China's Low-Productivity Innovation Drive: Evidence from Patents

Forthcoming *Comparative Political Studies*

Date: 22 September 2023

Yuen Yuen Ang, Johns Hopkins University

Nan Jia, USC Marshall School of Business

Yang Bo, USC Marshall School of Business

Kenneth Huang, National University of Singapore

Can China catch up with the United States technologically by mobilizing its bureaucracy and assigning ambitious targets to local governments? We analyze an original dataset of 4.6 million patents filed in China from 1990 through 2014 and paired this with a new, rigorous measure of patent novelty that approximates the quality of innovation. In 2006, China's central government launched a national campaign to promote indigenous innovation and introduced bureaucratic targets for patents. Our analysis finds evidence that these targets, combined with political competition, pushed local governments to "game the numbers" by channeling relatively more effort toward boosting non-novel—possibly junk—patents over novel patents. Nationally, this is reflected in a surge of aggregate patents paired with a falling ratio of novel patents. China's innovation drive is susceptible to manipulation and waste—it is enormous in scale but low in productivity.

"China's leaders see patents as rungs on the ladder to becoming an innovation powerhouse. So in five-year plans and through subsidies and official exhortations, they have encouraged locals to file patents. And locals have responded with gusto."

The Economist, 23 May 2014.[1]

"History shows that the advantage of our nation's socialist system, under the leadership of the Chinese Communist Party, lies in its ability to gets big things done, enabling China to achieve one after another 'mission impossible' and repeated miracles."

The People's Daily, 27 December 2019[2]

Political scientists have long debated whether there is an "authoritarian advantage" in growth promotion (Huntington, 1968; Kohli, 1986; Maravall, 1994; Przeworski & Limongi, 1993). In recent decades, this debate has been revived in the context of an ongoing "tech Cold War" between the United States and China (Segal, 2020). Dominance in cutting-edge technology lies at the heart of competition between the two superpowers. In Washington, U.S. politicians are worried about Beijing's perceived political advantage in technological catch-up. Casting China's innovation strategy as "whole-of-state industrial planning," Senator Marco Rubio described the Chinese political system as capable of mobilizing the entire government and society to achieve national goals with a single-minded determination that democracies lack.[3] Additionally, the Chinese leadership can set explicit targets that "encourage private and public firms to shape their decision-making around the plan's priorities."[4] The paramount leader of the Chinese Communist Party, Xi Jinping, has reinforced these perceptions by exhorting the party and government to leverage its "institutional advantage" and "new mobilization system" to ramp up technological advances.[5]

This geopolitical backdrop raises a high-stakes question: Can China *really* catch up with the United States technologically by mobilizing its bureaucracy and assigning ambitious targets to local governments? We examine this question empirically by focusing on patents—a standard indicator of innovation output used by analysts across disciplines, from business management and economics to political science (Jaffe & Trajtenberg, 2002; Taylor, 2016). Simply defined, a patent is an intellectual property granted by a government to an inventor. Patents constitute the largest repository of

---

[1] *The Economist.* (2014, May 23). "Ever more inventive mainland companies are building up their intellectual property."

[2] *The People's Daily*. (2019, December 27). "Concentrate our efforts on big things—Strengthen our self-confidence on the institutions."

[3] The Project for Strong Labor Markets and National Development. (2019). *Made in China 2025 and the Future of American Industry*. https://www.rubio.senate.gov/public/files/Rubio-China-2025-Report.pdf

[4] McBride, J. & Chatzky, A. (2019, May 13). Is 'Made in China 2025' a Threat to Global Trade? *Council on Foreign Relations*. https://www.cfr.org/backgrounder/made-china-2025-threat-global-trade

[5] Xi, J. P. (2021, May 28). *Xinhua Net*. http://www.xinhuanet.com/politics/leaders/2021-05/28/c_1127505377.htm

technological, applied, and commercialized knowledge in modern society, and for analytic purposes, they have the advantage of being measurable.[6] That is why "patents have been used as a basis for the economic analysis of innovative activity for almost a century" (Taylor 2016, p. 323). For forty years since the Patent Cooperation Treaty (an international patent law specifying unified procedures for filing patents) came into effect in 1978, the United States was always the world's top producer of patents. But in recent years, China quickly caught up, surpassing the United States in 2011.

In 2006, the Chinese central government launched a campaign to promote "indigenous innovation," with the goal of progressively replacing foreign technologies with homegrown ones (Segal, 2010). Shortly afterward, it assigned patent targets to local governments for the first time. On the surface, Beijing's race for patents appears to have been a roaring success. The number of patent applications surged domestically and internationally, a phenomenon described as "China's Great Leap Forward in patenting" (Hu et al., 2017). In 2010, *The Economist* predicted, "If China becomes the world's top patent-generator, the world's press will go wild."[7] Only one year later, this came true.[8]

While Western observers frequently gasp at the staggering numbers in China and its appearance of rapid catch-up, our empirical analysis reveals a more nuanced reality that distinguishes between the *quantity* and *quality* of innovation (at the level of individual patents) as well as between the *scale* and *productivity* of innovation (at the level of the national system).[9] The term "productivity" has two meaning that are related but not identical (Solow, 1957). The first meaning is *efficiency*: the ratio of inputs to outputs (Syverson, 2011, p. 329). The second meaning is *yield*: the ratio of high-quality innovation to total innovation. In the most productive scenario, a country produces innovation with a high share of top-quality products using the fewest resources possible. In a less productive scenario, a country produces innovation with a low share of quality products while using more and more resources over time. Our study is not focused on efficiency as we do not have measures of all the inputs for patent production in China. Instead, we are empirically focused on yield: the ratio of quality to total patents.[10]

Measuring the *quality* of innovation is much more difficult than measuring its quantity, even in sophisticated studies based on advanced economies. In this study, we analyze an original database of 4.6 million patents filed from 1990 through 2014 in 333 mainland Chinese cities. One strength of our database is that it covers a long period of time, before and after 2006, which marked a decisive shift in central priorities toward domestic innovation. To capture the quality of patents, we construct a new, rigorous measure—*patent novelty*—based on seminal theories in innovation that define novelty as the first combination of two domains of knowledge. This novelty measure was introduced in the study of "breakthrough innovation" (Fleming, 2007), and we are among the first to measure the novelty of Chinese patents using this rigorous criterion (see also Jia et al., 2019). Ours can be considered a measure of the most novel—or "the long tail" of—

[6] Another repository is academic publications, but they are geared toward basic science.
[7] *The Economist*. (2010, October 14). "Patents, yes; ideas, maybe."
[8] *Reuters.* (2011, December 11). "China Tops U.S, Japan to Become Top Patent Filer in 2011."
[9] Introduced in the 1980s, the concept of "national innovation systems" focuses on the relationship among actors in a system, rather than only on the individual components, as a driver of innovation performance.
[10] For an analogy, we can say that Researcher A, who produces only one quality article among ten, has a lower yield than Researcher B, who produces five quality articles among ten. To match B's quality output, A must produce 50 articles in total and many more low-quality products.

patents.[11] Only 6.9% of the 4.6 million patents in our dataset are coded as novel. As we detail in the Appendix, our criterion is stricter than conventional measures of patent quality.

Using patent novelty as a rigorous estimate of quality innovation, our study identifies the yield of quality innovation—the ratio of novel-to-total patents—both nationally over time and across subnational units of government. We find that following the 2006 national campaign to promote indigenous innovation, the total quantity of patents surged (Figure 1), but the share of novel patents has fallen steadily (Figure 3).

What could lie behind China's falling ratio of quality innovation after 2006? As anecdotal accounts in the Chinese media and recently published government reports suggest, one key culprit is bureaucratic gaming of patent targets, along with wasteful use of subsidies and public resources, and a proliferation of duplicative, junk patents (Caixin, 2019; China National Intellectual Property Administration [CNIPA], 2019, 2021). Using statistical evidence, our study aims to test whether such perverse behavior is occurring systematically. As we cannot directly observe or measure "gaming" behavior, we generate *indirect* evidence by examining if political factors influence patent production at the city level. If local officials are indeed "juking the stats" (Wallace, 2016), then we should expect two interacting political factors to be salient: (1) the introduction of patent targets after the 2006 national campaign on innovation, and (2) the intensity of competition for promotion among local leaders, which we measure as the closeness of fiscal performance among cities in each province.

In an ideal, frictionless world, the Chinese central government will design targets that induce local governments to produce quality patents. However, as numerous organizational studies point out regarding real-world experiences (Kerr, 1975), designing targets for quality innovation is inherently difficult because the desired outcome is multi-dimensional, hard to quantify (Dixit, 2002), and, almost by definition, unexpected or surprising (Wong, 2011). Further, there is a necessary trade-off between the quality and quantity of innovation (de Rassenfosse, 2013). Given these conditions, we expect local (city-level) leaders who are pressured to meet targets and impress their superiors to channel *relatively* more effort toward boosting non-novel patents over novel patents. Stated as a testable hypothesis, we expect that *after* the 2006 campaign, more intense competition will correlate with *more patents* produced, but with a *lower share of novel patents.*

Our regression analysis finds results supporting this hypothesis. By distinguishing between different dimensions of innovation performance (quantity vs. quality and scale vs. productivity) and delivering original findings from a large dataset of 4.6 million patents, we demonstrate that Beijing's innovation drive is *enormous in scale* but *low in productivity*. To be clear, this does not mean that China has utterly "failed" or that it lacks quality innovation in absolute volume; rather, lower productivity means that since 2006 China has been generating more non-novel—possibly junk—patents and consuming more resources to produce quality innovation. Consider one indicator: in 2007, for every 1,000 novel patents, China produced 11,000 total patents and the government spent 3 billion yuan in public funds on science and technology; in 2014, for the same number of novel patents, China produced 27,000 total patents and spent 6.2 billion yuan.

[11] As Fleming writes, "Almost all inventions are useless; a few are of moderate value; and only a very, very few are breakthroughs. Those breakthroughs constitute the 'long tail' of innovation" (2007, p. 69).

This overall inefficient pattern in Chinese state-led innovation is consistent with the larger paradox of China as a "low-productivity superpower" (West, 2019). China's total factor productivity (TFP), a standard measure of the efficiency of inputs, has fallen since 2008 and still has not picked up (Brandt et al., 2020; Liu, 2017). Our emphasis on productivity highlights "innovation efficiency" as an alternative dimension of performance,[12] one often overlooked by Western media and politicians awed by the sheer scale of outputs in China and by Beijing's expressed ambitions to dominate in technology.

Our study brings together three sets of literature that have traditionally belonged in separate spheres: great power competition, policy implementation in authoritarian governments, and the limits of target-setting in innovation. Today, both Biden and Xi frame U.S-China competition as a competition of political systems. In this context, "many issues of Chinese domestic politics are now issues of international politics" (Fravel et al., 2021, p. 1). China's ability to catch up with the United States in a technological race depends crucially on whether its bureaucracy can effectively implement central goals. In the Chinese bureaucracy, "gaming the numbers," from grain collection to GDP statistics, is an old problem (Wallace, 2023; Whiting, 2004). What is new is that setting targets and eliciting desired outcomes has proven much harder in cutting-edge innovation than in early-stage industrialization. Thus it is not enough to assess the strengths and weaknesses of China's political system vis-à-vis democracies only in terms of the scale of output and of the leadership's ambition. We should also pay attention to productivity and to the effects of bureaucratic incentives on policy outcomes.[13]

We next introduce the 2006 national campaign to promote indigenous innovation and specifically to boost patents. We then hypothesize how this campaign interacts with local political dynamics to shape outcomes. The presentation of our dataset and measurements is followed by the results of our regression analyses. Finally, we conclude.

Beijing's Drive for Indigenous Innovation

States play indispensable roles in industrial growth and innovation, especially among late industrializers aspiring to catch up. Governments can spur the economy by making long-term plans, building infrastructure, and investing in and subsidizing strategic industries. This vision of state-directed development materialized in the 1950s and 1980s in Japan, South Korea, Taiwan, and Singapore, collectively known as the "developmental states" (Evans, 1995; Kohli, 2004). China, as Jean Oi observes, showcases "a qualitatively new variety of developmental state" (1995, p. 1113) with "local governments in the lead role" (1999, p. 3). Even though China is a politically centralized regime, it is simultaneously one of the most economically and

[12] The Global Innovation Index (GII) includes "innovation efficiency" as one measure of innovation performance. But, in measuring efficiency, the GII measures only productivity (the Output Sub-Index over the Input Sub-Index) rather than yield, as we do. This is likely because measuring the quality of innovation in one country is difficult and even harder across countries.

[13] In China, policy outcomes are not only the result of leaders' vision and elite politics; they are also mediated by policy communication and implementation, which often produce unintended outcomes (Ang, 2022).

administratively decentralized countries in the world, featuring distinct regional growth models (Ang 2016; Breznitz & Murphree, 2011; Chen, 2014).

During its initial stages of development, China's economy took off by mass producing for export markets. Dismissed as a copycat, it relied on rich industrialized economies for imported technologies. Twenty-five years later, as China neared middle-income status, its government was no longer content with products "Made in China"—it wanted them to be "Invented in China." Yet China's bid to accelerate domestic innovation is not exclusively top-down. It is a hybrid of traditional state planning—featuring bureaucratic targets and state-selected megaprojects in cutting-edge technologies—paired with a bottom-up ecosystem comprising local state agencies, scientists, startups, and venture capitalists, akin to Silicon Valley (Appelbaum et al., 2011; Segal, 2010).

In 2006, the State Council issued "Guidelines on National Medium- and Long-Term for Science and Technology Development" (hereafter MLD), which placed "indigenous innovation" at the heart of China's economic strategy. Its stated ultimate objective was to become an innovative nation by 2020 and a world power in science and technology by 2050 (Segal, 2010). Unlike similar calls for innovation in the past, the 2006 campaign went beyond slogans. For the first time, the central government invested significant resources in and set explicit targets for patents production. As one group of innovation specialists noted, "China can afford to invest previously unimagined sums of money in developing science and technology that might produce long-range breakthroughs" (Appelbaum et al., 2011, p. 224). In 2006, the Organization Department of the CPC Central Committee, a powerful organ that oversees the assessment and promotion of local officials, introduced innovation to the cadre evaluation system. The MLD carried an announcement that "by 2020, China should rank among the top five in the world in terms of the annual number of invention patents granted to domestic applicants."[14]

In a series of follow-up directives, central planners aggressively raised the numerical targets for patents. In 2010, the State Council decreed that by 2015, the annual applications for all patents combined should reach 2 million, and there should be 3.3 invention patents per ten thousand people.[15] Four years later, it doubled the target for invention patents, to 6 by 2015 and 14 by 2020.[16] (Interestingly, in 2016, the target for 2020 was scaled back to 12 invention patents per ten thousand people,[17] indicating that earlier targets were overly ambitious.)

Local governments translated the broad, central-pronounced targets into finer targets by adopting patents as a quantifiable measure of innovation. For instance, Sichuan Province listed the number of patent applications as a "hard" target for city-level

---

[14] Organization Department of the CPC Central Committee. 2006. *Measures for Comprehensive Assessment and Evaluation of Local Leading Party and Government Bodies and Cadres That Reflect the Requirements of the Scientific Outlook on Development (for Trial Implementation)*.

[15] State Intellectual Property Office. 2010. *National Patent Development Strategy (2011–2020)*.

[16] State Council. *Action Plan for the in-Depth Implementation of the National Intellectual Property Strategy (2014–2020)*. 2014.

[17] State Council. *National Plan for Scientific and Technological Innovation During the Period of the 13th Five-year Plan*. 2016.

governments.[18] (Hard targets are those that must be met in order to pass the annual assessment, whereas soft targets are of secondary priority.) Guangdong Province included "invention patent applications per million people" in its Twelfth Five-Year Plan (2011–2015) and made it an evaluation metric for local governments down to the county level.[19] These new targets introduced from 2006, we will later show, had a significant effect on patent production, though not exactly in the direction that national leaders in Beijing wished or expected.

Dataset and Descriptive Patterns

Although there is no single perfect measure of innovation output, "patents have long been recognized as a very rich and potentially fruitful source of data for the study of innovation and technical change" (Hall, Jaffe & Trajtenberg, 2001, p. 4). Given that the concepts of knowledge and innovation are inherently elusive, patents serve a unique function in "quantifying the 'importance' or 'value' of innovations, measuring flows of technological knowledge, and characterizing the technological development" in ways that are comparable over time within a single country (Jaffe & Trajtenberg, 2002, p. 2).[20]

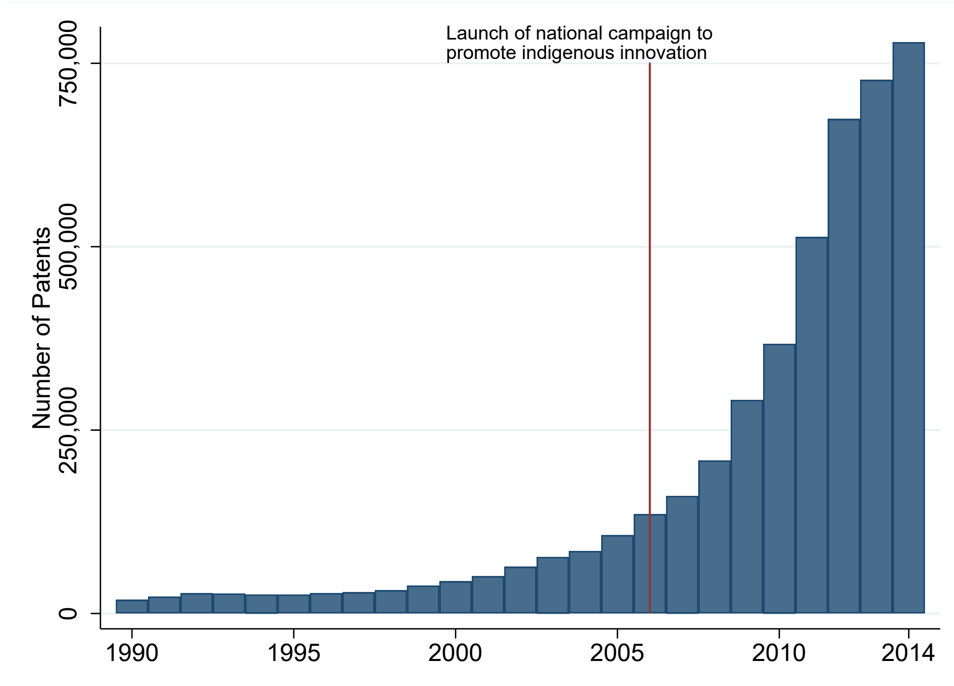
Furthermore, there are three broad categories of patents in China: invention, utility-model, and design patents. Invention patents require an inspection by patent-granting authorities and confer a longer period of protection. The procedures for granting utility-model patents are less stringent. However, a given product such as a circuit breaker can qualify for both invention or utility-model patents, depending on its features. Design patents apply to designs (e.g., logo designs) rather than to inventions. To capture the creation of new solutions and technologies relevant to Beijing's policy ambition of "indigeneous innovation," our analysis includes only invention and utility-model patents.

We employ an original dataset of all 4.6 million domestic patents filed from 1990 through 2014 with China's State Intellectual Property Office (SIPO)—renamed China National Intellectual Property Administration (CNIPA) in 2018—in 333 cities in mainland China. The dataset includes 1.1 million invention patents and 3.5 million utility-model patents. After the central government elevated indigenous innovation to a national agenda in 2006, the total number of domestic patents exploded, as shown in Figure 1. Before 2006, patents grew annually at a rate of 12.4% from 1990 to 2005. After 2006 the pace doubled, increasing annually at 24.4% from 2006 to 2014, reaching a cumulative total of 4.6 million patents in 2014. Media and policy outlets reported that China was "leaping ahead in the patent race" against the United States.[21]

---

[18] Li, Q. Y. (2012, June 12). Scientific and technological innovation are included in the assessment of local governments for the first time. *Sichuan Daily*.
[19] Liu, Q. Y. (2015, October 28). Patent applications in Qingyuan. *Nanfang Daily*.
[20] Economists find that firms' patents are strongly correlated with their profits and market value (Jaffe, 1986).
[21] Nebehay, S. (2020, April 4). In a first, China knocks U.S. from top spot in global patent race. *Reuters*.

Figure 1. China's Great Leap Forward in Patenting from 2006 Onward



But how much of this boom in patents is of good quality? Whereas counting the number of patents is easy, measuring their quality is much harder. It requires technical knowledge of patents and the ability to interpret the information accompanying each filed patent. One approach is treating the entire category of invention patents as a proxy for high-quality patents and comparing it with utility-model patents.[22] This is commonly used because invention patents undergo examination by the patents office and are conferred stronger rights than are utility-model patents. In China the total number of patents grew in both categories. The share of invention patents fluctuated within a small band, from 27.4% in 2006, to 22.8% in 2012, and to 26.6% in 2014. By this simple criterion, the share of quality innovation in China appears to be roughly constant.

However, invention patents are a coarse indicator of quality. As Hall, Jaffe, and Trajtenberg underscored, there is "tremendous heterogeneity in the 'value' of patents" within both the categories of invention and utility-model patents (2001, p. 4). Another common indicator of patent quality is citations, which also suffers from bias. By construction, older patents tend to accrue more citations than newer patents even though older patents are not necessarily of higher quality. More importantly, in China, citations to CNIPA-issued patents are voluntarily supplied by applicants, who may provide partial or no information at all (whereas in the U.S. patent system, citations are mandatory information). This has resulted in many CNIPA patents with missing citations. (In the Appendix, we discuss the limitations of other common indicators of patent quality such as patent renewals.)

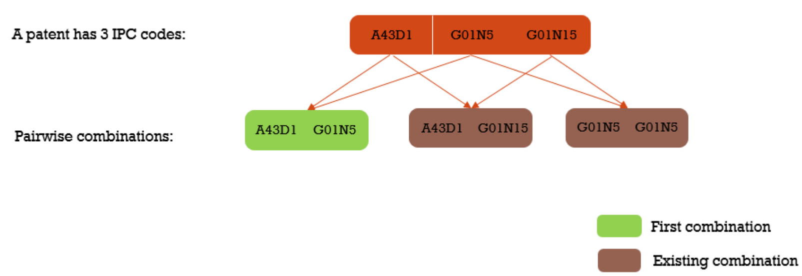
For a more precise and reliable measure of the quality of patents, we construct a new measure: *patent novelty*. Joseph Schumpeter (1943) famously defined innovation as

[22] *The Economist.* (2014, May 23).

new combinations of preexisting elements. Since then, scholars of innovation have conceptualized novelty as solutions drawing on fields of knowledge that were rarely or never combined before (Basalla, 1988; Gilfillan, 1970; Hall et al., 2001; Huang & Murray, 2009). Building on this literature, we code a patent as novel if it draws from at least two technology domains that were not previously combined in any prior patent.

Figure 2 illustrates an example of our coding method. In our dataset, each patent has one or multiple International Patent Classification codes, which indicate the technological clusters from which the patent draws. The sample patent has three patent classification codes, which produce up to three combinations. One of these combinations is the first such combination found in our dataset. Therefore, we code this patent as "novel." For ease of reference, we label the remaining patents that do not meet this criterion as "non-novel." This large residual category of 4.3 million non-novel patents may contain novel qualities not captured by our coding criteria, but our variable is designed to capture the most novel patents, or "the long tail of innovation" (Fleming 2007).

Figure 2. Example of How We Code a Novel Patent in our Dataset

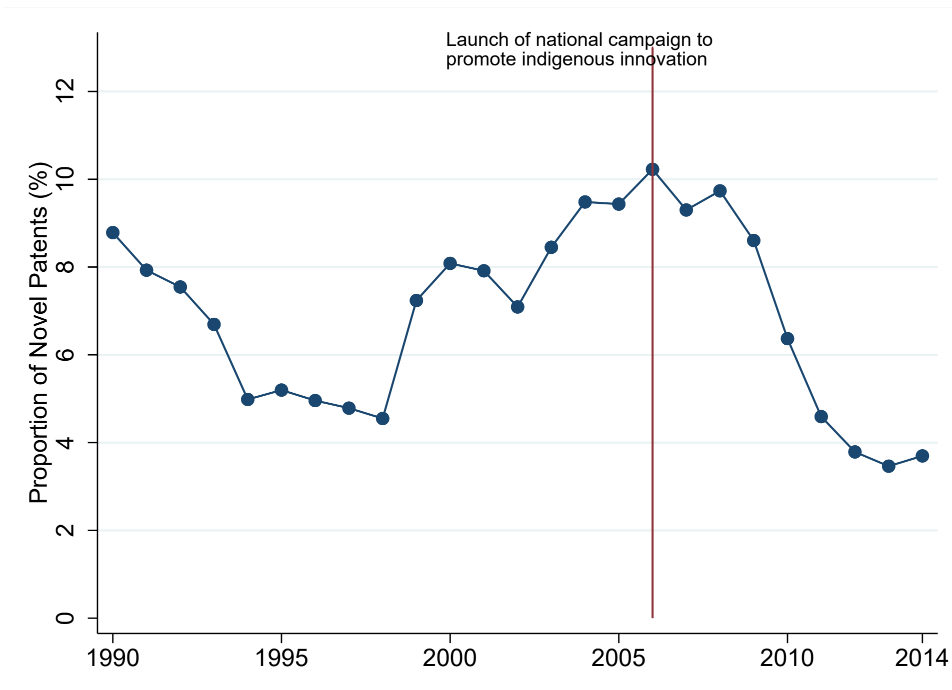


Our measure of patent novelty offers several advantages. First, we apply a uniform set of coding rules across a large dataset. It is one thing to subjectively judge the quality of an invention on a case-by-case basis, but another to create a variable across 4.6 million patents. (Table 2 lists examples of novel patents; in the Appendix we discuss one example). For data generation, we apply the same, theoretically motivated criteria across millions of patents by leveraging the key information that accompanies each patent filing.

Second, our measure presents a substantially higher bar than conventional indicators of patent quality. In our dataset, only 7.5% of invention patents and 5% of utility-model patents are coded as novel. We do not claim that novelty fully equates to quality, only that it captures a key dimension. Chinese companies have exceled in "applied" or "second-generation" innovation that makes small improvements upon existing products and manufacturing processes (Breznitz & Murphee, 2011). But while we acknowledge the commercial value of incremental innovation, our analysis aims to shed light on the advances in primary science and "critical technologies" that define U.S.-China competition. Our measure of patent novelty appropriately captures this type of innovation. For example, patents coded as novel in our dataset include wireless communication equipment, navigation systems for unmanned planes, and liquid crystal display (see Table 2).

A third major advantage of our measure is that local governments have neither incentives nor technical ability to game the metric we have constructed. By contrast, local governments can "game" any existing common metric. For example, the sudden uptick of invention patents from 2012 (22.8%) to 2014 (26.6%) may reflect the central government's introduction of invention patents as a higher-standard target in recent years. Our measure of patent novelty is not included as an evaluation target, and indeed, government actors are likely unaware of its existence. They cannot possibly manipulate outcomes to generate new IPC combinations in our dataset. Our measure of patent novelty, therefore, provides a robust indicator of quality innovation in China.

Figure 3. Falling Share of Novel Patents After 2006



Given China's "Great Leap Forward in patenting" (Hu et al., 2017), with total patents surging fivefold from 2006 to 2014, the absolute number of patents increased across all categories, including novel and non-novel patents. But the pace of growth has been concentrated among non-novel patents. From 2006 to 2014, the number of non-novel patents grew at an annual rate of 25.5%, while novel patents grew by only 9.6%. As Figure 3 shows, after the 2006 campaign, the share of total patents that were novel steadily dropped from 10.2% in 2006 to 3.7% in 2014. Could the falling ratio of novel patents be a natural trend arising from limits on the number of novel patents that can be produced? We do not have comparable descriptive data from another country,[23] but

[23] China and the United States have different patent filing systems, and the work of Fleming, Mingo & Chen (2007), on which we build does not discuss the ratio of novel patents.

judging from the Chinese context alone, the ratio of novel patents fluctuated prior to 2006; this suggests that as the total number of patents increases, the share of novel patents does not necessarily fall. Moreover, given the dramatic elevation of policy attention and resources dedicated to innovation after 2006,[24] the consistently falling ratio of novel patents appears even more surprising.

One possible explanation stands out: the trend illustrated in Figure 3 may reflect widespread gaming, filing of junk patents, and waste. Although patents are not produced directly by local governments (but rather by companies, universities, and individuals),[25] local governments can support, incentivize, and cajole relevant actors to file patents through an array of policies and measures. Besides enacting macro policies that improve the environment for all players (e.g., establishing innovation incubators), governments can disburse generous monetary incentives. In Zhejiang Province, the hub of private capitalism, every city government offered awards of varying amounts ranging from 4,000 yuan for each patent filed in Zhoushan City to 22,000 yuan in Quzhou City (see Appendix). Hangzhou City issued startups and entrepreneurs "innovation vouchers" to subsidize their purchase of goods and service from established laboratories and R&D platforms.[26] Governments desperate to inflate patent numbers can further resort to tactical means; for instance, patent agencies coach organizations and individuals to file multiple patents for the same invention.

Since 2006, the national obsession with innovation, accompanied by a flood of local government support and incentives, has made cheating a norm. An industry of "patent filing agents," who collect fees for churning out large numbers of patents—often of dubious quality—sprouted up (*Caixin*, 2019). Some agents sell patents to companies wanting to package themselves as "tech companies" to qualify for perks and subsidies (*Caixin*, 2021). "There is no lack of ludicrous patents," admitted one patent filing agent, who was anonymously interviewed by *Caixin* (2019). One patent was filed for "chicken soup eye drops," a homemade remedy comprised of chicken and herbs. "My industry is behaving dishonestly, but what lies behind our behavior is government policy," the agent said.

These media reports are corroborated by the central government's own recent admissions. In 2019, CNIPA publicly shamed 18 offenders, including one agent who filed 88 patents for each component within a single piece of equipment and another who submitted more than a hundred invention patents based on "clearly fabricated technological effects." Other offenses include "making superficial changes to old applications and passing them off as new applications, signing off on patent applications written by unqualified persons, and passing companies' patent applications to competitor firms." In 2021, CNIPA warned against "abnormal filing of patents" even more explicitly: "There are still some local governments that blindly pursue quantitative indicators… This seriously… hampers the innovation of enterprises, wastes public resources, and undermines the patent system."

---

[24] Consider one indicator: public expenditure on science and technology grew on average 22% annually between 2006 and 2012, amounting to a whopping increase of 2.4 trillion yuan within seven years.

[25] From 1990–2014, 52% of Chinese patents were produced by companies, 38% by individuals, and 9% by universities.

[26] Hangzhou City Committee of Science and Technology and Finance Bureau. 2018. *Measures for the Implementation of Technology Innovation Vouchers of Hangzhou City*.

Table 1. Examples of Non-Novel Patents in Our Dataset

Patent number	**Title**	**Assignee**	**Year filed**	**IPC codes**
CN104071432B	Portable wine bottle cork	Technology and Entrepreneurship Service Center of Chong'an District, Wuxi City	2014	B65D39
CN102152823B	Bicycle cell phone holder	Wang Dahai	2011	B62J11
CN102078245B	Adult T-shaped diaper and its manufacturing process	Zhejiang Yong Chuan Machinery Co., Ltd.	2010	A61F13
CN101564181B	Processing method of crisp fried sesame sunflower seeds	Ye Chengli	2009	A23L1
CN101310615B	Hot pot soup base and its preparation method	Deng Long	2008	A23L1

Table 2. Examples of Novel Patents in Our Dataset

Patent number	**Title**	**Assignee**	**Year filed**	**IPC codes**
CN103770911B	A deep sea observation buoy system based on inductive coupling and satellite communication technology	First Institute of Oceanography, State Oceanic Administration	2014	B63B22; H04B7
CN103256931B	Visual navigation system of unmanned planes	Tsinghua University	2011	B64C19; B64C39; G01C21
CN102464983B	Manufacturing of display and polymer-dispersed liquid crystal film	BOE Technology Group Co Ltd	2010	B29C69; C08J3; C09K19; G02F1
CN101459913B	Wireless communication system, central station, access equipment, and communication method	Huawei Technologies Co Ltd	2007	H04W16; H04W84; H04B10;
CN100358771C	A robot with flexible structures	Feng (Individual)	2004	B62D57; B62D61

In our dataset of 4.6 million patents, we cannot systematically tell which non-novel patent may be a junk patent like "chicken soup eye drops" without examining each case individually. Nonetheless, selected examples can provide some clues. Table 1 lists examples of patents coded as non-novel in our dataset, all of which draw from only one technological class. From the names of the products alone, we can tell that these patents, even if not junk, are certainly not revolutionary: bicycle cell phone holder; hot pot soup base; and method for frying sunflower seeds. To be sure, the large category of non-novel patents could contain useful patents, but the examples above, consistent with anecdotal accounts supplied by the Chinese media and regulators, suggest that the massive growth of non-novel patents—from 0.7 million in 2006 to 4.3 million in 2014—reflects a broader pattern of "abnormal filing of patents," using CNIPA's words of 2021.

Beyond anecdotes, is there *systematic* evidence that gaming has taken place since patent targets were introduced in 2006? To answer this question, we use a regression analysis to leverage considerable regional (city-level) variation in both the number of patents produced and the ratio of novel-to-total patents, neither of which correlates neatly with income levels. Figure 4 shows the distribution of patents in 2014 across the 333 mainland Chinese cities in our dataset; the four direct-administered municipalities of Beijing, Shanghai, Chongqing, and Tianjin are excluded. While wealthy coastal provinces generally produced more patents than inland and western provinces, geography and income levels do not align perfectly with patent production. Six of the top 20 cities filing the most patents—Zhengzhou in Henan, Changsha in Hunan, Hefei in Anhui, Xi'an in Shaanxi, Wuhan in Hubei, and Chengdu in Sichuan—were not from the coastal provinces. Cities also varied widely in their ratio of novel-to-total patents (Figure 5), which cannot be attributed to any universal "ceiling effect" across China. These descriptive patterns suggest a potential political story behind patent production; we turn to this story next.

Figure 4. Number of Patents Across Mainland Chinese Cities in 2014

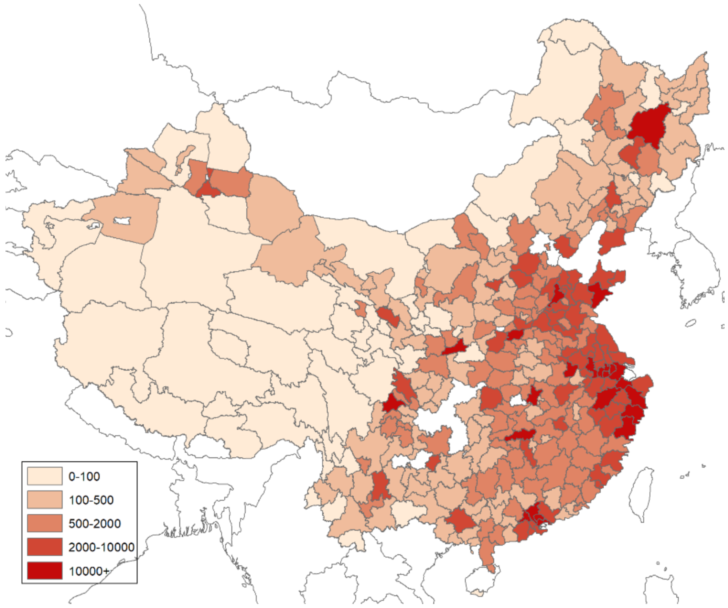
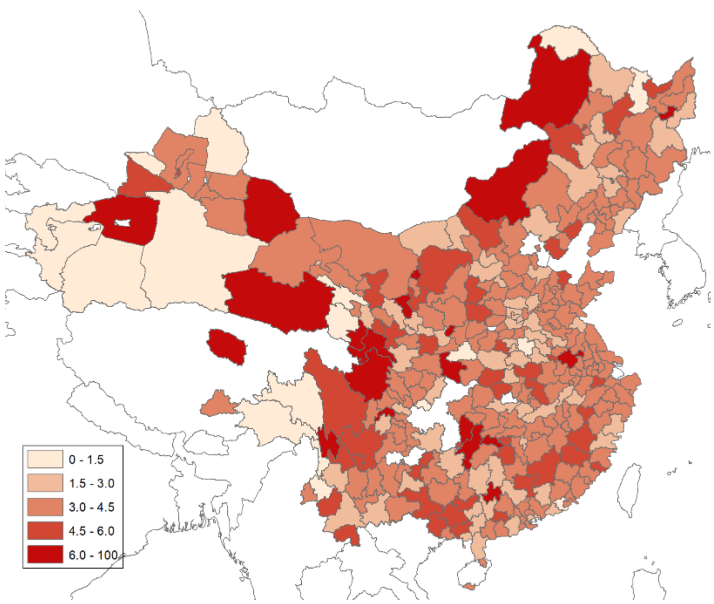


Figure 5. Share of Novel Patents Across Mainland Chinese Cities in 2014



National Campaign Meets Local Politics

If bureaucratic gaming of patent numbers were indeed widespread, then we should expect the interaction of two political variables—the launch of the national innovation campaign in 2006 and local political competition—to influence the production of patents.

Owing to its exceptional centralization of power and revolutionary roots, the CCP characteristically implements policies in the manner of "campaigns" (Ang, 2016; Perry, 2011): the paramount leader mobilizes the nation to work toward a single goal. The 2006 MLD is a long-term "campaign" in pursuit of indigenous innovation. Yet no campaign has the same effect across all of China; we hypothesize that campaigns are influenced by the degree of political competition. There is a sizable literature on career incentives in Chinese politics because, in an autocracy, such incentives are the functional equivalent of electoral incentives in democracies (Chen et al., 2005; Li & Zhou, 2005). We recognize that, in reality, the number of seats for promotion are very few, so reaching a single target does not guarantee promotion (Kostka & Yu, 2015). Even so, all officials must compete to simply remain in office, be transferred to a better location, or win the approval of higher-level patrons. To stand out from intense competition, officials must deliver key targets; after 2006, patents stand out as a top priority As Caixin (2021) notes, innovation became a national "obsession" after the 2006 campaign. "In practical terms, patents have become one of the government's easiest ways to measure success in innovation" (Caixin, 2021).

Two additional conditions, both well-established in the innovation literature, inform our expectations about how the specific interaction between political competition and the 2006 national campaign may have influenced patent production patterns. First, it is easier to set targets for quantity than for quality. "Counting beans" is easy. Beginning in 2006, the Chinese central government relied on two key metrics: annual filing of total patents and of the number of patents per thousand people. These numerical targets rose each year until 2016, when the target for 2020 was scaled back slightly. CNIPA's first mention of bureaucratic gaming was in 2018, when it warned against "blindly exploiting public funds to inflate patent numbers and deviating from central goals." This means that from 2006 to 2018—the period of our dataset—the Chinese government relied on coarse targets focusing on quantity. In an attempt to encourage quality patents, central planners initially set targets only for invention patents;[27] later, in 2010, they required invention, utility-model, and design patents to be filed.[28]

This problem is not unique to the Chinese bureaucracy. As Dixit incisively reminds us, there are sharp limits to applying principle-agent models, targets, and incentives to the public sector due, among other challenges, to the "multiplicity of dimensions of tasks" (2002, p. 697). This is especially true when measuring the *quality* of innovation, which not only has multiple dimensions but is also inherently uncertain, that is, successful innovation generates surprising features that are not anticipated in advance and may not initially be recognized (Wong, 2011). In Dixit's words, "Traditional

[27] State Council. 2006. *Guidelines on National Medium- and Long-Term for Science and Technology Development*.

[28] State Intellectual Property Office. 2010. *National Patent Development Strategy (2011–2020).*

incentives need selective application to specific agencies or tasks, namely those whose performance can be defined, quantified, and measured with some clarity" (e.g., industrial output and fiscal revenue). Applying "magic bullet solutions like competition or performance-based incentives" for complex tasks, Dixit cautions, is "naïve" (2002, p. 697; see also 2012).

The second condition is that low-quality innovation is easier to produce in large quantities than is high-quality innovation (de Rassenfosse, 2013). Take the examples of non-novel and novel patents in Tables 1 and 2. Little cost or effort is required to file numerous non-novel patents for products like "hot pot soup base" and "bicycle cell phone holder." Conversely, creating novel patents that combine multiple technological classes such as a wireless communication system takes significant investment, technical expertise, and time. To be clear, we do not expect officials to cease producing novel patents; for them, there is no loss in generating real innovation. Moreover, as cities accumulate macro-infrastructure supporting innovation over time, the absolute number of patents should increase across all categories. However, for local governments that are desperate to inflate numbers, pumping up non-novel patents clearly presents a more convenient option.

Combining the two conditions discussed above—the imposition of coarse numerical targets and the relative ease of producing non-novel patents—we expect city governments under higher competitive pressures to ramp up the number of all patents. More specifically, they will concentrate relatively more effort on increasing easy-to-produce, non-novel patents. Expressed as testable hypotheses:

H1: More intense local competition after 2006 correlates with a higher quantity of patents.

H2: More intense local competition after 2006 correlates with a lower share of novel patents.

Next, we test these hypotheses using our original dataset and measure of novelty.

Data and Methods

Provinces are the highest level of subnational government, followed by prefectural cities. Our sample, for the years 1990–2014, covers 333 cities in China excluding the four direct-administered municipalities: Beijing, Tianjin, Shanghai, and Chongqing. We exclude these cities from our sample because their political leaders are appointed by the central government and face different promotional criteria; therefore they have different political incentives from other city leaders. Our regression tests city-level variables. Even with the four central municipalities excluded, though, the 333 cities combined contributed 81% of total patents produced, which means our analysis applies to the vast majority of China. Focusing on the sub-provincial (city) level has the further advantage of capturing wider regional variation and both province-level and within-province effects, thereby generating richer and more robust empirical insights.

We draw on three large datasets to construct a novel city-year-level panel dataset.[29] The first dataset includes 4.6 million domestic, granted patents file from 1990

[29] Replication materials and code can be found at Ang et al (2023).

through 2014.[30] We first identify the cities where the patent assignees are located.[31] We then aggregate patents into each city-year cell based on applicants' addresses and application years.[32] The second dataset consists of city-level economic statistics, which we use to construct our measure of competition and city-level control variables. We collected this dataset from the *China Statistical Yearbooks*. The last dataset is based on the curriculum vitae of all 2,337 party secretaries—the top politicians of each city—for the years 1990 through 2014. We collected the CVs of party secretaries from the China Stock Market & Accounting Research (CSMAR) Database. To our best knowledge, this is the first study that matches the entire population of Chinese patents with the cities in which patent assignees are based and further pairs this data with political variables.[33]

Variables

Dependent Variables. The main outcomes of interest are the quantity of patents and the share of novel patents (see H1 and H2). To measure quantity, we count the *number of patents*, the total number of domestically granted patents produced (as indicated by filing a patent application) in each city in each year; we use the log transformation of this variable to reduce skewness. To approximate the quality of patents, we measure the *proportion of novel patents*: the number of novel patents (defined as the first combination of two domains of knowledge) divided by total patents.

Independent Variable 1: Political Competition. Voluminous empirical literature examines the effects of career incentives and non-electoral competition in the Chinese bureaucracy. No measure of incentives and competition is perfect, and each has its own strengths and weaknesses, as we review in the Appendix. Those who study "political cycles" focus on the tenure timeline of leaders, but we do not see any ex ante theory indicating in which year local officials would have the greatest incentives to promote innovation. A better indicator of local political dynamics is the *intensity of political competition* (IPC). The degree of subnational competition is uneven across China (Lü & Landry, 2014). Each province has multiple cities in its jurisdiction, and each province evaluates and ranks leaders across these cities. The more intense the competition, the better subnational leaders must perform on key indicators to outshine their competitors.

How can we best measure the intensity of competition? As Lü & Landry point out, due to the absence of election, "the intensity of interjurisdictional competition is inherently difficult to observe and quantify in authoritarian settings" (2014, p. 707). Making a spatial argument, they argue that competition for promotion will be more intense where there are more county-level jurisdictions within a province, as there are more contenders. While this is a creative way to capture variance in non-democratic

[30] Our baseline analysis excludes design patents and pools all invention and utility-model patents, which allows us to examine the average effects on innovation.
[31] Two percent of patents have multiple assignees. For these patents, we use the address of the first assignee. As a robustness check, we dropped this group and the results remained similar.
[32] Although it is not a precise date, the application year is the closest date for the production of an innovation; this practice is consistent with the existing literature (Murray & Stern, 2007; Jia et al., 2019).
[33] The patent assignee is the entity granted the property right to the patent. The patent applicant is the assignee while the patent application is under review. We use patent "assignee" and "applicant" interchangeably in this study.

competition, their measure is static (as the number of sub-provincial units rarely or never changes over time). In fact, as our measure will show, the degree of competition within a single province can change over time, and two cities in two different provinces—each with the same number of cities—can experience different levels of competition.[34]

For a more dynamic measure of political competition, we focus on the *closeness* of competition among city leaders within each province. This idea is already implicit in previous economic studies that characterize China's political system as a "tournament." When competing for promotion, local officials are not simply judged by their absolute performance but rather by their performance *relative* to a relevant peer group (Chen et al., 2005; Maskin, Qian & Xu, 2000). The peers of city governments are other cities within the same province. A classic article on tournament models by Ehrenberg and Bognanno (1990) argues that lead players will feel more competitive pressures and be inclined to improve if their performance is closer to that of other players. Combining these insights, we argue that one effective way to capture the intensity of competition among city leaders in China is to examine the "closeness" of their performance. When the economic performance indicators (EPIs) of cities within a province are closer, city leaders must work harder to distinguish themselves from their peers.

Based on the above, we create the variable *intensity of political competition* (*IPC*), which is the standard deviation of the EPI of all cities within the same province in a given year:

$$IPC_{c,t} = -\sqrt{\frac{\sum_{c=1}^{n}(EPI_{c,p,t} - \overline{EPI_{c,t}})^2}{n}} \tag{1}$$

where $EPI_{c,p,t}$ is the value of the EPI of city c within the province p in year t. The average of the EPIs of all cities within the same province and the same year is represented by $\overline{EPI_{c,t}}$. The number of cities within a given province is indexed by n. We multiply the standard deviation by -1 so that a larger value indicates more intensive competition among cities within the same province over the EPI. In the regression, we standardize this variable to make it easier to interpret its coefficient. Note that *IPC* takes the same value for all cities within a given province; in other words, it captures the intensity of competition across provinces. (In the Appendix, we present an alternative within-province measure of *IPC*, which yields similar results.)

For this analysis, we use the growth rate of fiscal revenue as a measure of EPI. Although the most commonly used indicator of economic performance is GDP growth (Chen et al., 2005; Li & Zhou, 2005; Persson & Zhuravskaya, 2016; Wu et al., 2013), recent studies report mixed results on its correlation with promotion (Landry et al., 2018; Shih et al., 2012). Fiscal revenue is found to be a more significant predictor of career outcomes (Landry et al., 2018; Lü & Landry, 2014). Moreover, whereas GDP can be fudged, fiscal revenues are funds that local governments have collected and spent. Note that closeness in fiscal performance is not determined by income levels; competition can be close in both rich and poor provinces (see Appendix). We include province-level GDP as a control.

In the Appendix, we provide several robustness checks, and our estimate of the effects of *IPC* remains robust. Measuring the closeness of competition using fiscal

[34] For example, Guangdong and Sichuan have 21 prefectural cities each, but the level of competition in Guangdong is greater than that in Sichuan in most years according to our measure.

revenue growth and GDP growth yields similar results, but we show only the former in the main text for parsimony. As a robustness check, we also run our regressions using a variant of Lü and Landry's spatial measure (we count city-level units instead of county-level units within each province) and find similar results. Our measure, which is dynamic rather than fixed by geography, shows how year-to-year changes in the intensity of competition correlate with patent production.

Independent Variable 2: Period After 2006 Campaign. Second, we measure the effects of the 2006 national innovation campaign using a dummy variable *Post-Campaign*, which is equal to 1 for the years after 2006 and 0 otherwise. As discussed, because specific patent targets were first introduced in 2006 and innovation outcomes first appeared in cadres' promotion guidelines afterward, we expect local politicians to prioritize patent production only after 2006. In other words, the intensity of competition should become salient *only after* 2006.

Control Variables. A host of other factors may shape patenting outcomes. We include two sets of control variables in the regression analysis. The first set are local economic conditions germane to innovation. *GDP per capita* captures the income level of a city. A wealthier city is more likely to have the necessary resources to spur innovation and patents. We include *provincial GDP* as a proxy for the availability of financial resources at the provincial level. *Population growth* is also believed to facilitate innovation because it increases market demand (Desmet, et al., 2018). The variable *FDI/GDP* is the ratio of foreign direct investment inflows to a city's gross domestic product. We include this variable because some argue that technology transfer and spillovers from foreign firms drive domestic innovation in China (Liu & Buck, 2007).

The second set of control variables captures the personal characteristics of the party secretaries; these variables include *Gender* (1 for female, 0 for male), *Age* (age of the party secretary), *Education* (the education level of the official: 1 = secondary school, 2 = high school, 3 = bachelor's degree, 4 = master's degree, 5 = doctoral degree), and *Minority* (equal to 1 if an official belongs to a ethnic minority group, and 0 otherwise). Table 3 summarizes all the above variables. Table A5 (Appendix) presents the correlation table.

Table 3. Descriptive Statistics

Variables	Mean	Median	S.D.	Obs.
1. Number of patents (log)	4.156	4.111	1.855	7,659
2. Share of novel patents (%)	6.043	5.714	5.404	7,421
3. Intensity of political competition (IPC)	0.000	0.232	0.998	5,849
4. Post-Campaign	0.261	0.000	0.439	7,659
5. GDP per capita (log)	9.576	9.532	0.930	6,149
6. Population growth	6.332	5.770	4.434	6,019
7. FDI/GDP	0.025	0.011	0.049	6,555
8. Gender	0.019	0.000	0.136	7,166
9. Age	51.328	52.000	4.288	6,308
10. Education	3.391	3.000	0.756	7,166
11. Ethnic minority	0.073	0.000	0.260	7,166
12. Provincial GDP (log)	8.069	8.136	1.300	7,659

Estimation Strategy. In the next section, we report regression results using the time frame of 1990–2012, which captures the entire leadership period of Hu and Wen, who launched the 2006 innovation campaign. This allows us to assess the effects of their leadership without the potential influence of policy changes under President Xi Jinping, who is widely seen as more authoritarian and ambitious than his predecessors. Our dataset includes only the first two years of Xi's term in office (2012–2014); including these years does not change our main results.

We employ a two-way fixed effects linear model to examine the effects of local political competition on local patent production outcomes, particularly after the national innovation campaign. The baseline regression function is specified as follows:

$$y_{c,t+1} = \beta_1 IPC_{c,t} \times Post\ Campaign_t + \beta_2 IPC_{c,t} + \boldsymbol{X'}_{c,t}\boldsymbol{\gamma}_1 + \boldsymbol{Z'}_{c,i,t}\boldsymbol{\gamma}_2 + \varphi_c + \delta_t + \varepsilon_{c,t} \quad (2)$$

where c indexes the city, t indexes the year, and y represents the log number of patents or the proportion of novel patents. We forward the dependent variable by one time period to account for the interval between the time of innovation and the date of patent application.[35] The vector $\boldsymbol{X}$ stands for economic indicators of the city and the corresponding province. The vector $\boldsymbol{Z}$ captures the personal characteristics of the local official i who is in office in a city in a given year. The symbol φ_c represents the city-fixed effect that captures all time-invariant and city-specific characteristics, such as local entrepreneurship rooted in a city's history. The indicator δ_t is the time-fixed effect that absorbs all city-invariant and year-specific shocks (including $Post_t$), such as the direct effect of the introduction of the 2006 national innovation drive. Standard errors are clustered at the city level to allow for arbitrary correlations of the error term, $\varepsilon_{c,t}$, over time within each city. The key parameter of interest is β_1. It captures the effect of one standard deviation increase in IPC on patent outcome before and after the 2006 national innovation campaign. Incentives to promote innovation that are unrelated to the 2006 campaign would be captured by β_2.

Results

Averaged Effects

Quantity of Patents. Model 1 in Table 4 presents regression results where the dependent variable is the number of patents. We include intensity of political competition (*IPC*) and its interaction term with *Post-Campaign*$_t$, while controlling for city and year fixed effects. The estimated coefficient of this interaction term is positive and statistically significant ($p < 0.01$). After including all the control variables in Model 2, the positive interaction effect between the *IPC* and *Post-Campaign*$_t$ persists. Concretely, one standard deviation increase in IPC is linked to a 9.8% growth in the number of patents after the national innovation campaign. This finding is consistent with H1: more intense local competition after 2006 correlates with a higher quantity of patents.

[35] We obtain similar results when we forward the dependent variable by two or three years.

Table 4. Joint Effects of 2006 Campaign and Political Competition on the Number and Share of Novel Patents

	(1)	(2)	(3)
Dependent Variable:	Number of patents (log)	Number of patents (log)	Share of novel patents (%)
IPC × Post-Campaign$_t$	0.151***	0.098***	-0.463***
	(0.021)	(0.018)	(0.114)
IPC	0.004	0.006	0.088
	(0.007)	(0.007)	(0.077)
GDP per capita (log)		0.055	0.288
		(0.062)	(0.274)
Population growth		-0.008*	-0.011
		(0.004)	(0.026)
FDI/GDP		-1.110**	5.122**
		(0.437)	(2.307)
Gender		0.015	-0.211
		(0.059)	(0.382)
Age		-0.002	0.006
		(0.003)	(0.015)
Education		0.002	0.042
		(0.018)	(0.089)
Minority		0.019	0.188
		(0.052)	(0.534)
Provincial GDP (log)		1.718***	0.740
		(0.200)	(0.782)
City fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
Observations	5,849	5,049	5,048
R-squared	0.837	0.861	0.257

Note: IPC stands for intensity of political competition. It is the minus standard deviation of the economic performance indictor (i.e., growth of fiscal revenues) of all cities within the same province in a given year. Standard errors in parentheses are clustered at the prefecture level. *** p<0.01, ** p<0.05, * p<0.1.

We comment briefly on the control variables. Our regression finds that FDI as a share of GDP is negatively correlated with the volume of domestic patents. While this may contradict some literature (Liu & Buck 2007), it is consistent with recent qualitative literature, which finds that when foreign companies dominate local economies, domestic innovators can be crowded out (Chen, 2014; Wong, 2011). Not surprisingly, wealthier provinces produce more patents. Yet it is notable that, after controlling for this factor, the intensity of peer competition among city leaders still registers a substantial and statistically significant effect.

Share of Novel Patents. Next, in Model 3, we examine H2: more intense local competition after 2006 correlates with a lower share of novel patents. Here, we examine the joint effects of *IPC* and *Post-Campaign*$_t$ on the proportion of novel patents. Consistent with our hypothesis, in Model 3 the estimated coefficient of the interaction term is negative and statistically significant ($p < 0.01$). The estimate indicates that one standard deviation increase in *IPC* is associated with a 0.46% decrease in the proportion of novel patents after the national innovation campaign. Note that this effect is not small, given that the average proportion of novel patents is only 6.04%. Moreover, in Model 3, the only statistically significant factor is the interaction term between *IPC* and *Post-Campaign*$_t$. In other words, the share of novel patents is not affected by other economic and control variables; rather, it is driven by the interaction of national policies and local politics.

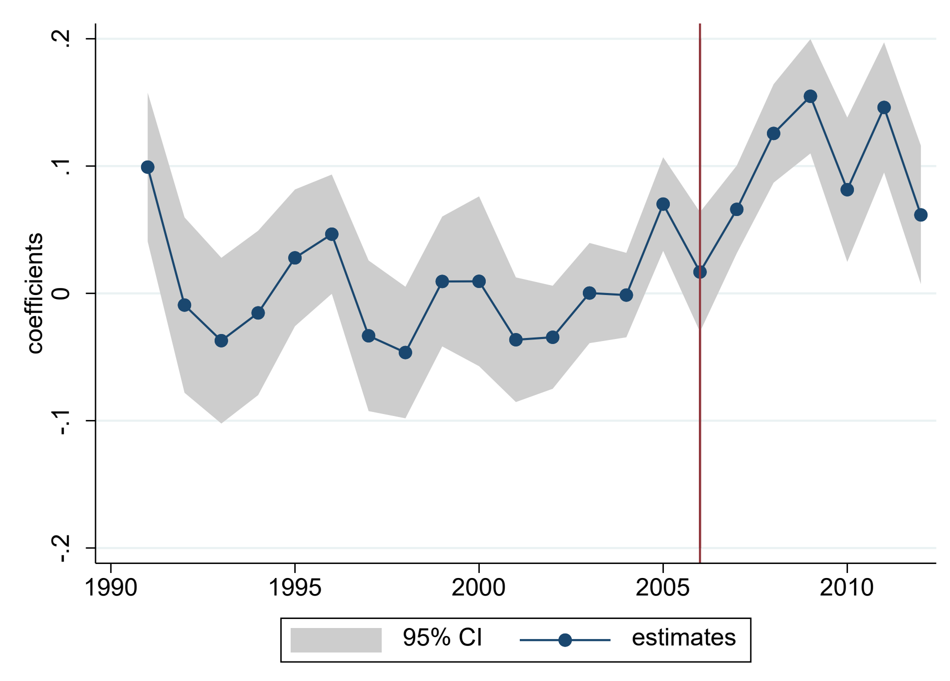
As an example, for 2010 the city of Fuzhou in Fujian province has an IPC score of 0.497; it produced 3,518 patents of which 204 were novel. Holding other factors constant, if Fuzhou experienced the same intensity of competition as Hangzhou City in Zhejiang province (IPC= 1.006), then we would expect it to produce 175 more patents and would expect the share of novel patents to fall from 5.8% to 5.6%.

Dynamic Effects

Above, we show only the averaged effects of local political competition on patent outcome before and after the 2006 innovation campaign. Next we unpack the interaction effect on a year-by-year basis. To do so, we replace$Post\ Compaign_t$ (a dummy variable of 1 after 2006 and 0 before 2006) with a series of dummy variables $Post_{t,k}$ that indicate the k^{th}year before or after 2006. This analysis reveals changes in the effects of local political competition on innovation outcomes *each year*, before and after the 2006 national campaign.

Quantity of Patents. Figure 6 plots the estimated coefficient of the interaction term between *IPC* and each year indicator, on the number of patents, conditional on the same set of control variables as Model 2 of Table 4. We find that prior to the launch of the national innovation campaign in 2006 (shown to the left of the red vertical line), the effect of *IPC* on the number of patents is not statistically significantly different from zero in most years. By contrast, immediately after 2006 (shown to the right of the red vertical line), this effect becomes positive and remains statistically significant. This pattern is consistent with our earlier results showing that the 2006 campaign induced city leaders who faced more competitive pressures to produce more patents as a means of standing out.

Figure 6. Effects of Political Competition on the Quantity of Patents

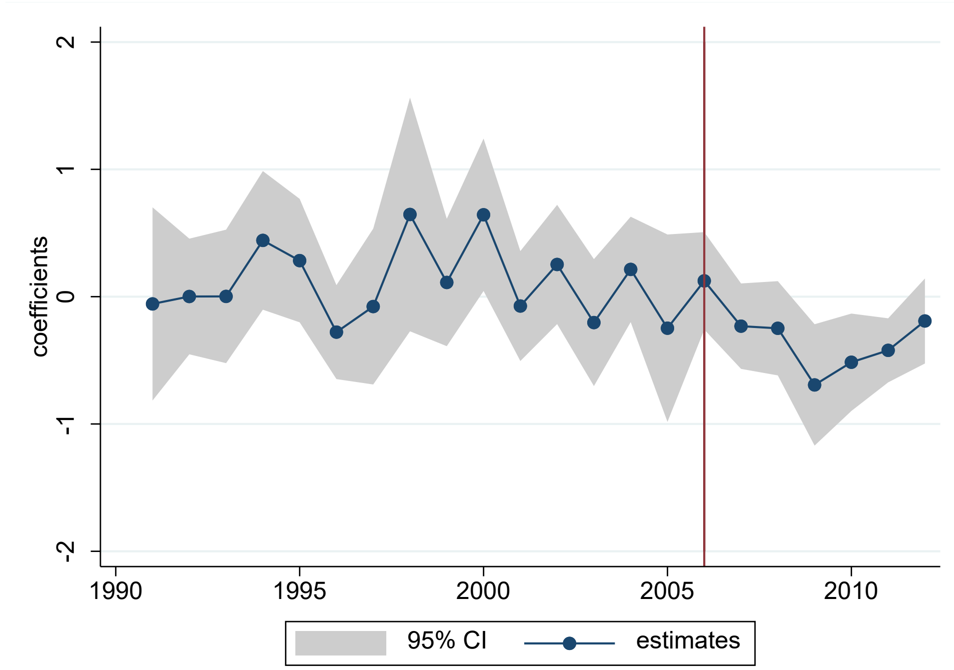


Note: This figure plots the year-by-year effects of intensity of political competition (IPC) on the number of patents (log). We use the same specification as in Model 2 of Table 4 but replace *Post* with a series of year dummies. The connected dots are the estimated coefficients of the interaction terms between IPC and each year. The shaded area shows the 95% confidence intervals. The vertical line marks the year 2006 when the national innovation campaign started.

It is also worth noting the year-by-year estimate of the effect of *GDP per capita* on the number of patents (see Figure A2 in the Appendix). Their correlation increased consistently each year before 2006. However, the effect of GDP per capita on patent output declined gradually after 2007. This suggests that political factors played an increasingly larger role than economic factors in the final years of the Hu administration.

Share of Novel Patents. We repeat the same procedure, but this time focus on the quality of patents. Figure 7 plots the estimated coefficients of the *IPC* on the proportion of novel patents each year. Again, we find that the yearly estimate of the effect of political competition as measured by the *IPC* hovers around zero (had no effect) in most years prior to 2006. After 2006, the estimated effect turns negative, becomes statistically significant in 2009, and stays in the negative range until 2012. These results reinforce our earlier findings that, after the 2006 campaign, stiff local competition is correlated with a larger number of patents but its effect on the share of novel patents is largely negative, suggesting that local governments channeled relatively more effort toward producing non-novel patents.

Figure 7. Effects of Political Competition on the Share of Novel Patents



Note: This figure plots the year-by-year effects of intensity of political competition (IPC) on the proportion of novel patents (%). We use the same specification as in Model 3 of Table 4 but replace *Post* with a series of year dummies. The connected dots are the estimated coefficients of the interaction terms between IPC and each year. The shaded area shows the 95% confidence intervals. The vertical line marks the year 2006 when the national innovation campaign started.

Elusive Targets

The story we have told so far is still unfolding. Some might wonder if the central government could not simply "solve" the problem by designing targets for quality patents. In practice, this is much harder than it may seem (Dixit, 2002; Kerr, 1975). CNIPA first acknowledged that targets were being manipulated in 2018; this means that central planners did not anticipate various cheating tactics for more than a decade after 2006. Subsequently, CNIPA tried to check the problem by publicly shaming cheaters in 2019 and reining in excessive subsidies for patent filings in 2021.

In 2021, the central government elevated the evaluation metric for the first time from "the number of invention patents" to "the number of high-value invention patents."[36] A patent is regarded as high-value if it meets additional conditions that include maintaining an invention patent for more than ten years.[37] Even though this is a

[36] Stata Council. 2021. *National Intellectual Property Protection and Use Plan for the 14th Five-Year Plan Period*.

[37] To maintain the enforceability of a patent, a patent holder must pay fees regularly during the enforceable period.

recent policy shift, there are already signs that local governments are upgrading their gaming tactics. For example, the government of Hefei City in Anhui immediately enacted a new patent subsidy policy that awards 8,000 yuan for each invention patent maintained for more than ten years.[38] This incentive may encourage inventors to maintain potentially low-quality patents, or to satisfy other requirements, just to count them as "high-value patents."

Refining targets does not fundamentally encourage high-quality innovation and research. For a relatable analogy, academics need only consider the struggles within our profession to find metrics that can accurately capture scholarly impact. A group of political scientists warned about the pitfalls of blindly relying on Google Scholar citations to evaluate the quality of scholarship and deciding promotions, but they acknowledged that there is no better alternative than a close contextual reading of individual cases (Jensenius et al., 2018). Nor is competition a panacea in academia or in the Chinese bureaucracy. As Landes et al. observe, "More fatally, this pressure [to meet publication targets] has turned academia into a rat race, leading to … a self-defeating and hence counter-productive pattern" (2012, p. 73) If these problems have not found an easy solution in academia, we should not expect the Chinese bureaucracy to find a quick fix either.

Conclusion

Using an original dataset and a new, rigorous measure of patent novelty, our study sheds new light on the efficacy of China's innovation drive. In assessing innovation performance, we bring attention to two different dimensions: scale and productivity. The ability of the Chinese political system to mobilize the bureaucracy and to set explicit targets for national goals makes it exceptionally effective at producing large-scale results (in this case, increasing the number of patents across all categories). However, when we consider productivity, a different picture emerges: the yield of quality innovation—as measured by the ratio of novel patents—has fallen steadily since 2006. Our regression results find that the filing of patents has been shaped significantly by the 2006 national campaign and by the degree of political competition. The salience of these political factors is consistent with media and policy reports about widespread bureaucratic gaming of top-down targets.

Although China is a low-productivity innovator, we stress that this may not necessarily doom the country's innovation aspirations because the government may be willing to tolerate inefficiency so long as this process produces enough "hits" to overcome "chokeholds" (critical technologies that the United States seeks to cut off from China) and to revolutionize the economy.[39] Expressed in a battleground analogy, China practices a "spray and pray" approach.[40] This logic has a precedent in China's earlier en

[38] Hefei City Government. "Notice on Implementing Quality Innovation in Relation to Intellectual Property Rights." Issued 26 Feb 2023.

[39] The Chinese government has called U.S. export controls on critical technology to China a "chokehold."

[40] Ironically, Seligman's article in *Foreign Policy* cited "a prominent tech leader with strong ties to the U.S. Department of Defense" for his criticism of the U.S. government's "spray and pray" approach in contrast to China's "far more concentrated" approach. In fact, our analysis shows that, in patents production, China's approach is decentralized and prone to producing lots of junk.

masse investment recruitment strategies, where local governments mobilized all agencies, regardless of formal functions, to prospect for investors. Although this was an inefficient approach that yielded many low-quality investment projects alongside a few good ones, it had the initial advantage of increasing the collective chances of success (Ang, 2016). Tech entrepreneur Kai-Fu Lee made a similar observation: “This process can be both highly inefficient and extraordinarily effective. When the long-term upside is so monumental, overpaying in the short term can be the right thing to do” (2018, p. 46).

Returning to the big picture of competition between great powers, our study moderates exaggerated views, stemming from both Washington and Beijing, about the “authoritarian” or “institutional” advantages of the Chinese political system in achieving strategic goals through national mobilization and target-setting. Going beyond a simplistic “fail versus succeed” binary, we shed new empirical light on the weaknesses and strengths of China’s innovation drive—large in scale but low in productivity. In the United States, the federal government “plays an absolutely central role” in coordinating and seed-funding innovation, and it could be more effective than the Chinese government, but “the public has been mostly kept in the dark about the workings of the [US] innovation system… [because, among other reasons] it does not fit with the claims of market fundamentalism” (Block & Keller 2011, p. 18). Borrowing a phrase from Jessica Weiss, if Washington appreciates the different comparative advantages and disadvantages of the American and Chinese systems, it should avoid “falling into the trap of trying to out-China China” (2022, p. 43)—that is, it should avoid blindly imitating China’s industrial policies and instead focus on shoring up America’s unique strengths.

References

Ang, Y. Y. (2016). *How China Escaped the Poverty Trap*. Cornell University Press.

Ang, Y. Y. (2022). Testimony before the U.S.-China Economic and Security Review Commission 'CCP Decision-Making and the 20th Party Congress' (January 27, 2022). Available at SSRN: https://ssrn.com/abstract=4390821

Ang, Y. Y., Jia, N., Yang, B., & Huang, K. G. (2023). Replication Data for: China's Low-Productivity Innovation Drive: Evidence from Patents. https://doi.org/10.7910/DVN/LX5YI2.

Appelbaum, R., Parker, R., Cao, C., & Gereffi, G. (2011). "China's (not so hidden) developmental state." In *State of Innovation*, eds., Block, Fred and Mathew Keller.

Basalla, G. (1988). *The evolution of technology*. Cambridge University Press.

Block, F., & Keller, M. R. (2011). State of Innovation: US Government Technology Policies, 1969–2008. *Boulder, CO: Paradigm*.

Brandt, L., Litwack, J., Mileva, E., Wang, L., Zhang, Y., & Zhao, L. (2020). *China's Productivity Slowdown and Future Growth Potential*.

Breznitz, D., & Murphree, M. (2011). *Run of the red queen: Government, innovation, globalization, and economic growth in China*. Yale University Press.

Caixin. (2019, May 8). "Insiders reveal chaos: this is how a patent superpower is forged" (in Chinese).

Caixin. (2021, April 14). "Self-styled 'godfather of patents' rises, falls on China's innovation obsession." (in English).

China National Intellectual Property Administration (CNIPA). 2018. *Notification on the Special Inspection of Patent Application Related Policies*.

China National Intellectual Property Administration (CNIPA). 2019. *18 Decisions Reprimanding Patent Agents*. English translation by Center for Security and Emerging Technology (CSET), unpublished.

China National Intellectual Property Administration (CNIPA). 2021. *Notice on Further Strictly Regulating Patent Application Behavior*. For an English translation by CSET, see https://cset.georgetown.edu/publication/notice-of-the-china-national-intellectual-property-administration-on-more-strictly-regulating-patent-applications/.

Chen, L. (2014). Varieties of global capital and the paradox of local upgrading in China. *Politics & Society*, *42*(2), 223–252.

Chen, Y., Li, H., & Zhou, L.-A. (2005). Relative performance evaluation and the turnover of provincial leaders in China. *Economics Letters*, *88*(3), 421–425.

de Rassenfosse, G. (2013). Do firms face a trade-off between the quantity and the quality of their inventions? *Research Policy*, *42*(5), 1072–1079.

Desmet, K., Nagy, D. K., & Rossi-Hansberg, E. (2018). The geography of development. *Journal of Political Economy*, *126*(3), 903–983.

Dixit, Avinash. "Bureaucracy, its reform and development." Review of Market Integration 4.2 (2012): 135-157.

Dixit, Avinash. "Incentives and organizations in the public sector: An interpretative review." Journal of human resources (2002): 696-727.

Ehrenberg, R. G., & Bognanno, M. L. (1990). Do tournaments have incentive effects? *Journal of Political Economy*, *98*(6), 1307–1324.

Evans, P. (1995). *Embedded Autonomy: States and Industrial Transformation*. Princeton, N.J.: Princeton University Press.

Fleming, L. (2007). Breakthroughs and the" long tail" of innovation. *MIT Sloan Management Review*, *49*(1), 69.

Fleming, L., Mingo, S., & Chen, D. (2007). Collaborative Brokerage, Generative Creativity, and Creative Success. *Administrative Science Quarterly*, *52*(3), 443–475.

Fravel, M. T., Manion, M., & Wang, Y. (2021). A "China in the World" paradigm for scholarship. *Studies in Comparative International Development*, *56*(1), 1–17.

Gilfillan, S. C. 1970. *The Sociology of Invention: An Essay in the Social Causes, Ways and Effects of Technological Invention*. MIT press.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). *The NBER patent citation data file: Lessons, insights and methodological tools*. National Bureau of Economic Research.

Hu, A. G. Z., Zhang, P., & Zhao, L. (2017). China as number one? Evidence from China's most recent patenting surge. *Journal of Development Economics*, *124*, 107–119.

Huang, K. G., & Murray, F. E. (2009). Does patent strategy shape the long-run supply of public knowledge? Evidence from human genetics. *Academy of Management Journal*, *52*(6), 1193–1221.

Huntington, S. P. (1968). *Political Order in Changing Societies*. Yale University Press.

Jaffe, A. B., & Trajtenberg, M. (2002). *Patents, citations, and innovations: A window on the knowledge economy*. MIT press.

Jensenius, F., Htun, M., Samuels, D., Singer, D., Lawrence, A., & Chwe, M. (2018). The Benefits and Pitfalls of Google Scholar. *PS: Political Science & Politics, 51*(4), 820-824.

Jia, N., Huang, K. G., & Man Zhang, C. (2019). Public governance, corporate governance, and firm innovation: An examination of state-owned enterprises. *Academy of Management Journal*, *62*(1), 220–247.

Kerr, S. (1975). On the folly of rewarding A, while hoping for B. *Academy of Management journal*, *18*(4), 769-783.

Kohli, A. (1986). Democracy and Development. In: Lewis, J.P. and Kallab, V., Eds., Development Strategies Reconsidered, Transaction Books, New Brunwick, 153-182.

Kohli, A. (2004). *State-directed development: political power and industrialization in the global periphery*. Cambridge university press.

Kostka, G., & Yu, X.F. (2015). Career backgrounds of municipal Party secretaries in China: why do so few municipal Party secretaries rise from the county level? *Modern China*, *41*(5), 467–505.

Landes, X., Marchman, M., & Nielsen, M. (2012). The academic rat race: Dilemmas and problems in the structure of academic competition, *Learning and Teaching*, *5*(2), 73-90.

Landry, P. F., Lü, X., & Duan, H. (2018). Does performance matter? Evaluating political selection along the Chinese administrative ladder. *Comparative Political Studies*, *51*(8), 1074–1105.

Lee, K.-F. (2018). *AI superpowers: China, Silicon Valley, and the new world order*. Houghton Mifflin Harcourt.

Li, H., & Zhou, L.-A. (2005). Political turnover and economic performance: the incentive role of personnel control in China. *Journal of Public Economics*, *89*(9–10), 1743–1762.

Liu, M. (2017). “Total Factor Productivity in China: Current Conditions, Problems, and Policy Solutions.” Hongkong: Lau Chor Tak Institute of Global Economics and Finance.

Liu, X., & Buck, T. (2007). Innovation performance and channels for international technology spillovers: Evidence from Chinese high-tech industries. *Research Policy*, *36*(3), 355–366.

Lü, X., & Landry, P. F. (2014). Show me the money: Interjurisdiction political competition and fiscal extraction in China. *American Political Science Review*, 706–722.

Maravall, J. M. (1994). The myth of the authoritarian advantage. *Journal of Democracy*, *5*(4), 17–31.

Maskin, E., Qian, Y., & Xu, C. (2000). Incentives, information, and organizational form. *The Review of Economic Studies*, *67*(2), 359–378.

Murray, F., & Stern, S. (2007). Do formal intellectual property rights hinder the free flow of scientific knowledge? An empirical test of the anti-commons hypothesis. *Journal of Economic Behavior & Organization*, *63*(4), 648–687.

Oi, J. C. (1995). The Role of the Local State in China’s Transitional Economy. *The China Quarterly*, *144*, 1132–1149.

Oi. J.C. (1999). *Rural China takes off: institutional foundations of economic reform*. University of California Press.

Perry, E. J. (2011). From mass campaigns to managed campaigns: “constructing a new socialist countryside.” In *Mao’s Invisible Hand* (pp. 30–61). Brill.

Persson, P., & Zhuravskaya, E. (2016). The limits of career concerns in federalism: Evidence from China. *Journal of the European Economic Association*, *14*(2), 338–374.

Przeworski, A. & Limongi, F. (1993). Political Regimes and Economic Growth. *Journal of Economic Perspectives 7*, 51–71

Schumpeter, J. A. (1943). *Capitalism, socialism and democracy. London:* George Allen.

Segal, A. (2010, September 28). China’s innovation wall: Beijing’s push for homegrown technology. *Foreign Affairs*, *28*.

Segal, A. (2020, September 9). The Coming Tech Cold War with China. *Foreign Affairs*, *9*.

Seligman, Lara (2018, October 16). “Pentagon criticized for spray and pray approach to innovation.” *Foreign Policy*.

Shih, V., Adolph, C., & Liu, M. (2012). Getting Ahead in the Communist Party: Explaining the Advancement of Central Committee Members in China. *American Political Science Review*, 166–187.

Solow, Robert M. “Technical Change and the Aggregate Production Function.” *The Review of Economics and Statistics*, vol. 39, no. 3, 1957, pp. 312–20

Syverson, C. (2011). What determines productivity? *Journal of Economic literature*, *49*(2), 326-365.

Taylor, M. Z. (2016). *The politics of innovation: Why some countries are better than others at science and technology*. Oxford University Press.

Wallace, J. (2023). *Seeking Truth and Hiding Facts: Information, Ideology, and Authoritarian Rule in China.* Oxford University Press.

Wallace, J. 2016, 'Juking the stats? Authoritarian Information problems in China', *British Journal of Political Science*, vol. 46, no. 1, pp. 11–29

Weiss, Jessica Chen. 2022. "The China Trap: U.S. Foreign Policy and the Perilous Logic of Zero-Sum Competition." *Foreign Affairs* 101 (5): 40–58

West, J. (2019, October 31). "China, a Low-Productivity Superpower." The Interpretator.

Whiting, Susan (2004). "The Cadre Evaluation System at the Grassroots: The Paradox of Party Rule," in Barry Naughton and Dali Yang, eds., Holding China Together (Cambridge University Press)

Wong, J. (2011). *Betting on Biotech: Innovation and the Limits of Asia's Developmental State*. Cornell University Press.

Wu, J., Deng, Y., Huang, J., Morck, R., & Yeung, B. (2013). *Incentives and outcomes: China's environmental policy* (No. w18754). National Bureau of Economic Research.