-0.008	0.016	0.020
	(0.028)	(0.014)	(0.005)	(0.004)	(0.006)	(0.019)
Observations	195	195	195	195	195	195
R-squared	0.132	0.109	0.413	0.079	0.121	0.269

Notes. Each column reports regression results where we regress a department's initial (1990-1995) topic share or exposure to China on various department characteristics. Share of collaboration with China is the share of a department's initial (1990-1995) publications involving any co-author affiliated with a China-based institution. Share of Chinese surnames is the share of Chinese surnames among all authors associated with its initial (1990-1995) publications. Each tier (or country group) is represented by a dummy variable equal to one if an institution is in the tier (or country group). The 5th tier (the lowest tier) and the US are used as the reference groups for tiers and country groups, respectively. Departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in each field. Countries are divided into five groups: US, UK, East Asia, Western Europe (excluding UK), and Other. The five topics presented have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). Robust standard errors are reported in parentheses. Data source: Web of Science InCites.

Table B4. Relationship between topic shares and institution characteristics: EE&CS

	Dep. Var.: Topic share over 1990-1995					Dep. Var.: Exposure to CN
	4.182 Data Structures, Algorithms & Complexity	4.47 Software Engineering	4.187 Security Systems	4.18 Power Systems & Electric Vehicles	4.13 Telecommunications	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of collaboration with CN; 1990-1995	-0.733	-0.207	-0.152	1.737	-0.363	2.927
	(1.012)	(0.745)	(0.225)	(0.522)	(0.218)	(4.241)
Share of Chinese surnames; 1990-1995	-0.417	0.001	-0.025	-0.086	0.005	-0.092
	(0.241)	(0.169)	(0.077)	(0.135)	(0.043)	(1.215)
4th tier	0.019	-0.032	-0.002	0.007	-0.000	0.035
	(0.027)	(0.016)	(0.007)	(0.024)	(0.005)	(0.139)
3rd tier	-0.014	-0.004	-0.002	-0.026	0.005	0.032
	(0.019)	(0.022)	(0.008)	(0.019)	(0.005)	(0.131)
2nd tier	0.017	0.002	-0.005	-0.028	0.005	-0.060
	(0.022)	(0.016)	(0.007)	(0.021)	(0.004)	(0.127)
1st tier	-0.000	-0.006	-0.003	-0.026	0.005	-0.049
	(0.024)	(0.017)	(0.007)	(0.022)	(0.004)	(0.139)
East Asia	-0.048	0.013	0.003	-0.006	0.007	0.046
	(0.034)	(0.017)	(0.009)	(0.028)	(0.007)	(0.132)
Europe	-0.027	0.049	-0.002	-0.011	0.010	-0.136
	(0.026)	(0.020)	(0.005)	(0.020)	(0.006)	(0.137)
UK	-0.047	0.075	0.001	0.001	-0.004	-0.032
	(0.021)	(0.038)	(0.005)	(0.018)	(0.005)	(0.154)
other	0.026	0.012	0.012	0.020	0.002	-0.010
	(0.023)	(0.014)	(0.007)	(0.020)	(0.003)	(0.103)
Observations	121	121	121	121	121	121
R-squared	0.123	0.202	0.071	0.132	0.092	0.030

Notes. Each column reports regression results where we regress a department's initial (1990-1995) topic share or exposure to China on various department characteristics. Share of collaboration with China is the share of a department's initial (1990-1995) publications involving any co-author affiliated with a China-based institution. Share of Chinese surnames is the share of Chinese surnames among all authors associated with its initial (1990-1995) publications. Each tier (or country group) is represented by a dummy variable equal to one if an institution is in the tier (or country group). The 5th tier (the lowest tier) and the US are used as the reference groups for tiers and country groups, respectively. Departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in each field. Countries are divided into five groups: US, UK, East Asia, Western Europe (excluding UK), and Other. The five topics presented have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). Robust standard errors are reported in parentheses. Data source: Web of Science InCites.

Table B5. Relationship between topic shares and institution characteristics: Physics

	Dep. Var.: Topic share over 1990-1995					**Dep. Var.: Exposure to CN**
	5.30 Superconductor Science	5.9 Particles & Fields	5.310 Resistive Switching	5.20 Astronomy & Astrophysics	5.135 Nuclear Physics	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of collaboration with CN; 1990-1995	-0.440	1.992	0.003	-0.051	0.041	-0.339
	(0.168)	(0.225)	(0.003)	(0.220)	(0.146)	(0.190)
Share of Chinese surnames; 1990-1995	1.233	-1.949	0.002	-0.370	-0.468	0.399
	(0.429)	(0.360)	(0.003)	(0.351)	(0.172)	(0.346)
4th tier	0.007	0.003	0.000	-0.005	0.013	0.002
	(0.020)	(0.034)	(0.000)	(0.023)	(0.018)	(0.026)
3rd tier	-0.020	0.036	0.000	0.023	0.012	-0.012
	(0.020)	(0.030)	(0.000)	(0.024)	(0.017)	(0.023)
2nd tier	0.002	0.044	-0.000	0.041	0.014	-0.046
	(0.020)	(0.029)	(0.000)	(0.024)	(0.018)	(0.020)
1st tier	-0.009	0.018	0.000	0.117	-0.023	-0.040
	(0.019)	(0.029)	(0.000)	(0.030)	(0.015)	(0.021)
East Asia	0.181	-0.159	0.000	-0.088	-0.010	-0.008
	(0.021)	(0.027)	(0.000)	(0.026)	(0.016)	(0.024)
Europe	0.084	-0.057	0.000	-0.007	0.002	-0.024
	(0.022)	(0.025)	(0.000)	(0.025)	(0.017)	(0.020)
UK	0.051	-0.076	0.001	0.074	-0.034	0.027
	(0.026)	(0.036)	(0.001)	(0.046)	(0.019)	(0.037)
other	0.032	-0.033	0.000	0.054	0.002	0.013
	(0.024)	(0.027)	(0.000)	(0.029)	(0.017)	(0.026)
Observations	196	196	196	196	196	196
R-squared	0.238	0.326	0.063	0.195	0.091	0.090

Notes. Each column reports regression results where we regress a department's initial (1990-1995) topic share or exposure to China on various department characteristics. Share of collaboration with China is the share of a department's initial (1990-1995) publications involving any co-author affiliated with a China-based institution. Share of Chinese surnames is the share of Chinese surnames among all authors associated with its initial (1990-1995) publications. Each tier (or country group) is represented by a dummy variable equal to one if an institution is in the tier (or country group). The 5th tier (the lowest tier) and the US are used as the reference groups for tiers and country groups, respectively. Departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in each field. Countries are divided into five groups: US, UK, East Asia, Western Europe (excluding UK), and Other. The five topics presented have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). Robust standard errors are reported in parentheses. Data source: Web of Science InCites.

Table B6. Relationship between topic shares and institution characteristics: EMS

	Dep. Var.: Topic share over 1990-1995					**Dep. Var.: Exposure to CN**
	7.133 Geotechnical Engineering	7.109 Ceramics	7.57 Modelling & Simulation	7.12 Metallurgical Engineering	7.301 Shape Memory Alloys	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of collaboration with CN; 1990-1995	-0.005	0.826	-0.344	0.572	-0.144	-0.602
	(0.125)	(0.488)	(0.600)	(0.968)	(0.161)	(0.910)
Share of Chinese surnames; 1990-1995	0.015	-0.152	-0.048	0.087	-0.020	0.503
	(0.036)	(0.070)	(0.120)	(0.176)	(0.048)	(0.322)
4th tier	0.014	0.007	0.039	-0.024	-0.008	0.072
	(0.008)	(0.018)	(0.028)	(0.031)	(0.018)	(0.064)
3rd tier	0.005	0.009	0.008	0.027	-0.019	0.053
	(0.008)	(0.017)	(0.026)	(0.031)	(0.015)	(0.053)
2nd tier	0.009	0.004	0.032	0.041	-0.017	-0.041
	(0.009)	(0.016)	(0.026)	(0.036)	(0.016)	(0.062)
1st tier	-0.000	0.007	0.035	0.021	-0.015	-0.017
	(0.007)	(0.018)	(0.026)	(0.031)	(0.015)	(0.060)
East Asia	-0.019	0.022	-0.093	0.077	0.047	-0.146
	(0.006)	(0.017)	(0.018)	(0.024)	(0.032)	(0.063)
Europe	-0.002	-0.013	-0.015	0.038	0.012	-0.013
	(0.006)	(0.015)	(0.022)	(0.027)	(0.009)	(0.048)
UK	0.010	-0.019	-0.039	0.066	-0.003	0.050
	(0.007)	(0.015)	(0.025)	(0.034)	(0.005)	(0.050)
other	0.039	-0.049	-0.049	-0.007	-0.004	0.330
	(0.011)	(0.014)	(0.021)	(0.024)	(0.003)	(0.065)
Observations	157	157	157	157	157	157
R-squared	0.207	0.104	0.120	0.110	0.140	0.283

Notes. Each column reports regression results where we regress a department's initial (1990-1995) topic share or exposure to China on various department characteristics. Share of collaboration with China is the share of a department's initial (1990-1995) publications involving any co-author affiliated with a China-based institution. Share of Chinese surnames is the share of Chinese surnames among all authors associated with its initial (1990-1995) publications. Each tier (or country group) is represented by a dummy variable equal to one if an institution is in the tier (or country group). The 5th tier (the lowest tier) and the US are used as the reference groups for tiers and country groups, respectively. Departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in each field. Countries are divided into five groups: US, UK, East Asia, Western Europe (excluding UK), and Other. The five topics presented have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). Robust standard errors are reported in parentheses. Data source: Web of Science InCites.

Table B7. Relationship between topic shares and institution characteristics: Earth

	Dep. Var.: Topic share over 1990-1995					Dep. Var.: Exposure to CN
	8.124 Environmental Sciences	8.93 Archaeology	8.8 Geochemistry, Geophysics & Geology	8.312 Gas Hydrates	8.242 Nuclear Geology	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of collaboration with CN; 1990-1995	3.952	-0.148	1.875	-0.090	0.225	1.277
	(2.333)	(0.490)	(1.511)	(0.066)	(0.233)	(2.579)
Share of Chinese surnames; 1990-1995	-0.991	-1.053	-1.060	0.021	-0.120	1.099
	(0.454)	(0.352)	(0.702)	(0.049)	(0.113)	(0.770)
4th tier	-0.000	-0.014	0.015	-0.005	0.013	-0.003
	(0.032)	(0.024)	(0.045)	(0.005)	(0.012)	(0.052)
3rd tier	-0.016	-0.031	-0.002	-0.004	-0.002	0.032
	(0.040)	(0.026)	(0.048)	(0.005)	(0.010)	(0.064)
2nd tier	-0.046	-0.025	0.100	-0.007	-0.010	-0.081
	(0.040)	(0.024)	(0.051)	(0.006)	(0.009)	(0.061)
1st tier	-0.066	-0.024	0.101	-0.005	-0.011	-0.089
	(0.037)	(0.022)	(0.042)	(0.006)	(0.009)	(0.056)
East Asia	-0.148	-0.081	0.088	0.007	0.040	-0.139
	(0.071)	(0.023)	(0.066)	(0.006)	(0.022)	(0.090)
Europe	-0.090	-0.027	0.119	-0.002	0.014	-0.117
	(0.034)	(0.024)	(0.046)	(0.004)	(0.010)	(0.056)
UK	-0.099	-0.014	0.128	-0.002	0.002	-0.155
	(0.036)	(0.024)	(0.047)	(0.003)	(0.008)	(0.056)
other	-0.103	-0.014	0.144	-0.003	-0.006	-0.155
	(0.025)	(0.017)	(0.038)	(0.004)	(0.005)	(0.048)
Observations	167	167	167	167	167	167
R-squared	0.203	0.089	0.196	0.046	0.157	0.181

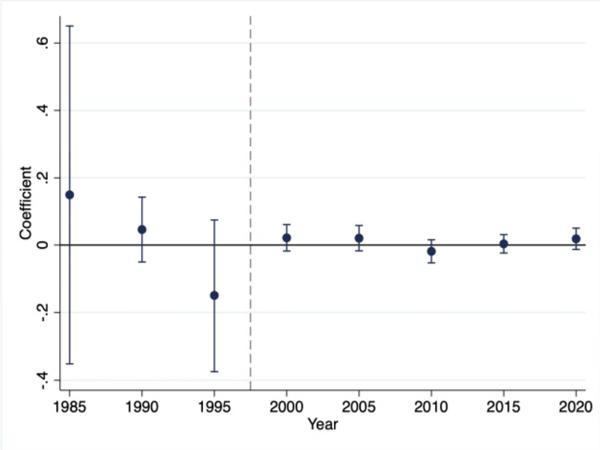
Notes. Each column reports regression results where we regress a department's initial (1990-1995) topic share or exposure to China on various department characteristics. Share of collaboration with China is the share of a department's initial (1990-1995) publications involving any co-author affiliated with a China-based institution. Share of Chinese surnames is the share of Chinese surnames among all authors associated with its initial (1990-1995) publications. Each tier (or country group) is represented by a dummy variable equal to one if an institution is in the tier (or country group). The 5th tier (the lowest tier) and the US are used as the reference groups for tiers and country groups, respectively. Departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in each field. Countries are divided into five groups: US, UK, East Asia, Western Europe (excluding UK), and Other. The five topics presented have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). Robust standard errors are reported in parentheses. Data source: Web of Science InCites.

Table B8. Relationship between topic shares and institution characteristics: Math

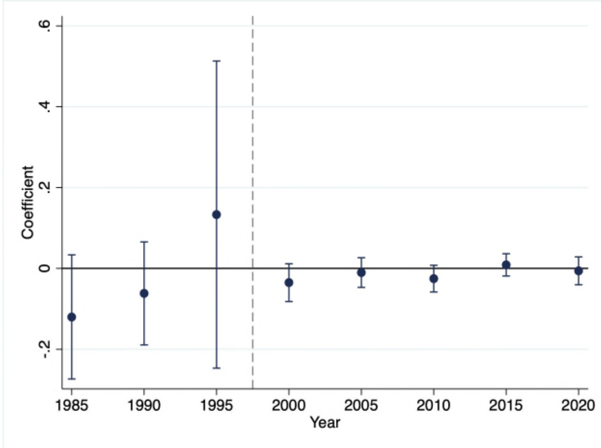
	Dep. Var.: Topic share over 1990-1995					**Dep. Var.:**
	9.162 Numerical Methods	9.28 Pure Maths	9.280 Algebra & Topology	9.92 Statistical Methods	9.50 Applied Statistics & Probability	**Exposure to CN**
	(1)	(2)	(3)	(4)	(5)	(6)
Share of collaboration with CN; 1990-1995	0.118	-1.186	-0.160	0.579	0.128	0.627
	(0.364)	(0.834)	(0.233)	(0.703)	(0.653)	(0.769)
Share of Chinese surnames; 1990-1995	-0.025	0.421	-0.115	-0.255	0.077	-0.167
	(0.181)	(0.463)	(0.129)	(0.397)	(0.311)	(0.374)
4th tier	0.018	-0.061	-0.005	-0.048	0.064	0.077
	(0.012)	(0.040)	(0.013)	(0.029)	(0.027)	(0.029)
3rd tier	0.016	-0.076	-0.014	-0.046	0.076	0.088
	(0.011)	(0.036)	(0.013)	(0.030)	(0.033)	(0.025)
2nd tier	0.026	-0.027	-0.024	0.001	0.019	0.067
	(0.013)	(0.040)	(0.013)	(0.037)	(0.025)	(0.032)
1st tier	0.010	-0.054	-0.020	-0.000	0.057	0.058
	(0.011)	(0.037)	(0.012)	(0.032)	(0.026)	(0.028)
East Asia	-0.022	0.139	-0.032	-0.193	0.066	-0.021
	(0.017)	(0.051)	(0.012)	(0.043)	(0.035)	(0.041)
Europe	0.002	0.080	-0.015	-0.149	0.074	0.017
	(0.016)	(0.040)	(0.012)	(0.036)	(0.037)	(0.033)
UK	0.041	0.027	-0.006	-0.079	-0.044	0.074
	(0.022)	(0.052)	(0.015)	(0.037)	(0.028)	(0.050)
other	0.001	0.024	0.024	-0.031	-0.015	-0.019
	(0.015)	(0.034)	(0.014)	(0.037)	(0.024)	(0.031)
Observations	148	148	148	148	148	148
R-squared	0.088	0.100	0.142	0.263	0.179	0.121

Notes. Each column reports regression results where we regress a department's initial (1990-1995) topic share or exposure to China on various department characteristics. Share of collaboration with China is the share of a department's initial (1990-1995) publications involving any co-author affiliated with a China-based institution. Share of Chinese surnames is the share of Chinese surnames among all authors associated with its initial (1990-1995) publications. Each tier (or country group) is represented by a dummy variable equal to one if an institution is in the tier (or country group). The 5th tier (the lowest tier) and the US are used as the reference groups for tiers and country groups, respectively. Departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in each field. Countries are divided into five groups: US, UK, East Asia, Western Europe (excluding UK), and Other. The five topics presented have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). Robust standard errors are reported in parentheses. Data source: Web of Science InCites.

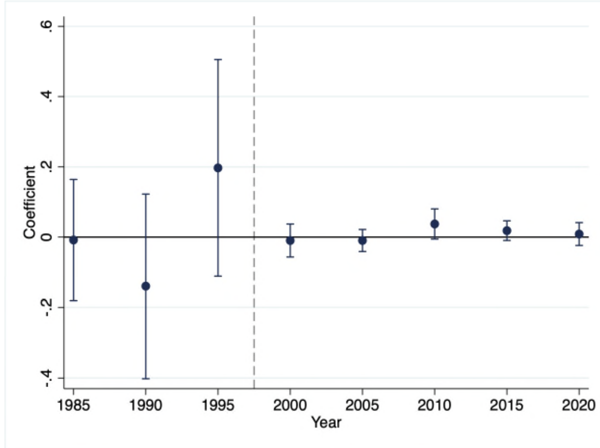
Figure B1. Five-year growth rates and initial topic shares: CLS



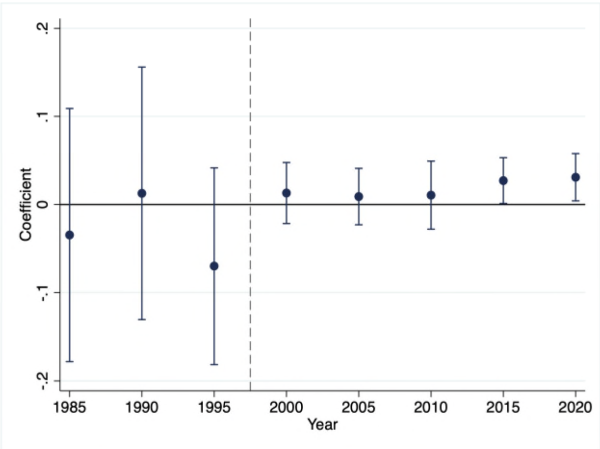
(A) 1.164



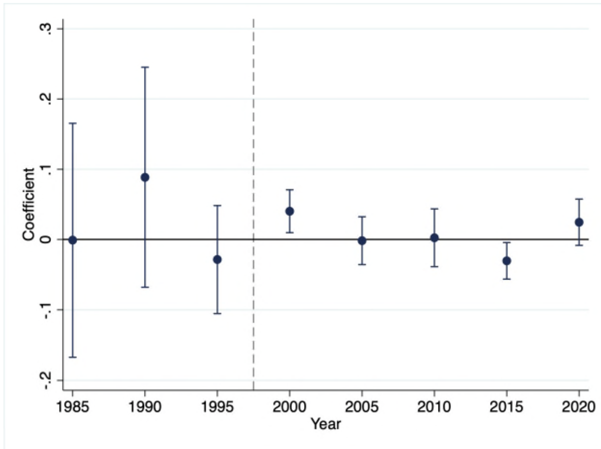
(B) 1.196



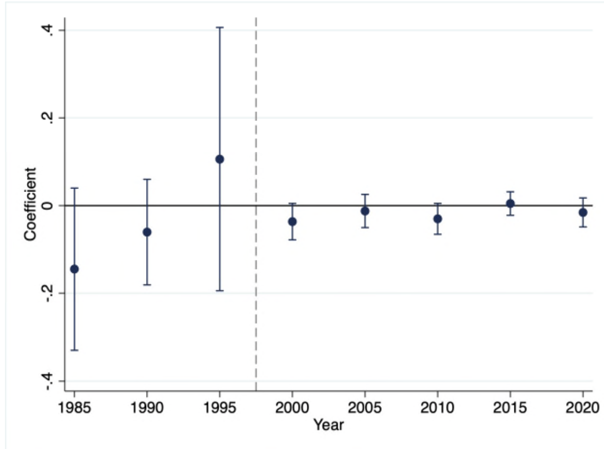
(C) 1.21



(D) 1.66



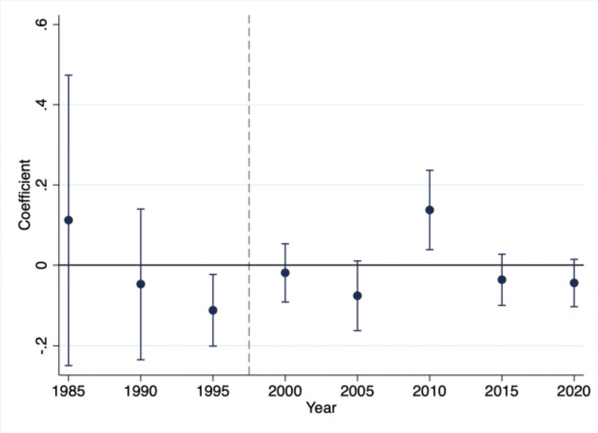
(E) 1.79



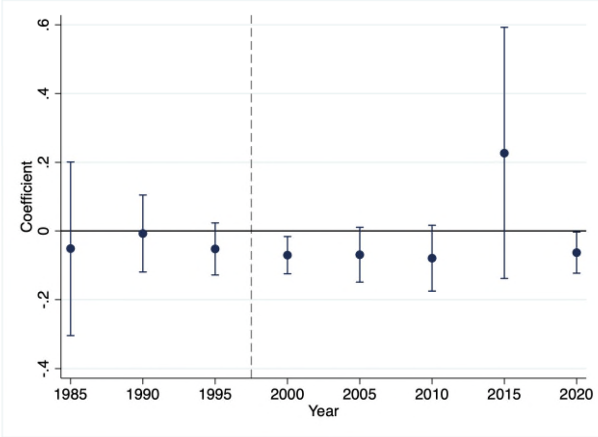
(F) Exposure to CN

Notes. Each panel plots regression results where we regress five-year growth rates of a department's top 10% cited output on its initial (1990-1995) topic share or exposure to China interacted with year dummies. The five-year growth rate in year t represents growth relative to year t-5. Each panel controls for tier-by-year FE and country-by-year FE. For tier-by-year FE, departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in the field. For country-by-year FE, there are five country groups: US, UK, East Asia, Western Europe (excluding UK), and others. The five topics presented in Panels (A) to (E) have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). The 95% confidence intervals are reported based on robust standard errors clustered by institution. N=1592. Data source: Web of Science InCites.

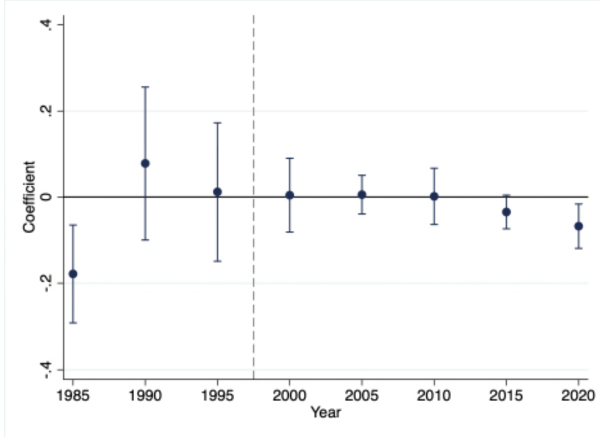
Figure B2. Five-year growth rates and initial topic shares: Chemistry



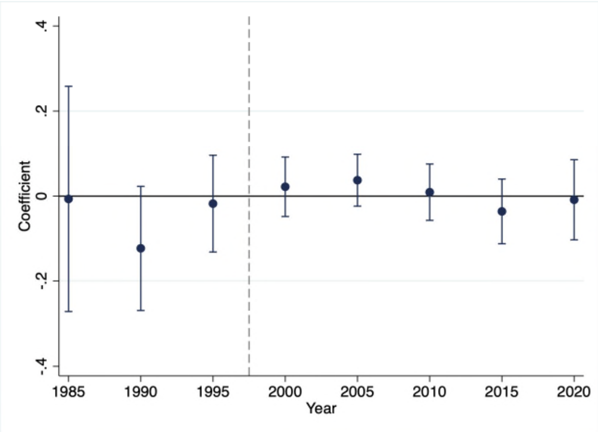
(A) 2.1



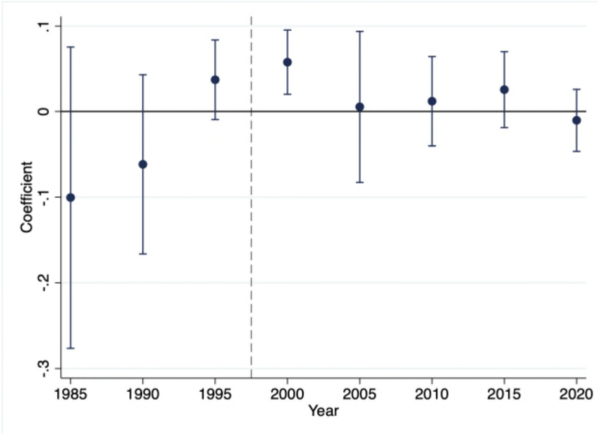
(B) 2.123



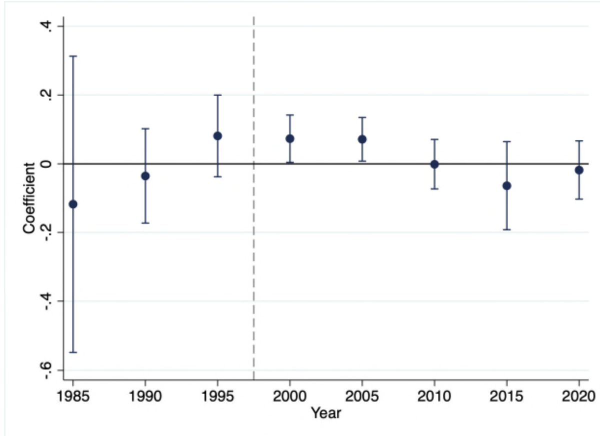
(C) 2.298



(D) 2.62



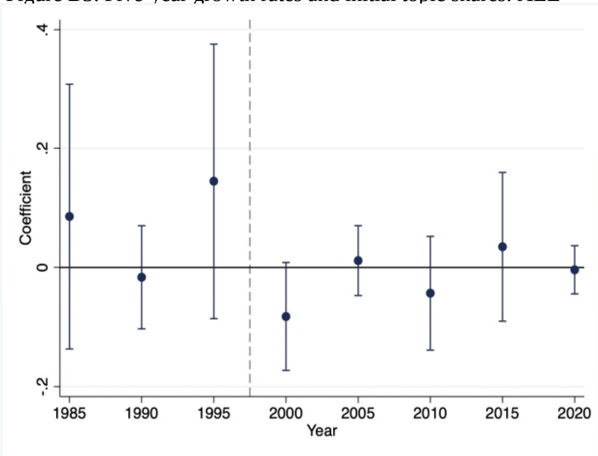
(E) 2.74



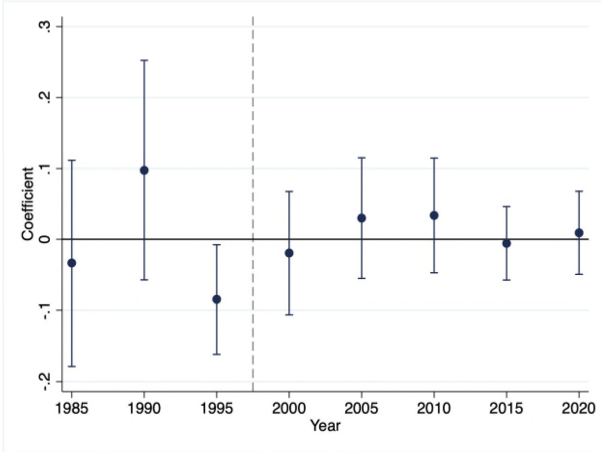
(F) Exposure to CN

Notes. Each panel plots regression results where we regress five-year growth rates of a department's top 10% cited output on its initial (1990-1995) topic share or exposure to China interacted with year dummies. The five-year growth rate in year t represents growth relative to year t-5. Each panel controls for tier-by-year FE and country-by-year FE. For tier-by-year FE, departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in the field. For country-by-year FE, there are five country groups: US, UK, East Asia, Western Europe (excluding UK), and others. The five topics presented in Panels (A) to (E) have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). The 95% confidence intervals are reported based on robust standard errors clustered by institution. N=1591. Data source: Web of Science InCites.

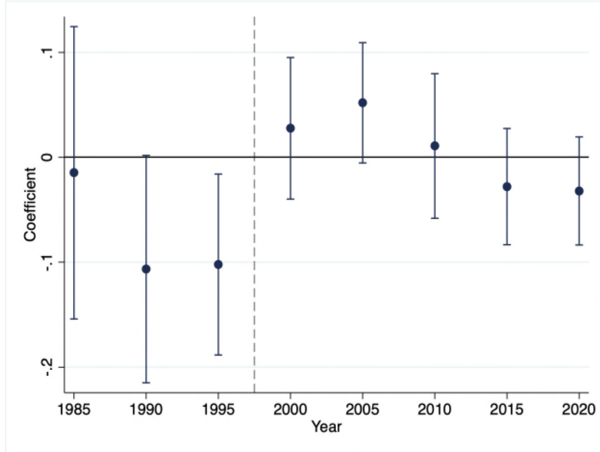
Figure B3. Five-year growth rates and initial topic shares: AEE



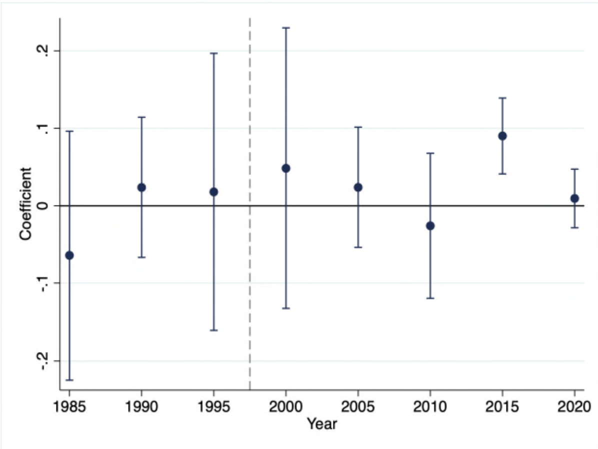
(A) 3.16



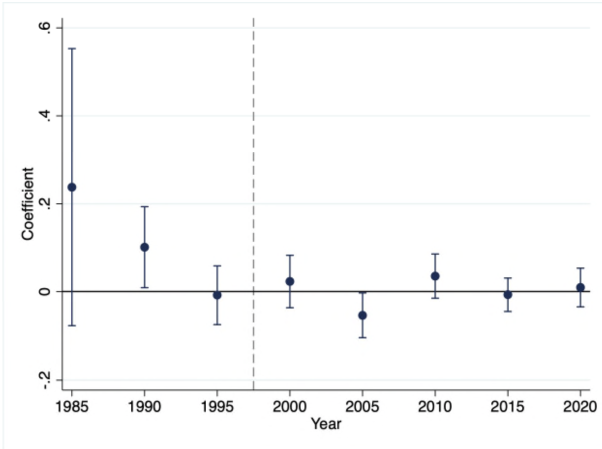
(B) 3.2



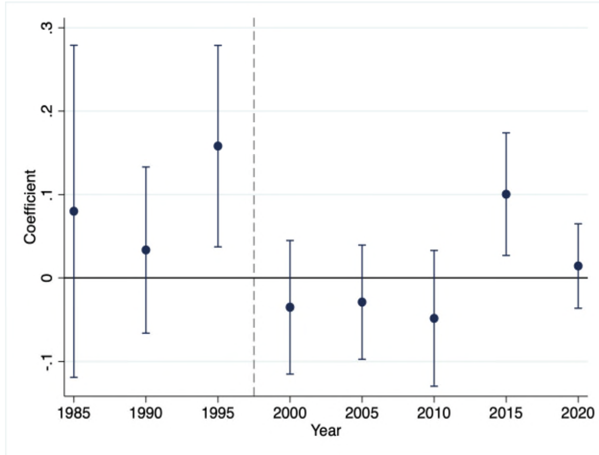
(C) 3.35



(D) 3.83



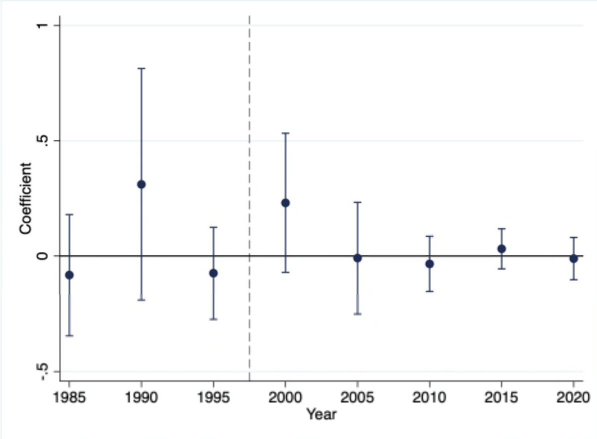
(E) 3.85



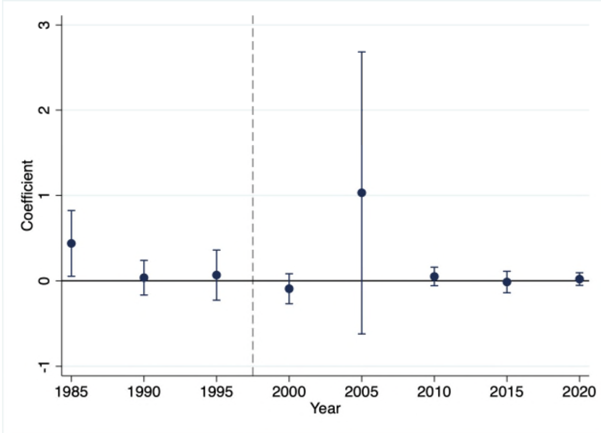
(F) Exposure to CN

Notes. Each panel plots regression results where we regress five-year growth rates of a department's top 10% cited output on its initial (1990-1995) topic share or exposure to China interacted with year dummies. The five-year growth rate in year t represents growth relative to year t-5. Each panel controls for tier-by-year FE and country-by-year FE. For tier-by-year FE, departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in the field. For country-by-year FE, there are five country groups: US, UK, East Asia, Western Europe (excluding UK), and others. The five topics presented in Panels (A) to (E) have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). The 95% confidence intervals are reported based on robust standard errors clustered by institution. N=1560. Data source: Web of Science InCites.

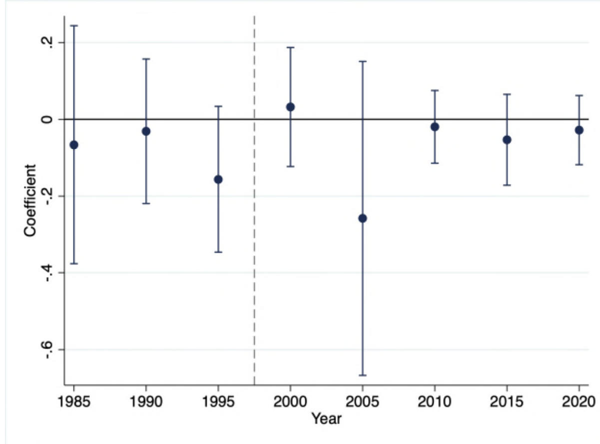
Figure B4. Five-year growth rates and initial topic shares: EE&CS



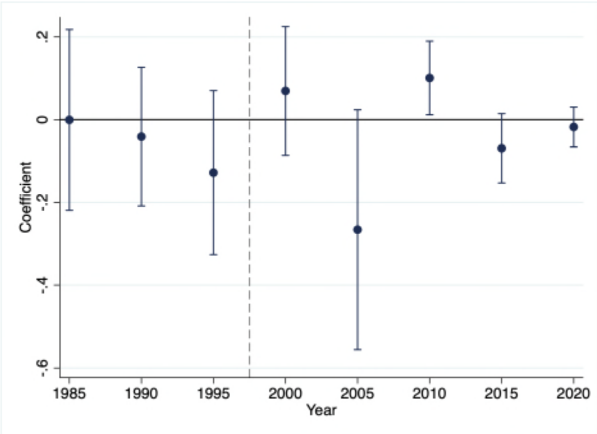
(A) 4.13



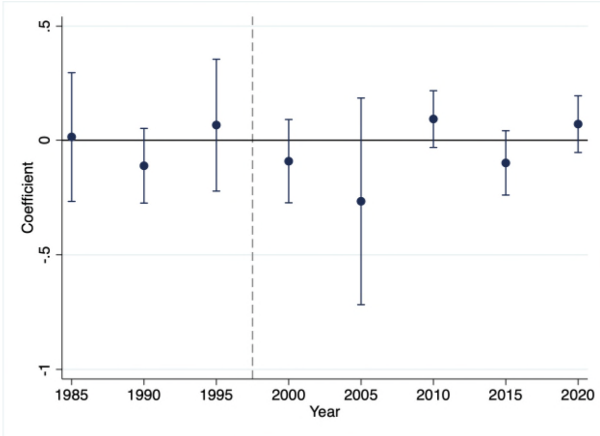
(B) 4.18



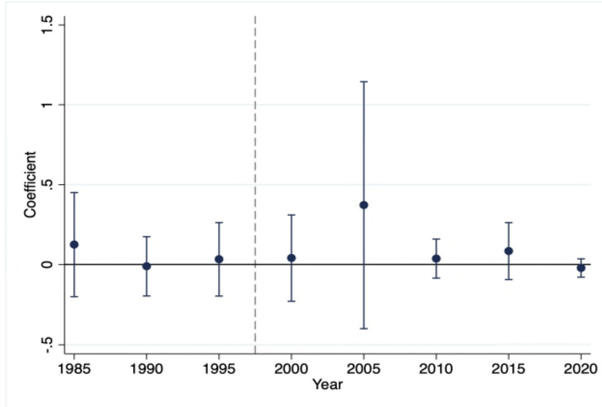
(C) 4.182



(D) 4.187



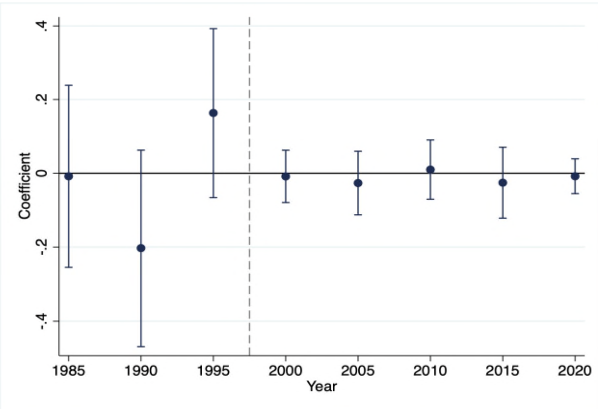
(E) 4.47



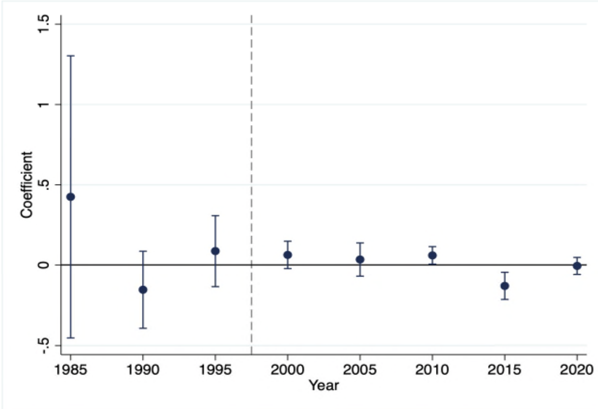
(F) Exposure to CN

Notes. Each panel plots regression results where we regress five-year growth rates of a department's top 10% cited output on its initial (1990-1995) topic share or exposure to China interacted with year dummies. The five-year growth rate in year t represents growth relative to year t-5. Each panel controls for tier-by-year FE and country-by-year FE. For tier-by-year FE, departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in the field. For country-by-year FE, there are five country groups: US, UK, East Asia, Western Europe (excluding UK), and others. The five topics presented in Panels (A) to (E) have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). The 95% confidence intervals are reported based on robust standard errors clustered by institution. N=968. Data source: Web of Science InCites.

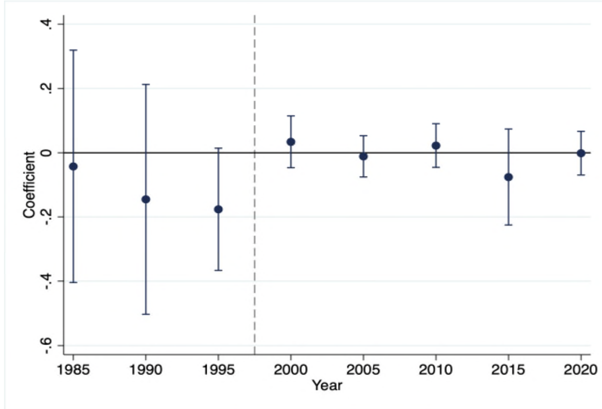
Figure B5. Five-year growth rates and initial topic shares: Physics



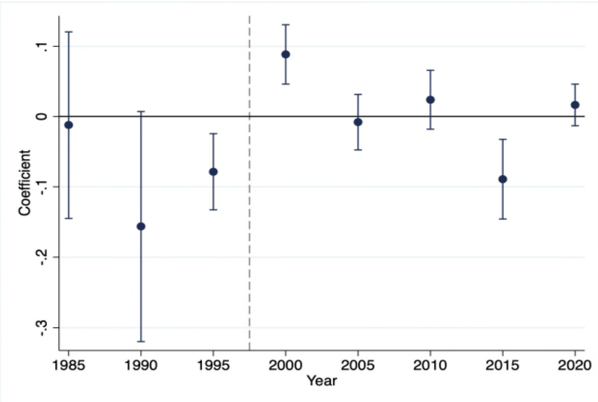
(A) 5.135



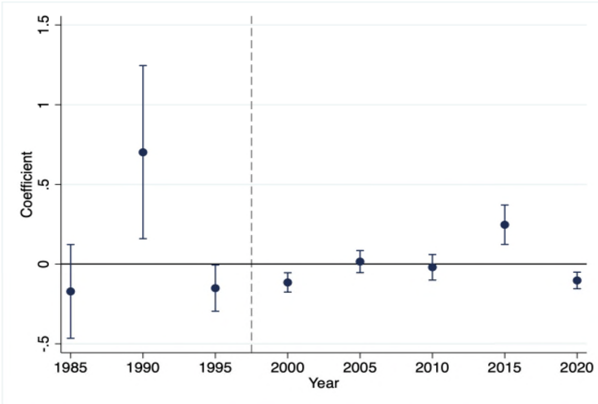
(B) 5.20



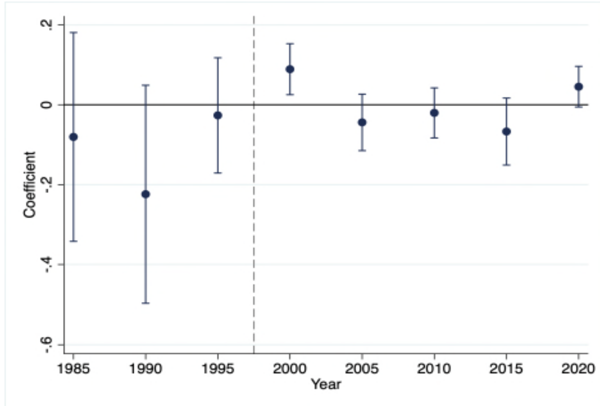
(C) 5.30



(D) 5.310



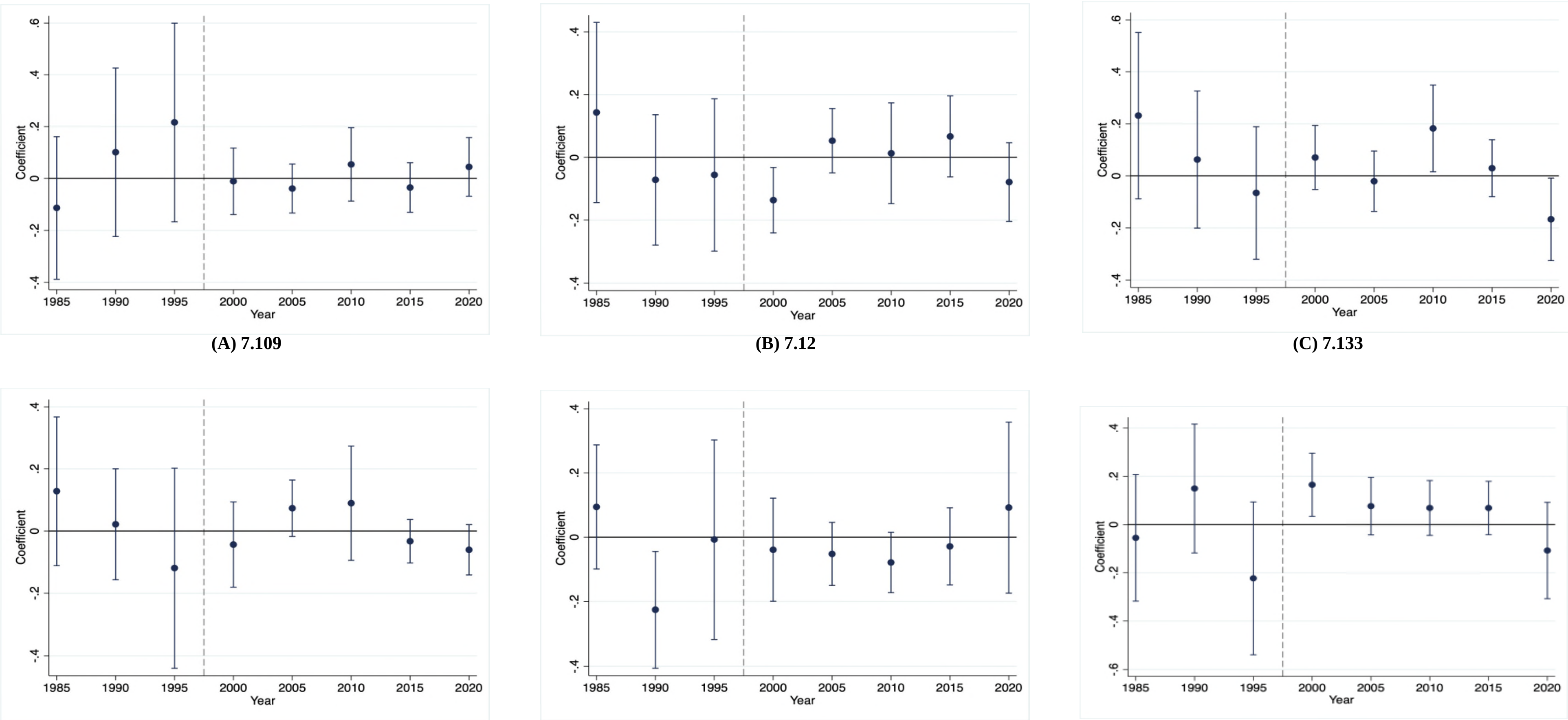
(E) 5.9



(F) Exposure to CN

Notes. Each panel plots regression results where we regress five-year growth rates of a department's top 10% cited output on its initial (1990-1995) topic share or exposure to China interacted with year dummies. The five-year growth rate in year t represents growth relative to year t-5. Each panel controls for tier-by-year FE and country-by-year FE. For tier-by-year FE, departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in the field. For country-by-year FE, there are five country groups: US, UK, East Asia, Western Europe (excluding UK), and others. The five topics presented in Panels (A) to (E) have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). The 95% confidence intervals are reported based on robust standard errors clustered by institution. N=1568. Data source: Web of Science InCites.

Figure B6. Five-year growth rates and initial topic shares: EMS

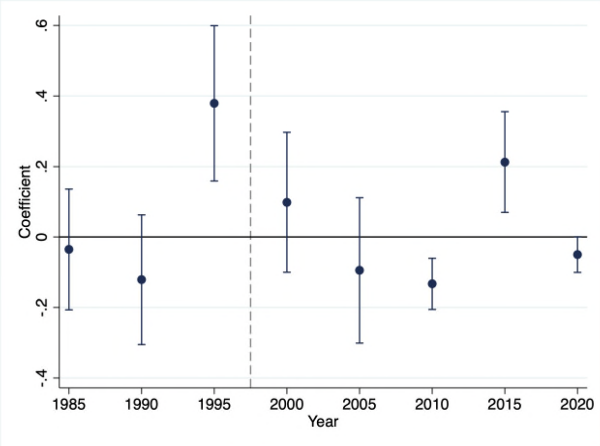


(A) 7.109 **(B) 7.12** **(C) 7.133**

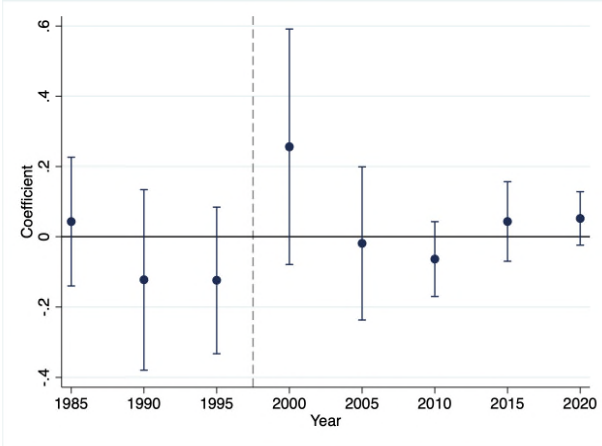
(D) 7.301 **(E) 7.57** **(F) Exposure to CN**

Notes. Each panel plots regression results where we regress five-year growth rates of a department's top 10% cited output on its initial (1990-1995) topic share or exposure to China interacted with year dummies. The five-year growth rate in year t represents growth relative to year t-5. Each panel controls for tier-by-year FE and country-by-year FE. For tier-by-year FE, departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in the field. For country-by-year FE, there are five country groups: US, UK, East Asia, Western Europe (excluding UK), and others. The five topics presented in Panels (A) to (E) have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). The 95% confidence intervals are reported based on robust standard errors clustered by institution. N=1255. Data source: Web of Science InCites.

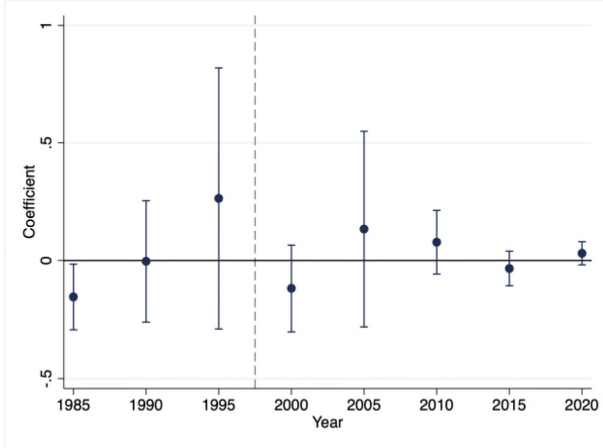
Figure B7. Five-year growth rates and initial topic shares: Earth



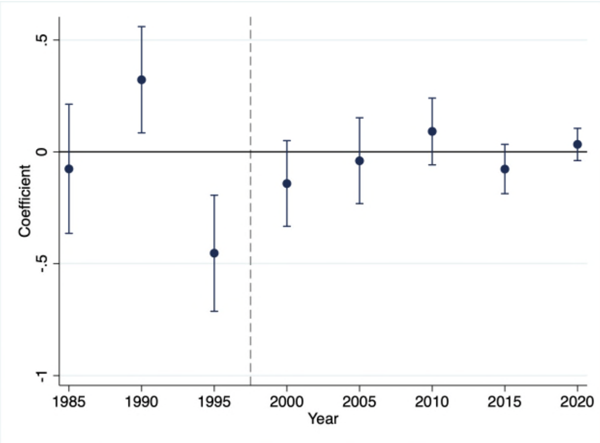
(A) 8.124



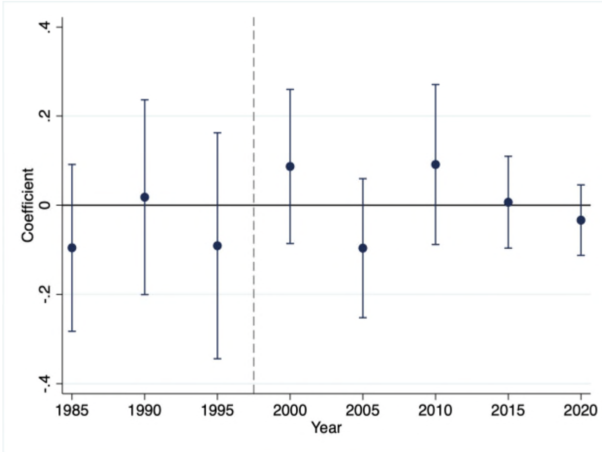
(B) 8.242



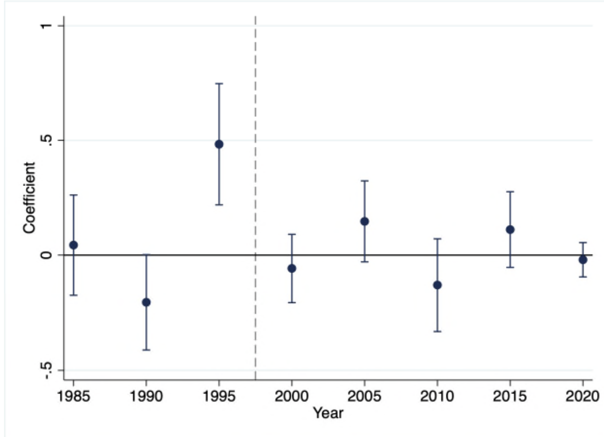
(C) 8.312



(D) 8.8



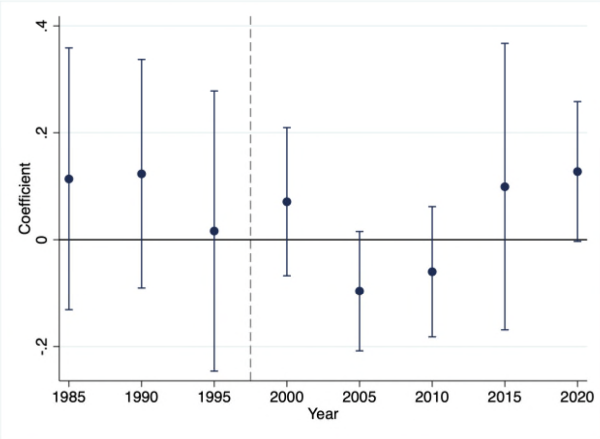
(E) 8.93



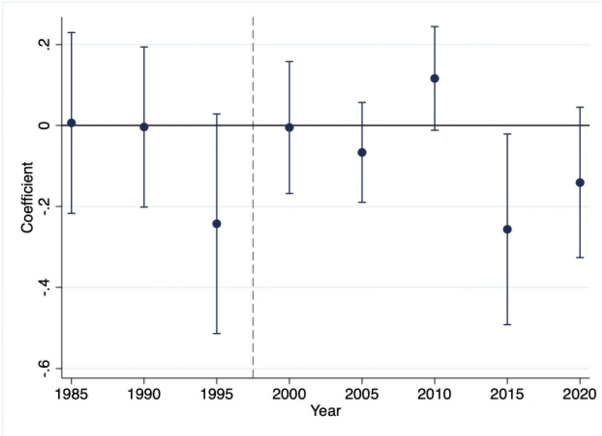
(F) Exposure to CN

Notes. Each panel plots regression results where we regress five-year growth rates of a department's top 10% cited output on its initial (1990-1995) topic share or exposure to China interacted with year dummies. The five-year growth rate in year t represents growth relative to year t-5. Each panel controls for tier-by-year FE and country-by-year FE. For tier-by-year FE, departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in the field. For country-by-year FE, there are five country groups: US, UK, East Asia, Western Europe (excluding UK), and others. The five topics presented in Panels (A) to (E) have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). The 95% confidence intervals are reported based on robust standard errors clustered by institution. N=1336. Data source: Web of Science InCites.

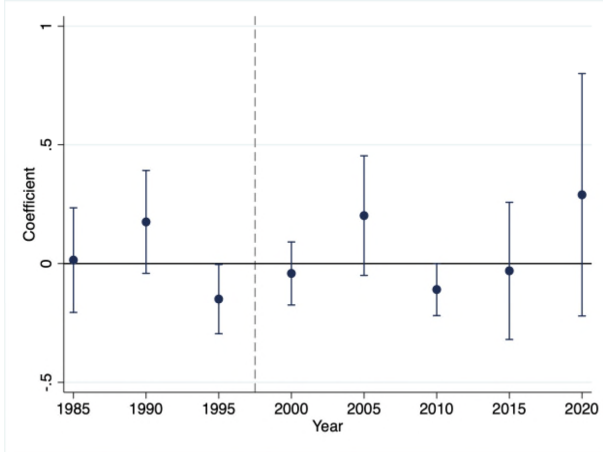
Figure B8. Five-year growth rates and initial topic shares: Math



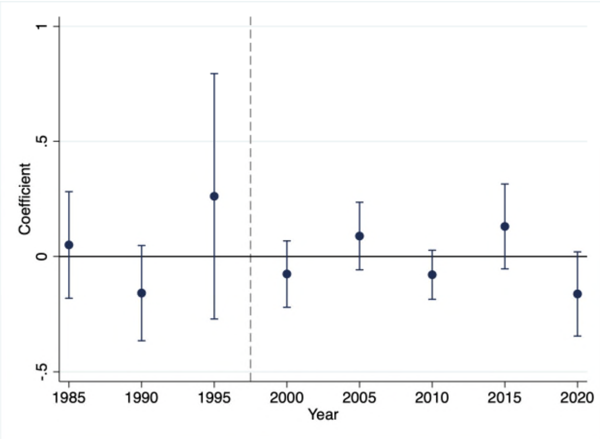
(A) 9.162



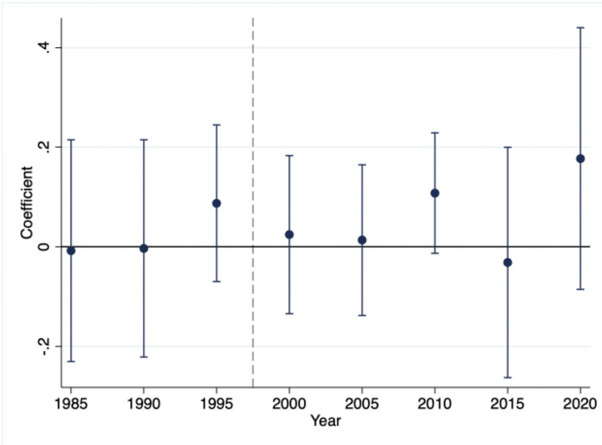
(B) 9.28



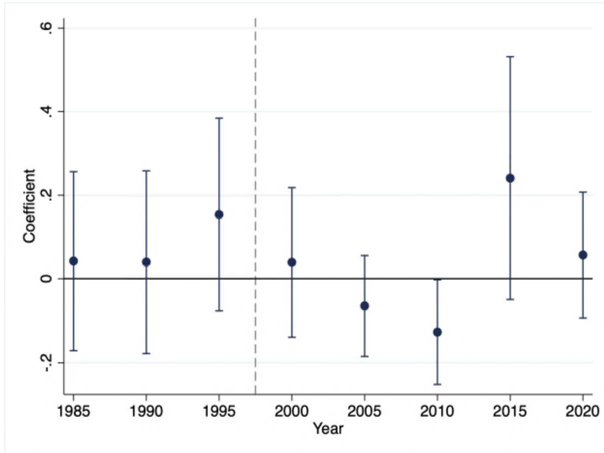
(C) 9.280



(D) 9.50



(E) 9.92



(F) Exposure to CN

Notes. Each panel plots regression results where we regress five-year growth rates of a department's top 10% cited output on its initial (1990-1995) topic share or exposure to China interacted with year dummies. The five-year growth rate in year t represents growth relative to year t-5. Each panel controls for tier-by-year FE and country-by-year FE. For tier-by-year FE, departments are divided into five equally sized tiers based on their top 10% cited publications between 1990 and 1995 in the field. For country-by-year FE, there are five country groups: US, UK, East Asia, Western Europe (excluding UK), and others. The five topics presented in Panels (A) to (E) have the largest Rotemberg weights in the field based on a variant of Panel D of Table 2 where the non-leave-one-out version of exposure to China is used as the main explanatory variable. Rotemberg weights are computed following Goldsmith-Pinkham et al. (2020). The 95% confidence intervals are reported based on robust standard errors clustered by institution. N=1174. Data source: Web of Science InCites.