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# Is China the New Dominant Scientific Powerhouse?

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**Abstract**

Recent evidence suggests that China has become a dominant force in global scientific innovation. Using a comprehensive 52-year panel from Scopus (1970-2022) spanning approximately 39 million publications across 22,189 journals, we construct field-normalized, quality-sensitive tiers that separate premier outlets (including "Top-3" journals per field) from mid-tier and bottom-tier venues. We document an exponential rise in China's output across all tiers including "Top-3" journals. Because affiliation-based counts understate China's innovation footprint, a surname-based reattribution provides an upper bound on diaspora effects, substantially shifting premier-journal leadership toward China. To explain this sharp productivity increase, we estimate a 155-country model of scientific productivity using a machine learning technique, the least absolute shrinkage and selection operator (LASSO), and show that China outperforms baseline predicted fundamentals by large margins. We use the Chinese government's investment into research and education to explain Chinese academic productivity in top journals, where the China-specific effect of research spending is multiple times larger than the baseline effect for other countries, consistent with a distinctive state-to-science transmission mechanism.

**Keywords** Higher education; Scientific innovation; Research productivity; Science of science; Government funding

**JEL Classification** I23; C55; D83; F22; O31; O32; O38

**Mathematics Subject Classification** 62P25; 62J07

## 1. Introduction

Recent research has examined China's rapid ascent in global science (Lu, 2022; Nature Index, 2025). Pisani et al. (2025) show that China has narrowed the gap with the United States in highly cited research. In a similar vein, Montaño Ramirez and Petersen (2026) document a structural transformation in global science, showing that the traditional Euro-American core has evolved toward a more multipolar system in which China occupies an increasingly central position. These studies provide compelling evidence that China is no longer a peripheral participant in global knowledge production but has emerged as a major force reshaping the geography and organization of science. In spite of this wealth of research, we still have much to learn about the depth of China's rise across the journal-quality hierarchy, the extent to which China's scientific footprint is missed because of its global diaspora, and the driving forces behind this exceptional trajectory. A more nuanced understanding of these dimensions would advance the existing literature and shed new light on the geopolitics of science.

We analyze the universe of scientific publications using a comprehensive 52-year panel (1970 - 2022) of more than 22,000 academic journals comprised of approximately 39 million publications, and we develop a quality-sensitive measurement framework that explicitly separates premier, mid-tier, and bottom-tier publication outlets. We document that Chinese scientists have exponentially increased their output, and when we factor in their large and successful diaspora of scientists (see Cyranoski et al., 2011; Franzoni et al., 2012), China is now the largest producer of top academic research globally. When we delineate by field and journal quality, China's success is not due to the "any publication anywhere" strategy as it is often alleged, since their contributions to top science outlets indicate quality-focused scholarship in strategic fields such as physics and mathematics, while also demonstrating significant inroads

into chemistry. These fields arguably form the basis of the tech revolution. The quality of scientific impact has also risen, as evidenced by their outsized citations that have been increasing over time. Surprisingly, when we factor the Chinese diaspora in the USA and across the globe, we see that Chinese scientists rank at the top of nearly every single major scientific domain.

We conduct formal multivariate tests to understand the rise of China in scientific publishing. Our objective is to estimate structural drivers of scientific productivity and distinguish whether China's success is natural and organic (i.e., determined in part by its large population and economic growth) or whether it is governmental investment into key strategic areas to drive national goals. Prior work suggests that the relation between country characteristics and innovation is complex and depends on a host of factors (Ben-David, 1984; Furman et al., 2002; May, 1997; Price, 1963). We see that China consistently overperforms its country-level fundamentals by up to 1000%. Two government-controlled characteristics, research spending and national education expenditure, exhibit a uniquely strong link to scientific output in China. Error correction models show that China is the only country where year-over-year changes in government research spending significantly predict changes in elite publications, and a panel model with country fixed effects confirms that the marginal effect of research spending on Top-3 publications is 16 times larger for China than for other major research nations. This indicates that the Chinese model is unique, and there is a direct transmission mechanism between state investment and scientific output in China's institutional context, as previously suggested by Sun and Cao (2014), as well as Tang et al. (2022). Together with qualitative evidence on targeted national R&D programs (Sun & Cao, 2014), these results suggest that strategic government investment has been the primary driver of China's scientific expansion.

Chinese governmental investment in key strategic areas that drive national goals has overwhelmed other countries' increased productivity efforts, with Europe suffering the most and the U.S. losing ground, even as the total academic "pie" has expanded. China has substantially increased its share of publications in premier journals, altering the distribution of global scientific output and fundamentally reshaping the global scientific hierarchy in just 20 years. The country's innovation model today resembles a high-intensity, "brute-force" modernization strategy with massive volume and rising presence in premier outlets, with its quality trajectory visibly upward throughout.

This paper contributes to research on China's scientific rise by highlighting several previously underexplored dimensions. First, while prior studies have documented China's growing presence in highly cited research (Lu, 2022; Nature Index, 2025; Pisani et al., 2025), we assess scientific dominance through a quality-sensitive journal hierarchy spanning more than five decades. This approach enables us to distinguish growth in overall research output from penetration into premier journals, where scientific agendas, reputations, and rewards are disproportionately shaped. Second, we show that affiliation-based measures understate China's scientific footprint because they exclude contributions from the Chinese diaspora (see Franzoni et al., 2012; Xie & Freeman, 2019). Finally, we build on the research stream that has examined the drivers of country-level innovation (Furman et al., 2002), where we benchmark China's performance against country-level fundamentals and identify state investment in research as a distinctive mechanism underlying its exceptional scientific overperformance, a highly unique state-to-science mechanism.

This paper proceeds as follows. Section 2 presents the literature review, followed by the data and methods. Section 4 presents the results, followed by the conclusion and limitations.

Online Resource 1 contains appendices with detailed explanations of the methods and results, and a link to the replication code and data. Throughout the paper, references to Appendices A-K, Figure A.1, and Tables A.1-A.8 refer to Online Resource 1.

## 2. Literature Review

### *2.1. Chinese Investment into R&D*

Over the past four decades, China has moved from a minor participant to a central player in global science. China has been investing in R&D since the late 90s, quadrupling its expenditures as a percentage of GDP. This spending began to increase steadily after the property rights reforms of the late 80s (Oi & Walder, 1999), and the market reforms of the 90s (Guan & Yam, 2015), and rose further following the anti-corruption campaign waged by the government in the 2010s (Huang et al., 2017). Currently, R&D is 2.68% of GDP, and its 2024 budget exhibited an 8.3% increase in R&D expenditures over 2023 values (National Bureau of Statistics of China, 2025), surpassing the OECD average of 2.4%, and is roughly equal to U.S. investment in dollar terms. It is remarkable that even with the setbacks of the COVID-19 pandemic and the Trump trade war of 2018, R&D expenditures still increased from 2.36% to 2.68% as a share of GDP in the last five-year period. These include national, state-level, and mega-science programs, which include key technologies and high-tech programs (Lu, 2022).

However, there is one key difference between U.S. investment and the Chinese one, namely that government spending on R&D in China is 60% more than its U.S. counterpart, with the implication that China has more freedom and funds devoted to strategic investments in sectors that it considers to be key (OECD, 2025). Studies of state-subsidized R&D in China show that such programs have been successful: Guo et al. (2016) find that entities backed by the state show a superior performance as compared to privately backed ones, and Tang et al. (2022)

further show that these programs contribute to technological innovation, especially in high-tech enterprises.

In academia, there has been substantial investment by the Chinese government, talent return programs, and especially sharp gains in strategic sectors such as engineering and tech (Mayer, 2012; Zhou & Leydesdorff, 2006). Much has been said about the recent evidence that China has matched or surpassed leading countries on several academic output metrics, yet the debate still persists as to whether leadership in volume equates to dominance in scientific innovation (Marginson, 2022; Tollefson, 2018; Zhu & Liu, 2020). In this section, we review the prior papers that have examined the contributions of China to the world of science, which helps shape our arguments and highlights our contribution.

### *2.2. Chinese Academic Productivity*

A number of papers indicate that China is already the global leader in many academic disciplines (Liu, 2020; Pisani et al., 2025; Tollefson, 2018; Zhou & Leydesdorff, 2006). Yet, total productivity volume is often a misleading measure of scientific leadership as many publication outlets have no sizeable impact (or no impact at all), and volume itself does not measure agenda-setting in high-impact outlets, or boundary-pushing advances. For example, even if China is the world's largest producer of scientific papers, it is not the first in impact (i.e., citations), and its presence is uneven across fields, with its strongest presence in segments of the physical sciences (Basu et al., 2018; Marginson, 2022; Xie et al., 2014).

Measuring Chinese academic productivity is further complicated by the fact that there is domestic science, international co-authorships, and international embedding by Chinese nationals who work in foreign institutions. Thus, any measure of Chinese scientific productivity has to account for the contribution of global partners (He, 2009; Wagner et al., 2015; Zhang et al., 2018). Moreover, as documented by Liu et al. (2021) and also observed in our data, projects

involving Chinese scientists involve large teams and large infrastructure, where oftentimes it is unclear how to divide the academic credit between project leaders and other participants.

Accounting for Chinese-language journals and Chinese researchers in the diaspora has further effects on the measurement of scientific output. Wang et al. (2018) document the sizeable expansion of Chinese journals (with modest impact factors), while Xie and Freeman (2019) account for diaspora-authored publications, which conclude that one-third of global articles and citations can be attributed to China.

The discussion above indicates that it is hard to measure scientific productivity, and results are sensitive to design choices made by the researcher. It is widely accepted that measuring academic productivity is subjective and depends on the period examined, discipline, and measurement criteria (Gingras, 2016; Hicks et al., 2015). To overcome these limitations, our measurement choices have a clear objective, which is to conduct a comprehensive analysis in evaluating research productivity, whereby inferences are not sensitive to design choices.

### *2.3. Co-authorships, International Collaborations, and Chinese Research Mobility*

One method through which scientists complete successful projects is through collaboration, where resources are pooled, and expertise is complemented. Co-authorship boosts quality, and Chinese scientists are no different in this aspect of innovation. Some studies document that China's collaboration network is dominated by the U.S., constituting roughly 30% of China's internationally coauthored articles, particularly in physics and biology (Niu & Qiu, 2014). In Europe, Wang et al. (2017) find collaborations span Belgium, Sweden, and Denmark, driven by disciplinary proximity (Zhang & Guo, 2017). In health care sciences, Chinese papers co-authored with North American and European partners had a higher impact than those with Asian partners (Chen et al., 2016), and Tang (2013) documents that top Chinese scientists are also those most engaged in international collaboration.

Collaborative patterns have evolved in time, where Chinese researchers have moved from being peripheral fringe players to near-central project leaders of large research teams. Bibliometric data show a rise in China's co-authored output with G7 partners since the 1990s, with the United States being the most important collaborator (He, 2009). Wagner et al. (2015) find that by the mid-2010s, the two countries had become each other's top partners. Zhu et al. (2021) find that roughly one-third of China's Nature Index high-impact articles in 2018 were coauthored with U.S. scholars. Network analyses of Web of Science co-authorships show that China has the largest gains in centrality, and a rise in papers with Chinese first / corresponding authors, suggesting a transition from peripheral actor to near-center leaders in large research teams (Veugelers, 2017; Zhang et al., 2018).

Cao et al. (2020) document the large size of overseas Chinese researchers and argue that returning scientists disproportionately co-publish with former hosts, enabling local Chinese researchers to be part of an international scientific community. International mobility is another factor driving the rise of Chinese scientific innovation. Jonkers and Tijssen (2008) find that returning premier Chinese researchers, partly due to government efforts to relocate overseas talent, publish more and at a higher impact than domestically trained peers, while maintaining their prior international collaborations and networks.

Finally, another distinguishing characteristic of Chinese science is that it progresses by sheer brute force of manpower, as large teams and resources are pooled together, with large teams accommodating international collaborations. An analysis of 26 million Web of Science publications shows that China's output is unusually dominated by large teams, particularly in the natural sciences (Liu et al., 2021). This highlights China's strength in deploying scale to solve critical problems (Basu et al., 2018; Marginson, 2022).

*2.4. Focused Government Investment and Innovation*

Chinese progress has not been random. Rather, Mayer (2012) shows it is the result of a systematic policy by the centralized government. Monetary and non-pecuniary incentives have been high, as universities and institutes in China are rewarded for international publishing (Liu, 2020; Shu et al., 2022). The process is monitored heavily for quality control, with predatory journals blacklisted and public funds available only for a select list of endorsed "high-quality journals" (Xu, 2024). More recently, Shu et al. (2022) find that there has been an explicit pursuit to elevate locally published scientific journals to counter the Western dominance over research paradigms.

Chinese government grants have encouraged international collaborations. National Natural Science Foundation of China (NSFC) grant data indicate that top Western countries constitute the majority of joint grants. U.S.-based partners account for more than 50%, with the rest being split between Australia, the Netherlands, Spain, Japan, Germany, and Sweden (Yuan et al., 2018).

Moreover, Chinese research productivity is neither organic nor random, but in fact follows a carefully choreographed investment pattern by the central government into areas deemed of national interest. These have been particularly intensified under President Xi Jinping, including the Strategic Emerging Industries (recurring five-year plans), Made in China (starting 2015), New Generation of AI Development Plan, and other funds, including the National Integrated Circuit Investment Fund.

In terms of university research, the Science and Technology Development Plan includes steps to attract overseas talent and the development of science parks. For example, Hu (2020) documents that the bulk of National Science Foundation of China funding goes to mathematics, physics, life sciences, engineering, information technology, and the earth sciences. It argues that

these grants have increased publication rates, quality, and impact. Other studies have found similar conclusions when examining different sectors supported by the Chinese government, including biotechnology (Zhang et al., 2011), and big data research (Huang et al., 2016). Thus, it is not surprising that China ranks first in the U.S. National Science Foundation's Science & Engineering Indicators (Tollefson, 2018). Similarly, article counts reveal strengths in chemistry, physics, materials science, and applied physics (Fu & Ho, 2013), while in medicine, the U.S. generally holds the edge (Xie et al., 2014).

## 3. Data and Methods

### *3.1. Data Source and Sample Construction*

We gathered journal article data from Scopus. We downloaded the title, author information, affiliation, journal subject classification, number of citations, and other information relevant for our analyses. Our initial sample consists of roughly 39 million publications across 22,189 scientific journals, in all fields, spanning the years 1970 - 2022. Our sample covers most of the disciplines as defined by Scopus: Biochemistry, Genetics and Molecular Biology; Business, Management, and Accounting; Chemical Engineering; Chemistry; Computer Science; Decision Sciences; Earth and Planetary Science; Economics, Finance, and Econometrics; Energy; Engineering; Environmental Science; Health Professions; Immunology and Microbiology; Mathematics; Medicine; Multidisciplinary; Neuroscience; Pharmacology, Toxicology and Pharmaceutics; Physics and Astronomy. We do not examine "peace" and "literature" as these do not exclusively deal with scientific innovation.

We do not use a constant sample with full data, as this reduces the span of our dataset. The final sample varies by the type of analysis, as data is not uniform across our dataset. For example, some articles have incomplete author information, or citation data is missing, etc. For

our main analyses, we utilize a final sample with a start year of 1980, as earlier years have numerous missing observations and variables, and Chinese authors are virtually absent from most journal articles. Moreover, the 1970s are the start date of many journals that achieved subsequent quality credentials, thus we start our measurements directly after.

Overall, the data provides rich information and is of high quality. Sampling indicates that our dataset is accurate at a level of higher than 99%, giving us confidence in our analyses. However, errors remain - these range from errors in affiliations that we could not classify, or changing journal names or ISSN numbers, where we cannot track articles and authors through time. To correct these errors, we used a large language model (Anthropic's Claude Opus), followed by large-scale manual checks. Moreover, in some subsets of our analyses, where samples are smaller, we manually check that all data points are correct (i.e., Top-3 related analyses). We do not expect any remaining data errors to affect our inferences.

### *3.2. Measuring Scientific Output, Journal Quality, and Citation Impact*

We analyze productivity by geographic region, where China is our focal country of interest. We classify as Chinese productivity all articles published by authors located in mainland China from the year 1970 to 1996. Starting in 1997, we also include articles originating from Hong Kong. We don't include Chinese nationals working in non-Chinese universities in our main results. To make a tractable presentation of the analyses, we focus on four geographic regions: China, the U.S., Europe, and the rest of the world. We examine all subjects of academic publishing, with a particular emphasis on the hard sciences that form the core of the Nobel subject areas and the Fields medal: physics, chemistry, physiology / medicine, and mathematics. We assign productivity scores to regions based on author contributions. This is similar to the methodology adopted by the Nature Index when attributing scientific productivity (Nature Index, n.d.). For example, if an article has a Bolivian, Chinese, and two U.S.-based researchers, we

assign scores of 0.25, 0.25, and 0.5 to the respective regions. We further delineate our data by journal quality to better understand the impact of China on the academic research landscape. To do so, we rely on citation analysis. Developed more than 75 years ago (Garfield, 1955, 1972), article citations offer an easy to calculate measure of the diffusion and acceptance of ideas, and as a result, a research article's impact on the next generation of scientific innovation.

To categorize our journals, we split them into three categories based on citation intensity: top journals, mid-level journals, and the bottom-tier journals. We standardize by research field the citations per number of publications for each journal-year and apply an age penalty that decreases in value the older a journal is. That eliminates the possibility that our ranking will be biased towards newer journals that are more subject to "citation-washing" (Ibrahim et al., 2025). Based on this standardized citation score, we form three groups, namely a journal that is in the top 1% of citations, top 2 - 10%, and the remaining journals go to a third and final bucket (bottom tier). Our cutoffs are chosen based on our observation that outside the top 10%, there is a steep drop in citations, and are in line with prior research that suggests that 70-90% of academic journals have low scientific impact (Craig et al., 2014; Seglen, 1992). Although our cutoffs are arbitrary, reasonable changes to our research design choices do not alter our inferences.

We do the following procedure to rank journals into the above-discussed quality tiers. We first drop all journals with less than a total of 150 publications, then drop all journals that have less than 10 publications per year. For each journal, we calculate total citations per total publications, and we also compute journal age from the time it first appeared in our database. For each Scopus field, we compute *z*-scores based on the median citations per publication and its median absolute deviation. We do so by Scopus-provided fields (engineering, biology, decision

science, etc.).[1] These *z*-scores are multiplied by the age penalty factor, which is derived from a Sigmoid function. The variable term is defined as (-0.5*(Journal Age - 5)) to ensure that younger, high-citation journals do not skew the ranking.[2] We then apply these age-adjusted within-fields *z*-scores to the broader Nobel category a field belongs to, to arrive at our journal rankings. These research design choices are unlikely to affect our inferences, as we conduct multiple robustness checks to ensure the stability of our results. For example, broadening or narrowing our journal categorizations does not affect our inferences. Results also do not change if we vary our 1% or 2 - 10% breakdowns, as using 0.5% or 5% yields similar inferences. Our objective is not to construct the definitive ranking of journals, but merely to obtain a suitable proxy that leads to unbiased analyses.[3]

Our next quality categorization is classifying journals as whether they are the top three most highly regarded journals in their field (Top-3). It is well known that researchers disproportionately value publications in Top-3 journals in the field of science (Milojević, 2020), mathematics (Schlenker, 2020), medicine (Kirk, 2014), and the social sciences (Smith, 2004). Publication in such journals, considered colloquially as the "big three," "holy trinity," or "top three," has a disproportionately large effect on prestige, promotion, and scientific funding. This

[1] We note that we construct *z*-scores that are not aggregated by Nobel prize field, but by Scopus indicated sub-fields. The rationale is that there is large heterogeneity in the citation patterns of journals across sub-fields, within a broad Nobel field categorization. Using narrower fields is more suitable to standardize a journal's citations, and should give more prevalence to high quality journals in specialized (low-citation) fields. If a journal has more than one sub-field within Scopus, we randomly select one. Our inferences are robust to this methodological choice.

[2] Applying a multiplicative penalty factor (a fraction between 0 and 1) to a zero-centered *z*-score effectively reduces negative values, bringing below-median journals closer to the top than their actual performance would suggest. However, since any journal with a negative *z*-score is already well below the top 10% threshold, these mathematical adjustments only rearrange rankings within the "bottom tier" category and do not change our classifications of elite quality tiers.

[3] It can be seen from the graphical analyses that classification shifts across journal categorizations (top tier, middle tier, bottom tier) do not affect inferences regarding the ascent of Chinese academic innovation. Such shifts have minimal quantitative effects, without loss of inference.

breakdown into Top-3 journals is particularly pertinent for Chinese researchers who can receive up to $165,000 bonuses for publishing in top journals such as Science or Nature (Quan et al., 2017). Numerous organizations have compiled and prepared lists of select journals that they consider to be the top in their field, including the Shanghai ranking of universities (ShanghaiRanking Consultancy, n.d.), Australian Research Council's "Excellence in Research for Australia" program (Australian Research Council, n.d.), UK's Research Excellence Framework (Research Excellence Framework, n.d.), and the Financial Times ranking of business schools (Financial Times, 2016). These journal excellence lists include a select few journals from each field based on scientific prestige and impact. National ministries and universities are known to value such publications and provide monetary incentives for such top publications.[4]

Our list of Top-3 journals includes well-known, usual suspects, such as The New England Journal of Medicine, Science, Nature, Nature Materials, Cancer, Reviews of Modern Physics, etc. (see Table A.1 for the list of journals). We do not claim to create a definitive journal ranking. Our objective is merely to get a proxy for what constitutes scientific excellence. Further details are provided in the appendices, Appendix B: Research Design and Methodology, and descriptive statistics are available in Table A.2.

We also calculate the citation intensity of journals as our final proxy for scientific quality. Our methodology adjusts citations for co-authorship, if a paper has 9 cites and a total of 3 authors, each from China, the US, and Europe, each region gets 3 cites. Newer papers automatically have fewer cites as they have had less time for exposure and dissemination. To

[4] In addition to the Top-3 journals that we present in Table A.1, we replicate our results using other highly reputable journals such as Cell, Nucleic Acid Research, Bioinformatics, Journal of Chemical Physics, Journal of Computational Chemistry, Journal of the American Chemical Society, Journal of the Royal Statistical Society Series B, Journal of the American Statistical Association, Annals of Statistics, Physical Review Letters, Physical Review B, Astrophysical Journal, with similar inferences.

account for such time trends, we use standardized citation data adjusted by year and field. These results are presented in Figure A.1.

### *3.3. Modelling the Drivers of Scientific Productivity*

Given that there is no formal and definitively accepted model of country-level scientific innovation, we draw inspiration from the extant literature and cast a wide net. We estimate a structural model of country-level scientific productivity starting with more than 50 potentially causal characteristics.

Additionally, we use machine learning statistical estimation techniques (LASSO) to optimize for predictive value and fit. We omit China from the model because we want to use it for out-of-sample prediction purposes. We use fitted values from this regression to calculate a specific country's "predicted" publication score in Top-3 journals. We use this to compare each country to its actual performance.

For this set of analyses, we convert our article / year panel into a country / year panel for our Top-3 journals. Theoretically, we can have up to 195 countries x 52 years (1970 - 2022). However, many countries did not exist in the initial time period (including those from the Soviet bloc, colonial Africa, etc.), and some countries do not have sufficient scientific output (i.e., Vatican, San Marino, Seychelles, Cape Verde, among a long list of others). Moreover, in our data, scientific output was trivial in the vast majority of countries in the earlier time period. Hence, including the earlier time period in our analyses would induce noise in our estimation. Given that we are attempting to understand the performance of China today, we need to benchmark it to comparable countries in a similar time period. Since Chinese science has exhibited growth since 2000, we conduct our analysis over the 2000 - 2022 period. Therefore, our final sample is a panel of 2,265 country / years. These comprise 23 observations for China, and 2,242 for other country / years.

For our estimation, we use a variety of country / year variables measuring economic, institutional, educational, social, geographic, and political data. These variables range from standard economic data such as GDP and GDP / capita, to measures of political rights, high school mathematics scores and education levels, globalization indexes, country temperature levels, urbanization, etc. To select a tractable subset with the highest predicting power from a starting point of a set of more than 50 variables of interest, we use LASSO regressions.[5] This is potentially more efficient than using simple correlation analysis or OLS when constructing predictive models (Tibshirani, 1996). Stepwise selection models tend to overfit, especially when independent variables are correlated, which is often the case in country-level data. We obtain an optimal alpha of 0.0139 with a CV score of 0.695. Lasso selects 10 variables. Variables that are multicollinear are automatically dropped post-selection ($r > 0.85$; *Academic Freedom*, *Political Centrality*, and *Urban Population*). We obtain a final set of 7 variables: the logarithmic form of total population (*LogPopulation*), GDP per capita (*GDP/Capita*), corruption (*Corruption*), the average temperature of the host country, proxying for food security and colonial history (*Temperature*), the square root of globalization ($Globalization^{1/2}$), the participation of elites (*Elite_Participation*), and political rights (*Political_Rights*). Please note that we do not use GDP as a predictor, although it is highly significant, because we include its two components, GDP per capita and population, individually. A multicollinearity check indicates that all variables have a VIF value of less than 5.

[5] LASSO regressions (least absolute shrinkage and selection operator) enable us to sift through our large number of predictive variables and select the most relevant ones (Tibshirani, 1996). We prefer LASSO over alternative estimation techniques based on its superior out-of-sample predictive performance, as assessed by cross-validated $R^2$. In unreported robustness tests we also use an RFECV model (recursive feature elimination with cross-validation) as proposed by Guyon et al. (2002). This method starts with all the variables, trains a model using machine learning, removes the least important ones, and then repeats. RFECV allows us to choose systematic, out-of-sample validated regressors. This estimation process selects 11 variables, and our initial inferences when using LASSO remain intact.

We estimate models in which the number of articles in Top-3 journals per country-year is the dependent variable. Model 1 estimates the base specification, while Model 2 adds year fixed effects. We use a panel of 2,242 country / year observations, and China is excluded from the estimation sample so that its predicted scientific output can be evaluated out of sample.

Having established a country-level benchmark for expected scientific productivity, we next examine whether China's overperformance is associated with state investment in research and education, as a potential factor contributing to China's ascent. Top Chinese research universities are government-funded (e.g., Fudan, Tsinghua, Peking, Zhejiang), investing in key technologies through national and regional R&D programs (Sun & Cao, 2014). To examine how Chinese government spending is reflected in research output, we use three variables: *Research Spending* (the total dollar value of governmental research expenditures), *Doctoral Graduates* (total number of yearly Ph.D. graduates), and *Education Spending / GDP* (government's yearly education budget, normalized by GDP). To address the concern that trending variables may produce spuriously high correlations, we employ three trend-robust specifications: country-specific error correction models (ECM) that separate short-run dynamics from long-run equilibrium, a panel regression with country fixed effects and China interaction terms, and 5-year long-differenced regressions that remove common time trends.

Panel A of Table A.8 reports error correction models (ECM) estimated separately for each of the seven countries. We select these countries because they are the largest research-producing nations for which consistent annual data on government research expenditure and education spending are available over the 2002-2022 period. The ECM first estimates the long-run equilibrium relationship between publications and the investment variables in levels, then models year-over-year changes as a function of (i) deviations from this equilibrium (the error correction

term) and (ii) contemporaneous changes in the explanatory variables (the short-run effects). The ECM specification allows us to test whether deviations from the long-run relationship are corrected over time. We also use Engle-Granger augmented Dickey-Fuller tests to assess whether the levels relationship is stationary.

## 4. Results

### *4.1. China's Rise Across Journal Quality Tiers*

Figure 1 presents our first set of results. The graph depicts scientific publishing in all fields by geographic region and is organized into four quadrants in a clockwise manner in order of decreasing scientific quality. Quadrant 1 depicts publishing in Top-3 journals (15 journals), and indicates that high-quality scientific publishing was nonexistent in China in the 1970s and 1980s. The last 20 years exhibit a sharp productivity increase in top journals, where China now accounts for a large fraction of global scientific output.

Quadrant 2 of Figure 1 depicts the top 1% of journals in terms of quality (a select group of 155 journals). Here we see a large contrast with respect to Quadrant 1, and China is now even closer to the U.S. and Europe. As of 2022, U.S.-based authors published 12,333 scientific papers in the top 1% journals, followed by Europe (9,254), China (6,801), and the rest of the world. Nonetheless, a simple extrapolation of trends indicates that this Chinese productivity gap in high quality outlets is closing quickly. Quadrants 3 and 4 are for journals ranked in the top 2 - 10% and the bottom-tier, respectively. Outside the top 1%, it is evident that China is the global leader in these quality tiers.

Overall, the results in Figure 1 indicate that China-based authors are consistently improving and publishing in reputable academic journals. The trend is monotonically upward over the 52-year period, and they have strongly increased their output in top-level outlets and are

dominating mid-tier journals. Their productivity in low-level journals is high and expected, given their large number of universities and researchers. There does not seem to be a drive toward "any publication anywhere" - instead, their inroads into top science indicate quality-focused scholarship.

Table A.6 reports Top-3 productivity by country, where we aggregate the fractional publication of authors based on their location and academic discipline, over the period 2015 - 2022 (and again over 2020 - 2022), and take the average of all disciplines. As such, results are equal-weighted results of our 5 disciplines, with all scores relative to the highest score of 100. We present the publication count of these ranked countries in Table A.6, Panel A.

Panel B of Table A.6 provides further evidence on the rise of China in premier publications, as we compare 2022 to the year 2000. We compare the relative rise of regions to understand which countries China is displacing. We see that in the earlier period, the U.S. constituted 47% of premier publications, decreasing to 42% in 2022. This 5.2% reduction is less than the 10.1% reduction in Europe, which saw its share decrease from 38.1% to 28%. In contrast, China's share grew from less than 1% to 15.2%, while the rest of the world combined also grew from 14% to 14.8%. We see that although the publication "pie" has grown in size, the rapid rise of China has still succeeded in offsetting other countries' productivity. In turn, Europe lost ground the most, declining in both absolute and relative terms. The U.S. held up better than Europe but still decreased in relative terms.

### *4.2. Field-Level Performance, Citation Impact, and Diaspora Effects*

We further break down Figure 1 into various fields of science (e.g., Physics, Chemistry), and present results for publications in only the Top-3 journals. These show a unanimous increase in scientific output in all fields of science by Chinese researchers presented in Figure 2. The biggest gains are in Physics, Mathematics, and Chemistry, with inroads in the fields of medicine

and economics. The same conclusion can be drawn about the citation intensity of articles co-authored by Chinese scientists (see Figure A.1). These patterns documenting the increase in scientific output and impact are statistically significant (see Tables A.3, A.4).

Our analyses thus far have focused on researchers based in China. However, this understates the influence of Chinese researchers on the global innovation landscape. It is well known that China exports a large number of its scientists abroad, whether to pursue advanced education or to work (Cyranoski et al., 2011; Franzoni et al., 2012). We use a nationality-name dictionary to conduct a name-based author disambiguation. When we re-examine the authorship of papers appearing in the Top-3 journals, we can see the extent of total Chinese penetration. For example, 34.1% of top mathematics papers, globally, have at least one Chinese-surname author (see Table A.5). In Figure 3, we show the number of papers that have at least one Chinese or U.S. author, in Top-3 journals. At first glance, we see that research papers that include a U.S.-based scientist are more than twice the number of those that include an author from China. However, when we do a name-based adjustment by subtracting Chinese nationals living in the USA and adding them to the China score, we see that the gap shifts. Chinese scientists now easily outnumber those of the US. We also find that China comes first in the Top-3 journals in Physics, Chemistry, and Mathematics, and a close second to the U.S. in medicine (see Figure 4). We caveat our analysis as we inadvertently capture other Asian nationals and second or third generation Chinese who are by birth U.S. nationals (discussed further in Section 5 below).

### *4.3. Explaining China's Overperformance*

Table A.7 presents the results of our country-level model estimation, where the number of articles in Top-3 journals, per country, is the dependent variable (*Articles_Top3*). Model (1) estimates the base model, while Model 2 adds year fixed effects. Excluding China from the

specification, the model obtains an adjusted R-squared of 0.688. Population is positively related to scientific productivity, corruption is negatively related, GDP / capita is positive, temperature is negative, globalization is negative, participation of elites is positive, and finally, political rights are also positive. Except for political rights, all variables are individually significant at the 1%-level. The largest predictor of scientific output is the population of the host country, where a standard deviation increase in the independent variable leads to a 0.485 change in the standard deviation of the dependent variable. The rest of the variables have the following economic effects: 0.445, 0.237, 0.152, 0.121, 0.085, and 0.034, for corruption, GDP per capita, temperature, the square root of globalization, elite participation, and political rights, respectively.

Next, we compare each country to its actual performance Figure 5 graphs the evolution of China's expected versus actual scientific output and compares it to that of the U.S. For China, both expected and actual values exhibit an increase through time, as China became richer and less corrupt, its predicted innovation also grew (grey dashed line). However, its actual performance simultaneously grew at a much sharper rate (red solid line). In contrast, we see that research productivity is stagnant and non-increasing in the USA.

We use fitted values from our regression in Model (1), Table A.7, to calculate a specific country's "predicted" publication score in Top-3 journals. These results are reported in Panel B of Table A.7. Focusing on China, and in comparison to 155 countries in our sample over a 22-year period, the improvement of Chinese research is clearly evident. There is a gradual increase starting from -8% in 2000 to almost 200% ten years later, and currently it stands at almost 1,000%. China publishes 2-10 times more Top-3 scientific papers than what is warranted by its fundamentals alone.

We also construct a country-based relative innovation index that is weighted 60% in relation to total scientific output, and 40% in relation to per capita efficiency. This measure is inspired by Furman et al. (2002), but unlike their multi-dimensional model, we calculate innovation as a function of two factors, total output and its efficiency. We see that China's position shifts downward, where now its innovation index is a fifth of the U.S., and two-thirds that of Germany. As such, China's innovation miracle is essentially a "brute-force" modernization strategy. They have massive output despite low efficiency, and they overperform through deliberate state-level investment. Data indicates that their low efficiency in converting human resources to scientific output indicates that there is major growth potential ahead, as their uneven internal geographic development stabilizes (Xing et al., 2025).[6]

Before turning to the short-run investment effects reported in Figure 6, we first assess whether the long-run ECM specification is valid. A significant negative error correction term confirms that the long-run relationship is genuine rather than spurious (i.e., deviations from equilibrium are corrected over time). Cointegration tests (Engle-Granger augmented Dickey-Fuller) confirm that the levels relationship is stationary for China (ADF = -4.74), supporting the validity of the long-run specification.[7]

[6] Innovation should be a function of total output and output efficiency. Absolute output captures global scientific footprint and network effects; per-capita output captures conversion efficiency of human resources into publications. Compared with other major countries, China ranks near the top in absolute output but low on per-capita efficiency, so its composite innovation index is highly weight-sensitive. The measure is normalized against the top 25 research producing countries in Top-3 journals.

[7] Engle-Granger cointegration tests confirm that the long-run levels relationship is stationary for China, the USA, Germany, and Sweden, but not for Japan, the Netherlands, or Spain. We report ECM results for all countries for comparability, but note that the long-run equilibrium interpretation is most reliable for the cointegrated cases. The short-run coefficients remain interpretable regardless of cointegration status, as they estimate the contemporaneous association between changes in the variables. Unreported first-differences models for these countries corroborate this finding.

Figure 6 presents three complementary analyses testing whether government research spending predicts elite scientific output. Panel A reports short-run effects from an error correction model and shows that China is the only country where short-run changes in research spending significantly predict changes in Top-3 publications (2.07, $p = 0.02$). No other country shows a significant positive short-run effect. Spain exhibits a significant negative coefficient (-1.81, $p < 0.10$), while the remaining countries show small and insignificant effects. This indicates that the direct channel from government research expenditure to elite scientific output operates uniquely in China.

Panel B formally tests whether the effect of state investment is significantly stronger for China than for other countries. It reports results from a panel regression pooling all seven countries, with country fixed effects, a cubic time trend, and China interaction terms. The interaction coefficient for *China*Research Spending* is large and highly significant (1.91, $p < 0.01$), while the baseline coefficient for other countries is small and insignificant (0.13). The total effect for China (2.04) is thus 16 times the baseline effect for other nations, confirming that the marginal response of scientific output to government research spending is uniquely strong in China.[8]

As a further robustness check, Panel C reports adjusted R-squared values from country-specific 5-year long-differenced regressions, which remove common trends by examining whether 5-year changes in investment predict 5-year changes in publications. China achieves the highest explanatory power (adj. $R^2 = 0.36$, $p = 0.04$), followed by the USA (0.21, $p = 0.09$), with no other country achieving statistical significance. Panels A - C of Table A.8 further discuss these

[8] We note that Panel B uses only seven clusters for the clustered standard errors, which may lead to over-rejection in small samples (see Cameron & Miller, 2015). As a robustness check, we verify that the 5-year long-differenced regressions in Figure 6C, which do not rely on clustering, corroborate the same pattern.

issues and provide an expanded explanation of the statistical results. These converging results across three distinct trend-robust methodologies provide strong evidence that the state-to-science transmission mechanism is genuine and unique to China.

It is evident that China's rise is driven by government investment, contrasting with the U.S. model of government grants intersecting with autonomous decisions by universities leveraging private/corporate funding. Research is capital-intensive, risky, and needs long-term planning, ingredients that are best suited for country-level investments (see Grant & Lewison, 1997). Results are surprising, though not entirely unexpected.

Complementing these formal analyses, the descriptive magnitudes are striking. Over the last 20 years, research spending has more than doubled, doctoral graduates have almost quadrupled from 23,446 in 2004 to 82,320 in 2022, and education spending increased by 66%, from 2.4% of GDP to 4.02%. By contrast, these same figures are stagnant in other research leading nations. These large spending increases by the Chinese government are investments that have yielded consistent and accelerating scientific success.

## 5. Conclusion and Limitations

Taken together, our evidence supports three conclusions. First, China has reshaped the global scientific hierarchy in the last two decades by systematically capturing journal space that was traditionally dominated by Western countries. Second, the country's innovation model today resembles a high-intensity modernization strategy, with massive volume and rising presence in premier outlets, potentially driven by government investment. Third, once we measure what matters (quality-tiered outlets, Top-3 presence, and within-journal impact) and the global Chinese diaspora, the Chinese academic landscape shifts from a "high-volume/low-impact" critique to a different portrait: China is dominating Top-3 scientific productivity.

This study should be interpreted with some caveats. We use a nationality-name dictionary to conduct a name-based author disambiguation for U.S.-based researchers, which might inadvertently capture Taiwanese, Singaporean, and other Asian authors. Moreover, we also potentially include second or third generation Chinese who are by birth U.S. nationals, hence, our data in Figure 3 represents an upper but realistic bound for Chinese academic productivity in the diaspora. Despite this limitation, the conclusions drawn from this study are clear: China is excelling in the strategic fields of physics, mathematics, and chemistry, with its quality trajectory visibly upward in all fields for the foreseeable horizon.

## Declarations


### *Funding*
No funding was received for conducting this study.


### *Competing interests*
The authors have no relevant financial or non-financial interests to disclose.

### *Ethics approval*
Not applicable.

### *Data availability*
The bibliometric data used in this study were obtained from Scopus (Elsevier) under licence; restrictions apply to the redistribution of these data, so the raw Scopus records are not publicly available. The underlying data that can be shared, together with the Python code to replicate the main results, are available on OSF at https://osf.io/e67kp/overview?view_only=28a95b04aa7b4d87b18866d97c147ea9. Data and code for the analyses reported only in Online Resource 1 are available from the corresponding author upon reasonable request. Details of the replication package are provided in Appendix K of Online Resource 1.

### *Code availability*
The Python code to replicate the main results is available on OSF at the link above (see Appendix K of Online Resource 1).

### *Author contributions*
Salvador Carmona, Timothy Fogarty, Hrvoje Kurtović, and Garen Markarian each contributed to conceptualization, methodology, investigation, data curation, formal analysis, writing - original draft, writing - review & editing, visualization, supervision, project administration, and validation. All authors read and approved the final manuscript.

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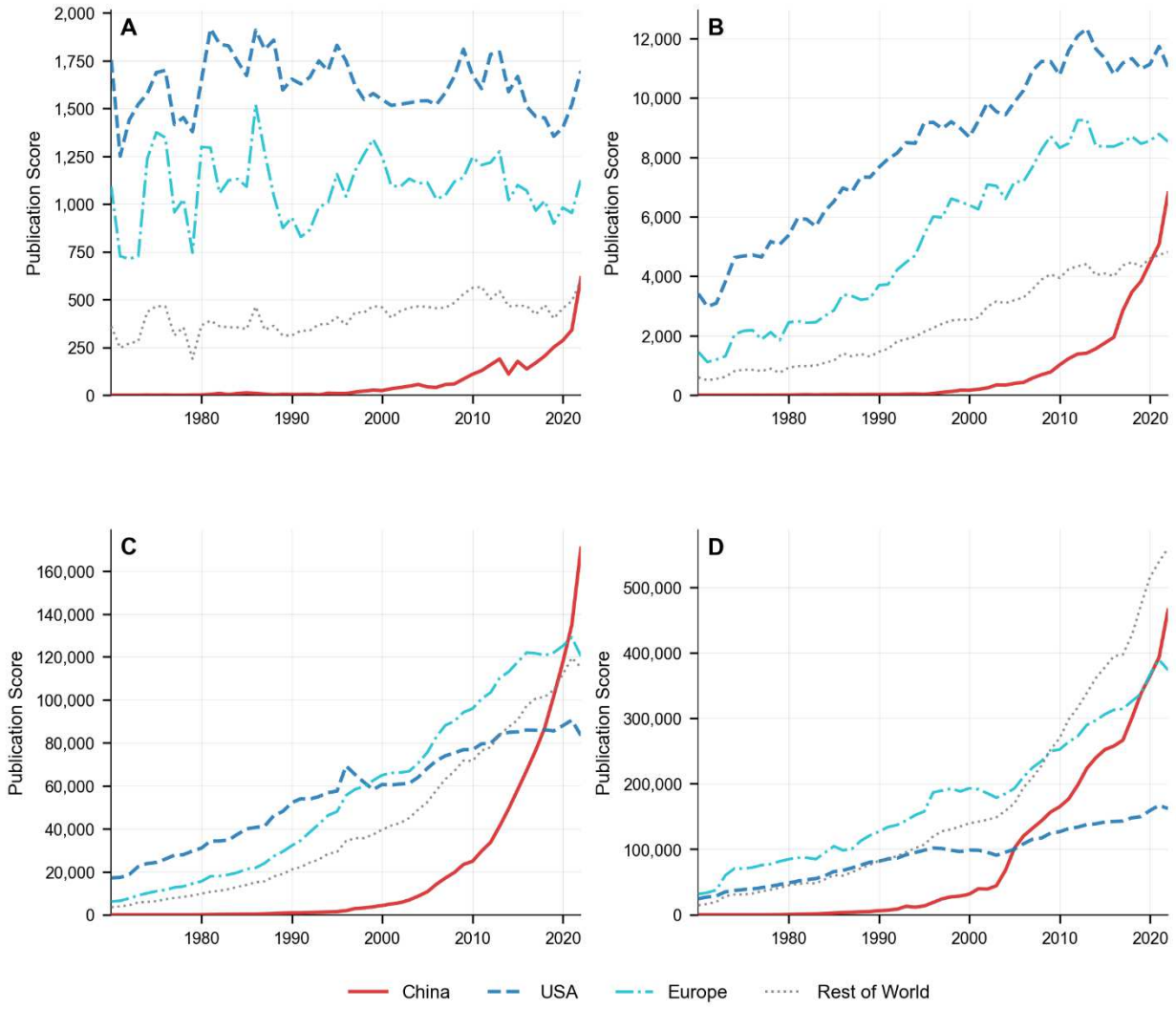


**Fig. 1 China's rapid ascent across all tiers of scientific publication quality (1970-2022).** Global scientific publication trends by geographic region, disaggregated by journal quality tier and representing author-weighted contributions aggregated across fields from Scopus. (A) Top-3 journals per field (elite outlets determined by citation analysis). (B) Top 1% of journals by citation impact. (C) Top 2-10% of journals. (D) Bottom tier (below the top 10%). China's output increased from near-zero to a substantial presence across all tiers: 614 publications in Top-3, 6,801 in top 1%, 170,626 in top 2-10%, and 465,504 in the bottom tier by 2022. In mid-tier and bottom-tier categories, China surpassed both the USA and Europe by 2022, while the USA maintained leadership in Top-3 (1,697 publications) and top 1% (12,333 publications). Although global publication volume expanded substantially over this period, China's growth represented the displacement of historically Western-dominated journal space. Solid red line, China; dashed blue line, USA; dash-dot teal line, Europe; dotted gray line, Rest of World. Method is further explained in Appendix B (Online Resource 1). The results are disaggregated by research area for the Top-3 journals in Fig. 2

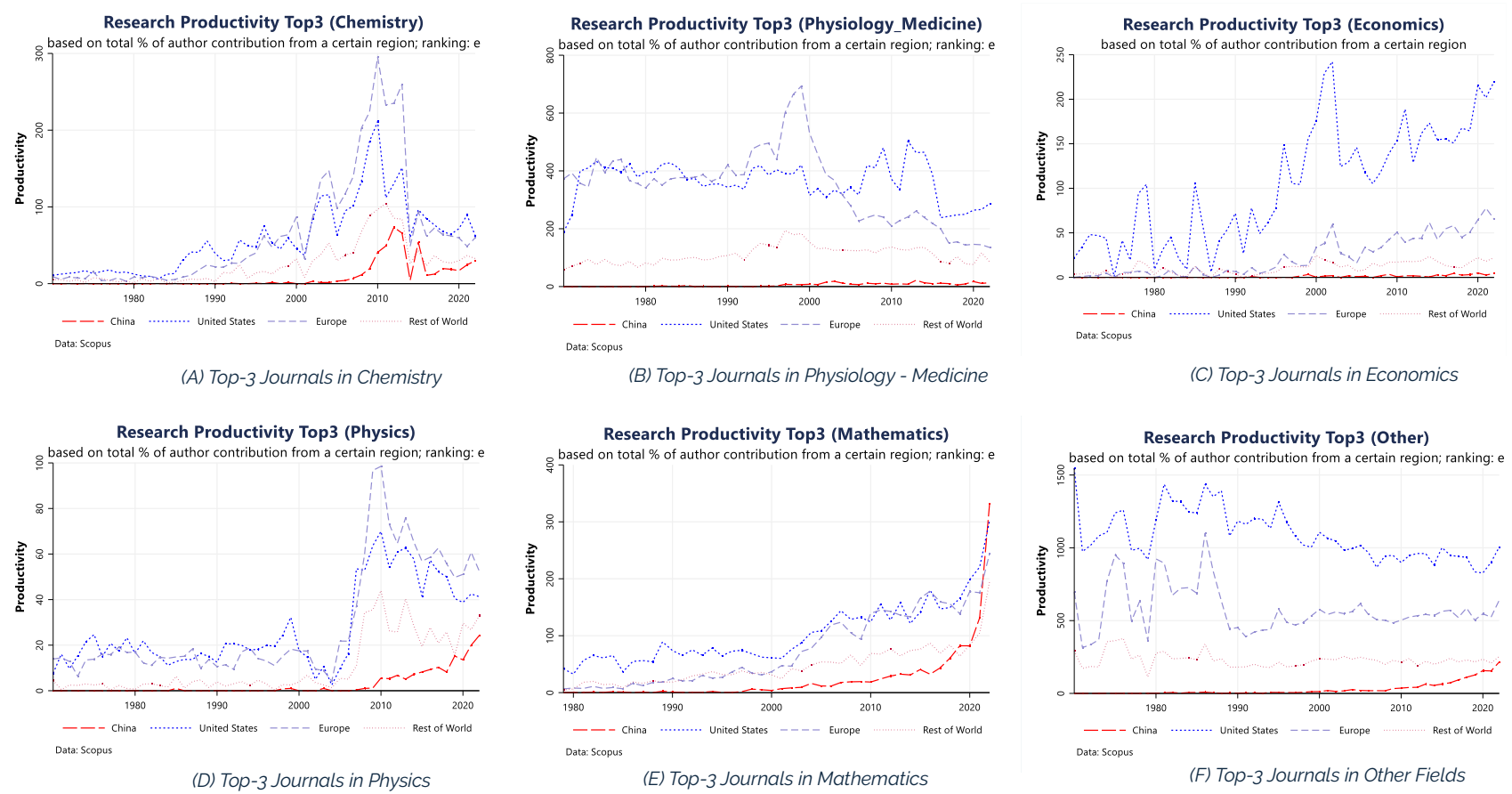


**Fig. 2 China's Research Productivity in Top 3 Journals by Field (1970-2022).** This figure shows research productivity across regions: China, United States, Europe, and Rest of World. Data are obtained from Scopus, covering 39 million publications from 22,189 journals over 52 years (1970-2022). Figures are organized clockwise in rows from the top left: Figures (A)-(F) report productivity in the Top-3 journals in chemistry, medicine/physiology, economics, physics, mathematics, and "other." Productivity is measured as the total percentage of author contributions from a given region. Methods and analysis are explained further in Appendix C (Online Resource 1)

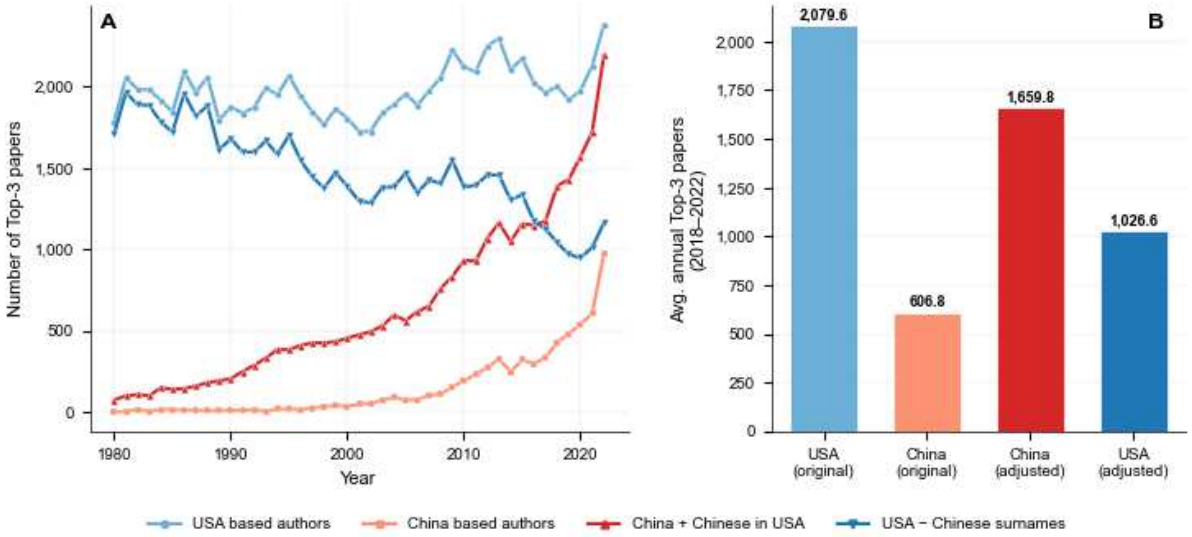


**Fig. 3 Adjustments to Chinese surnames highlight the extent of Chinese scientific contributions in Top-3 journals.** (A) A time series of paper counts from Top-3 journals for the USA and China, before and after adjusting for Chinese-surnamed authors affiliated with US institutions (1980-2022). The light-colored lines represent unadjusted counts based solely on institutional affiliation, while the dark-colored lines indicate adjusted counts where USA-affiliated papers with at least one Chinese-surnamed author are reassigned from the USA to China. Prior to adjustment, the USA consistently led China throughout the period. Following the adjustment, China has surpassed the USA in recent years, achieving an average of 1,659.8 papers per year compared to 1,026.6 for the adjusted USA (2018-2022). (B) Recent averages (2018-2022) comparing original and adjusted paper counts. The adjustment reallocates 50.6% of the USA's Top-3 paper count, highlighting the significant presence of Chinese-surnamed researchers at US institutions. This surname-based reattribution offers an upper limit on the diaspora effect, as it may misclassify some non-Chinese East Asian authors. Results using author-equivalent scores, which weight each paper by $1/n$ authors, display a qualitatively similar pattern. Method and analysis are further explained in Appendix G (Online Resource 1). The results are disaggregated by research area for the Top-3 journals in Fig. 4

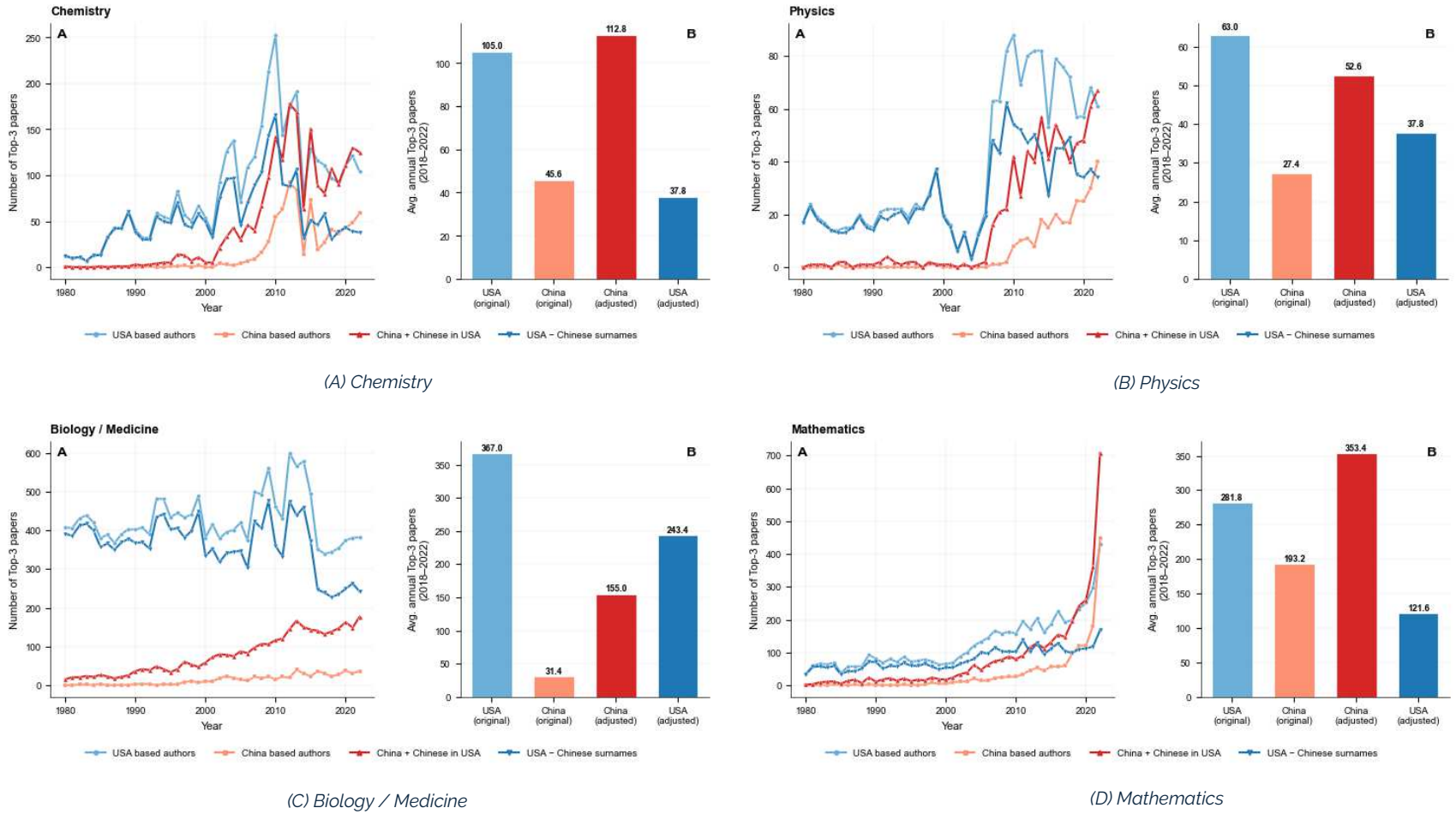


**Fig. 4 Field-Specific Adjustments to Chinese Surnames Reveal Patterns in Chinese Contributions to Top-3 Journals.** This figure shows annual Top-3 journal publication counts across four fields: (A) chemistry, (B) physics, (C) physiology/medicine, and (D) mathematics, from 1980-2022. For each field, Panel A presents time series of paper counts for the USA and China, based on institutional affiliation. Light-colored lines indicate original counts, while dark-colored lines reflect adjusted counts in which USA-affiliated papers with at least one Chinese-surnamed author are reassigned from the USA to China.
Panel B reports recent averages (2018-2022), comparing original and adjusted counts for both countries. Paper counts are derived from publications in Top-3 journals within each field. The surname-based adjustment provides an upper-bound estimate of diaspora contributions. Method and analysis are further explained in Appendix G (Online Resource 1)

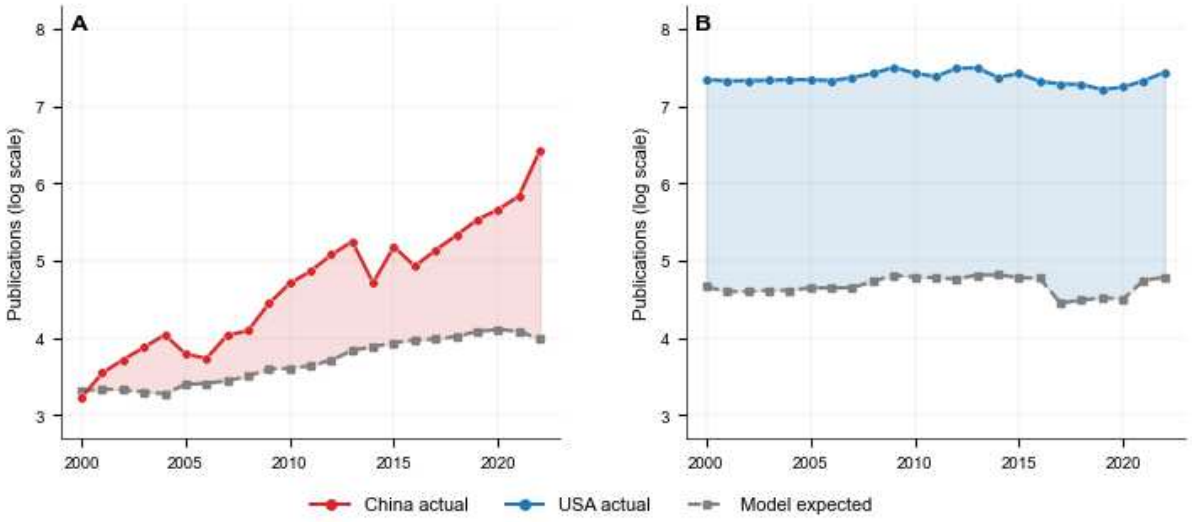


**Fig. 5 Contrasting innovation trajectories in China and the USA (2000-2022).** The actual Top-3 journal publications (solid lines) are compared to model-based expectations (dashed grey line) for (A) China and (B) the USA. The models predict publications based on GDP per capita, population, corruption indices, and institutional quality variables, using OLS regression on all countries except the target nation. The Y-axis displays log-transformed publication counts, while shaded areas highlight gaps between actual and expected performance. The USA shows consistent over-performance (+1,380% average) throughout the period, reflecting its accumulated institutional advantages, including world-leading universities, R&D infrastructure, and venture capital. China demonstrates accelerating over-performance (+218% average, widening post-2010), indicating a strategic, government-led emergence. Although the USA's absolute over-performance surpasses that of China, the differing trajectories - established dominance (high baseline, consistent) versus strategic emergence (lower baseline, accelerating) - highlight distinct mechanisms of scientific leadership with implications for future global competition. The Top-3 journals represent the most-cited publications across Nobel fields (physics, chemistry, medicine, mathematics) and multidisciplinary journals (Science, Nature, MIS). Method is further explained in Appendix I (Online Resource 1)

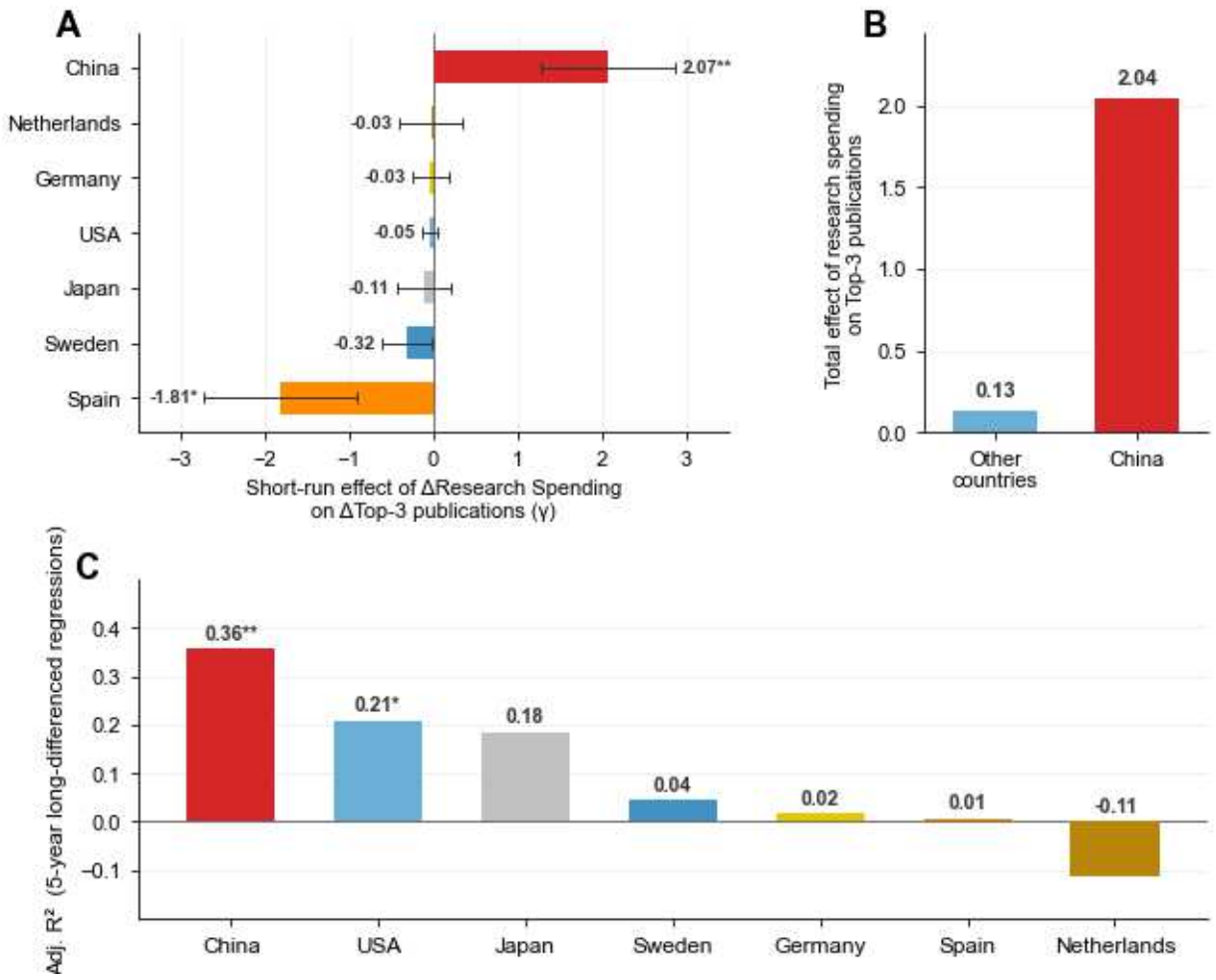


**Fig. 6 Government investment as a driver of scientific productivity.** (A) Short-run effect of changes in government research spending on changes in Top-3 journal publications, estimated from country-specific error correction models (ECM) over 2002-2022. Each bar represents the ECM coefficient for *Research Spending*, with error bars indicating one standard error. China is the only country with a statistically significant positive effect (2.07, $p = 0.02$), indicating that year-over-year increases in government research expenditure translate into immediate gains in elite scientific output. No other country exhibits a significant short-run research spending effect, suggesting that this direct state-to-publication channel is unique to China. (B) Total effect of research spending on Top-3 publications from a panel regression pooling all seven countries, with country fixed effects, a cubic time trend, and China interaction terms. The China-specific effect is 16 times larger than the baseline effect for other countries, confirming that China's scientific output responds to government investment at a magnitude that is largely absent in Western countries, where elite scientific production is shaped by decentralized university systems, private R&D, and corporate funding. (C) Adjusted R-squared values from country-specific 5-year long-differenced regressions ($\Delta_5 Y \sim \Delta_5 X$), which remove common time trends while preserving more statistical power than annual first differences. China achieves the highest explanatory power (adj. $R^2 = 0.36$, $p = 0.04$), followed by the USA (0.21, $p = 0.09$), while no other country reaches statistical significance, further corroborating that state investment variables are uniquely predictive of Chinese scientific output. All specifications use two government investment variables: total governmental research expenditures (*Research Spending*) and government education budget normalized by GDP (*Education Spending / GDP*). Full regression coefficients, cointegration diagnostics, and significance levels are reported in Table A.8, and further methodological details can be found in Appendix J (Online Resource 1)

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- ESM1OnlineResource1.pdf