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CHINESE SPUTNIK MOMENTS?

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ABSTRACT

China's technological progress in recent decades has been viewed with admiration, alarm, and (in some cases) doubt. To better understand the Chinese innovation ecosystem, we compile a dataset of almost 14 million domestic Chinese patent publications. We focus on the subset of critical technologies identified by the U.S. Department of Defense. Several surprising patterns emerge from the data: Chinese patenting is strongly associated with other measures of innovative progress; patents are not concentrated in corporate giants such as Huawei; universities have played a key role in innovation, much greater than state-owned enterprises or government-owned facilities; and fewer than one in ten Chinese critical technology patents involves an inventor with U.S. experience or training. Finally, using four text-based measures of patent quality, we show that the rise of Chinese patenting in critical technologies has not been associated with a decline in quality relative to the U.S. awards.

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1 Introduction

Technological innovation in China by almost any measure has surged in recent decades. Domestic patent publications are one example: they increased from roughly 30,000 annually in 2000 to 1.85 million in 2022, when they exceeded U.S. patent counts by nearly a factor of three. Looking specifically at the 14 Critical Technology Areas designated by the U.S. Department of Defense (DoD), annual Chinese patent publications rose from fewer than 10,000 in the early 2000s to more than 400,000 by 2022. Figure 1 presents these trends.[1]

The interpretation of the rise of Chinese innovation, however, has been controversial. A number of analysts have claimed that the commonly used innovation indicators overstate Chinese progress. In the context of patents, critics have pointed to the powerful incentives that exist for Chinese entities to undertake patent filings and the very low share of these filings that are also filed overseas (Li, 2012; Eberhardt et al., 2017). More generally, questions have been raised about the extent to which innovations have truly originated in China, as opposed to being results of intellectual property misappropriation and/or skilled immigration from Western nations.[2] Academic work has reinforced these concerns, showing, for instance, that Chinese total factor productivity (TFP) growth slowed substantially during the 2010s, even as other innovation metrics accelerated (Wei et al., 2017).

Others point to instances of the dramatic Chinese technological progress. In January 2025, for instance, the Chinese firm DeepSeek released its R1 large language model, which was then believed to approach the performance of leading U.S. models at substantially lower cost and compute intensity. The release was widely described as a "Sputnik moment" for American technological leadership.[3] Similar reactions followed China's 2021 test of a nuclear-capable hypersonic missile, which reportedly surprised U.S. intelligence agencies and was described by General Mark Milley as "close to" a Sputnik moment.[4] These episodes have supported positive assessments of China's innovative capacity.

This paper seeks to understand use patent data—a detailed if imperfect measure of innovation—to understand the Chinese innovative ecosystem. The data reveal an innovation

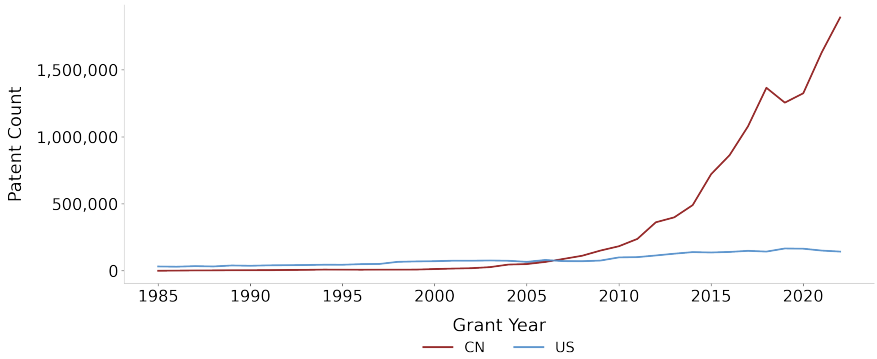
[1]The Critical Technology Areas (henceforth referred to as "critical technologies") are: Advanced Computing and Software, Advanced Materials, Biotechnology, Directed Energy, Future Generation Wireless Technology, Human-Machine Interfaces, Hypersonics, Integrated Network Systems-of-Systems, Integrated Sensing and Cyber, Microelectronics, Quantum Sciences, Renewable Energy Generation and Storage, Space Technology, and Trusted AI and Autonomy. Appendix B.1 provides further details about the subfields that are part of each technology. This list was established in 2018 and updated in 2025.

[2]Examples include Chafetz (2023), He (2021), and Kersten et al. (2022).

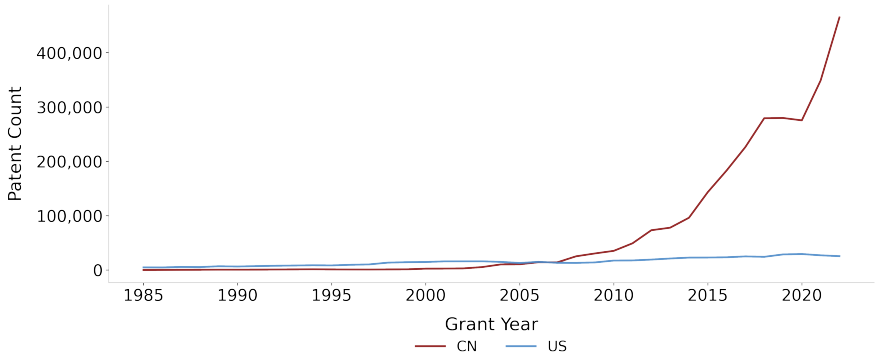
[3]See, e.g., Ruwitch (2025), Cassidy (2025), and Acemoglu (2025). By mid-2026, Chinese large language models, led by DeepSeek, represented 46% of token use by U.S. firms (https://finance.yahoo.com/technology/ai/articles/chinese-ai-models-now-capture-020440715.html).

[4]See Sevastopulo (2021); see also Sanger and Broad (2021).

Figure 1: Patenting in the U.S. and China



(a) All domestic patents, China vs. U.S.



(b) Critical technology patents, China vs. U.S.

Notes: Figure 1a reports the annual counts of all domestic patent publications in China (red) and the United States (blue) patent grants between 1985 and 2022. Figure 1b reports the annual counts in 14 Critical Technology Areas designated by the U.S. Department of Defense in 2018. Figure A.1 reports these counts separately for each of the 14 technologies.

system that is more broad-based, more university-centered, and less dominated by state-owned enterprises, large national champions, or U.S.-trained returnees than many standard narratives suggest. Moreover, the results underscore the credibility of anecdotal accounts of Chinese innovative progress, such as the DeepSeek and hypersonic cases above.

This paper examines five frequently articulated perceptions about Chinese innovation. We first address the observation that China's patent explosion coincided with weak TFP growth, raising concerns that Chinese patents reflected only incremental innovation. We find that quality-weighted Chinese patenting is strongly correlated with independent measures of scientific output within technology areas, suggesting that patent counts contain meaningful information about underlying innovative activity. Moreover, although aggregate Chinese patent counts are extremely large, they are less unusual when scaled by the size of China's science, technology, engineering, and mathematics (STEM) workforce.

The second relates to the role of large firms. Chinese patents, even in frontier technologies, are not dominated by a handful of giants like Huawei. In fact, innovation activity in China is considerably less concentrated among large firms than in the United States. The top-ten assignee share in Chinese critical technologies declined from roughly ten percent in the late 1990s to four percent by 2022, substantially below the U.S. level of roughly 20 percent.

The third perception concerns the direct involvement of the Chinese government in the production of innovation. (We do not consider subsidies and other incentives.) State-owned enterprises and the government together account for less than four percent of Chinese critical technology patents. Instead, innovation in critical technologies is concentrated among private firms, which account for 58 percent of patents, and universities, which account for 27 percent. The university share is particularly striking: it is roughly eight times larger than the U.S. share of 3.3 percent.

We then address a fourth belief, which highlights the role of returnees from the U.S. in Chinese innovation. We find little evidence that Chinese innovation is primarily driven by U.S.-trained returnees. Fewer than ten percent of Chinese critical technology patent publications involve an inventor with prior U.S. work experience, a share that has declined since 2019. The fraction involving inventors with U.S. PhDs remains below one percent throughout the sample. We document a striking asymmetry running in the opposite direction: the share of U.S. patents involving inventors with non-U.S. Western foreign work experience has climbed to 22 percent, more than twice the corresponding Chinese peak.

Finally, we seek to understand whether the rapid expansion of Chinese patenting was associated with a deterioration of patent quality. To do so, we evaluate patent quality using four complementary text-based measures that capture textual novelty, textual influence within

and across countries, and proximity to the scientific frontier.

In particular, we assess the quality of domestic Chinese innovation, over time and in comparison to domestic U.S. Patent and Trademark Office (USPTO) patents. While each measure is imperfect in isolation, together the four metrics tell consistent and complementary stories. Despite the growth of Chinese critical technology patenting, there was no apparent decline in quality relative to other awards. Chinese patents in virtually all critical technologies gained textual importance relative to U.S. patents between 2006 and 2021. The share of Chinese critical technology patents that mention economically salient bigrams, as extracted from U.S. patents and earnings calls (Kalyani et al., 2025), has risen from under two% to 16% between 1995 and 2022. Chinese patents are closer to the scientific frontier, as measured by the set of most highly cited academic articles within each technology, than their U.S. counterparts in several technologies.

This paper contributes to a growing literature studying innovation and technological change in China (Holmes et al., 2015; Aghion et al., 2015; Fang et al., 2017; Wei et al., 2017; Chen et al., 2021; König et al., 2022; Aghion et al., 2023; Beraja et al., 2023; Han et al., 2024; Qiu et al., 2025; Bai et al., 2025). By constructing a large-scale dataset linking Chinese patents, organizations, inventors, and scientific activity across critical technologies, we provide new evidence about the nature of the Chinese innovation ecosystem.

2 Assembling Data on the Universe of Chinese Patents

To construct the China patent dataset, this paper follows a methodology as close as possible to that pursued with the U.S. patent data since the inception of the first patent project at the National Bureau of Economic Research (Griliches, 1984)). We emulate many of the key steps undertaken in the literature using the USPTO data, such as the compilation of citations (Jaffe and Trajtenberg, 2002) and the identification of their sources (Alcácer and Gittelman, 2006), the calculation of KPST measures of textual novelty (Kelly et al., 2021), the construction of international patent families (Putnam, 1997), the disambiguation of assignees (e.g., Jaffe and Trajtenberg (2002) and Magerman et al. (2006)), the identification of venture-backed patents (Bernstein et al., 2016), and the linkage of inventors to their social media profiles (Sharoni, 2024).[5]

Before turning to the results, we highlight several key methodological challenges in studying

[5]In Appendix A.1, we provide a brief history of how patenting has evolved in China. Formally, it is modeled after the European and U.S. patent offices. While Chinese firms were initially unsophisticated about patents, both firms and universities have become more savvy about claim drafting and filing strategies since the early 2010s.

Chinese patents and how we overcome them.

Unlike in the U.S., there is no single complete database of Chinese patents. Rather than relying on one dataset, we instead needed to combine three datasets: the CNIPA Patent Search and Analysis database (which must be gathered in China by Chinese nationals), the European Patent Office's (EPO) PATSTAT Global dataset, and the Google Patents database. In particular, while the records of Chinese patents in the PATSTAT database have been supplemented with a variety of useful information, it does not include all patents in the CNIPA database (a problem that reoccurs in India and seemingly other nations). Therefore, the information must be drawn and combined from each of the three databases, with extensive de-duplication and merging of records required.[6]

A related issue is the frequency with which Chinese patent filings are never examined. CNIPA applicants must request that their patent be reviewed within the first 36 months after publication, or the application is deemed to have been withdrawn (Tong et al., 2018). Reflecting both the higher fees associated with patent examination requests and the emphasis of many "patent quota" incentive schemes on patent applications rather than awards (Fuller, 2016), many patent publications in China are of applications that are never examined. Analyses of USPTO data typically focus exclusively on issued patents. This focus reflects the fact that, unlike in China, a large fraction of U.S. patent applications are ultimately issued.[7] Throughout the analysis below, we will focus on employing the last version of each CNIPA publication as of September 2023, whether of a patent award or an application.

The citation practice in China is also incomparable to the U.S. (see Huang (2021) for an overview of Chinese citation practice). There are few citations made in Chinese patents by Chinese applicants in particular. This makes it difficult to use citations as measures of quality for Chinese patents. Figure A.2 illustrates the dearth of citations in the Chinese data, especially before the early 2000s. Furthermore, given the extent of price limits in Chinese stock markets (Zhang et al. (2022) is a recent discussion), which have been widely understood since the work of Fama (1988) to impede price discovery and efficiency, we do not consider a Kogan et al. (2017)-style analysis of patent value based on market reactions to the award of patent grants.

[6]Many policy studies of Chinese innovation have focused on filings or awards in the U.S. (e.g., U.S. Patent and Trademark Office, Office of Policy and International Affairs (2022); Atkinson (2024)). Only 3.5% of Chinese patent publications in our sample are filed in the U.S. In Appendix A.2, we investigate the decision to file domestic Chinese patent publications in the U.S. and find that the percentage has been falling over time. While critical technologies that are dual-use are more likely to be filed in the U.S., those with primarily military applications are less likely. Moreover, "breakthrough" patents are significantly less likely to be filed in the U.S.

[7]When one adjusts for the refilling of rejected filings, the acceptance rate of U.S. patent applications is very high: the estimated rates are between 71% and 85%. See, for instance, Carley et al. (2015).

Finally, following the conventions of the economics of innovation literature (e.g., Jaffe and Trajtenberg (2002)), we focus exclusively on the most important patent class, termed invention patents in China, which resemble utility patents in the U.S.

We create a corresponding set of U.S. patent awards to use as a benchmark. To identify U.S. awards, we only include U.S. utility patents with at least one assignee identified by the USPTO as a U.S. organization. In the cases where the assignee is unclassified by the USPTO or is simply denoted as an individual, we examine the location associated with the inventor in the patent and include it if it is in the U.S. We examine all patents awarded by the USPTO between January 1985 (the inception of the Chinese patent system) and September 2023 (the time we collected the Chinese patent data).

For much of the analysis, we compare (a) CNIPA publications with Chinese inventors and/or assignees with (b) U.S. awards involving U.S. inventors and/or assignees. To identify the domestic Chinese awards, we use the coding of nationality by CNIPA. Of the 16.4 million Chinese publications in our sample, 13.7 million are by Chinese inventors and/or assignees.

2.1 Identifying Critical Technologies

An important aspect of our analysis is that we document these patterns not only for the full universe of Chinese patents, but also separately across 14 critical technologies. Doing so is challenging because these technologies do not map cleanly into the the two closely related patent classification schemes used in the U.S. and China (the Combined (CPC) and International Patent Classification (IPC) schemes, respectively). Technologies like Advanced Materials and Hypersonics can span multiple patent classifications.

We thus proceed by turning to the Defense Technical Information Center, a part of the U.S. DoD. Its Dimensions Analytics database seeks to compile unclassified publications, grants, and patents filed by or linked to funding by the DoD and/or the Office of the Director of National Intelligence/Intelligence Advanced Research Projects Activity.[8]

We focus on the 14 "Critical Technology Areas" identified by the U.S. Office of the Undersecretary of Defense for Research and Engineering in 2018. For each critical technology, we collected the full set of corresponding patent awards and constructed sets of CPC subclasses and keywords associated with them.[9] Instead of manually extracting keywords from the

[8]This list combines (1) patents assigned to these organizations and (2) patents generated through grants made by them, even if assigned to another entity, such as a university or private contractor.

[9]A patent can be classified into several CPC subclasses, and multiple patents are associated with each critical technology. We only include CPC subclasses that represented the primary classification of 80% of the DTIC-identified awards in each technology. For instance, if the most populous subclasses represented 40%, 25%, 20%, and 10% of the awards in a DTIC category, we would only use the first three subclasses.

patents, we use the keywords identified and presented by the DTIC at the top of each patent's entry. These phrases appear to be less noisy than the language of the patents or the grant abstracts themselves. We removed stopwords, destemmed words, and kept all bigrams (including those based on trigrams, as explained in Appendix B.1) associated with each award in a given technology.

We matched all Chinese and U.S. patent publications to one, multiple, or no critical technologies based on two conditions: (a) the patent's primary CPC or IPC subclass belonged to the set associated with a critical technology, and (b) its title and/or abstract included at least one unique bigram associated with that technology.

Table 1 presents patent counts by technology. China has more cumulative critical technology patents than the United States in every category. The largest absolute gap is in Advanced Materials (1.93 million Chinese patents vs. 0.27 million in the U.S.); but AI and Renewable Energy also show large gaps. As a share of each country's total domestic patents, the differences are less dramatic, but Advanced Materials, Renewable Energy Generation and Storage, Integrated Sensing and Cyber, and AI account for larger shares of Chinese patenting. Chinese innovation in each of these frontier technologies accelerated after 2010; about a decade before the first discussions of Chinese "Sputnik moments" in the U.S. media.

3 Assessing Beliefs about Chinese Innovation

We now use this dataset to explore some of the common claims about Chinese innovation. In particular, we highlight that five commonly articulated beliefs are misleading.

3.1 Belief 1: Chinese patents contain little meaningful information about innovation quality

As highlighted in the second paragraph of the introduction, Chinese patents are sometimes dismissed as an artifact of state incentive schemes rather than as evidence of invention. Two diagnostic exercises, reported in Figure 2, argue that the Chinese patent record does track invention in critical technologies.

First, the level of patenting in China is not anomalous when normalized by inventive inputs. The ratio of cumulative domestic patent applications to STEM tertiary graduates between 2014 and 2021 is 0.67 in China and 0.64 in the United States. When we look across

Furthermore, while PatentsView indicates the primary assignment of U.S. awards, we develop our own methodology to infer a Chinese patent's primary CPC subclass. This process is described in Appendix B.2.

Table 1: Patent Publication Counts by Critical Technologies

Panel A: China Domestic Patent Publications

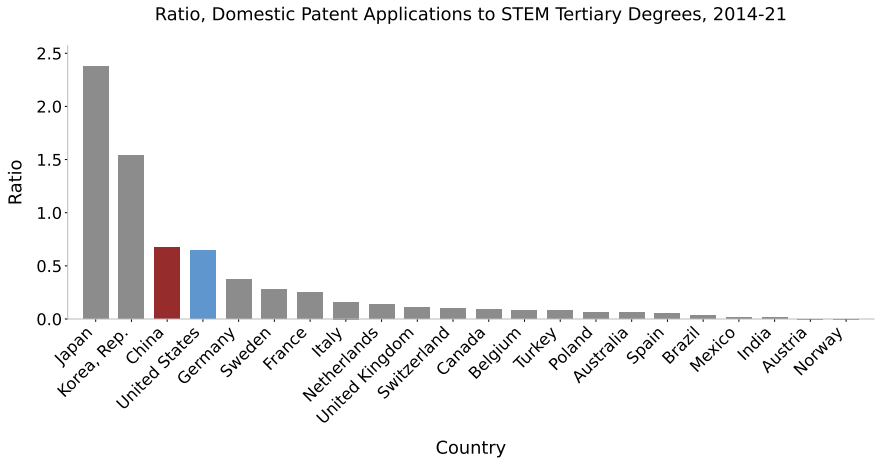
Technology	Count	Percentage
Advanced Computing and Software	31,411	0.23%
Advanced Materials	1,929,602	14.04%
Biotechnology	25,459	0.19%
Directed Energy	301	0.00%
Future Generation Wireless Technology	70,930	0.52%
Human Machine Interfaces	32,854	0.24%
Hypersonics	54	0.00%
Integrated Network Systems of Systems	206	0.00%
Integrated Sensing and Cyber	184,712	1.34%
Microelectronics	211,920	1.54%
Quantum Sciences	8,716	0.06%
Renewable Energy Generation and Storage	322,430	2.35%
Space Technology	987	0.01%
Trusted AI and Autonomy	463,261	3.37%

Panel B: U.S. Domestic Patent Publications

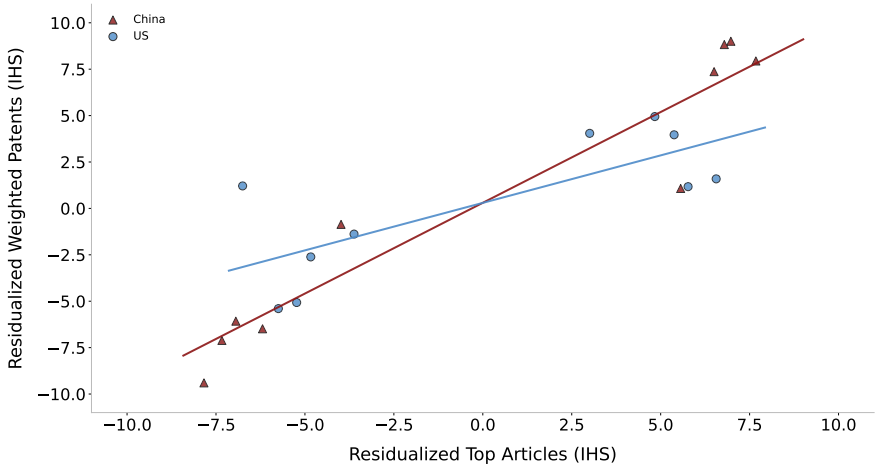
Technology	Count	Percentage
Advanced Computing and Software	21,871	0.67%
Advanced Materials	271,391	8.26%
Biotechnology	13,069	0.40%
Directed Energy	233	0.01%
Future Generation Wireless Technology	29,644	0.90%
Human Machine Interfaces	9,994	0.30%
Hypersonics	42	0.00%
Integrated Network Systems of Systems	127	0.00%
Integrated Sensing and Cyber	53,061	1.62%
Microelectronics	93,457	2.84%
Quantum Sciences	2,567	0.08%
Renewable Energy Generation and Storage	61,195	1.86%
Space Technology	229	0.01%
Trusted AI and Autonomy	87,479	2.66%

Notes: This table reports the number of patent publications and the share of total domestic patent publications, by critical technology, between 1985 and 2023, separately for China (Panel A) and the U.S. (Panel B). Technologies are sorted alphabetically within each panel.

Figure 2: Patent Filings per STEM Graduate and KPST-Weighted Patents vs. Top-Decile Scientific Articles



(a) Patent applications per 1,000 STEM graduates



(b) KPST-weighted patents vs. top-decile cited scientific articles

Notes: Panel (a) reports cumulative domestic patent applications per 1,000 tertiary STEM graduates, averaged over 2014 to 2021, for the top-30 economies by GDP for which the education data are available. The patent series is from WIPO Indicator 1 (total patent applications, direct and PCT national-phase entries); the STEM graduate series is from the U.S. NSF Science and Engineering Indicators and the OECD. Panel (b) is a binned scatter of the relationship between annual KPST-weighted patent counts (using one-year forward similarity) and the count of scientific articles in the top decile of citations in the corresponding critical technology. The publication data are drawn from the Australian Strategic Policy Institute's Critical Technology Tracker. Both axes are demeaned by year and technology fixed effects and IHS-transformed. The sample covers 13 of the 14 critical technologies and grant/publication years from 2003 to 2023; ASPI categories are mapped to DTIC categories using the crosswalk in Appendix B.1. The respective coefficients (and standard errors) are 0.98 (0.06) (China) and 0.51 (0.08) (U.S.).

the top-30 GDP economies for which the education data are available, the ratio is higher in Japan and Korea, but well above many peers in both the developed and developing world.

Second, the technologies and years in which more critical technology patents are issued are also those in which more high-impact scientific publications appear. We compare KPST-weighted annual patent counts in each critical technology with the count of papers in the top decile of citations in the corresponding technology from the Australian Strategic Policy Institute's Critical Technology Tracker, mapping ASPI categories to DTIC categories for 13 of our 14 technologies (Appendix B.1). After demeaning by year and technology fixed effects and applying an inverse hyperbolic sine transformation, the binned scatter shows a positive association between weighted patenting and top-cited publications in both countries. The slope is somewhat steeper in China than in the United States. Among other papers, Hausman (2022) and Lerner et al. (2024) argue that the patenting–science relationship in the U.S. is causal.[10]

3.2 Belief 2: Chinese patenting is dominated by a few giants

Much of the U.S. policy discussions and actions motivated by Chinese innovation have focused on the very largest firms. Analysts have argued that these Chinese national champion firms, such as Huawei, Semiconductor Manufacturing International Corporation, and Tencent, are deeply intertwined with the industrial and economic security goals of the Chinese Communist Party and benefit from massive public subsidies and other favorable treatment (see, for instance, Thiessen (2024) and Shatz and Egel (2025)). Many of the U.S. government's efforts to limit knowledge flows to China, such as the Entity List, have focused on these firms.

The data suggest, however, that concentration in Chinese critical technology patents is low and has declined substantially over time. The Chinese top-ten assignee share peaked at roughly 10 to 11 percent in the late 1990s and mid-2000s before falling to approximately four percent by 2022; the top-50 share peaked near 26 percent in 2004 and declined to roughly 13 percent by the end of the sample (Figure 3).

By contrast, U.S. critical technology patents have remained considerably more concentrated throughout the period. The U.S. top-ten share has remained close to 20 percent, while the top-50 share has fluctuated within a relatively narrow range between 37 and 41 percent.

[10] In a similar but unreported analysis, we examine the relationship between weighted critical patents and proxies for local economic development for 31 provincial-level units between 2006 and 2023, controlling for period and provincial fixed effects. We see a strong association between prior critical technology patenting and various measures of provincial growth: gross domestic product, per capita GDP, industrial output, employment, and population. The results are robust to using unweighted patent data or an inverse hyperbolic sine (IHS) transform of the continuous variables.

By 2022, the U.S. top-ten concentration ratio was approximately five times larger than the Chinese ratio. Figure A.8 and Figure A.9 present these facts separately by technology.

3.3 Belief 3: Chinese critical technology innovation is primarily produced through direct state ownership

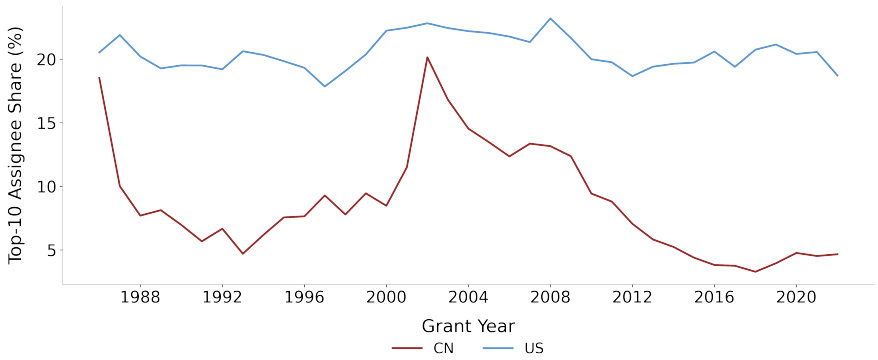
Many of the policy discussions about Chinese innovation have highlighted the role of state-owned enterprises and government bodies such as the Peoples Liberation Army. We therefore look at who is filing critical technology patents, with the caveat that we can only look at direct patent assignments, and not the myriad of formal and informal incentives that the parties may have received (Fang et al., 2025; Banares-Sanchez et al., 2026).

We find that Chinese critical technology patenting is dominated by private firms and universities, rather than by state-owned enterprises. Private firms account for 58.3 percent of cumulative Chinese critical technology patents, while public universities account for 26.6 percent. By contrast, state-owned enterprises and the government together account for less than four percent of cumulative patenting activity. The remainder is attributable to hospitals, individual inventors, government-affiliated nonprofits, and unclassified entities.

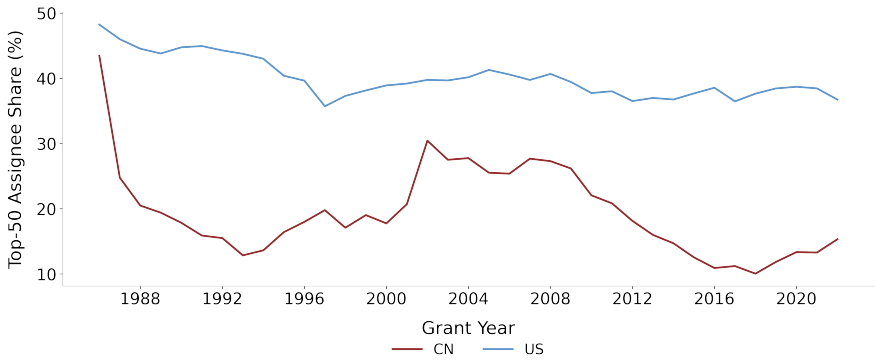
Figure 4 reports the evolution of the annual patent flow by assignee type. The two dominant sectors—private firms and universities—expand together throughout the sample period. By 2022, private firms account for approximately 56 percent of annual Chinese critical technology patents and universities for roughly 32 percent. Huawei is the single largest private-sector assignee. Within the university sector, the seven universities administered by the Ministry of Industry and Information Technology—the "Seven Sons of National Defense"—account for 2.1 percent of cumulative patenting activity.

The university share is the clearest point of divergence between the Chinese and U.S. innovation systems. In China, universities account for 26.6 percent of cumulative critical technology patents but only 17.6 percent of overall domestic patenting, implying that university inventive activity is disproportionately concentrated in strategically important technologies. In the United States, the corresponding shares are 3.3 percent of critical technology patents and 4.4 percent of overall domestic patents (Table A.2). U.S. universities therefore represent a relatively small and stable share of patenting activity both within and outside critical technologies. The cross-country difference in university critical technology patenting—a 26.6 percent share in China versus 3.3 percent in the United States—is approximately eightfold. U.S. critical technology patenting remains overwhelmingly corporate, with firms accounting for 94.9 percent of cumulative patents. IBM, the largest assignee, has 33,322 patents.

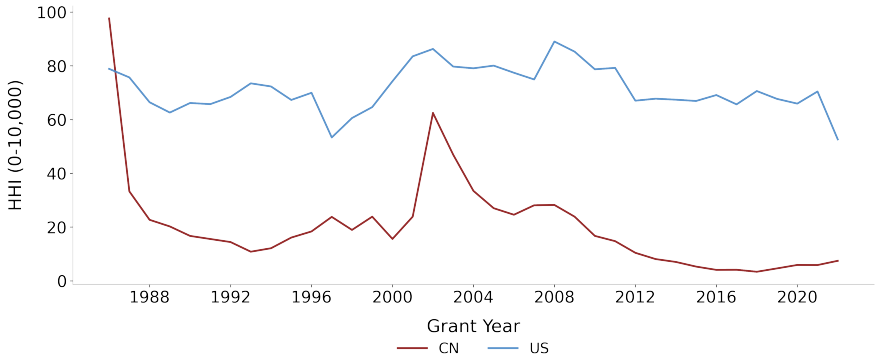
Figure 3: Assignee Concentration in Critical Technologies: China and United States



(a) Top Ten Share



(b) Top 50 Share



(c) HHI

Notes: Each panel reports one annual measure of assignee concentration in the 14 critical technologies, comparing domestic Chinese patent publications and domestic U.S. utility patents side by side. Panel (a) reports the "Top Ten Share," Panel (b) reports the "Top 50 Share," and Panel (c) reports the "HHI." "Top Ten Share" and "Top 50 Share" are the fractions of all domestic critical technology patents in each year accounted for by the ten and 50 largest assignees, respectively. "HHI" is the Herfindahl-Hirschman Index computed across all assignees in each year. The same DTIC-based critical technology classification is applied to both samples. Concentration refers to the distribution of patenting across assignees, not to product-market concentration. The sample covers grant years 1995 to 2023.

The organizational structure of Chinese patents reflects a distinctive role of its higher-education sector. In Figure A.10, we show that universities are important across all individual critical technologies but with significant heterogeneity. Biotechnology and AI patents have a larger share of university assignees than others; Human Machine Interfaces and Renewable Energy have much smaller shares of university patents.

This institutional structure is consistent with longstanding Chinese industrial and science policy. The 1996 Law on Promoting the Transformation of Scientific and Technological Achievements, substantially revised in 2015, granted universities expanded autonomy to license and transfer intellectual property arising from publicly funded research and required that researchers receive at least 50 percent of commercialization income. These reforms complemented other coordination mechanisms, including the establishment of more than 100 nationally designated university science parks and the 2011 Collaborative Innovation Centers initiative.

Taken together, the organizational composition and concentration evidence describe a Chinese critical technology patent system dominated by private firms and public universities, with a small direct role for government or state-owned enterprises. Relative to the U.S., the Chinese system is also substantially less concentrated and characterized by a broader base. The state's role therefore appears primarily coordinative rather than directly productive: inventive activity is shaped through institutional mechanisms—most notably the higher-education system, technology-transfer institutions, public incentive schemes, and procurement priorities—rather than through state ownership of the principal patent-producing organizations.

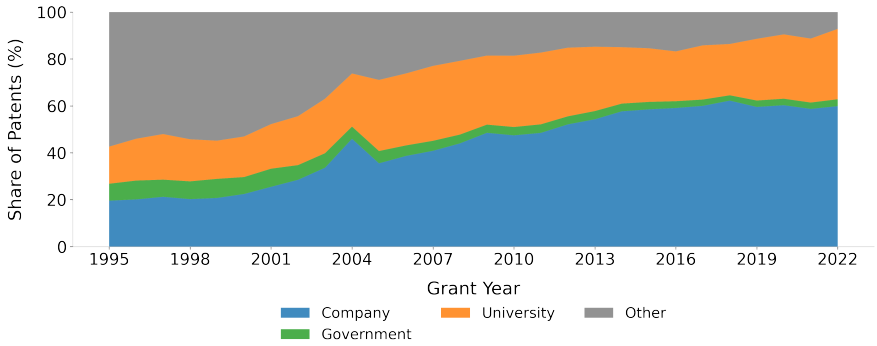
3.4 Belief 4: Chinese innovation is driven by U.S.-trained returnees

U.S. policymakers have employed a number of mechanisms to limit knowledge flows associated with inventor mobility to China, motivated by fears that such movements are a major source of technological leakage to its rival. These have included regulations banning U.S. citizens and residents from subsequently working on certain Chinese projects, legislation to limit Chinese recruitment of U.S. technologists,[11] and at least informal pressure on American firms to reduce headcount at Chinese research facilities. Most visible have been the prosecutions of individuals alleged to have transferred technology to China under the Defend Trade Secrets and Economic Espionage Acts.[12]

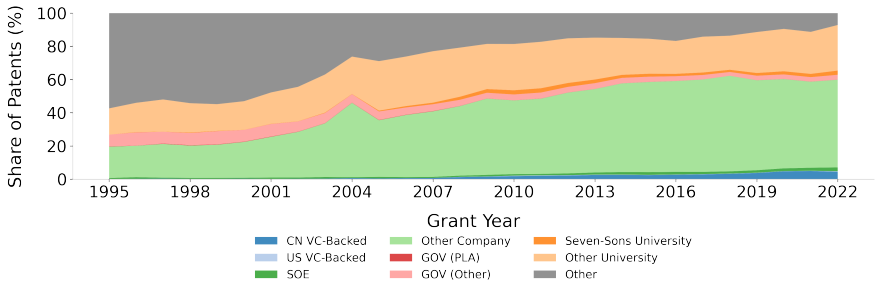
[11] Section 10632 of the CHIPS and Science Act of 2022 (Public Law No. 117-167) is an example. Subsequent legislative efforts, such as the Malign Foreign Talent Recruitment Program Definition Clarification Act (H.R. 7686) passed by the U.S. House in September 2024, have sought to strengthen these curbs.

[12] One example is Linwei Ding, who left Google in 2024 with the intention of starting a Shanghai-based startup. He was indicted soon after and accused of stealing sensitive technology related to Google's

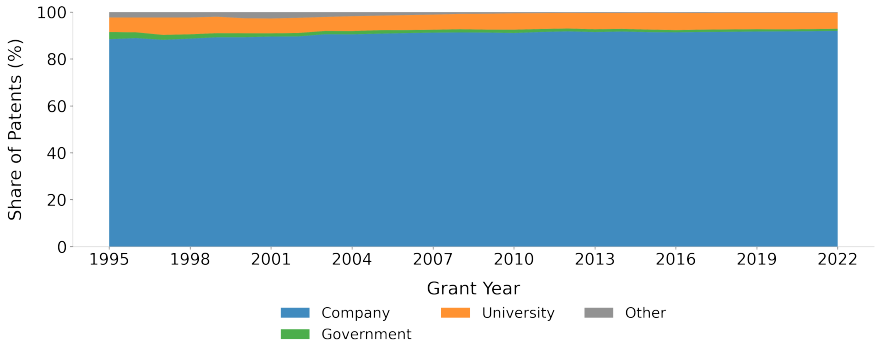
Figure 4: Organizational Composition of Critical Technology Patenting: China and United States



(a) China



(b) China - Detailed



(c) United States

Notes: The panels report the annual percentage composition of domestic invention (China) and utility (U.S.) patents in the 14 critical technologies by assignee type and grant year. Assignees are classified using CNIPA records, TianYanCha, PitchBook, and the DISCERN database (for U.S. patents). "CN VC-Backed" in Panel (b) includes all firms that received funding from Chinese venture capital investors; "US VC-Backed" includes those firms that received at least some funding from U.S. investors. "SOE" in Panel (b) includes majority state-owned enterprises. "Other Company" in Panel (b) includes all non-SOE firms not backed by Chinese or U.S. venture capitalists. "GOV (PLA)" in Panel (b) includes entities linked to the People's Liberation Army (China). "Other University" in Panel (b) includes all higher-education institutions except the "Seven Sons of National Defense." "Other" includes hospitals, unclassified entities, and individual assignees. The sample covers grant years 1995 to 2022.

But direct foreign inventor linkages account for only a small minority of Chinese critical technology patenting. Figure 5 reports the annual share of Chinese critical technology patents associated with at least one inventor whose matched public professional profile—constructed from Revelio Labs' LinkedIn data—indicates foreign education or work experience. The largest series corresponds to U.S. work experience. This share rises steadily after the mid-2000s, peaks at just under ten percent of patents in 2019, and declines to approximately 6.5 percent by 2022. Inventor linkages to Germany, Japan, Korea, and the United Kingdom follow a qualitatively similar but smaller pattern, peaking near 6.5 percent in 2019. The share of patents with at least one inventor holding a U.S. degree peaks below five percent and falls to roughly 2.5 percent by 2022, while the share associated with a U.S. PhD inventor remains below one percent throughout the sample. Across all measures, the modal Chinese critical technology patent contains no inventor with an observable foreign educational or employment background.

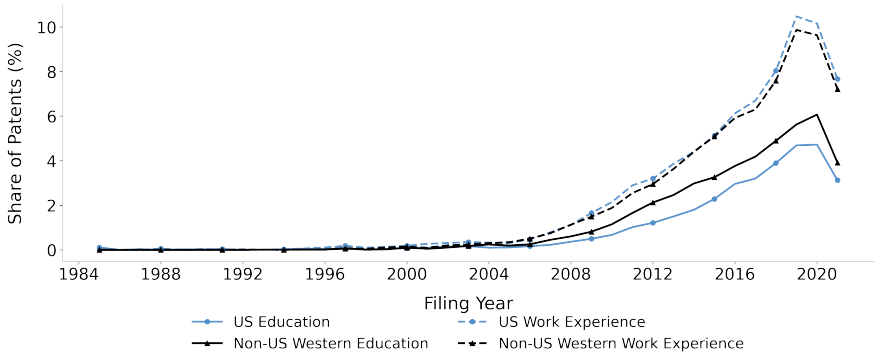
The cross-country comparison runs counter to the conventional narrative. Figure 5 reports the same measures for the full universe of 13.7 million domestic Chinese patents and 3.3 million domestic U.S. utility patents. In the United States, the share of patents involving at least one inventor with non-U.S. Western work experience reaches approximately 22 percent in 2019—more than twice the corresponding Chinese peak of ten percent with U.S. work experience. Similarly, the share of U.S. patents involving an inventor with Chinese education or employment experience peaks near six percent. At the aggregate patent-system level, the U.S. innovation system appears substantially more reliant on foreign inventor linkages than the Chinese system, contrary to the common framing that emphasizes foreign talent as the primary driver of Chinese innovation.

Both countries exhibit a sharp decline in measured foreign exposure after 2019. In China, share of patents with returnees from the U.S. dropped by four percentage points. Several factors complicate interpretation of these late-sample dynamics. The COVID-19 pandemic substantially disrupted international mobility, the China Initiative and expanded export-control restrictions altered the institutional environment governing U.S.–China scientific collaboration, and inventors may have become less willing to disclose foreign affiliations in public professional profiles after 2019. In addition, recent patent cohorts are mechanically less likely to contain fully observed employment histories because matched profile information accumulates over time. Accordingly, our conclusions about the post-2019 dynamics must be viewed with caution.

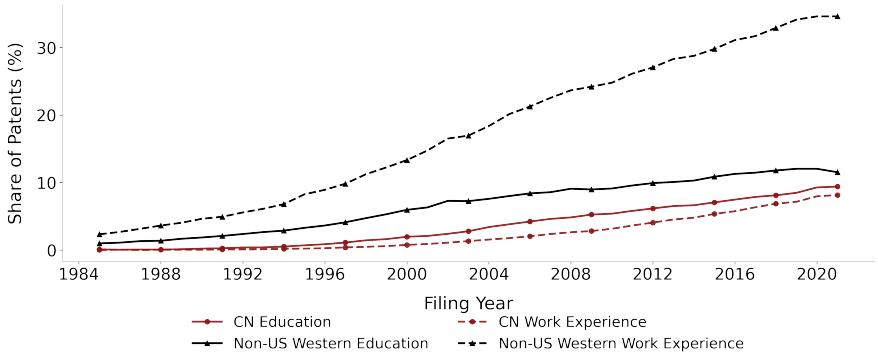
Direct inventor mobility therefore does not appear to be the dominant mechanism through

supercomputing chips used to power AI models like Gemini.

Figure 5: Inventor Foreign Linkages: All Domestic Patents, China and United States



(a) China: Foreign-trained or foreign-experienced inventor shares



(b) United States: Foreign-trained or foreign-experienced inventor shares

Notes: Each panel reports the annual share of domestic patents that have at least one inventor whose matched public professional profile indicates the listed foreign education or work history. Panel A covers all 13.7 million domestic Chinese invention patents and reports CN-side foreign exposure (U.S. and non-U.S. Western education and the corresponding work experience series). Panel B covers all 3.3 million domestic U.S. utility patents and reports U.S.-side foreign exposure (CN and non-U.S. Western education and experience). The horizontal axis is filing year. The sample covers filing years 1985 to 2021.

which Chinese critical technology patenting connects to the global knowledge frontier, at least insofar as such linkages can be observed through matched professional-profile data. Knowledge may instead diffuse through broader channels—including scientific publications, multinational production networks, conferences, and the global circulation of technical documents—that do not require observable foreign-trained inventors on Chinese patents themselves.

3.5 Belief 5: Increasing Chinese innovation is associated with a decline in quality

A major concern about using commonly employed innovation metrics to assess Chinese activity is that the explosion in volume may be driven by incremental activity. In the context of patents, this claim has been made in both academic (Boeing et al., 2024; Kang et al., 2025) and practitioner (He, 2021) accounts. We utilize the full text of Chinese patents to construct four measures that explore this concern.

3.5.1 Measures of Quality

KPST. The first of the four measures is the KPST score, which compares a patent's textual similarity to patents granted in the subsequent years with its similarity to patents granted in preceding years.[13] For the purpose of this paper, we focus on five-year forward and five-year backwards similarities. Patents whose language differs more from prior publications and is more similar to future publications receive higher scores. We compute KPST scores using English translations of Chinese patents obtained through Google Patents, which allows us to avoid the segmentation challenges associated with Chinese-language text processing (Wong et al., 2022). Even with this simplification, the computation remains substantial, involving approximately a quarter quadrillion pairwise patent-text comparisons.

Raw KPST scores can grow mechanically over time with the quantity of patents. To ensure that KPST scores are comparable across patents, we residualize each patent's KPST score with respect to its filing year. Following Kelly et al. (2021), we identify patents in the top decile of the adjusted KPST distribution as "breakthrough" patents.[14]

KPST-XN. The within-country KPST measure characterizes the distribution of patent quality within each country but does not permit direct comparisons between Chinese and U.S.

[13] Formally, for patent p, the KPST score is defined as

$$KPST_p = \frac{\frac{1}{|\mathcal{F}(p)|}\sum_{j\in\mathcal{F}(p)} s_{pj}}{\frac{1}{|\mathcal{B}(p)|}\sum_{j\in\mathcal{B}(p)} s_{pj}},$$

where s_{pj} denotes the textual similarity between patents p and j, $\mathcal{F}(p)$ denotes the set of patents granted after patent p, and $\mathcal{B}(p)$ denotes the set of patents granted before patent p. Intuitively, patents with high KPST scores are textually more similar to future patents than to past patents and therefore capture novel combinations of ideas that later diffuse through the patent corpus. We refer interested readers to Kelly et al. (2021) for a more detailed treatment of this measure.

[14] The limited patent citations in Chinese patents are at least somewhat correlated with KPST scores of importance. This claim is illustrated in Figure A.3, which plots a binned scatterplot of the relationship between five-year KPST scores and time-and-technology-adjusted citations (following the methodology in Lerner and Seru (2021)). The greater monotonicity of the relationship in critical technology patents is apparent.

patents, because scores are normalized relative to each country's own patent corpus. Thus, they only allow us characterize the quality of critical technology patents relative to other domestic ones in that nation.

To address this limitation, we construct a cross-national variant, which we refer to as KPST-XN. Specifically, for each technology-year cell, we pool Chinese and U.S. patents into a common corpus and compute the same forward-to-backward similarity ratio using the pooled distribution, restricting attention to cells containing at least ten patents. To extend coverage through recent years, we use a one-year forward window in the pooled construction while retaining the five-year backward window. Because the absolute level of textual similarity is sensitive to translation noise and institutional differences in patent drafting practices, we focus on changes in the relative position of Chinese patents over time. Concretely, we focus on the share of breakthrough patents that are Chinese or American in each year. A higher number indicates a larger share of Chinese patents among all breakthrough patents in a year.

Disruptive bigrams. Both the KPST and KPST-XN scores evaluate the novelty of each patent publication's language as a whole relative to other patents. An alternative measure traces the diffusion of exact language related to frontier technologies in the patents. To do this, we use the set of disruptive bigrams collected by Kalyani et al. (2025). The authors identify 276 novel technology-related word pairs that first appear in patent text and subsequently diffuse into at least 100 U.S. corporate earnings calls between 2002 and 2019, including phrases like "machine learning," "cloud computing," and "smart phone." We compute, for each country-by-year pair, the share of critical technology patents whose title or abstract contains at least one disruptive bigram. The measure captures the extent to which Chinese patent publications employ commercially salient technological language relative to rates in comparable U.S. awards.

Distance from the scientific frontier. Our fourth measure benchmarks patents against the contemporaneous scientific frontier. For each critical technology and year from 2005 to 2023, we identify the top 1,000 most-cited academic papers in OpenAlex whose primary topic maps to the technology through the ASPI-to-DTIC crosswalk described in Appendix B.1. We embed each paper using SPECTER2, a transformer model trained on scientific text, and define the frontier for a given technology-year cell as the unit-normalized centroid of those embeddings. We then embed patent titles and abstracts using the same model and compute the cosine similarity between each patent and the contemporaneous frontier-year centroid. We calculate each patent's lag from the scientific frontier as the difference between its publication year and the frontier year to which its cosine similarity is the largest. Appendix B.3 provides

a formal treatment.

To ensure that Chinese patents do not appear close to the global frontier merely because Chinese-authored papers increasingly dominate frontier science itself, our baseline specification excludes papers with a Chinese first author from the frontier construction. This adjustment is quantitatively important: by 2023, Chinese first authors account for between 23 and 56 percent of the unfiltered frontier corpus across the 13 technologies with sufficient OpenAlex coverage (Figure A.4).

3.5.2 Quality Trends

Each text-based quality metric that we define in Section 3.5.1 helps us establish a complementary fact about how the quality of Chinese patents has changed over time.

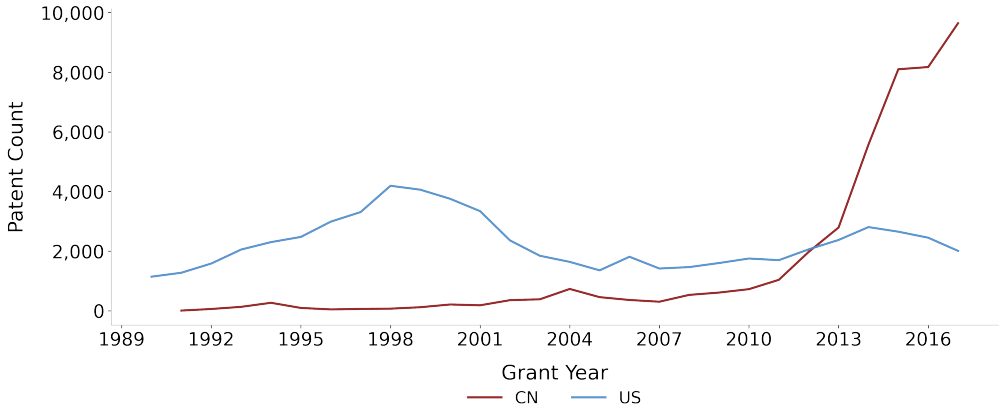
First, we examine whether the surge in Chinese patenting was accompanied by a decline in patent quality. We measure quality using the count of breakthrough patents, defined as patents whose residualized KPST score falls within the top decile of all domestic Chinese patents. Breakthrough patents are thus the subset of the most influential patents within China across all years.

We find that the total number of breakthrough critical technology patent publications in China rose sharply after 2010. Figure 6 shows this pattern for all critical technology patents; Figure A.5 provides a breakdown by technology. Furthermore, the share of Chinese critical technology patents that are breakthrough remained broadly stable since 2005 despite the explosion in patenting activity. These facts together suggest that the increase in patent quantity did not come at the expense of quality. The share of critical technology patents that are breakthrough, however, remains higher within the U.S. than in China over all years.

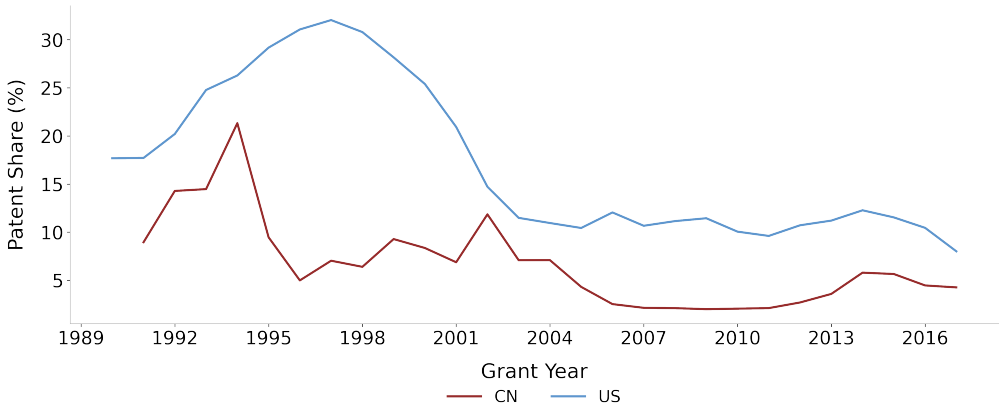
Of the 14 critical technologies, only five show this recent explosion in breakthrough patents in China: Advanced Materials, Integrated Sensing and Cyber, Renewable Energy Generation and Storage, Microelectronics, and Trusted AI and Autonomy. The U.S. continues to dominate—in counts of breakthrough patents—in Advanced Computing and Software, Future Generation Wireless Technology, and Quantum Sciences.

Second, we examine how quality has changed over time given the combined corpus of patents filed in both the U.S. and China. As noted above, the KPST-XN measure extends the methodology of KPST by pooling patents from the U.S. and China within each technology and recomputing the KPST score. Once again, we focus on "breakthrough" patents that fall in the top decile of the adjusted measure. We only compute this score for the nine technologies for which there were enough patents in both the U.S. and China to allow us to compute these

Figure 6: Critical Technology Breakthrough Patents by Year, China vs. U.S.



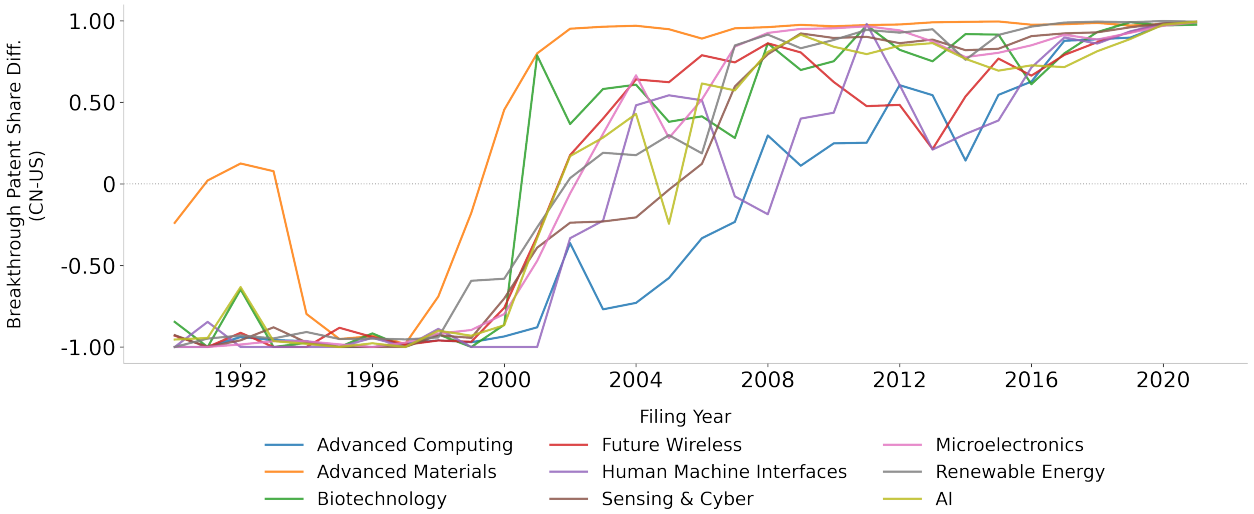
(a) Breakthrough patent counts



(b) Breakthrough patent shares

Notes: This figure reports the annual count and share of breakthrough critical technology patent publications—defined as those in the top decile of within-country adjusted five-year KPST scores—for China (red) and the U.S. (blue). Further details on the construction of this measure are presented in Section 3.5.1.

Figure 7: Cross-National KPST (KPST-XN): Share of Chinese Breakthrough Patents



Notes: Each line reports, within a technology and year, the share of Chinese patent publications classified as breakthrough minus the corresponding share of U.S. patents. Breakthrough patents are identified using the KPST-XN measure, which extends Kelly et al. (2021) by pooling Chinese and U.S. patent publications within each technology into a common corpus so that patents from both countries are evaluated relative to the same textual baseline. We residualize KPST-XN scores using filing-year fixed effects to account for secular changes in patent language and counts over time. A patent is classified as breakthrough if its residualized KPST-XN score exceeds the 90th percentile of the pooled distribution within that technology.

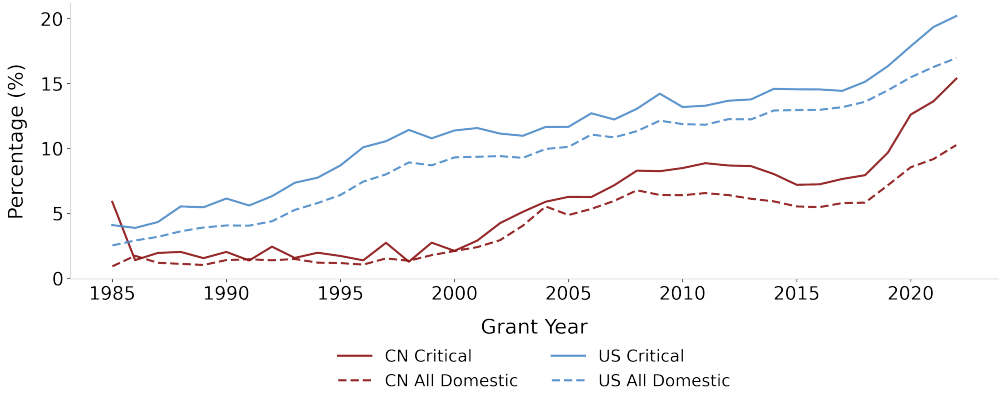
scores.

Figure 7 presents the difference between the share of Chinese patents and the share of American patents within the set of breakthrough patents in each technology. Three facts emerge. Since the early 2000s, the Chinese share has been steadily improving in all nine of the technologies. However, there are large differences in when the Chinese share overtakes the American share; for Advanced Materials, this overtaking happens in the early 2000s. The Chinese advantage in Advanced Computing and Human Machine Interfaces shows up almost a decade later. In AI, Chinese catch-up has happened more recently, after 2016.

Next, we turn to studying the share of patents that have disruptive bigrams from the dictionary provided in Kalyani et al. (2025). We find that that the share of Chinese critical technology patents with at least one such bigram rose from less than 2 percent in early 1990s to 16 percent in 2022. The U.S. critical technology share rose from roughly 4% to roughly 20% over the same period. The Chinese rise accelerates sharply after 2000 and again after 2015, with the cross-country gap narrowing over time.

There is significant heterogeneity in quality across technologies using this measure. As reported in Figure A.6, three patterns emerge. In Advanced Materials, Advanced Computing and Software, Microelectronics, Quantum Sciences, and Integrated Sensing and Cyber, the

Figure 8: Disruptive-Bigram Share of Patent Publications, China vs. U.S.



Notes: The figure reports the share of domestic patent publications containing at least one disruptive technology bigram, as defined by Kalyani et al. (2025). Disruptive bigrams are word pairs that first appear in patent text and subsequently appear in 100 or more U.S. corporate earnings calls between 2002 and 2019. The figure reports the share among all domestic patents and among patents in the 14 critical technologies. China is in red; the U.S. is in blue. The sample covers publication years 1985 to 2022.

Chinese share has caught up to the U.S. share: in Advanced Materials, both countries reach roughly 7% by 2022, with the Chinese line crossing the U.S. line around 2021. In Renewable Energy Generation and Storage, the Chinese share moved above the U.S. share by the mid-2000s. The gap has subsequently widened: by 2022, China is at about 14% against the U.S. at about 8%. In Biotechnology, Future Generation Wireless Technology, Trusted AI and Autonomy, and Human-Machine Interfaces, the U.S. retains a small lead, with the gap narrowing across all four cases since 2015.

The dictionary is built from U.S. patents and U.S. earnings calls and thus may be biased against Chinese patent text: translated Chinese patent text may not employ the same expressions as native U.S. patent text. Despite the bias, the Chinese share has caught up to or exceeded the U.S. share in six of the 14 technologies. The persistent U.S. lead in Biotechnology, Future Wireless, Trusted AI, and Human-Machine Interfaces is consistent with a strong U.S. innovative position in those four technologies.

Our final measure compares patent text to the contemporaneous scientific frontier. We employ two specifications using the frontier-similarity framework. In the *backward-looking* specification, patents are compared to the contemporaneous and earlier scientific frontiers, capturing the extent to which patented inventions engage with the state of scientific knowledge available at the time of patenting. In the *forward-looking* specification, earlier patent cohorts are compared to later scientific frontiers, capturing the extent to which patents anticipate the subsequent evolution of frontier science. Both perspectives yield similar conclusions.

Figure 9 reports the backward-looking specification. For each country and grant year, we

compute the median scientific lag across patents and plot the difference between the Chinese and U.S. medians. More negative values indicate that Chinese patents are closer to the scientific frontier, while a value of zero implies that patents in the two countries are equally distant from the frontier. The x-axis reports patent grant year. Because the frontier itself evolves over time, the absolute level of the measure is less informative than changes in relative positioning across countries.

Several technologies, including Advanced Computing, Biotechnology, AI, Directed Energy, and Hypersonics, show little systematic difference between Chinese and U.S. patents over time. By contrast, in Future Generation Wireless Technology, Advanced Materials, and Integrated Sensing and Cyber, Chinese patents move substantially closer to the frontier relative to U.S. patents. In some technologies, such as Renewable Energy Generation and Storage, the relative position fluctuates considerably across grant years. Figure A.7 reports the analogous forward-looking specification and yields broadly similar findings.

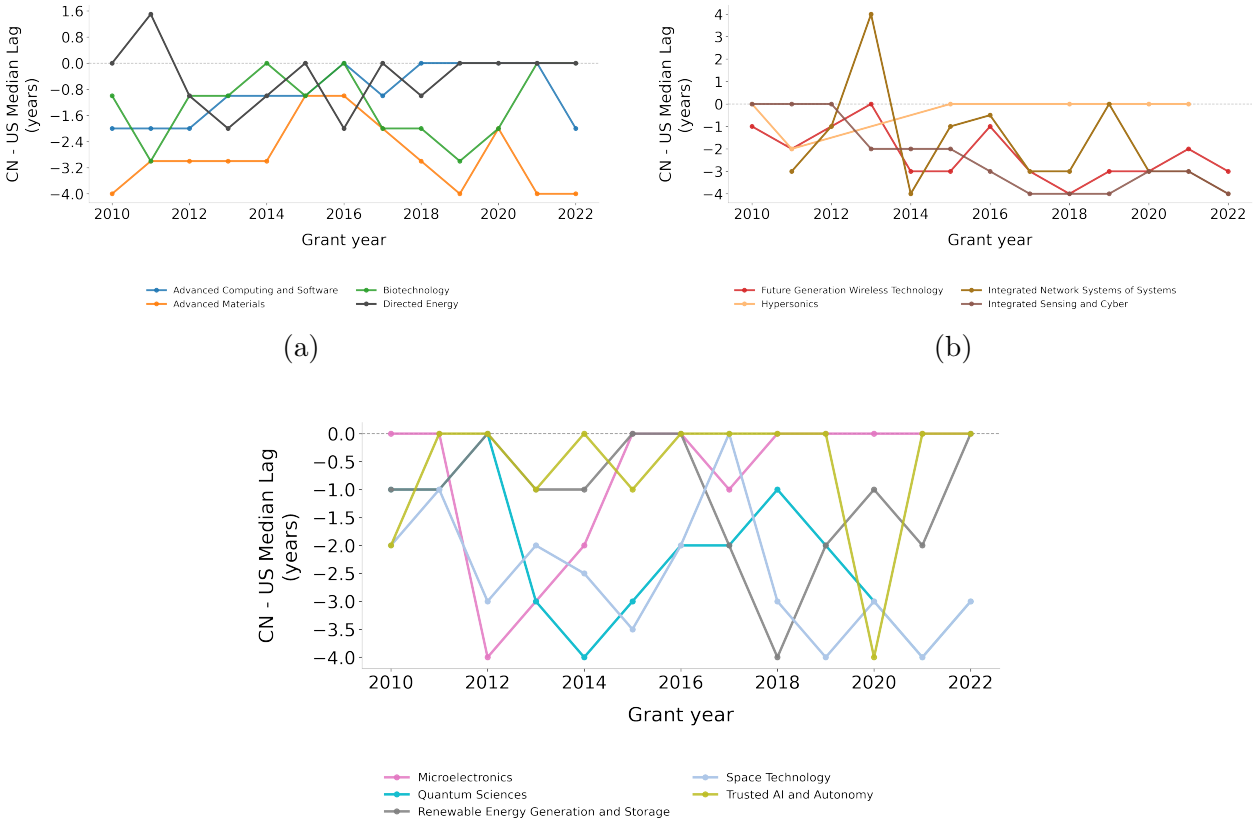
Summary. The four textual measures yield a consistent picture. The rise in Chinese critical technology patenting since 2005 has been accompanied by few changes in textual importance within China's own patent corpus, by relative gains against U.S. patents on directly comparable textual measures, by convergence in commercially salient technological vocabulary, and by increasingly close alignment with the global scientific frontier. The evidence therefore points to broad-based convergence in innovation quality, even if convergence remains uneven across technologies, with striking Chinese progress seen in Advanced Materials, Renewable Energy Generation and Storage, Microelectronics, Advanced Computing and Software, Integrated Sensing and Cyber, and Quantum Sciences.

4 Conclusion

Patents, while an imperfect measure, have long been used to understand innovation in Western nations. In this paper, we use Chinese domestic awards to shed light on the Chinese innovative ecosystem.

We suggest that many preconceptions about Chinese innovation are at odds with what is revealed by the patent data. Chinese critical technology patenting is dominated by private firms and public universities rather than state-owned enterprises, with universities playing a far larger role than in the United States. Also distinct from the United States is the low overall share of large firms. Direct foreign inventor linkages remain limited: fewer than ten percent of Chinese critical technology patents involve inventors with U.S. training or employment, while the U.S. patent system itself exhibits substantially greater reliance on inventors with foreign

Figure 9: Similarity to the Academic Frontier



(a) (b)

(c)

Notes: These figures report the difference in the scientific lag between Chinese and U.S. patents across technologies, with technologies split across panels for readability. For every patent, we compute the cosine similarity between the patent embedding and the vector representation of the scientific frontier in its technology field for each of the five years *preceding* the patent's publication. The patent's scientific lag is defined as the frontier year associated with the highest cosine similarity. For each country and grant year, we compute the median scientific lag across patents and plot the difference between the Chinese and U.S. medians. The scientific frontier is constructed from the top-1,000 most-cited papers within each technology-year cell, excluding papers whose first author is affiliated with a Chinese institution. Patent embeddings are generated from patent titles and abstracts, while frontier-paper embeddings are generated from OpenAlex titles and abstracts mapped into DTIC technology categories using the ASPI-to-DTIC crosswalk. All embeddings are computed using the SPECTER2 model. A negative value means Chinese patents are closer to the frontier than the corresponding US patents granted in the same year. Further details on the construction of this measure are presented in Appendix B.3.

backgrounds than the Chinese system. Finally, the increase in Chinese critical technology patenting has not come at the cost of quality. Chinese patents have converged towards or even exceeded U.S. patents using several textual measures in most critical technologies, despite the massive increase in volume.

The analysis suggests several avenues for further exploration. Foremost among them is the role of Chinese universities in the innovation system, particularly their interactions with industry. While the ties between U.S. and Chinese academics have attracted increasing interest (e.g., Aghion et al. (2023), Qiu et al. (2025), and Nagaraj and Yao (2026)), much more needs to be done to understand how the commercialization of Chinese academic findings works, as well as the tradeoffs associated with these approaches relative to those commonplace in the United States and much of the West.

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Appendices

A Institutional Details

A.1 The Chinese Patent System

The modern Chinese patent law was enacted at the 4th Meeting of the Standing Committee of the Sixth National People's Congress on March 12, 1984 (https://english.cnipa.gov.cn/col/col3068/index.html). The founders of the People's Republic had envisioned a patent system more than three decades earlier, but the earlier system was quickly abandoned due to the perceived incompatibility of patents and socialism (Cheng, 2023).

Article 22 of the Patent Law of China requires that inventions and utility models for which patent rights are to be granted shall be ones that are novel, creative, and of practical use. These tests are roughly akin to the notions of novelty, non-obviousness, and enablement articulated in U.S. patent law (35 U.S.C. §101-103). In particular, the creativity criteria resemble the tests used to determine obviousness in *Graham v. John Deere* (383 U.S. 1, 17–18 (1966)).

Even in light of these changes, it is natural to be concerned that Chinese patents are very different from those granted in other nations. For instance, were the scope of Chinese awards very narrow, as has been documented to characterize historical Japanese patents, the high counts of awards might be illusionary.

To examine this question, we proceed in two ways. The first approach is to look at the claims in all patents (regardless if awarded to domestic or foreign assignees) issued in the two nations. We focus on the number of words in the claims section. Appendix Figure A.11 presents this comparison for all patent publications between 1985 and 2021. We see that the relative length of the claims section in Chinese and U.S. patents have remained consistent, with the Chinese claims sections about 20% shorter than the U.S. ones. There is no evidence of dramatic shifts in claims from this analysis.

The second approach was to interview a number of patent attorneys who has expertise in working with Chinese firms and CNIPA. They highlighted in their conversations several points:

- In its formal structure, the Chinese patent system is modeled after the European patent system, and thus quite similar to the U.S. on many dimensions. In the past decade in particular, the Chinese government has espoused that a well-operating patent system is

strongly linked to technological progress.

- Chinese firms were initially quite unsophisticated about patents, seeking to maximize the amount of awards, reflecting the incentives introduced by innovation tax credits, corporate schemes, or pressures from provincial or local authorities to boost patenting. Firms frequently sought to minimize the costs associated with filing, even if it meant foregoing opportunities to obtain broader patents by redrafting applications. Many of the resulting patents were narrow ones that were relatively easy to invent around.

- Over the course of the second half of the 2010 and early 2020s, Chinese firms have become more sophisticated in understanding the importance of effective claim drafting and patent prosecution. As a result of this growing awareness, firms have placed greater emphasis on obtaining broader claims, often through repeated rounds of interactions with CNIPA while pursuing an award.

- Many of the same differences in patenting across fields seen in the U.S. are apparent in China as well, with biotechnology firms seeking broad protection and information technology firms filing large number of awards that may be more helpful when negotiating standards-based patent pools and cross-licensing.

- As universities have become increasingly involved in technology licensing (both domestically and increasingly internationally in the case of pharmaceuticals), there has been more emphasis on effective patent prosecution.

A.2 Selection into U.S. Filings

As we noted in the introduction, many policy-oriented studies of Chinese inventions have relied on Chinese filings with the USPTO. One question is to what extent this gives a reasonable picture of Chinese activity.

With this question in mind, we analyze which Chinese patent publications had corresponding U.S. filings. (The way in which we identify these cross-filed awards, which we compute as of mid-2024, is described in Lerner et al. (2025).) A striking initial fact is that only 3.5% of the Chinese domestic patents have a corresponding U.S. award. (The share is much higher for many other nations.) This number must be considered in context. First, many Chinese patent publications were abandoned after initial publication, presumably reflecting the incentives of many Chinese inventors. Second, some Chinese patents may still be under examination

and eventually issued by the USPTO.[15] Nonetheless, it is clear that a very small number of Chinese patent publications have corresponding U.S. awards.

Panel A of Appendix Table A.3 shows an analysis of the probability that Chinese patent publications between 1985 and 2023 had corresponding U.S. awards. It highlights that while critical technologies with dual-use applications were more likely to be filed in the U.S., the subset of patents associated with three critical technologies with more military applications – directed energy, hypersonics, and space – were *less* likely to be filed in the U.S.

Appendix Figure A.12 highlights the year and firm type fixed effects from this regression. Panel A shows that while the probability of a U.S. filing increased in the late 1990s, it underwent a precipitous decline around 2010 and has remained depressed since. Panel B shows that while private corporations, venture-backed firms, and non-profit research institutions are more likely to file in the U.S., Seven Sons universities are less likely to do so.[16]

Panel B of Appendix Table A.3 takes another look at these issues, computing the probability of Chinese patents being filed in the U.S. if they were breakthrough patents, again using an OLS specification. Owners of breakthrough patents are significantly less likely to seek patent protection in the U.S. While critical technologies are more likely to be filed in the U.S., technologies in the areas relating most closely to defense were again substantially less likely to be filed in the U.S.

B Data Construction

B.1 Assigning Patents and Articles to Critical Technologies

As discussed in the text, we link U.S. and Chinese patents to the 14 technologies listed as critical by the DoD. Our starting point is the dataset released by the Defense Technical Information Center (https://dtic.dimensions.ai/discover/patent), which catalogs the patents "linked to DoD funding." We scraped all information for the patents linked to each critical technology, including its CPC/IPC codes and related keywords. The related keywords are generated by the DTIC itself and correspond to monograms, bigrams, and trigrams extracted from the title and abstract of each patent. On average, there are 10 keywords per patent. In total, we scraped data for 24,536 patents, corresponding to about 7,498 unique

[15] It should be noted, however, that the USPTO has been criticized for its extremely rapid reviews of Chinese patent applications as a part of the Global IP5 Prosecution Highway program. See, for instance, https://patentlyo.com/patent/2025/01/chinese-patents-through.html and https://www.law360.com/articles/1687432/uspto-s-speed-on-some-china-patents-bears-a-closer-look.

[16] The unreported baseline is the "Other/Unknown" assignee types, which largely consist of individuals. The "Company" group in the chart excludes SOEs and VC-backed firms, since those are broken out separately.

keywords and 170 unique CPC subclasses related to each of the 14 technologies. A sample page is shown in Example 1 below.

We further process this information to create a technology-level dataset, where each technology is associated with all the CPC/IPC subclassses and keywords related to its associated patents. We look at the top CPC subclasses associated with each category, up until 80% of the associated patents have a primary assignment in one of the subclasses.

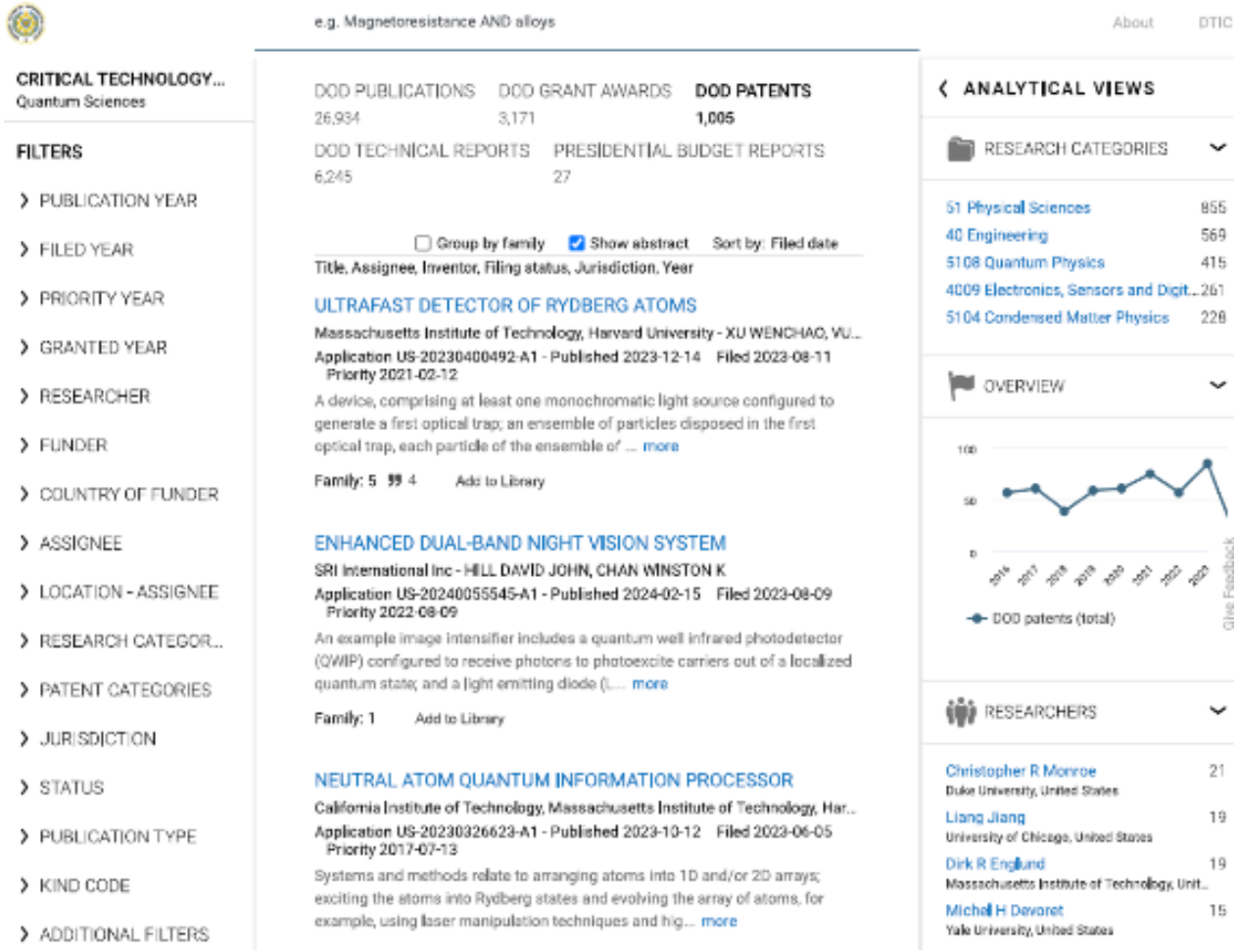
To ensure that we do not spuriously match too many patents to technologies, we only use bigrams uniquely related to a single technology. To do this, we drop all monograms and convert all keywords with more than two words to bigrams. For example, "Deep Neural Network", related to Patent US-20230412472, gets split into the following set of bigrams: [deep neural, deep network, neural network]. We delete bigrams associated with more than one critical technology, so we focus only on unique bigrams. The final dataset has 161,622 bigrams, with 11,544 unique bigrams on average per technology. Using the Chinese and U.S. domestic patents, we associate patents with technologies if they share at least one major CPC/IPC subclass and one unique bigram with the technology.[17]

For the scientific articles, we rely on the classification work done by the Australian Strategic Policy Institute. Their approach, summarized at https://techtracker.aspi.org.au/methodology/, tabulates articles in Web of Science (WoS) that are in the top 10% of citations. Articles with authors from multiple nations are allocated proportionately. The data set excludes bibliographic records deemed not to reflect research advances such as book reviews, retracted publications, and letters submitted to academic journals. Moreover, we use data on articles and citations only from journals listed in WoS's core collection, which has strict editorial selection and evaluation processes that exclude most open access journals. Citation datasets such as the Russian Science Citation and the Chinese Science Citation databases were deliberately excluded due to concerns about strategic citations of peers' papers.

We mapped the APSI critical technology categories to the DTIC ones based on the similarity between the technology descriptions of these technologies. The classification is as follows: (1) Advanced Computing and Software: Advanced data analytics, High-performance

[17]We implemented two alternative ways to determine which patents belonged to critical technologies. First, we collected the list of critical technologies from policy documents released by the U.S. and Chinese governments, such as the "Made in China 2025" plan. We manually read through them and linked them to CPC/IPC classes, and then pulled patents based on their CPC/IPC assignments. Second, we constructed a set of keywords associated with each of the critical technologies pulled from the policy documents and tagged patents based on shared keywords. Neither of these methods was particularly satisfactory; manually assigning CPC/IPC to critical technologies is potentially difficult to replicate and justify without extensive domain-specific knowledge. Furthermore, some CPC/IPC categories were very large, potentially leading to several spurious matches. The assignment is based on policy-based keywords and simpler words relative to the technical jargon in patents, potentially leading to under-matching.

Example 1: Example of a DITC Record



Notes: This exhibit shows an example patent record from the Defense Technical Information Center (DTIC) for Quantum Sciences.

computing, and Mesh and infrastructure computing; (2) Advanced Materials: Additive manufacturing, Advanced composites, Advanced explosives and energetic materials, Advanced magnets and superconductors, Coatings, Nanoscale materials, Novel metamaterials, and Smart materials; (3) Biotechnology: Genetic engineering, Genomic sequencing, Novel antibiotics, Synthetic biotechnology, and Vaccines; (4) Directed Energy: Directed energy; (5) Future Generation Wireless Technology: Advanced radio-frequency communications; (6) Hypersonics: Advanced aircraft engines (including hypersonics) and Hypersonic detection; (7) Integrated Network Systems of Systems: Advanced optical communications and Advanced underwater communications; (8) Integrated Sensing and Cyber: Inertial navigation sensors, Magnetic field sensors, Multispectral and hyperspectral sensors, Photonic sensors, Radar, and Sonar and acoustic sensors; (9) Microelectronics: Advanced integrated circuit design; (10) Quantum Sciences: Post-quantum cryptography, Quantum communications, Quantum computing, and Quantum sensing; (11) Renewable Energy Generation and Storage: Biofuels, Electric batteries, Hydrogen/ammonia, and Photovolatics; (12) Space Technology: Satellite positioning, Small satellites, and Space launch systems; and (13) Trusted AI and Autonomy: Adversarial AI, AI algorithms, Drones, swarming and collaborative, Machine learning, and Natural language processing.

We include below a snapshot of the operational inputs to the two-screen classification procedure for a sample of three technologies. We report for Advanced Materials, Trusted AI and Autonomy, and Biotech, the following inputs: the set of major CPC subclasses, the leading DTIC keywords used to construct the technology-specific bigram dictionary, the resulting count of Chinese and U.S. domestic patents, and five sample patent identifiers from each side. The major CPC subclasses are the smallest set whose patents account for 80 percent of the DTIC-tagged awards in that category; the keyword lists are the most frequent terms extracted from the corresponding DTIC entries, with bigrams shared across multiple technologies removed before screening. Lerner et al. (2025) report the full bigram dictionaries and the per-category match diagnostics.

Advanced Materials	
CPC Codes (51)	H01L, G01N, G02B, A61K, C08G, H10K, H01M, H10N, C23C, G02F, C09D, C01B, C22C, C04B, B22F, H01J, B01J, B29C, C09K, A61L, C08F, G03F, C30B, H01S, C08J, B01D, H05K, B32B, G11C, C12N, H03H, H01F, C07H, H01B, A61B, B81C, G01J, G01R, B23K, C07K, C12Q, C25D, F01D, H01Q, A61F, C07D, H01G, C08L, C08K, C22F, C06B

Advanced Materials *(continued)*	
DTIC Keywords	Substrate, Methods, Fabrication, Method, Nanoparticles, Compositions, Polymer, Carbon nanotubes, Apparatus, Devices, Polymers, Nanostructures, Graphene, Thin film, Piezoelectric, Electrodes, Thin films, Preparation, Materials, Polymerization, ...
CN Patents	1,929,602
CN Sample IDs	`CN115857287B`, `CN111211329A`, `CN108254873B`, `CN109686987B`, `CN114894658A`
US Patents	275,270
US Sample IDs	`7420679`, `7566442`, `5726798`, `10335757`, `4777198`

Trusted AI and Autonomy	
CPC Codes (31)	`G06N`, `G06F`, `G06T`, `B25J`, `B62D`, `A61B`, `B64C`, `G06V`, `G05D`, `G05B`, `G10L`, `F01D`, `G01N`, `G01C`, `F02C`, `B64D`, `G01S`, `A61F`, `H04L`, `F42B`, `H04W`, `H03K`, `G02B`, `G01R`, `H04N`, `B64G`, `G01B`, `B64U`, `H04B`, `G16H`, `A61N`
DTIC Keywords	Control system, Neural network, Method, Machine learning, Apparatus, Methods, System, Systems, Aircraft, Processor, Gas turbine engine, Neural networks, Sensors, Controller, Training, Actuator, Robot, Flight control system, Feature extraction, Autonomous, ...
CN Patents	463,261
CN Sample IDs	`CN105550986B`, `CN113311376A`, `CN101458779A`, `CN113171065A`, `CN102279311A`
US Patents	83,924
US Sample IDs	`11609746`, `6366294`, `11442267`, `8525910`, `10945153`

Biotechnology	
CPC Codes (12)	`A61K`, `A61L`, `C12N`, `C07K`, `C12P`, `A61F`, `A61B`, `G01N`, `A61M`, `C08G`, `F03G`, `C12Q`
DTIC Keywords	Drug delivery, Methods, Compositions, Gene therapy, Biomedical applications, Biocompatible, Tissue engineering, Biodegradable, Biocompatibility, Polynucleotides, Nanoparticles, Kits, Materials, Substrate, Systems, Silk fibroin, Devices, Encapsulation, Scaffolds, Tissue regeneration, ...
CN Patents	25,459

Biotechnology *(continued)*	
CN Sample IDs	CN111925987B, CN115806990A, CN109694883B, CN114053261A, CN110760527B
US Patents	12,763
US Sample IDs	8785600, 9682078, 6410008, 11572590, 10596213

The 14 CTAs cover the following subfields (Fast Track Acition Subcommittee on Critical and Emerging Technologies, 2022):

1. Advanced Computing and Software
    - Supercomputing, Edge computing, Cloud computing, Data storage, Computing architectures, Data processing and analysis techniques
2. Advanced Materials
    - Materials by design and material genomics, Materials with new properties, Materials with substantial improvements to existing properties, Material property characterization and lifecycle assessment
3. Biotechnology
    - Nucleic acid and protein synthesis, Genome and protein engineering including design tools, Multi-omics and other biometrology, bioinformatics, predictive modeling, and analytical tools for functional phenotypes, Engineering of multicellular systems, Engineering of viral and viral delivery systems, Biomanufacturing and bioprocessing technologies
4. Directed Energy
    - Lasers, High-power microwaves, Particle beams
5. Future Generation Wireless Technology
    - Next-generation wireless networks, including 5G and 6G, Optical links and fiber technologies,
6. Human-Machine Interfaces
    - Augmented reality, Virtual reality, Brain-computer interfaces, Human-machine teaming

7. Hypersonics

    - Propulsion, Aerodynamics and control, Materials, Detection, tracking, and characterization, Defense

8. Integrated Network System-of-Systems

    - Radio-frequency (RF) and mixed-signal circuits, antennas, filters, and components, Spectrum management technologies, Terrestrial/undersea cables, Satellite-based communications, Hardware, firmware, and software, Communications and network security, Mesh networks/infrastructure independent communication technologies

9. Integrated Sensing and Cyber (in the 2022 report, "Advanced and Networked Sensing and Signature Management"

    - Payloads, sensors, and instruments, Sensor processing and data fusion, Adaptive optics, Remote sensing of the Earth, Signature management, Nuclear materials detection and characterization, Chemical weapons detection and characterization, Biological weapons detection and characterization, Emerging pathogens detection and characterization, Transportation-sector sensing, Security-sector sensing, Health-sector sensing, Energy-sector sensing, Building-sector sensing, Environmental-sector sensing

10. Microelectronics

    - Design and electronic design automation tools, Manufacturing process technologies and manufacturing equipment, Beyond complementary metal-oxide-semiconductor (CMOS) technology, Heterogeneous integration and advanced packaging, Specialized/tailored hardware components for artificial intelligence, natural and hostile radiation environments, RF and optical components, high-power devices, and other critical applications, Novel materials for advanced microelectronics, Wide-bandgap and ultra-wide-bandgap technologies for power management, distribution, and transmission

11. Quantum Science

    - Quantum computing, Materials, isotopes, and fabrication techniques for quantum devices, Post-quantum cryptography, Quantum sensing, Quantum networking

12. Renewable Energy Generation and Storage

- Renewable generation, Renewable and sustainable fuels, Energy storage, Electric and hybrid engines, Batteries, Grid integration technologies, Energy-efficiency technologies

13. Space Technology

    - On-orbit servicing, assembly, and manufacturing, Commoditized satellite buses, Low-cost launch vehicles, Sensors for local and wide-field imaging, Space propulsion, Resilient positioning, navigation, and timing (PNT), Cryogenic fluid management, Entry, descent, and landing

14. Trusted AI and Autonomy

    - Machine learning, Deep learning, Reinforcement learning, Sensory perception and recognition, Next-generation AI, Planning, reasoning, and decision making, Safe and/or secure AI

B.2 Assigning a Primary Patent Class to Chinese Patents

The USPTO clearly delineates a primary technology class for each patent. These originally used the U.S. Patent Classification scheme, which was a highly idiosyncratic and non-nested scheme. The bulk of the world's patent offices, including CNIPA, used the World Intellectual Property Organization's International Patent Classification scheme, which had about 600 subclasses (e.g., A61K or G06F).

Between 2011 and 2015, the USPTO transitioned to the Combined Patent Classification scheme, jointly developed by the EPO and the USPTO. The scheme mirrors exactly the IPC at the patent subclass level (apart from class Y02). Much of the recent research using U.S. patents has employed the primary CPC classification (which PatentsView has backfilled for earlier patents).

In Chinese patents, one or more patent classes (using the IPC scheme) are indicated at the top of the patent, with the first one often indicated in bold. In some cases, multiple IPC classes are indicated in bold. There is no documentation that we are aware of that suggests the CNIPA makes a designation akin to the USPTO's primary class.

In all our Chinese patent datasets (EPO, CNIPA, and Google), we observe multiple IPC codes for each patent without any primary code being tagged. To be consistent in assigning a primary IPC code to each patent, we take the modal four-digit IPC class as the primary class. When there are multiple modal classes, we choose one at random.

B.3 Distance to the Frontier

We are interested in measuring how far American and Chinese patents are from the global scientific frontier. We define the frontier as the set of top-cited scientific publications within field-year cells and embed both patents and scientific publications in a shared semantic space. Distance to the frontier is then measured by the proximity of each patent to frontier publications, allowing us to map each invention to the frontier year it most closely resembles. This yields a transparent measure of "science lag," defined as the gap between the patent's grant year and the frontier year it is closest to. Unlike prior work, which relies on productivity or citation networks, our approach captures the content-based alignment between technological innovation and the evolving scientific frontier.

Formally, define the scientific frontier $\mathcal{F}_{k,t}$ as the set of scientific publications in field k and year t that lie in the top 10% of the forward citation distribution within (k, t) cells. This definition yields a time-varying frontier reflecting the most influential contemporaneous scientific advances in a field.

Each frontier paper $f \in \mathcal{F}_{k,t}$ is embedded in a semantic space using the text of its title and abstract. Let e_f denote the resulting embedding.

We construct a field-year frontier embedding by averaging the embeddings of frontier papers:

$$E_{k,t} = \frac{1}{|\mathcal{F}_{k,t}|} \sum_{f \in \mathcal{F}_{k,t}} e_f. \tag{1}$$

This embedding summarizes the semantic content of the scientific frontier in field k at time t.

Each patent p is similarly embedded using its title and abstract. Let e_p denote the embedding of patent p, and let t_p denote its grant year.

We define the similarity between patent p and the frontier in year t as:

$$S(p,t) = \cos(e_p, E_{k,t}). \tag{2}$$

We map each patent to the frontier year that it most closely resembles using the peak similarity measure. The peak alignment year is:

$$t^*(p) = \arg\max_t S(p,t), \tag{3}$$

We define the distance to the scientific frontier, or *science lag*, as:

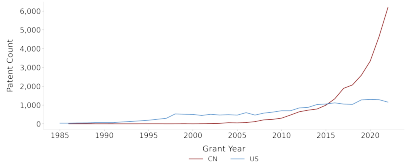
$$\text{ScienceLag}_p = t_p - t^*(p) \tag{4}$$

This measure captures how closely the semantic content of a patent aligns with the evolving scientific frontier over time.

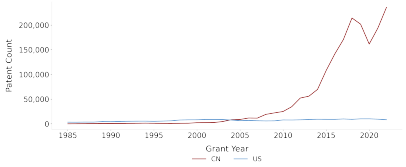
This methodology bridges expands the usual approach of measuring the distance between patents and the scientific frontier that uses patent's in-text citations to academic articles (Lerner and Seru, 2021). In the spirit of Hoberg and Phillips (2016) and related papers, we map the semantic space of scientific fields and measure similarity between patents and science.

A Supplementary Figures and Tables

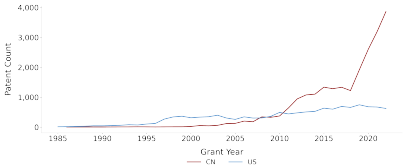
Figure A.1: Chinese and U.S. Domestic Patent Publications in Critical Technologies, by Technology



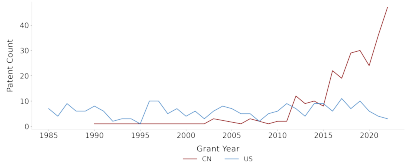
(a) Advanced Computing and Software



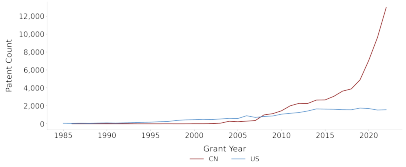
(b) Advanced Materials



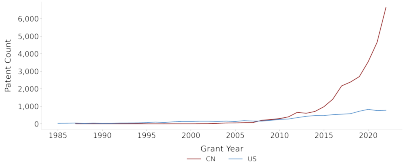
(c) Biotechnology



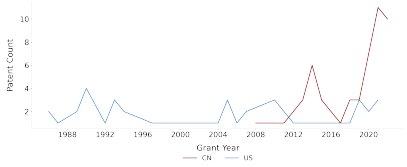
(d) Directed Energy



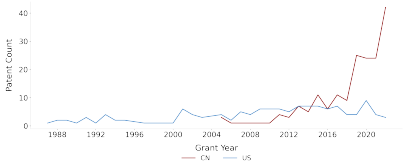
(e) Future Generation Wireless Technology



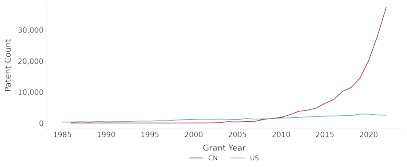
(f) Human Machine Interfaces



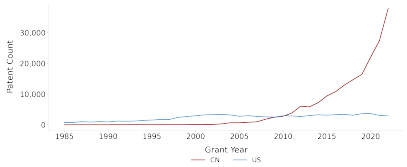
(g) Hypersonics



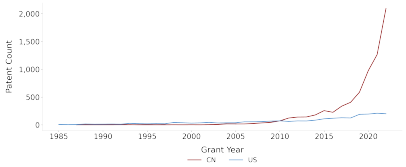
(h) Integrated Network Systems of Systems



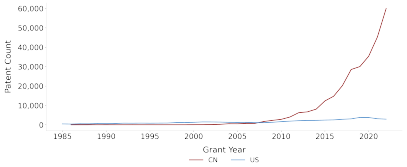
(i) Integrated Sensing and Cyber



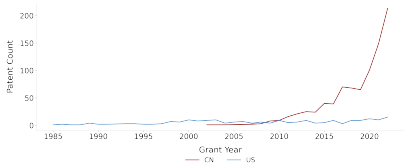
(j) Microelectronics



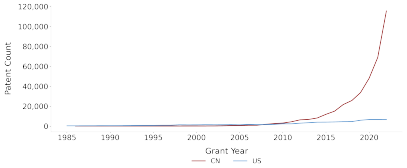
(k) Quantum Sciences



(l) Renewable Energy Generation and Storage



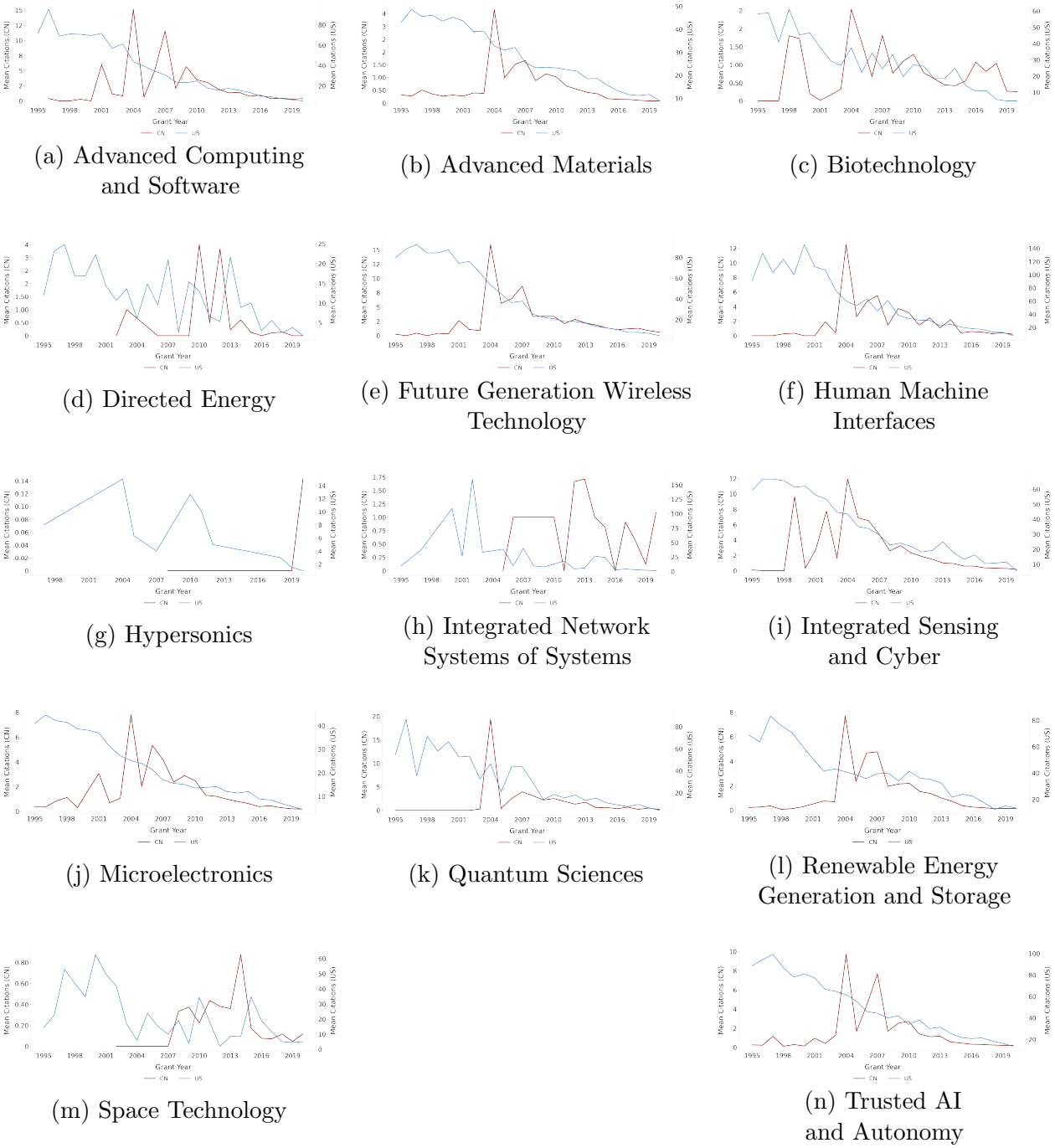
(m) Space Technology



(n) Trusted AI and Autonomy

Notes: Each panel presents the annual count of domestic patent publications in one of the 14 critical technologies, for China and the U.S. The Chinese sample consists of invention patent publications from CNIPA; the U.S. sample consists of utility patents from the USPTO. Both samples are restricted to domestic assignees. The same DTIC-based classification is applied to both countries. The sample covers grant years 1985 to 2023. The vertical-axis scale differs across panels.

Figure A.2: Forward Citations per Patent, China vs. U.S., by Critical Technology



(a) Advanced Computing and Software

(b) Advanced Materials

(c) Biotechnology

(d) Directed Energy

(e) Future Generation Wireless Technology

(f) Human Machine Interfaces

(g) Hypersonics

(h) Integrated Network Systems of Systems

(i) Integrated Sensing and Cyber

(j) Microelectronics

(k) Quantum Sciences

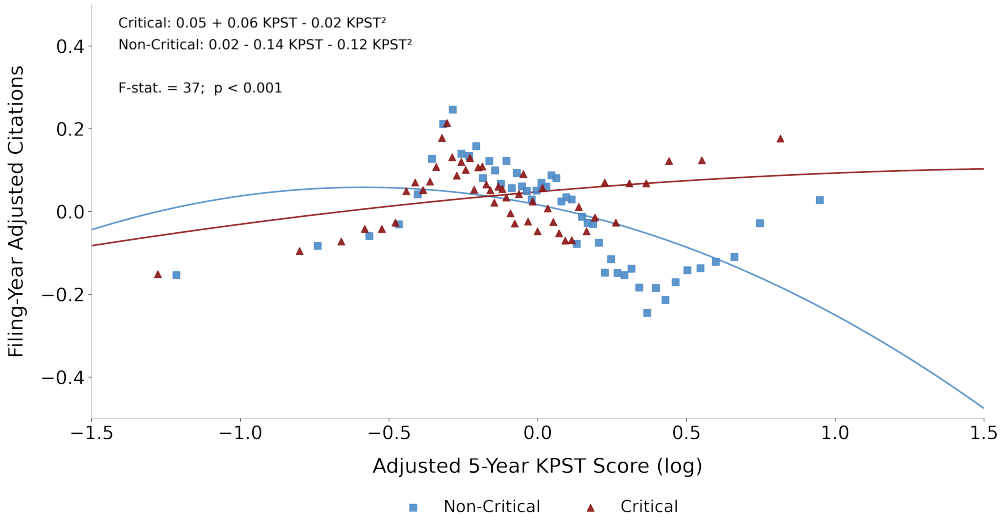
(l) Renewable Energy Generation and Storage

(m) Space Technology

(n) Trusted AI and Autonomy

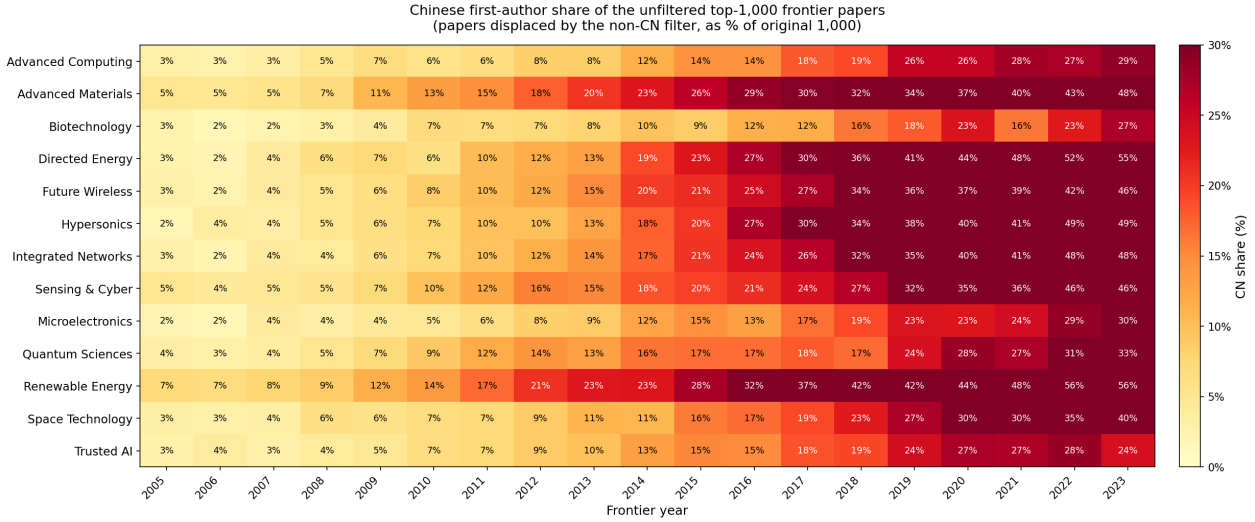
Notes: Each panel reports mean forward citations per domestic patent, separately for China (red) and the U.S. (blue), in one of the 14 critical technologies. Citations are tabulated as of September 2023. The sample covers grant years 1985 to 2017, the truncation reflecting the need for several years of subsequent data to allow forward citations to accrue.

Figure A.3: Correlation Between KPST Scores and Citation Counts for Chinese Patents



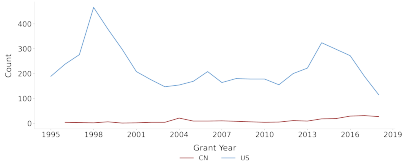
Notes: This figure presents a binned scatterplot (with 50 bins) of five-year KPST scores and time-and-technology adjusted citations for Chinese domestic patent publications. The relationships for critical technology and other patent publications are presented separately. We also present an estimated relationship for the two series (using a quadratic regression specification), as well as test statistics from a comparison of the two estimations.

Figure A.4: Chinese First-Author Share of the Unfiltered Top-1,000 Frontier Papers, by Technology and Year

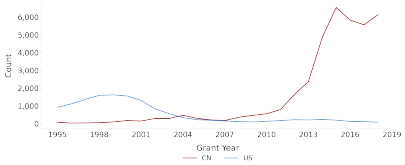


Notes: Heatmap of the share of the unfiltered top-1,000 most-cited papers in each (technology, year) cell whose first author is affiliated with a Chinese institution. Cells with darker shading have a higher Chinese-first-author share. By 2023, Chinese first authors account for between 23 and 56 percent of the unfiltered frontier academic corpus across the 13 graphed critical technologies, with the highest shares in Renewable Energy Generation and Storage (56%), Networks (47%), Sensing & Cyber (46%), Advanced Materials (41%), and Directed Energy (41%). The frontier-similarity figures in the main text and in appendix use a frontier from which Chinese first-author papers have been removed, so that the comparison reveals how Chinese and U.S. patents track non-Chinese science.

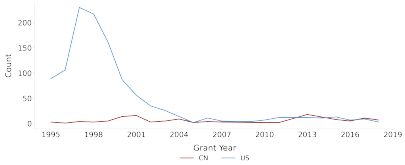
Figure A.5: Count of Breakthrough Patents (KPST), China vs. U.S., by Critical Technology



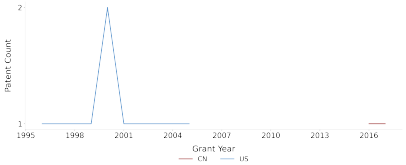
(a) Advanced Computing and Software



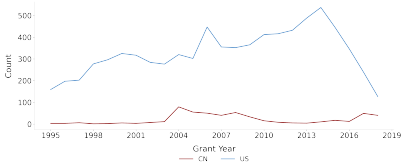
(b) Advanced Materials



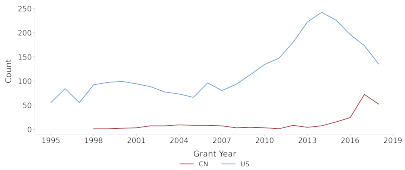
(c) Biotechnology



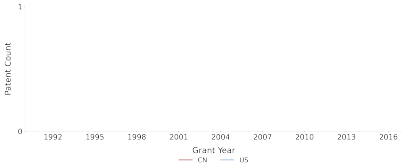
(d) Directed Energy



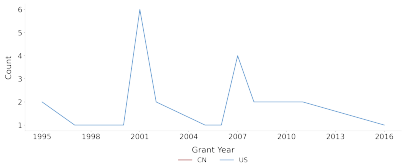
(e) Future Generation Wireless Technology



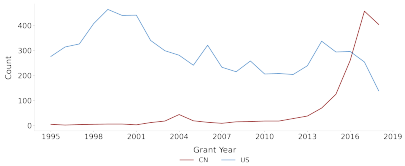
(f) Human Machine Interfaces



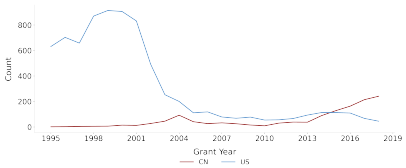
(g) Hypersonics



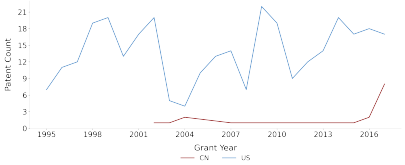
(h) Integrated Network Systems of Systems



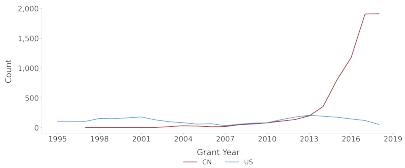
(i) Integrated Sensing and Cyber



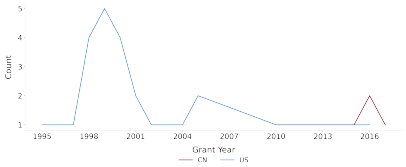
(j) Microelectronics



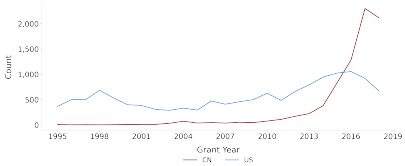
(k) Quantum Sciences



(l) Renewable Energy Generation and Storage



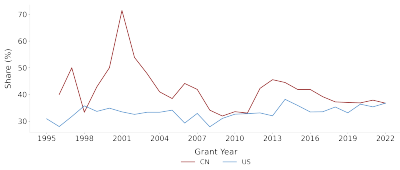
(m) Space Technology



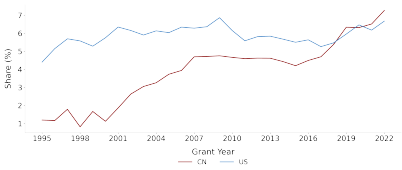
(n) Trusted AI and Autonomy

Notes: Each panel reports the count of patents in the top decile of the filing-year-adjusted within-country KPST five-year importance score, separately for China and the U.S., in one of the 14 critical technologies. The KPST five-year score (Kelly et al., 2021) measures how similar a patent's text is to those issued in the subsequent five years relative to those in the prior five years; the score requires five years of subsequent data, so the series ends at the 2018 grant year. The sample covers grant years 1985 to 2018.

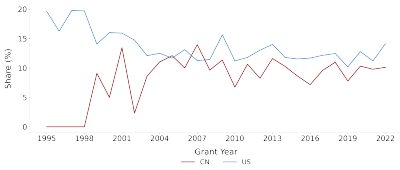
Figure A.6: Disruptive-Bigram Share of Patent Publications, China vs. U.S., by Critical Technology



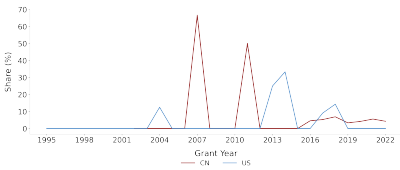
(a) Advanced Computing and Software



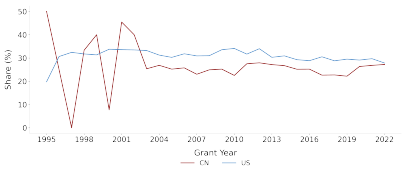
(b) Advanced Materials



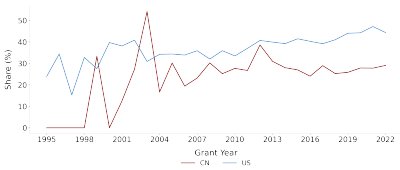
(c) Biotechnology



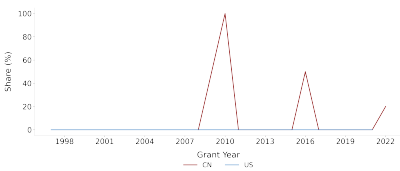
(d) Directed Energy



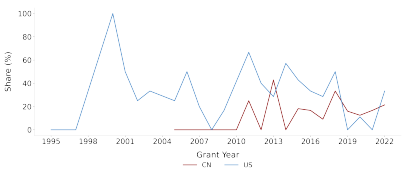
(e) Future Generation Wireless Technology



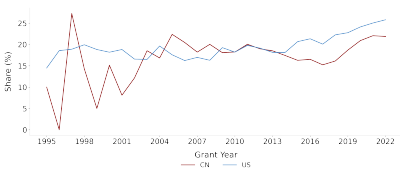
(f) Human Machine Interfaces



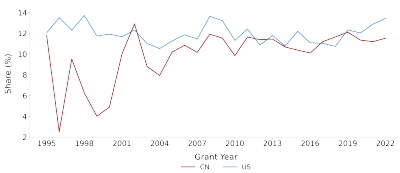
(g) Hypersonics



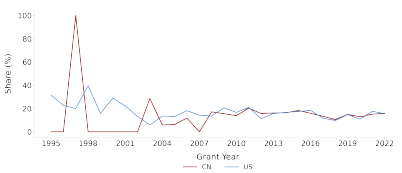
(h) Integrated Network Systems of Systems



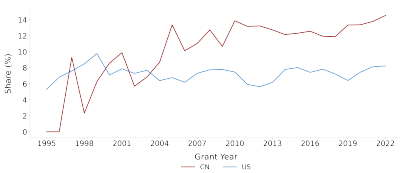
(i) Integrated Sensing and Cyber



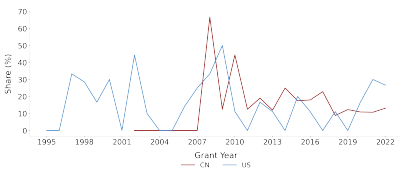
(j) Microelectronics



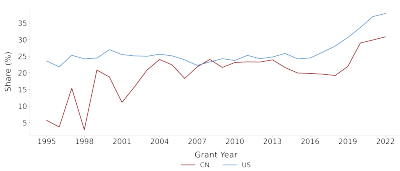
(k) Quantum Sciences



(l) Renewable Energy Generation and Storage



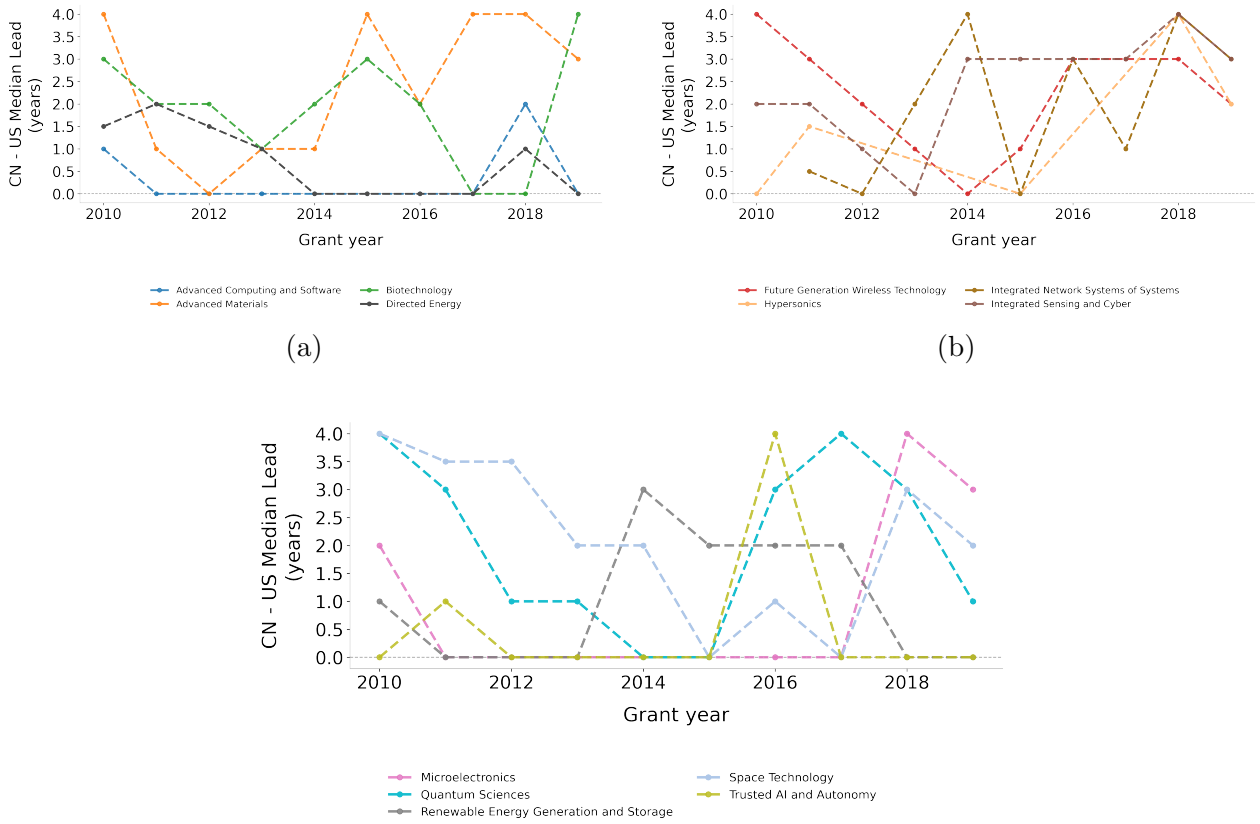
(m) Space Technology



(n) Trusted AI and Autonomy

Notes: Each panel reports the share of domestic patent publications containing at least one disruptive technology bigram, separately for China (red) and the U.S. (blue), in one of the 14 critical technologies. Disruptive bigrams are defined as in Kalyani et al. (2025). The sample covers publication years 1985 to 2023.

Figure A.7: Similarity to the Academic Frontier–Forward



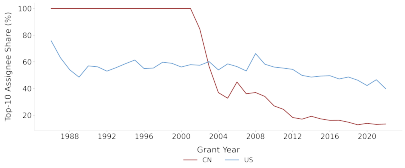
(a)

(b)

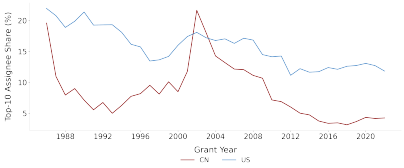
(c)

Notes: These figures report the difference in scientific lag between Chinese and U.S. patents across technologies, with technologies split across panels for readability. For every patent, we compute the cosine similarity between the patent embedding and the vector representation of the scientific frontier in its technology field for each of the five years *following* the patent's publication. The patent's scientific lag is defined as the frontier year associated with the highest cosine similarity. For each country and grant year, we compute the median scientific lag across patents and plot the difference between the Chinese and U.S. medians. The scientific frontier is constructed from the top-1,000 most-cited papers within each technology-year cell, excluding papers whose first author is affiliated with a Chinese institution. Patent embeddings are generated from patent titles and abstracts, while frontier-paper embeddings are generated from OpenAlex titles and abstracts mapped into DTIC technology categories using the ASPI-to-DTIC crosswalk. All embeddings are computed using the SPECTER2 model. A negative value means Chinese patents are closer to the frontier than the corresponding US patents granted in the same year.

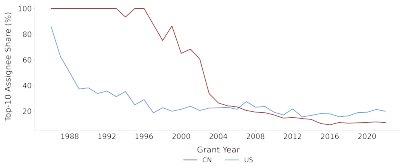
Figure A.8: Top-10 Assignee Share of Domestic Critical-Technology Patenting, China vs. U.S., by Critical Technology



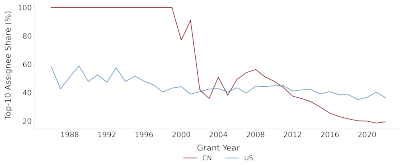
(a) Advanced Computing and Software



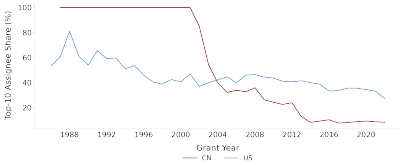
(b) Advanced Materials



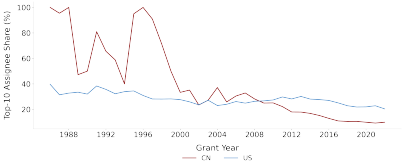
(c) Biotechnology



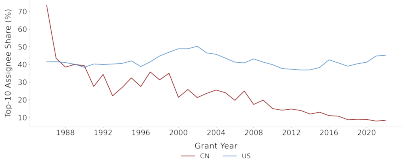
(d) Future Generation Wireless Technology



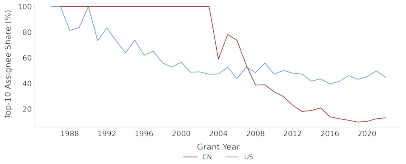
(e) Human Machine Interfaces



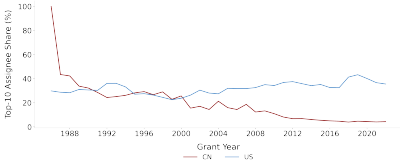
(f) Integrated Sensing and Cyber



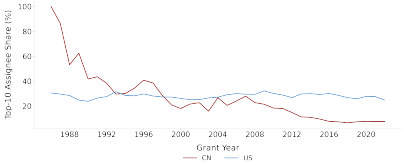
(g) Microelectronics



(h) Quantum Sciences



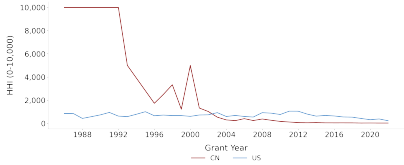
(i) Renewable Energy Generation and Storage



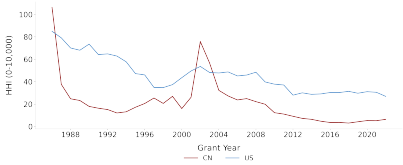
(j) Trusted AI and Autonomy

Notes: Each panel reports the annual share of domestic patent grants accounted for by the ten largest assignees within a critical technology, separately for China and the U.S. The Chinese sample consists of invention patent publications from CNIPA; the U.S. sample consists of utility patents from the USPTO. Both samples are restricted to domestic assignees. The sample covers grant years 1985 to 2023. We omit technologies for which we do not have enough data to compute top-10 assignee shares.

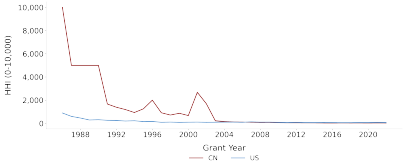
Figure A.9: Assignee Herfindahl-Hirschman Index in Domestic Critical-Technology Patenting, China vs. U.S., by Critical Technology



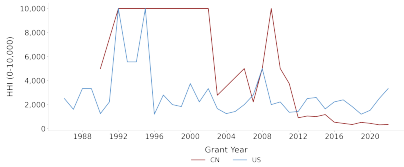
(a) Advanced Computing and Software



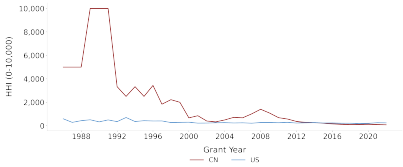
(b) Advanced Materials



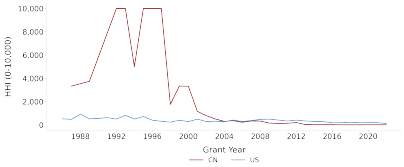
(c) Biotechnology



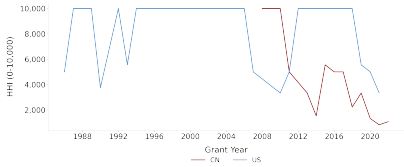
(d) Directed Energy



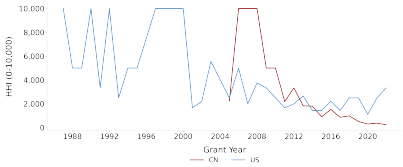
(e) Future Generation Wireless Technology



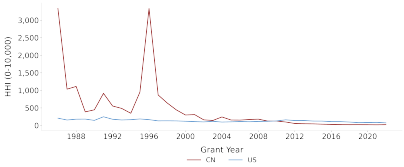
(f) Human Machine Interfaces



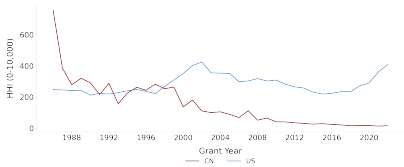
(g) Hypersonics



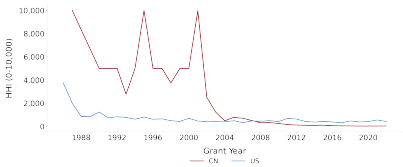
(h) Integrated Network Systems of Systems



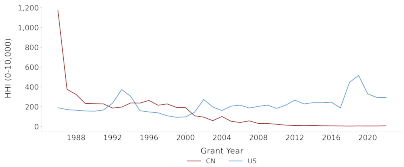
(i) Integrated Sensing and Cyber



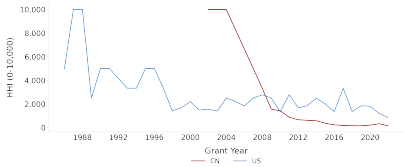
(j) Microelectronics



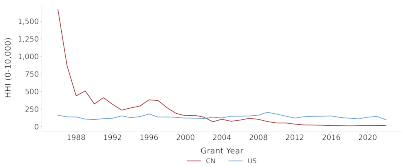
(k) Quantum Sciences



(l) Renewable Energy Generation and Storage



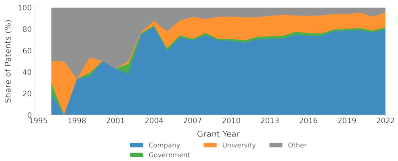
(m) Space Technology



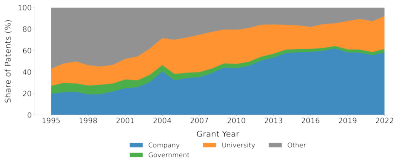
(n) Trusted AI and Autonomy

Notes: Each panel reports the annual Herfindahl-Hirschman Index (HHI) of assignee concentration within a critical technology, separately for China and the U.S. The HHI is computed across assignees of domestic patents granted in each year within that technology. The Chinese sample consists of invention patent publications from CNIPA; the U.S. sample consists of utility patents from the USPTO. Both samples are restricted to domestic assignees. The sample covers grant years 1985 to 2023.

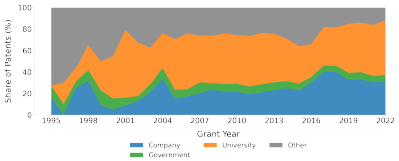
Figure A.10: Organization Shares in Chinese Critical-Technology Patenting, by Critical Technology



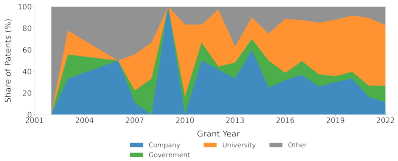
(a) Advanced Computing and Software



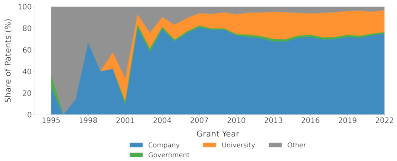
(b) Advanced Materials



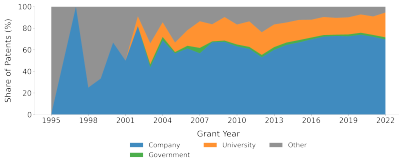
(c) Biotechnology



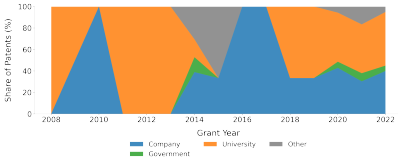
(d) Directed Energy



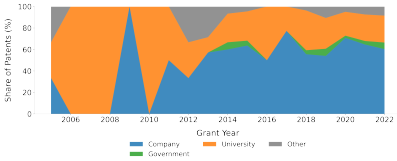
(e) Future Generation Wireless Technology



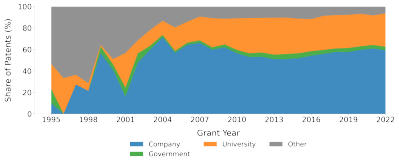
(f) Human Machine Interfaces



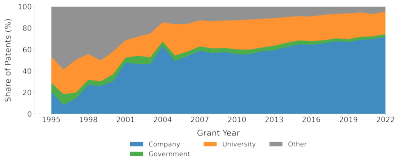
(g) Hypersonics



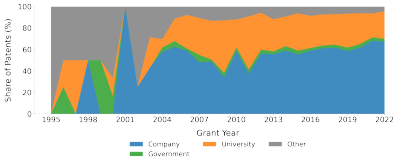
(h) Integrated Network Systems of Systems



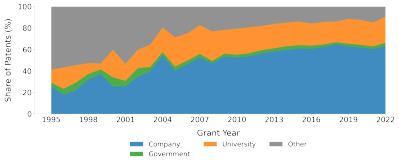
(i) Integrated Sensing and Cyber



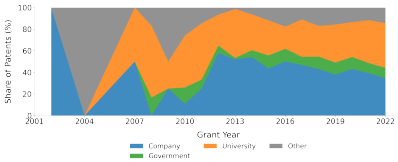
(j) Microelectronics



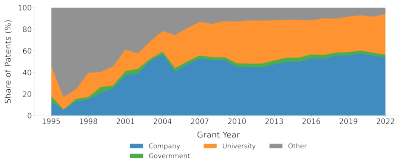
(k) Quantum Sciences



(l) Renewable Energy Generation and Storage



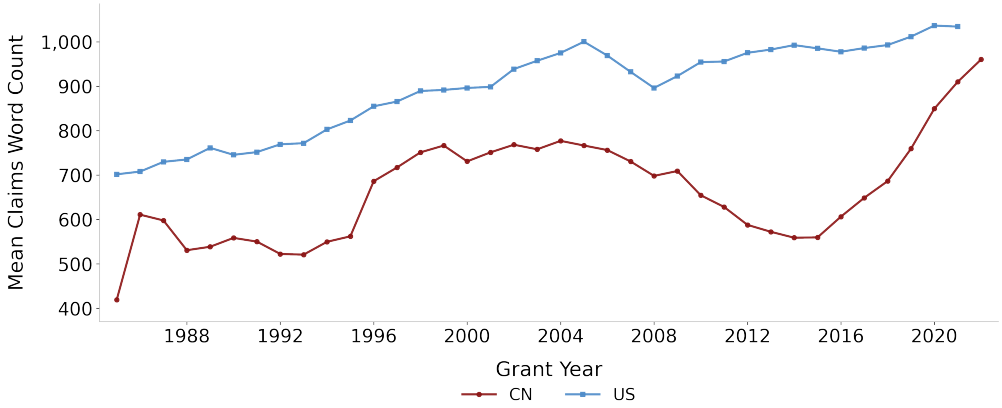
(m) Space Technology



(n) Trusted AI and Autonomy

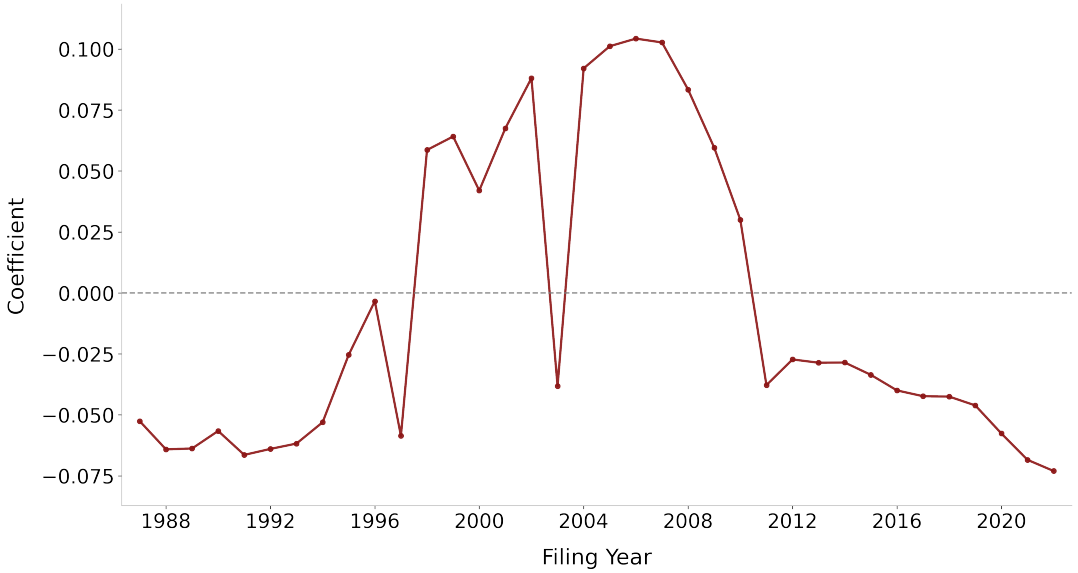
Notes: Each panel reports the annual percentage composition of domestic Chinese invention patent publications in one of the 14 critical technologies by assignee type and grant year. Each vertical slice within a panel sums to 100 percent. Assignee classifications follow the same definitions used elsewhere in the paper. The sample covers grant years 1985 to 2022.

Figure A.11: Mean Claims Word Count by Year, China and U.S.

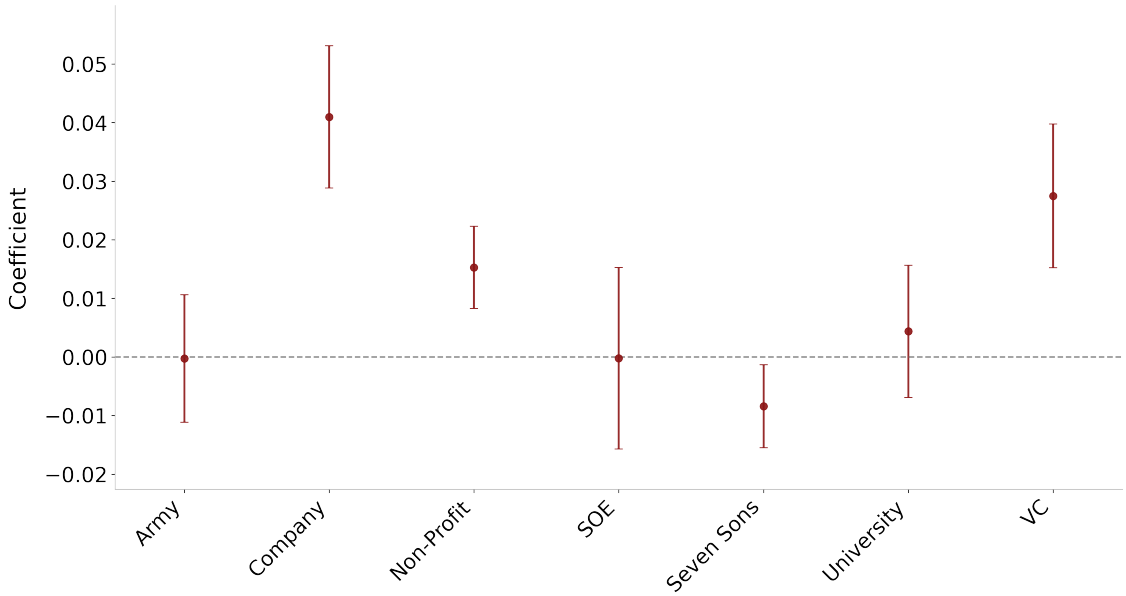


Notes: This figure presents the mean number of words in the claims section in all Chinese and U.S. patent publications in the sample (in each case, both those assigned to domestic and foreign entities), by year of publication.

Figure A.12: Likelihood of Chinese Patent Publications Being Filed in the U.S.



(a) Likelihood of Chinese Patent Publications Being Filed in the U.S., by Publication Year



(b) Likelihood of Chinese Patent Publications Being Filed in the U.S., by Assignee Type

Notes: This figure shows the year and assignee sector fixed effects from the regression reported in Panel A of Table A.3.

Table A.1: Critical Patent Publications by Assignee Characteristics (China and U.S.)

Panel A: Top 10 Chinese Assignees of Critical Chinese Patent Publications		
Assignee Name	**Count**	**Percentage**
Huawei Technology	19,477	0.65%
Zhejiang University	18,645	0.62%
South China University of Technology	13,727	0.46%
Tsinghua University	13,335	0.45%
Tianjin University	12,794	0.43%
University of Electronic Sci & Tech of China	11,896	0.40%
Southeast University	11,600	0.39%
Harbin Institute of Technology	11,300	0.38%
Boe Tech Group	10,044	0.34%
ZTE	8,866	0.30%
Panel B: Assignee Sector — China Domestic Critical Patent Publications		
Assignee Sector	**Count**	**Percentage**
Company	1,746,025	58.39%
CN VC-Backed	109,976	3.68%
US VC-Backed	5,904	0.20%
State-Owned Enterprise	49,975	1.67%
Other	1,580,170	52.85%
Government	88,955	2.98%
Army	1,402	0.05%
Other	87,553	2.93%
Hospital	13,015	0.44%
Individual	243,612	8.15%
Non-Profit	88,955	2.98%
University	793,345	26.53%
Seven-Sons	57,620	1.93%
Other	735,725	24.61%
Unknown	16,134	0.54%
Panel C: Top 10 U.S. Assignees of Critical U.S. Patent Publications		
Assignee Name	**Count**	**Percentage**
IBM	29,386	4.97%
General Electric	13,352	2.26%

Micron Technology	12,480	2.11%
Intel	10,735	1.82%
Texas Instruments	7,575	1.28%
Qualcomm	6,708	1.13%
Apple	4,869	0.82%
United Technologies	4,668	0.79%
Google	4,488	0.76%
Boeing	4,276	0.72%

Panel D: Assignee Sector — U.S. Domestic Critical Patent Publications

Assignee Sector	**Count**	**Percentage**
Corporate	534,973	90.12%
Public University	23,685	3.99%
Private University	14,927	2.51%
Hospital	2,719	0.46%
Research Institution	1,624	0.27%
Individual	2,278	0.38%
Government	9,144	1.54%
Other	4,240	0.71%

Notes: This table summarizes patent publications in critical technology fields at the assignee level, separately for Chinese and U.S. domestic patents. Panel A reports the top ten assignees in China based on the total number of critical technology patent publications. Panel B decomposes Chinese domestic critical patent publications by assignee sector. Panel C presents the top ten U.S. patent assignees in critical technologies. Panel D shows the sectoral distribution of U.S. domestic critical patent publications. In this tabulation, we use each domestic assignee-by-critical patent publication pair as an observation, and calculate the patent counts and shares accordingly.

Table A.2: Assignee Characteristics of All Patent Publications (China and U.S.)

Panel A: Top 10 Chinese Patent Publication Assignees		
Assignee Name	**Count**	**Percentage**
Huawei Technology	97,869	0.71%
ZTE	55,066	0.40%
Zhejiang University	49,895	0.36%
State Grid Corp of China	38,188	0.28%
Tencent Technology	38,074	0.28%
Tsinghua University	37,167	0.27%
Southeast University	32,577	0.24%
Tianjin University	31,869	0.23%
South China University of Technology	31,239	0.23%
Harbin Institute of Technology	29,369	0.21%
Panel B: Assignee Sector — China Domestic Patent Publications		
Assignee Sector	**Count**	**Percentage**
Company	8,697,794	63.28%
CN VC-Backed	476,046	3.46%
US VC-Backed	30,960	0.23%
State-Owned Enterprise	272,212	1.98%
Other	7,918,575	57.61%
Government	311,083	2.26%
Army	4,604	0.03%
Other	306,480	2.23%
Hospital	58,343	0.42%
Individual	1,895,244	13.79%
Non-Profit	311,083	2.26%
University	2,368,214	17.23%
Seven-Sons	149,176	1.09%
Other	2,219,038	16.14%
Unknown	102,889	0.75%
Panel C: Top 10 U.S. Patent Publication Assignees		
Assignee Name	**Count**	**Percentage**
IBM	153,233	4.70%
Intel	48,144	1.48%

General Electric	42,585	1.31%
Micron Technology	34,317	1.05%
Qualcomm	33,404	1.03%
Apple	27,109	0.83%
Microsoft	26,216	0.80%
Texas Instruments	25,847	0.79%
HP	25,522	0.78%
Google	25,135	0.77%

Panel D: Assignee Sector — U.S. Domestic Patent Publications

Assignee Sector	**Count**	**Percentage**
Corporate	3,055,632	93.01%
Public University	80,115	2.44%
Private University	48,308	1.47%
Hospital	9,597	0.29%
Research Institution	5,279	0.16%
Individual	28,532	0.87%
Government	36,746	1.12%
Other	20,914	0.64%

Notes: This table summarizes assignees of Chinese and U.S. domestic patent publications. Panel A reports the top ten patent publication assignees in China by total count. Panel B decomposes Chinese domestic patent publications by assignee sector. Panel C lists the top ten U.S. patent publication assignees (through May 2022). Panel D provides the corresponding sectoral breakdown for U.S. domestic patent publications. In this tabulation, we use each domestic assignee-by-patent publication pair as an observation, and calculate the patent counts and shares accordingly.

Table A.3: Likelihood of Chinese Patent Publications Being Filed in the U.S.

Panel A: Critical technology categories

	𝟙[Patent is Cross-filed in the US]
𝟙[Critical – military]	−0.004
	(0.005)
𝟙[Critical – dual use]	0.002***
	(0.000)
Filing Year FEs	Yes
Primary CPC FEs	Yes
Assignee Sector FEs	Yes
R^2	0.049
Data Sample	CN-Assigned Only
Data Period	1985–2023
Observations	13,687,357

Panel B: Critical technology interacted with breakthrough status

	𝟙[Patent is Cross-filed in the US]		
	(1)	(2)	(3)
𝟙[Breakthrough Patent]	−0.026***	−0.027***	−0.027***
	(0.000)	(0.000)	(0.000)
𝟙[Critical Patent]		0.001**	
		(0.000)	
𝟙[Critical – military]			−0.019**
			(0.009)
𝟙[Critical – dual use]			0.001**
			(0.000)
𝟙[Breakthrough Critical Patent]		0.007***	
		(0.001)	
𝟙[Breakthrough Critical – military]			0.096
			(0.062)
𝟙[Breakthrough Critical – dual use]			0.007***
			(0.001)
Filing Year FEs	Yes	Yes	Yes
Primary CPC FEs	Yes	Yes	Yes
Assignee Sector FEs	Yes	Yes	Yes
R^2	0.054	0.054	0.054
Data Sample	CN-Assigned Only	CN-Assigned Only	CN-Assigned Only
Data Period	1991–2017	1991–2017	1991–2017
Observations	6,506,699	6,506,699	6,506,699

Notes: The two panels show the results of ordinary least squares regressions. The dependent variable is *Patent is Cross-filed in the US*, an indicator that is one if a patent publication is cross-filed in the U.S. The independent variables are *Breakthrough Patent*, an indicator that is one if a patent publication has a filing-year-adjusted five-year KPST score greater than or equal to the 90th percentile filing-year-adjusted five-year KPST score among all patents; *Critical Patent*, an indicator that is one if a patent publication belongs to any of the 14 critical technologies defined in the text of the paper; *Critical - military*, an indicator that is one if a patent publication belongs to any of the three most militarily-oriented critical technologies (Directed Energy, Hypersonics, and Space); *Critical - dual use*, an indicator that is one if a patent publication belongs the 11 other critical technologies; *Breakthrough Critical Patent*, *Breakthrough Critical - military*, and *Breakthrough Critical - dual use* are indicators that are one if a critical, critical-military, or critical-dual-use patent publication is also a breakthrough one, respectively. The sample consists of all domestic Chinese patent publications. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$