参赛队员姓名: Bo Xin Zhao

中学: 上海美国学校浦西

省份: 上海

国家/地区: 中国，南方赛区

指导教师姓名: 郎有泽

指导教师单位: 复旦大学

论文题目: Trump’s Impact on Chinese Innovation: Evidence from Patents

Trump's Impact on Chinese Innovation: Evidence from Patents

Bo Xin Zhao
Shanghai American School Puxi

Abstract

Recent literature has shown that political tension between countries can affect innovation. After Trump's election and its subsequent impact on Chinese innovation, two contrasting mechanisms have emerged. The knowledge diffusion framework suggests that such tensions adversely impacted Chinese inventors, whereas transaction cost economics proposes that Chinese inventors improved their self-reliance. Utilizing the unexpected "Trump shock" as an opportunity for study, we apply a differences-in-differences model on patent data from the United States Patent and Trademark Office (USPTO) to identify the causal effects of political tension on Chinese innovation. Using similar regions nearby China as the control group, we find that while innovation in most regions was negatively affected by the Trump shock, China performed comparatively better in patent quality, quantity, and search distance following the shock. Results remain consistent across robustness checks. Further heterogeneity analysis shows that inventors with larger collaboration networks and Chinese firms in southern urban cities performed better. Our research contributes to the understanding of knowledge diffusion and transaction costs, and we highlight the importance of uncovering the unintended effects of politics.

Keywords: Political economy, Transaction cost, Knowledge diffusion, Innovation, Trump

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1. Introduction

Innovation has been proven to be the engine of economic growth (Romer, 1990; Aghion & Howitt, 1992). Although many factors, such as breakthroughs in basic science, influence the pace and direction of innovation, economists have begun to focus, at least since President Donald Trump came to power, on the important role of politics in shaping investments in innovation (Aghion et al., 2023; Engelberg et al., 2022; Jia et al., 2023). In this paper, we ask: How do political shocks in the U.S. affect innovation in China? How do firms in China react to these shocks?

Politics can affect innovation through two competing mechanisms: On the one hand, political decisions affect collaboration and knowledge diffusion across countries and individuals, which might negatively hurt firms' innovation (Aghion et al., 2023; Jia et al., 2023). On the other hand, political shocks may raise the transaction cost of acquiring patents, which forces the firms to invent independently and increase innovation output (Williamson, 1983). From our perspective, the question is not whether one or the other is exclusively at work; instead, it is more important to examine which one outweighs the other, on average, and which contextual conditions amplify one process relative to the other.

Recent debates about how Trump affects innovation in China illustrate the dilemma: While some expect Trump's policies on immigration, communication, and collaboration restrictions to heavily affect the volume, quality, and direction of Chinese research due to the increasing cost of getting funding resources from the U.S., others view it as a chance for Chinese firms to catch up and decrease reliance on the technology of other countries. Firms often have to make the critical decision on whether to invest resources in internal patent invention (make it) or pursue external acquisition (buy it). Among all the factors affecting firms' decision to "make" or to "buy," one of the most significant is the transaction cost. The political shock from Trump increased the transaction cost of buying patents and forced the firms in China to create.

However, empirically identifying the effect of the political shock on innovation is challenging due to several obstacles. First, many other factors confound the estimation of the effect. For example, China's National 15-year Plan for Science and Technology Development was implemented over a decade ago, showing how China had been attempting to develop its indigenous innovation even without substantial political shocks (Sun & Cao, 2021). Second, Chinese data on specific Chinese political decisions and the behavior of inventors in China are limited and have unestablished veracity.

This paper takes advantage of the election of Donald Trump as an opportunity for naturalistic observation to investigate the effect of political conflict on innovation. Donald Trump was overwhelmingly predicted to lose to Hillary Clinton (Katz, 2016), and he won the Electoral College vote, not the popular vote (Shaw, 2016). These factors illustrate how Trump's win was an unexpected, exogenous shock. Other papers have used similar reasoning to justify the identification of Trump's election victory as a shock (Engelberg et al., 2022; Child et al., 2021).

To empirically identify the impacts of Trump on Chinese inventors, we apply a differences-in-differences (DID) approach, utilizing data from the USPTO. We use patents, inventors, and firms from China as our treatment group and estimate the causal effect with a control group containing innovation from Japan, South Korea, Taiwan, and Singapore.

There is no simple, one-dimensional method to measuring innovation; as such, we construct numerous dependent variables indicative of innovative output at the patent, inventor, and firm levels. The quantity of patents is the number of patents granted, and the quality of patents is measured through the number of citations received. Furthermore, we construct two variables that indicate search distance. First, technological distance is defined to be the extent to which a patent searches distant knowledge fields during the invention process. In this case, knowledge fields are based on each patent's respective Cooperative Patent Classification (CPC) subclasses, a categorization system that denotes the fields of every patent. The second search distance measure is cognitive distance, measuring the extent to which inventors searched for knowledge with low visibility. These distance measures reflect the chances of meaningful innovation, as previous literature has established that larger search distances heighten the occurrence of serendipitous discoveries (Arts & Fleming, 2018; Zheng & Wang, 2020).

We find that following the Trump shock, China has produced higher patent quality, patent quantity, and search distance compared to its regional counterparts. The quality of Chinese patents improved 17.8% relative to the control group on average, technological distance improved by 5.4%, and the ratio of U.S. patents cited increased by 6.6%. These results remained consistent across the patent, inventor, and firm levels. In fact, inventors saw a 17.7% increase in patent quality on average.

Moreover, robustness checks reinforce the evidence of China's change from relying on licensing U.S. patents to investing in domestic innovation. To address concerns regarding time lags and COVID-19, we change the post-election indicator to 2017 and extend the timeframe to include 2023. The regression results remain statistically significant and positive. We also employ other measures of communication and search distance, which bring similar regression results, demonstrating the robustness of our indicators. Overall, our analysis strongly supports the transaction cost hypothesis that China was catalyzed into developing its domestic innovation, but it also affirms aspects of the knowledge diffusion theory by showing how all examined countries were negatively impacted in some way.

We further find that the impact was more pronounced across certain fields of research: Chinese patents related to semiconductors and electricity saw a quality increase of 20.3% relative to the control group following the Trump shock. This analysis affirms the importance of the "technosphere" in the status quo.

Furthermore, other heterogeneous results show that larger inventor networks contributed to greater innovative output, and the geographical location of a firm — whether it was in urban or in southern China — made a difference in its response to the Trump shock. Notably, inventors in the top 95th percentile uniquely improved their patent quality by a statistically significant 32.2%, firms located in big cities improved their patent quality by 27.4% compared to other firms, and southern Chinese firms improved their patent quality by a statistically significant 25.1% compared to northern Chinese firms which did not demonstrate statistically significant improvement.

This paper contributes to several parts of the existing literature. First, it contributes to prior research surrounding the understanding of how politics affects innovation. Previous studies have highlighted the role of decreasing labor mobility, collaboration, communication, and expectation (Kim & Marschke, 2005; Møen, 2005; Atkin et al., 2022; Aghion et al., 2023; Jia et al., 2023). We add a new perspective, transaction cost, and emphasize the importance of firms' strategic decisions. Secondly, there is a significant amount of attention devoted to studying factors that affect the innovation of firms (Marx et al., 2009; Dustmann & Preston, 2019; Atkin et al., 2022; Wuchty et al., 2007). We add new evidence showing how disruptive institutional change can be a source of the changing nature of innovation. Lastly, we provide new empirical evidence for the transaction cost literature by testing the theory in a novel international context.

Moreover, this paper will have implications for policymakers. The tension between China and the U.S. has aroused attention among academics, the public, and policymakers. Without fully understanding how political tension affects the economies of China and the U.S., it is difficult for government officials to find a comprehensive way to react to the rising issues in foreign affairs. This paper sheds light on one of the most critical aspects of an economy —

innovation — and helps policymakers better understand the true weight of their political decisions.

The rest of the paper proceeds as follows: Section 2 provides background for the Trump Administration and its actions; Section 3 establishes two competing theoretical frameworks and develops three hypotheses; Section 4 illustrates the construction of the variables in detail; Section 5 analyzes the results of the DID regression approach; Section 6 discusses this study's findings while providing insight into the limitations of this study; and Section 7 concludes.

2. Background about the Trump Administration

2.1 Trump's Unexpected Election Victory

Before the election, the overwhelming majority of mainstream news media predicted Donald Trump would lose to Hillary Clinton (Katz, 2016). These predictions were in part because Trump had a non-political background as a celebrity businessman (Child et al., 2021). Despite losing the popular vote, Trump became president by achieving a majority in the Electoral College (Shaw, 2016). Subsequently, major news outlets such as The Guardian (2016) have described the election as "one of the most improbable political victories in modern U.S. history" and one that "shattered expectations." Even Fox News, a pro-Trump Republican outlet, echoed that the event was a "historic election upset" (2016).

Given that the majority of onlookers did not expect a businessman who had never held office before to win the 2016 election, it is reasonable to deduce that the election was an exogenous shock to the world as much as it was to the U.S.

2.2 Trump's Actions to China

Trump's anti-China stance began long before he took office. During the 2016 presidential debates with Hillary Clinton, he repudiated China's unfair trade policies and publicly claimed that "[the Chinese] are taking [Americans'] jobs" and "are using our country as a piggy bank to rebuild China" (Beech, 2016).

Trump heightened tensions with China from the outset by accepting a congratulatory call from Taiwan President Tsai Ing-Wen, pressuring China to urge North Korea to limit nuclear weapons testing, and taking stances against China regarding controversies such as control of the sea, naval operations, and territorial disputes (Sutter, 2017). Throughout his presidency, Trump's foreign policy was remarkably inconsistent. In 2018, other members of his department increased the tensions with China, exemplified by Vice President Pence's confrontational speech directed at China, stating that the "[U.S.] will not stand down" (Perlez, 2018).

In November 2018, the Department of Justice launched the China Initiative to "protect U.S. intellectual property and technologies against Chinese Economic Espionage." However, studies have shown its prejudice against researchers and inventors of Chinese origin (Aghion et al., 2023). It significantly increased the bureaucratical and logistical challenges of collaboration between U.S. and Chinese inventors, leading to the systematic exclusion of targeted researchers from U.S. institutions.

Moreover, the escalation of the trade war affected China's access to U.S. markets. Following the first tariffs levied against China in 2018, China retaliated. In total, taxes from tariffs increased by almost $80 billion during the Trump administration, affecting more than $380 billion of trade (York, 2022). Consequently, U.S. import volumes from China decreased from 2018 to 2021, even before the pandemic halted global supply chains. From 2018 onward, the majority of Americans had decided that the U.S. and China were "mostly rivals" as opposed to "mostly partners" (Kim, 2021).

On top of this, Trump issued Proclamation 10043 in 2020, an immigration restriction targeted against Chinese students and researchers. The Proclamation effectively denied and revoked the visas of numerous Chinese students and researchers given any association with the People's Liberation Army or certain universities (Anderson, 2023). By four months, the U.S. claimed it had revoked more than 1,000 visas of Chinese citizens (BBC, 2020), and in 2021, it refused 1,964 visas. Furthermore, these figures understate the true impact of immigration restrictions, as Chinese individuals who would have otherwise applied for visas were discouraged from doing so.

China's front-running technology corporations have also been targeted by Trump. Huawei, one of China's largest technology corporations and the second-largest seller of smartphones in the world, and ZTE, another China-based technology corporation, were prevented from buying parts from U.S. companies (Stewart, 2018). Trump's executive order also added their various subsidiaries to a trade blacklist. In a similar vein, executive orders in 2020 banned popular social media applications TikTok and Wechat from U.S. app stores, albeit later rescinded by Biden (Lerman, 2020).

2.3 Trump Sparked Debate and Attention

The election of Trump and his subsequent actions have sparked controversial debate in both society and academia. To start, Chinese society was divided over which candidate would be preferable. According to some polls, a slight majority of Chinese citizens preferred Trump over Hillary Clinton prior to the election (Lai, 2016). Hillary had been known for a track record of controversial interference with China's government, yet Trump also used hawkish rhetoric against China throughout his presidential campaign. In a sense, it was picking between the lesser of the two evils. Chinese government officials likewise swayed back and forth. Some officials favored Hillary — who was already outspoken in her views — over Trump, whose potential actions were largely unknown (Asia Society, 2016). However, following the election, President Xi publicly underscored China's rejuvenation, partly thanks to Trump's unilateral and nationalist foreign policy. President Xi further claimed to support investing in "Chinese solutions" to international problems resulting from the void that the U.S. was creating (Doshi, 2020). Still, rewards came with risks, and Chinese officials have been weary of unpredictable American confrontation and threats during the Trump administration.

In the U.S., academics and voters have been split over assessing Trump's impacts on innovation. Historically, the U.S. has relied on attracting the world's talent, yet Trump's implantation of national security measures, visa restrictions, and travel restrictions have undermined the China-U.S. STEM pipeline (Burke, 2021). While the government has argued that these approaches and restrictions were necessary, others have underscored their negative impact on the U.S. economy (Ahmed & Bick, 2017).

During the COVID-19 pandemic, relations worsened as Trump's antagonism toward China heightened. In part galvanized by Trump's finger-pointing, 73% of U.S. adults claimed they had an unfavorable view of China in 2020 (Pew Research Center, 2020). As victims of anti-Asian sentiment, Chinese individuals reflected that their opinion of the U.S. drastically turned hostile during the Trump presidency (McCaig, 2022). These rapid fluctuations of opinion have generated hot debates and warrant further investigation regarding Trump’s impacts, specifically on Chinese innovation.

3. Literature Review and Hypotheses

Two prominent conflicting sides have theorized how the Trump shock affected innovation. On the one hand, researchers have posited that the Trump shock affected Chinese innovation negatively by restricting knowledge diffusion — including talent mobility, immigration, and communication — between the U.S. and China. On the other hand, viewing the Trump shock through the lens of transaction cost economics would indicate that the U.S. catalyzed China into more self-reliant innovation, pushing it to perform comparatively better than its regional counterparts.

3.1 Politics and Knowledge Diffusion

First, the former theory that the period of Trump inhibited Chinese innovation revolves around emphasizing three well-researched determinants of the breadth and depth of innovation: labor and talent mobility (Kim & Marschke, 2005; Møen, 2005; Belenzon & Schankerman, 2013; Agarwal et al., 2009), communication (Atkin et al., 2022; Agrawal & Goldfarb, 2008), and collaboration (Aghion et al., 2023; Jia et al., 2023).

Labor and talent mobility is defined as the ease and likelihood of people moving to different economies. Despite the age of the Internet, the movement of people is a potent facilitator of knowledge exchange, which is crucial to innovation (Dustmann & Preston, 2019). Hence, limitations to labor mobility can directly hamper innovation. Similar to how non-compete contracts decrease the innovative productivity of a region by limiting the labor mobility thereof (Marx et al., 2009), changes in immigration could affect inventors across the world. Moreover, talent mobility is especially paramount in recent developing country contexts (Fry, 2023), and its importance cannot be understated in the Chinese context. Google was blocked in 2014, and installing a virtual private network (VPN) to bypass the firewall was burdensome, so Chinese researchers have particularly relied on labor mobility and social networks. This is evidenced by Zheng & Wang's (2020) analysis of the negative effect of the Google blockade on Chinese search distance due to their reliance on the West. During the Trump administration, the U.S. president's restriction of immigration in the form of limiting visas of certain Chinese researchers and students contributed to fewer academic exchanges between American and Chinese researchers.

The Trump shock also theoretically hampered communication between Chinese and American scholars. The aforementioned immigration restrictions reduced Chinese and American scholars' face-to-face interactions, which play a surprisingly significant role in knowledge spillovers (Atkin et al., 2022). In addition to the immigration restrictions, which directly restricted certain Chinese scholars from traveling to the U.S., worsened relations following the trade war and other schisms contributed to further distance between Chinese and American scholars. The trade war significantly reduced market access (Fajgelbaum & Khandelwal, 2022), and worsened relations due to anti-Chinese sentiment during the Trump administration may have led to less motivation and optimism in pursuing innovation. Given how Engelberg et al. (2022) demonstrated that willingness and ability to be productive directly affects effort and productivity, Trump's influence on Chinese researchers' sentiment and optimism could have made them more likely to overexploit recent information, patent less, and pursue fewer serendipitous leads.

Lastly, collaboration among researchers of varied specializations is becoming increasingly effective in knowledge production (Hofstra et al., 2020; Boone et al., 2019). Teams produce high-impact research with more frequently cited patents than solo authors in nearly all fields (Wuchty et al., 2007). The importance of collaboration and coauthoring is shown in the rising number of U.S.-China collaboration projects up until the Trump administration (Aghion et al., 2023; Jia et al., 2023). However, the 2018 China Initiative, among other restrictions, directly reduced collaboration between American and Chinese scholars. These actions disintegrated teams into solo authors and split teams into smaller, more homogenous ones. Fos, Kempf, and Tsoutsoura (2021) have illustrated how firms perform worse when misaligned executives with divergent perspectives leave an executive team; the same theoretical backbone applies to American coauthors leaving inventing teams: the teams likely perform worse without multifaced viewpoints.

All of this could affect innovation by limiting search distance and decreasing the quantity and quality of Chinese patents compared to patents from South Korea, Taiwan, Singapore, and Japan. Therefore, following this theory, the following hypothesis can be made:

Hypothesis 1*: Following the Trump shock, China performed comparatively worse on the patent, assignee, and inventor levels, showing decreases in quality of patents (measured by number of citations received), quantity of patents, and search distance relative to that of the control group, including Singapore, Japan, Taiwan, and South Korea.*

3.2 Politics and Transaction Cost

Transaction cost is the cost when making an economic trade in a market. The amount of transaction cost directly influences the decision between vertically integrating and outsourcing. In other words, the cost is a significant factor in firms' decision to buy something from the market or to make it themselves (Leiblein et al., 2002). Depending on the fit of governance, transaction attributes, and broader context, the transaction cost also plays a prominent role in defining the organizational boundaries of a firm (Mosakowski, 1991). In recent years, there has been a shift to the market for knowledge and technology, where the two are treated as definable and tradeable commodities (Arora et al., 2004). In this market, transaction cost determines whether firms buy or sell their innovation.

This framework provides a new perspective on the impact of the Trump shock. The framework of knowledge diffusion in the previous subsection theorized that the political shock harmed Chinese innovation by hampering labor and talent mobility, communication, and collaboration. However, viewing the shock through the lens of transaction cost economics indicates the opposite hypothesis: the Trump shock has done nothing short of incentivizing China to become more self-reliant in innovating.

To begin with, China's research and development (R&D) strategy pre-2016 was to predominantly outsource innovation. With relatively low transaction costs, China was inclined to utilize a number of technology acquisition strategies, including licensing patents, equipment purchasing, acquiring foreign firms, and other outsourcing arrangements with foreign nations (Choung & Koo, 2023; Edamura et al., 2014). Overall, the potential to tap into specialized capabilities from other sources while minimizing internal costs was a principal advantage of outsourcing, despite its drawbacks of reduced coordination and information transfer (Leiblein et al., 2002).

The Trump shock drastically changed transaction costs by introducing many political and geopolitical uncertainties. To begin, Trump's lack of a previous political record made many Chinese officials nervous (Asia Society, 2016). These fears were confirmed in 2018 when Trump suddenly banned exporting goods to ZTE, a large Chinese telecoms company — ZTE was brought near bankruptcy within days (The Economist, 2018). Likewise, Trump implemented sudden export bans on Fujian Jinhua, a Chinese integrated circuit company (The Economist, 2018). Following this, Trump continued to bar sales of sensitive technologies to certain Chinese companies and blacklisted 28 Chinese organizations (Swanson & Kang, 2020). These access restrictions on U.S. technology immediately added to the transaction costs of Chinese firms. Not only were many goods outright banned, but the uncertainty in transaction costs made U.S. technology no longer a sustainable option for China.

As a result, Chinese firms and the government were incentivized to become more self-reliant through a variety of mechanisms. Most notably, these efforts were epitomized in the Made in China 2025 strategy and Five-Year Plan (2016-2020), when China increased its R&D spending by double-digits annually to become the world's second-largest R&D investor behind the U.S. (Gill, 2021). Other mechanisms included establishing programs that attracted engineers from elsewhere (The Economist, 2018). Acknowledging its previous drawbacks, the government also began enforcing better intellectual property protection to attract foreign domestic investment (Salitskii & Salitskaya, 2022).

Some researchers, such as Hu et al. (2017), point out that China's propensity to seek patents may have been motivated by "non-innovation related motives" that resulted in quantity being prioritized over quality. Even though China's low grant ratio (WIPO, 2021) indeed illustrates that some Chinese patents were more quantity-oriented than driven by innovation-related motives, there was nevertheless a substantial amount of frequently cited granted Chinese patents following China's surge in investment. The government was incentivized to spur genuine development and innovation for their own economic benefit, especially given that they could no longer reliably depend on licensing and acquiring foreign technology.

Using this theoretical framework, we hypothesize that transaction costs had significantly more impact on Chinese innovation than knowledge diffusion: The U.S. government's restrictions that limited China's access to American technology sparked internal change and the urgent need to circumnavigate challenges. Hence, China performed relatively well compared to nearby Asian regions because the Trump administration's actions incentivized China to make rather than buy inventions, reform its organizational structure, and become more nationalistic in sentiment. As a result, we posit that Chinese inventors have performed comparatively better in search distance and patent quality because of the incentives to gather information from a wider variety of sources. We further theorize that the number of U.S. patents cited by Chinese patents also increased following the shock — despite worsened relations — because of the need to cite high-quality patents, many of which are of U.S. origin.

Hypothesis 2*: Following the Trump shock, China performed comparatively better on the patent, assignee, and inventor levels, showing increases in quality of patents (measured by number of citations received), quantity of patents, and search distance relative to that of the control group, including Singapore, Japan, Taiwan, and South Korea.*

3.3 Moderating Effects: Patent Class, Inventor Network, and Location Factors

Patent class

The fields of patents vary widely, entailing varying attention and resources allocated to different fields depending on their importance. China's emphasis has been on the "technosphere": semiconductors, A.I., quantum communication and information processing, biotechnology, 5G, and more (Salitskii & Salitskaya, 2022). Although significant efforts in developing these fields of technology started in 2015 with the Made in China 2025 strategy, the actions during the Trump administration significantly contributed to greater incentives for China to become self-reliant. For example, the U.S. began technological decoupling with the trade war. The export bans on ZTE mentioned earlier served as warnings to Chinese tech companies, including Huawei, Alibaba, and Baidu (The Economist, 2018). These uncertainties contributed to increasing Chinese tech firms' transaction costs. Later, Huawei getting banned from the U.S. market during the trade war further directly undermined the possibility of licensing or buying U.S. inventions as an option.

President Xi announced, "Scientific and technological innovation has become the main battlefield of the international strategic game" (Salitskii & Salitskaya, 2022). The national strategy shifted focus onto developing these fields of technology while decoupling from previous reliance on importing technology from the U.S.

In this study, we argue that China's greater emphasis on high-tech fields such as semiconductors and 5G following political shocks contributed to better performance than other fields. Hence, we propose the following heterogeneity hypothesis:

Hypothesis 3.A*: Following the Trump shock, the quality of Chinese patents (measured by number of citations received) in fields of technology (including semiconductors and electricity) performed better relative to that of patents in other fields.*

Inventor network

Of the many factors that go into innovation, the inventor network has been stated by literature to be an integral part. Collaboration networks, usually created when inventors work or interact together, result in the facilitation of knowledge transfer and the discovery of various perspectives. For instance, Paruchuri & Awate (2017) illustrate how individuals with higher reach to others have more depth and breadth of organizational knowledge. In fact, Singh (2005) demonstrated that interpersonal networks influenced patterns of knowledge diffusion more than regional or firm boundaries. This literature suggests that prominent Chinese inventors with large collaboration networks and outreach may have been hindered less by the possible adverse effects of the Trump shock outlined in hypothesis 1 (Section 3.1) and facilitated more by the benefits of self-reliance illustrated in hypothesis 2 (Section 3.2).

In the context of utilizing patent data, the size of an inventor's network can be indicated by the number of their granted patents and whether they have U.S. coauthors, both of which are correlated with their access to broader information flows and development of relationships in the field. Hence, we propose the following hypothesis:

Hypothesis 3.B*: The impact of the Trump shock on the quality of patents by Chinese inventors (measured by the average number of citations received) was comparatively better for* *inventors with greater prominence, who had the highest numbers of granted patents and collaborated with U.S. coauthors.*

Location

Another aspect that influences innovation is the location of firms. The physical location of a firm and its nominal attribution directly determine the number of available resources and the nature of region-specific policies, with both affecting innovation.

Literature has paid much attention to agglomeration, the phenomenon of firms preferring to cluster in large cities (Carlino & Kerr, 2015). Agglomeration has resulted in a growing rural-urban disparity in China, with unequal infrastructure, employment, social welfare, and global connectivity; figures indicate that socioeconomic disparity has been growing year on year, ranking China's rural-urban income gap as one of the largest around the globe (Yao & Jiang, 2021). Research has shown that the concentrated development of urban areas has resulted in the spatial concentration of innovation because firms and startups prefer to operate in cities that host the nation's leading institutions and attract the most talent (Carlino & Kerr, 2015).

Moreover, China is also displaying a growing north-south gap. Evidence of this gap is clearly reflected in the data on differences in human resources, spending, exports, and industrial production between the North and South. The growing gap is partially a result of regional policies. While the local governments of southern regions tend to tolerate a greater variety of market entities and flexible economic policies, northern local governments tend to remain more traditional. The inequality is especially apparent in the tech industry, with the headquarters of major tech companies such as Huawei, Tencent, Alibaba, and BYD residing in southern cities. The north-south gap also has historical roots: Deng Xiaoping's Open Door policy in 1978 spurred special economic zones along southern coastal cities such as Shenzhen and Xiamen while essentially continuing practices in northern cities (Chen et al., 2003).

Hence, we hypothesize that the location of a Chinese firm — whether rural or urban and whether northern or southern — influences its response to the Trump shock. Specifically, we propose the following hypothesis:

Hypothesis 3.C*: The impact of the Trump shock on the quality of patents by Chinese firms (measured by the average number of citations received) was comparatively better for firms located in big cities and in the Southern parts of China.*

4. Method

4.1 Data and Sample

This paper's primary data source is the patent data from the United States Patent and Trademark Office (USPTO). This source was chosen because of the work of previous scholars and its clear, expansive, and transparent data. Due to USPTO's international recognition and utility, prior studies about patents and innovation have conducted their analyses using figures from the same source (Engelberg et al. 2022; Zheng and Wang 2020).

Specifically, we downloaded the data through the PatentsView website, an analysis platform created by USPTO. We chose to analyze granted patents instead of patent applications because granted patents have higher quality thresholds and more comprehensive citation data. For the type of granted patent, we chose to discard design, reissue, and plant-type patents, keeping only utility patents — as is standard in literature — because they are more accurate indicators of innovation compared to patents of other types. For instance, utility patents protect the functionality of an invention, whereas design patents protect ornamental appearance. Finally, we use the backward citations of a focal patent, which patent applicants use to cite prior art. We include both applicant-added and examiner-added citations because they are valuable indicators of knowledge flow and search behavior (Jaffe et al., 2000; Nerkar, 2003).

Our full data sample includes all patents granted between 2012 and 2022. In our primary regressions, we restrict the time frame to patents granted between 2012 and 2020 to fully capture four years before and after the Trump shock in 2016. We also implemented robustness checks that examine regression results, including years after 2020 and moving the shock from 2016 to 2017.

We conduct a differences-in-differences approach to establish causal inferences. For this analysis, we chose a control group comprised of geographically proximate East Asian countries that shared economic, political, and cultural similarities. The control group includes South Korea, Singapore, Taiwan, and Japan. The assignee locations attributed to each focal patent are used to identify the country of that patent; in other words, the firm's location identifies the country to which the patent belongs. In the end, 992,455 patents from China and the control group are identified, but this data is narrowed into a sample of 300,178 patents for regression analysis after keeping patents that have technological distance data.

4.2 Dependent Variables

Number of citations received

A patent's quality is indicated by the number of citations it receives. This measurement has been used in well-established literature (Henderson et al., 2005; Hall et al., 2005; Engelberg et al., 2022), and it makes intuitive sense. For instance, patents frequently cited by others tend to have higher economic value and visibility.

To construct this numerical indicator of patent quality, we use the full citation dataset of all countries and restrict it to patents from China and the control group, which are on the receiving end of citations. We determine the year the citation was made by the year the citing patent was granted. Simply counting and adding the number of citations received per patent would result in an issue: older patents likely have been cited more times, as they have been granted and visible for longer periods. To control for this time effect, we restrict the time interval to define the dependent variable as the number of citations received by a focal patent immediately two years after the year it was granted. For instance, if patent X was granted in 2014, we counted the number of citations received by patent X from 2014 to 2016. Similarly, patents granted in 2020 included citations from 2020 to 2022.

The ratio of U.S. patents cited to all patents

In the opposite direction, the patents cited by a focal patent are also valuable indicators of search behavior. Determining the origin of these cited patents provides meaningful insight into the extent of knowledge diffusion and communication between countries. To construct this variable, we begin by restricting the full citation dataset of all countries to focal patents from China and the control group; focal patents are the patents granted between 2016 and 2022 that cite other patents. After determining the country of the patents cited by using the location of their assignee, we construct a binary indicator of whether the location is the U.S. Moreover, we count the total number of citations made by focal patents. Then, we use the following equation to calculate the ratio of the number of cited patents of U.S. origin to the number of total cited patents:

$$Ratio_{focal\ patent\ i} = \frac{\#\ of\ U.S.origin\ patents\ cited\ by\ focal\ patent\ i}{\#\ of\ total\ patents\ cited\ by\ focal\ patent\ i}$$

Technological distance

Technological distance measures the extent to which a patent searches distant knowledge fields during the invention process. The construction of this variable is based on previous literature. Specifically, we follow in the footsteps of Zheng and Wang (2020). In order to find the knowledge distance of a specific focal patent, the overall strategy is to take the mean or aggregate of the focal patent's knowledge distance with the patents it has cited. We first find the typical knowledge distance between two CPC subclasses by constructing a cross-citation matrix using the citation data of patents granted between 2012 and 2022. Specifically, $C_t^{A \to B}$ represents the ratio of citations made from patents in subclass A to patents in subclass B, as illustrated in the equation below:

$$C_t^{A \to B} = \frac{\#\ of\ citations\ from\ patents\ in\ subclass\ A\ to\ patents\ in\ subclass\ B}{\#\ of\ total\ citations\ made\ by\ patents\ in\ subclass\ A}$$

Where t refers to a specific given year. Having this ratio, we can determine the knowledge proximity between subclasses by offsetting $C_t^{A \to B}$ with the random possibility of any patent citing patents in subclass B. In other words, C_t^B represents the proportion of citations to patents in subclass B over the total number of citations:

$$C_t^B = \frac{\#\ of\ citations\ to\ patents\ in\ subclass\ B}{\#\ of\ total\ citations\ made}$$

Hence, knowledge proximity between two subclasses in a given year t can be represented by the following:

$$Knowledge\ proximity_t^{A \to B} = C_t^{A \to B} - C_t^B$$

Since knowledge proximity is always less than 1, knowledge distance can be calculated as:

$$Knowledge\ distance_t^{A \to B} = 1 - Knowledge\ proximity_t^{A \to B}$$

Given this cross-citation matrix with the knowledge distance between two CPC subclasses, we can construct the patent-level knowledge distance by matching the focal patent and its cited patent to CPC subclasses, which derives its knowledge distance. However, since each patent can have more than one CPC subclass, we take the mean of all the possible knowledge distance values from different subclass combinations between a focal patent and its cited patent. In the equation below, α represents the set of all of the focal patent *i*'s CPC subclasses, and β represents the set of those for patent *j*.

$$Knowledge\ distance^{i \to j} = \frac{1}{\#\ of\ combinations\ between\ \alpha\ and\ \beta} \times \sum_{\substack{A \in \alpha \\ B \in \beta}} Knowledge\ distance^{\ A \to B}$$

After this step, we have one knowledge distance value between a focal patent and every patent it cites. In our main regression results, we use the mean of all the knowledge distances of a focal patent and the natural log of this mean to minimize skewness. The set S contains all the patent *js* that the focal patent cites.

$$Technological\ distance\ mean_i = \frac{1}{\#\ of\ citing\ patents\ in\ set\ S} \times \sum\nolimits_{j \in S} Knowledge\ distance^{\ i \to j}$$

We also implement robustness checks by running the same regression on the sum of the variables without a natural log.

$$Technological\ distance\ sum_i = \sum\nolimits_{j \in S} Knowledge\ distance^{\ i \to j}$$

Cognitive distance

Cognitive distance measures the extent to which inventors avoided the local search trap to search for prior art and knowledge with low visibility. Building on work from Zheng and Wang (2020), we construct this variable through two measures: temporal visibility and assignee visibility.

Temporal visibility indicates how recent the cited patent *j* is. We first take the difference between the last year the patent *j* was cited and the year when the focal patent *i* made the citation. This value would be more positive for a more recent and prominent patent *j*. For example, a patent *j* that was cited by patent *i* in 2016 but also most recently cited in 2023 would have a visibility of 7, whereas if the same patent was most recently cited in 2020, it would have a visibility of 4. Hence, the visibility is calculated as:

$$Temporal\ visibility_{j\ for\ i} = year_{patent\ j\ was\ most\ recently\ cited} - year_{\ patent\ i\ cited\ patent\ j}$$

Assignee visibility measured the prominence of an assignee. Specifically, it measured the prominence of patent *j*'s assignee in patent *j*'s field based on its ranking in the number of granted patents in the field from 2012 to 2022. To deal with the fact that a patent could have more than one CPC subclass, we constructed the visibility as the maximum ranking of an assignee in any of their fields because they would likely be most known for that.

Subsequently, we calculated cognitive distance by first standardizing and aggregating temporal and assignee visibility. Then, we took the reciprocal of the sum so that larger visibilities would correspond with smaller distances. Once we had the measure of cognitive distance for each focal patent and its cited patent *j*'s, we aggregated the cognitive distances across the cited patent *j*'s in set S for each focal patent, as shown in the following equation:

$$Cognitive\ distance_i = \sum\nolimits_{j \in S} \frac{1}{Temporal\ visibility_j + Assignee\ visibility_j}$$

4.3 Independent Variables

The independent variables in this study include *China*, an indicator of whether the firm is located in China, and the *Trump shock*, an indicator of whether the year is post-2016 (in robustness checks, we change this post to 2017 to reinforce the causation effect).

4.4 Moderators (Heterogeneity)

Patent class

Results in the dependent variable can vary significantly depending on the Cooperative Patent Classification (CPC) patent class, a system jointly developed by the European Patent Office (EPO) and USPTO. The CPC class system categorizes patents into eight distinct classes ranging from class A to class H. Specifically, class H best represents the "technosphere" mentioned in section 3.3; class H includes semiconductors, electric elements, electric communication, and electronic circuitry.

On the official USPTO database, each patent on the data is attributed to one or more CPC classes, as there is possibility for overlap. We determine the primary CPC class of a patent by choosing the one that goes first in the CPC sequence, which ranks CPC classes of a patent by their relevance to the patent.

Inventor network

This moderating variable captures the size of the network of inventors. It is composed of two parts: first, whether the inventor is in the top 95^{th} percentile for creating patents; and second, whether the inventor has a U.S. coauthor.

In constructing the former, we ranked inventors based on the number of granted patents they produced from 2012-2022, marking them with the indicator if they had produced a number in the top 95^{th} percentile of all inventors.

We determined whether the inventor has a U.S. coauthor by matching the inventors of a patent to their inventor I.D. and location. We use a binary indicator for inventors in the treatment and control group that do have a U.S. coauthor.

Location

We construct two indicators for the location of a patent, in addition to its country: whether it is in northern China or a big city.

First, we asked ChatGPT for a list of major cities in the treatment and control groups. This allowed for a binary indicator of whether a focal patent's location is a big city.

Secondly, for the treatment group, China, we use the coordinates of the location of the firm to determine whether its location is in northern or southern China. In this study, we follow the consensus that the Qin-Huai line, roughly the 33rd parallel, is the geographical demarcation between northern and southern China. This definition classifies Beijing and Tianjin as northern cities and Shanghai and Shenzhen as southern cities.

4.5 Control Variables

The control variables used vary depending on the regression. For the four primary dependent variables, we control for the inventor number of patents per year, assignee number of patents per year, inventor number of U.S. coauthors, whether the inventor is in the top 95th percentile, and whether the location is a big city. Controlling for northern and southern cities is omitted, as this indicator only applies to patents in the treatment group, China.

4.6 Differences-in-differences Regression

Given the dependent variables, independent variables, moderators, and control variables described above, we use the following equation for regression analysis:

$$Y_{it} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i Post_t + controls + \varepsilon_{it}$$

In the equation, i refers to the firm (assignee), individual inventor, or focal patent; t refers to the year; Y indicates the dependent variable; $Treat$ refers to the treatment group, China; $Post$ refers to the post-election indicator (whether the year is past 2016); $controls$ include the control variables outlined in Section 4.5; and ε_{it} indicates the error.

We chose the control group of Singapore, Japan, Taiwan, and South Korea by matching China with geographically proximate regions that were the most economically and culturally similar. Innovative activity in these regions was substantially more similar to China compared to European nations or the U.S.

5. Results

5.1 Main Results

Table 1 Summary statistics and T-tests in overall sample

	Mean		Difference	S.E.	N
	Non-China	China			
Ln (mean of technological distance)	-0.133	-0.107	-0.026***	0.000	300178
Cognitive distance (standardized)	-28.607	-16.063	-12.544	16.169	273417
Inventor number of patents per year	7.091	6.086	1.005***	0.059	288001
Inventor number of U.S. coauthors	3.684	10.629	-6.946***	0.077	288001
Assignee number of patents per year	2725.456	483.474	2241.982***	13.084	300178
Total number of patents cited	7.149	5.982	1.168***	0.071	300178
Number of U.S. patents cited	2.869	2.504	0.365***	0.038	300178
Ratio of U.S. to all patents cited	0.380	0.423	-0.043***	0.002	300178
Number of citations received per patent	0.451	0.355	0.096***	0.008	300178

*** $p < .001$

The table above illustrates the summary statistics and t-tests in the sample. With these results, we recognize that though China and the countries in the control group are geographically proximate and share many cultural, political, and economic similarities, this is not a perfect control group. Nonetheless, many other papers have used this practice (Zheng & Wang, 2020), and the relative differences between the treatment and control group picked are less than if a different group of countries was picked for the control group.

Table 2 Assignee and inventor level results

VARIABLES	(1) **Assignee** Number of patents	(2) Number of citations received per patent	(3) **Inventor** Number of patents	(4) Number of citations received per patent
Treatment (1 = China)	-0.583	-0.119	0.213***	-0.147***
	(4.184)	(0.158)	(0.0335)	(0.0316)
Post (1 = after 2016)	-1.650***	-0.244***	-0.0620***	-0.305***
	(0.561)	(0.0212)	(0.00625)	(0.00588)
Treatment X Post	10.73***	0.0249	0.370***	0.0600***
	(1.354)	(0.0511)	(0.0240)	(0.0225)
Constant	16.22***	0.504***	1.738***	0.559***

VARIABLES	(1) **Assignee** Number of patents	(2) Number of citations received per patent	(3) **Inventor** Number of patents	(4) Number of citations received per patent
	(1.148)	(0.0433)	(0.00549)	(0.00516)
Observations	56,489	56,489	478,275	478,275
R-squared	0.935	0.418	0.638	0.329

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The table above features the first two columns at the assignee (firm) level and columns 3 and 4 at the inventor level. At each level, the dependent variables include the number of patents and the average number of citations received per patent, which measure the quantity and quality of patents, respectively. The assignee level demonstrates that patent-owning organizations based in China versus nearby regions were not statistically significantly different before the Trump shock. The coefficient before post is negative for both, reflecting Trump's impacts on the rest of the world in terms of quantity and quality of patents. The statistically significant interaction term is 10.73 for the number of patents, which, given the sample's mean of 15.2, indicates that Chinese assignees increased the production of patents by 70.5% relative to assignees of nearby regions (Singapore, Japan, Taiwan, and South Korea) after the Trump shock.

At the inventor level, the number of citations received per patent increased by approximately 17.7% (given its sample mean of 0.34) for patents with Chinese inventors relative to the control group. At the same time, the number of patents from Chinese inventors increased by 0.370 relative to the control group after the Trump shock.

These results fit in line with hypothesis 2: China’s organizations became increasingly self-reliant after the Trump shock. While nearby regions such as Singapore, Japan, Taiwan, and South Korea were also affected by the shock, they had weaker incentives to become self-reliant because they could still rely on buying U.S. inventions with relatively low transaction costs.

Table 3 Effects of the Trump shock on dependent variables

VARIABLES	(1) Number of citations received	(2) Ratio of U.S. patents cited to all patents	(3) Mean technological distance	(4) Cognitive distance
Treatment (1 = China)	-0.106***	-0.0156***	0.00426***	29.34
	(0.0146)	(0.00299)	(0.000695)	(35.70)
Post (1 = after 2016)	-0.171***	-0.00506***	0.00469***	-37.67*
	(0.00514)	(0.00163)	(0.000379)	(19.26)
Treatment X Post	0.0680***	0.0251***	0.00714***	2.457
	(0.0175)	(0.00363)	(0.000843)	(43.53)
Inventor number of patents per year	0.00396***	-0.00118***	-0.000358***	-3.284***
	(0.000110)	(6.39e-05)	(1.48e-05)	(0.739)
Assignee number of patents per year	5.19e-06***	-4.53e-06***	1.57e-06***	-0.00938***
	(1.17e-06)	(2.71e-07)	(6.29e-08)	(0.00318)
Big city	-0.0154***	-0.0116***	0.00628***	5.497
	(0.00567)	(0.00170)	(0.000396)	(20.27)
Inventor number of U.S. coauthors	0.000571***	0.000894***	1.51e-05	-4.948***
	(0.000197)	(4.28e-05)	(9.93e-06)	(0.503)
Inventor top 95th percentile	0.135***	-0.0248***	-0.00218***	15.34
	(0.00520)	(0.00163)	(0.000378)	(19.19)
Constant	0.509***	0.420***	-0.137***	46.26**
	(0.00492)	(0.00169)	(0.000392)	(19.98)
Observations	691,998	229,170	227,961	210,351
R-squared	0.016	0.096	0.440	0.006

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The first column displays the effects of the Trump shock on the number of citations received per patent, which measures the quality of patents. The regression results show that before the Trump shock, the treatment group on average received 0.106 fewer citations per patent than those of the control group. This coefficient is statistically significant. Given that the mean number of citations per patent for the sample is 0.38, 0.106 number of citations is around 27.7% fewer citations than that of the control group. This result is consistent with the common perception that Chinese patents were historically lower quality than their East-Asian counterparts. As expected, the coefficient before the post illustrates how the control group decreased somewhat in response to the Trump shock, which indicates that the election and presidency of Trump affected the rest of the world. After the Trump shock, the average number of citations received per patent in China was 0.0680 higher than those received by nearby regions (including Singapore, Japan, Taiwan, and South Korea). This statistically significant change is approximately 17.8% of the mean number of citations per patent. Therefore, China's improvement in patent quality relative to comparable regions supports the hypothesis that Chinese innovators became more self-reliant and robust following the Trump shock. Because the transaction costs of relying on licensing U.S. innovation increased, firms began developing their own innovation, leading to more experience and productivity in innovation and, thereby, higher quality patents.

The second column illustrates the ratio of citations of U.S. patents made by the focal patent to the total number of citations made. The post coefficient partially supports the hypothesis of knowledge diffusion decreasing following the Trump shock, as it shows the control group’s ratio decreasing after 2016. However, the interaction term illustrates the impacts on China: knowledge diffusion may exist, but it is not a main driver. China began to catch up with comparable regions by taking full advantage of existing knowledge. This conjecture is supported by China’s relative increase in the ratio of U.S. patents cited; the U.S. is a leader in innovation, so taking full advantage of knowledge would entail citing more U.S. patents.

Similarly, the effect of the Trump shock on technological distance is shown in the third column. After the Trump shock, the control group somewhat increased in distance, yet China began displaying 5.4% larger technological distance (given its sample mean of 0.13) compared to nearby regions. This similarly reaffirms China’s heightened propensity to internalize the innovation process following the Trump shock due to higher transaction costs of outsourcing.

Lastly, the fourth column shows cognitive distance. While the interaction term is not statistically significant, it is positive, providing evidence to support the hypothesis that Chinese firms became independently stronger innovators. The results indicate that there is a chance that Chinese firms increased their cognitive distance by 8.6% (given its sample mean of 28.6) compared to nearby regions. Recent literature has discussed make it or buy it, and these results overall reflect that China, compared to the control group, was incentivized to invest drastically more in its internal innovation rather than rely on foreign technology.

5.2 Heterogeneity Analysis

Table 4 Patent class moderating effect on the quality of patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Class A	Class B	Class C	Class D	Class E	Class F	Class G	Class H
Treatment (1 = China)	-0.0550	-0.0538	-0.218***	-0.155	-0.171*	0.229***	-0.101***	-0.130***
	(0.133)	(0.0539)	(0.0281)	(0.175)	(0.0884)	(0.0579)	(0.0248)	(0.0214)
Post (1 = after 2016)	-0.0117	-0.196***	-0.0906***	-0.169***	-0.362***	-0.169***	-0.123***	-0.226***
	(0.0484)	(0.0150)	(0.0110)	(0.0479)	(0.0427)	(0.0182)	(0.00830)	(0.00802)
Treatment X Post	0.290*	0.161**	0.0866**	0.575***	0.185*	-0.0528	-0.0119	0.0864***
	(0.155)	(0.0651)	(0.0352)	(0.205)	(0.106)	(0.0713)	(0.0289)	(0.0259)
Inventor number of patents per year	0.0125***	0.00243**	0.000273	0.0135**	0.00743	0.00813***	0.00261***	0.00412***
	(0.00411)	(0.00111)	(0.000485)	(0.00556)	(0.00597)	(0.00118)	(0.000251)	(0.000124)
Assignee number of patents per year	-8.46e-06	5.96e-06	-4.14e-06	-1.47e-05	-6.51e-05**	5.10e-06	2.98e-06*	7.18e-06***
	(1.53e-05)	(6.12e-06)	(3.70e-06)	(1.47e-05)	(2.90e-05)	(7.47e-06)	(1.73e-06)	(1.63e-06)
Big city	-0.0825	-0.0661***	-0.0279**	-0.0381	-0.0571	0.0660***	-0.0407***	0.0112
	(0.0510)	(0.0180)	(0.0108)	(0.0643)	(0.0425)	(0.0194)	(0.00949)	(0.00872)
Inventor number of U.S. coauthors	-0.000650	-0.000609	0.00415***	-0.00446**	-0.00328	0.000856	0.000735**	0.000391
	(0.00217)	(0.000819)	(0.000466)	(0.00213)	(0.00224)	(0.00118)	(0.000303)	(0.000279)
Inventor top 95th percentile	0.00228	0.110***	0.127***	0.120**	0.0704	0.0891***	0.148***	0.153***
	(0.0561)	(0.0166)	(0.0120)	(0.0588)	(0.0542)	(0.0201)	(0.00832)	(0.00797)
Constant	0.532***	0.575***	0.310***	0.469***	0.846***	0.479***	0.483***	0.534***
	(0.0454)	(0.0141)	(0.00964)	(0.0617)	(0.0401)	(0.0169)	(0.00784)	(0.00801)
Observations	31,437	74,335	43,374	2,909	4,165	36,974	209,525	289,279

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Class A	Class B	Class C	Class D	Class E	Class F	Class G	Class H
R-squared	0.019	0.020	0.016	0.049	0.065	0.021	0.010	0.015

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4 displays the specific results of difference-in-difference analysis for eight possible CPC patent classes. The numbers shown indicate the number of citations received per patent, an indicator that models the quality of the patent. The interaction term row illustrates that class D and H are the two statistically significant patent classes among the eight. Class D only has 2,909 patents, making it of little economic significance. On the other hand, class H is especially intriguing, as the CPC class includes fields such as electric communication, electric elements, information technologies, communication technologies, and semiconductor devices. Moreover, the quality of Chinese patents in class H showed an improvement of a substantial 20.3% (given its sample mean of 0.42) relative to those of Singapore, Japan, Taiwan, and South Korea. This provides support for hypothesis 3.A developed in section 3.3. It is evident that the Chinese government placed special emphasis on the electric communication and semiconductor industries because these were the industries where it faced the sharpest rise in transaction costs and uncertainty following the 2016 election.

Table 5 Inventor network moderating effect on the quality of patents

VARIABLES	(1) Not Top 95th Percentile	(2) Top 95th Percentile	(3) No U.S. Coauthor	(4) U.S. Coauthor
Treatment (1 = China)	-0.0543***	-0.187***	-0.0711***	-0.174***
	(0.0179)	(0.0250)	(0.0194)	(0.0228)
Post (1 = after 2016)	-0.151***	-0.198***	-0.159***	-0.207***
	(0.00656)	(0.00823)	(0.00588)	(0.0105)
Treatment X Post	0.00486	0.155***	0.0676***	0.0882***
	(0.0217)	(0.0292)	(0.0233)	(0.0275)
Inventor number of patents per year	0.0211***	0.00382***	0.00388***	0.00479***
	(0.00217)	(0.000117)	(0.000114)	(0.000392)
Assignee number of patents per year	7.43e-06***	2.55e-06	7.60e-06***	-3.68e-07
	(1.57e-06)	(1.77e-06)	(1.37e-06)	(2.27e-06)
Inventor number of U.S. coauthors	0.00362***	-4.36e-05		
	(0.000451)	(0.000230)		

VARIABLES	(1) Not Top 95th Percentile	(2) Top 95th Percentile	(3) No U.S. Coauthor	(4) U.S. Coauthor
Inventor top 95th percentile			0.153***	0.0662***
			(0.00620)	(0.0109)
Big city	-0.0147**	-0.0151	0.00892	-0.0780***
	(0.00713)	(0.00934)	(0.00657)	(0.0113)
Constant	0.449***	0.676***	0.475***	0.627***
	(0.00722)	(0.00781)	(0.00552)	(0.0111)
Observations	399,468	292,489	501,113	190,835
R-squared	0.010	0.022	0.017	0.015

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5 shows the impacts of the characteristics of inventors on the number of citations received by patents. The table indicates that inventors in the top 95^{th} percentile were paramount in China's relative improvement in patent quality. Top 95^{th} percentile inventors demonstrated a uniquely statistically significant 32.5% improvement in patent quality (given its sample mean of 0.48), whereas non-top 95^{th} percentile inventors did not show a significant improvement in patent quality. Moreover, columns 3 and 4 indicate that inventors with U.S. coauthors likewise demonstrated a more critical role in contributing to patent quality. Chinese inventors with U.S. coauthors improved their patent quality by19.7% (given its sample mean of 0.45), whereas those without U.S. coauthors improved their patent quality by 18.7% (given its sample mean of 0.36), resulting in a small yet noticeable difference of 1%. Given the vast literature on inventor networks, these results reinforce the importance of expansive communication and collaboration networks.

Table 6 Location moderating effect on the quality of patents

VARIABLES	(1) Not big city	(2) Big city	(3) Northern firm	(4) Southern firm
Treatment (1 = China)	-0.114***	-0.0512*	-0.180***	-0.0896***
	(0.0169)	(0.0301)	(0.0320)	(0.0162)
Post (1 = after 2016)	-0.165***	-0.187***	-0.171***	-0.171***
	(0.00614)	(0.00946)	(0.00522)	(0.00518)
Treatment X Post	0.0398**	0.139***	0.0599	0.0704***
	(0.0201)	(0.0357)	(0.0381)	(0.0194)
Inventor number of patents per year	0.00846***	0.00339***	0.00381***	0.00391***
	(0.000423)	(0.000118)	(0.000110)	(0.000111)
Assignee number of patents	2.83e-06**	7.04e-05***	5.22e-06***	6.09e-06***

VARIABLES	(1) Not big city	(2) Big city	(3) Northern firm	(4) Southern firm
per year				
	(1.21e-06)	(6.47e-06)	(1.14e-06)	(1.14e-06)
Inventor number of U.S. coauthors	0.000685***	-0.000371	0.00142***	0.000817***
	(0.000232)	(0.000380)	(0.000265)	(0.000212)
Inventor top 95th percentile	0.102***	0.135***	0.131***	0.135***
	(0.00663)	(0.00984)	(0.00549)	(0.00529)
Constant	0.505***	0.458***	0.504***	0.502***
	(0.00543)	(0.00877)	(0.00461)	(0.00454)
Observations	489,138	202,813	614,829	676,296
R-squared	0.017	0.019	0.013	0.016

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The heterogeneity of geographical location can be seen in Table 6. Columns 1 and 2 compare the regression results between patents with firms located in big cities versus those not in big cities. The interaction term illustrates how the patents with the former characteristic demonstrated more statically significant results. Furthermore, the patent quality of firms in big cities improved by 37.7% (given its sample mean of 0.38), whereas the patent quality of firms not in big cities improved by only 10.3% (given its sample mean of 0.37), overall resulting in big city firms performing better by 27.4%. This analysis provides evidence that China's rural and urban areas are growing further apart in a uniquely impactful manner.

Columns 3 and 4 compare patents with firms located in northern China versus southern China. The interaction term is more positive and uniquely statistically significant for southern firms: they produced patents of 25.1% higher quality following the shock (given its sample mean of 0.28). This performance falls in line with expectations and historical trends of northern versus southern China, illustrating southern China’s greater propensity for innovation. Taken together, columns in Table 6 affirm hypothesis 3.C, showing how regional inequality indeed played an instrumental role in determining the success of China’s responses.

5.3 Robustness Checks

Table 7 Robustness checks

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Number of citations received			Total number of U.S. patents cited	Sum technological distance
	Original	2017 shock	Extend timeline		
Treatment (1 = China)	-0.106***	-0.0891***	-0.0982***	-0.346***	-1.442***
	(0.0146)	(0.0125)	(0.0125)	(0.0149)	(0.109)
Post (1 = after 2016)	-0.171***	-0.156***	-0.321***	-0.00325	-1.123***
	(0.00514)	(0.00527)	(0.00397)	(0.00472)	(0.0558)
Treatment X Post	0.0680***	0.0484***	0.0361***	0.245***	0.274**
	(0.0175)	(0.0165)	(0.0138)	(0.0163)	(0.125)
Inventor number of patents per year	0.00396***	0.00396***	0.00365***	-0.000371***	0.0275***
	(0.000110)	(0.000110)	(8.94e-05)	(0.000106)	(0.00198)
Assignee number of patents per year	5.19e-06***	4.81e-06***	5.88e-06***	-5.41e-05***	-5.70e-05***
	(1.17e-06)	(1.17e-06)	(8.63e-07)	(1.03e-06)	(8.90e-06)
Inventor number of U.S. coauthors	0.000571***	0.000568***	0.000121	0.00386***	0.0287***
	(0.000197)	(0.000197)	(0.000135)	(0.000161)	(0.00137)
Inventor top 95th percentile	0.135***	0.133***	0.106***	-0.0970***	0.215***
	(0.00520)	(0.00520)	(0.00385)	(0.00456)	(0.0533)
Big city	-0.0154***	-0.0168***	-0.0132***	-0.106***	-0.852***
	(0.00567)	(0.00567)	(0.00413)	(0.00490)	(0.0562)
Number of total patents cited				0.478***	
				(0.000221)	
Constant	0.509***	0.483***	0.519***	0.00922*	6.311***
	(0.00492)	(0.00467)	(0.00399)	(0.00474)	(0.0590)
Observations	691,998	691,998	953,340	953,340	287,970
R-squared	0.016	0.016	0.019	0.834	0.025

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

We conducted numerous robustness checks to validate our findings. The dependent variable that measures patent quality through the number of citations received per patent is used. Columns 2 and 3 address concerns over the timeline of Trump's shock, such as having a time lag between the Trump election and his impact and the role of the COVID-19 pandemic. Columns 4 and 5 address data-oriented concerns by providing distinct ways of measuring U.S. patents cited and technological distance but ultimately providing similar regression results.

First, we analyze and compare regression results between the original time frame, changing the post to 2017, and extending the time frame to 2023. To begin with, we changed the shock indicator to 2017 to account for a possible time lag between the Trump shock and its impacts on Chinese innovation. As shown in column 2 of the table above, the interaction coefficient remains largely the same as that of column 1, the original, after changing the post to 2017. Comparing the two interaction terms, we can see that both are statistically significant and positive, indicating that both empirical methods supported hypothesis two (China becoming more self-reliant relative to comparable regions). Their comparability reflects how the political shock indeed had immediate ramifications upon the organizational decisions of Chinese firms, as well as long-term effects.

Secondly, we extend the time frame of the entire sample to include the COVID-19 pandemic, the period from 2020 to 2023. Likewise, as illustrated in column 3, the interaction term in this extended time frame remains positive and statistically significant, buttressing hypothesis two by showing how the effects of the political shock continued even years after the end of Trump's term and the start of a global pandemic. Nonetheless, the interaction and post coefficients in the extended timeframe are comparatively smaller than those of columns 1 and 2, showing how COVID-19 negatively affected the entire world's development.

Thirdly, column 4 shows the analysis of the number of U.S. patents cited in place of the ratio of U.S. patents cited dependent variable used in Table 3. After controlling for the number of all patents cited in this regression, we find that the interaction term remains similarly positive and statistically significant, demonstrating how the two indicators are largely interchangeable.

Lastly, our fourth robustness check in column 5 comprises of taking the sum of technological distance in place of the mean of technological distance used in Table 3. The sum of technological distance aggregates all the pairwise technological distances between a focal patent and the patents it has cited. This method of summing distances entails a larger distance for granted patents that made more citations, which may be slightly inaccurate in determining the authentic technological distances in patents. This slight difference is reflected in how the interaction term from this regression is slightly less statistically significant than the regression using the mean of technological distance. Hence, this study improves upon prior studies, such as Zheng and Wang (2020), by focusing on the mean of technological distance, which may be a more accurate measure of actual search distance.

6. Discussion

Though the vast majority of the literature has traditionally focused on internal characteristics of a country that affect its innovative capacity, it is now becoming apparent that political actions — even those across the world — can affect a country's innovation. The central question of this study concerns how the election and administration of Trump affected innovation in China. The Trump shock has sparked significant debates in academic and non-academic worlds. There are two major perspectives regarding how politics can affect innovation. The perspective of knowledge diffusion argues that Trump's actions hurt Chinese innovation by limiting communication, collaboration, and labor mobility (Kim & Marschke, 2005; Møen, 2005; Atkin et al., 2022; Aghion et al., 2023; Jia et al., 2023). In contrast, the transaction cost perspective argues that Trump gave a chance for China to decrease its reliance on U.S. innovation by raising the cost of pursuing external acquisition (Arora et al., 2004; Choung & Koo, 2023; Edamura et al., 2014; Salitskii & Salitskaya, 2022). We develop both frameworks by acknowledging that the central question of this debate is not about which perspective is correct but rather the extent to which either perspective has occurred in the real world.

Through our empirical analysis and regression results, we find that inventors and firms in China experienced relative increases in patent quality, quantity, and search distance following the Trump shock. These results support the transaction cost hypothesis being the more dominant one. Furthermore, our results demonstrate that the impacts of the shock are heterogeneous. Innovative capacity, measured by patent quality, was comparatively higher for fields related to electricity and semiconductors, supporting the hypothesis that China seized the opportunity to catch up in the technosphere. In addition, we found that inventors with more extensive collaboration networks were the frontrunners for China's improved performance. Lastly, our heterogeneity results reaffirm the geographical inequality between northern and southern China, as well as rural and urban areas; firms in big cities and southern China demonstrated better performance following the shock.

Our paper makes several contributions to literature. First, we add to the overall framework of innovation by examining evidence of external political shocks. We overcome obstacles to collecting empirical data by using the USPTO dataset to examine the Trump administration following Trump's election victory as a natural experiment.

Secondly, we add nuance to the literature on knowledge diffusion. On the one hand, our results demonstrate that knowledge diffusion is still a critical part of innovation: following the shock, the countries in the control group were negatively impacted due to limitations in communication, collaboration, and talent mobility. The heterogeneity results also reinforce previous findings that diversified teams perform better (Fos et al., 2021), as we found that Chinese inventors working with U.S. coauthors tended to produce higher-quality patents following the election of Trump. On the other hand, our study shows that knowledge diffusion may only be one part of the larger picture when considering the impacts of political actions on innovation. The differences-in-differences regression results show that attempts at self-reliance in response to sufficient incentives outweighed possible limitations and restrictions in communication and collaboration between international inventors.

Thirdly, we add to transaction cost economics by illustrating how transaction costs are expanding to apply to innovation in the 21st century (Arora et al., 2004). China's better performance compared to Singapore, South Korea, Taiwan, and Japan illustrates that heightened transaction costs in "buying" resources from the U.S. incentivized China to pursue internal vertical integration. Some scholars have noted China's tendency to rely on U.S. technology (Choung & Koo, 2023; Aghion et al., 2023), but few have studied the shocks that catalyzed China into becoming more self-reliant. Moreover, some studies focused on China’s push for innovation, such as the Made in China 2025 plan (Hu et al., 2017; Salitskii & Salitskaya, 2022), but these papers have utilized local Chinese databases for data instead of USPTO, which is more transparent, reliable, and international. Hence, our findings indicate that China's act of catching up is being reflected on the international stage.

Our paper also provides a novel perspective to policymakers. China's unexpectedly flexible response to Trump's actions illustrates how policies aimed to ostensibly stifle competitors can have large inadvertent effects by pushing competitors to become more self-reliant and powerful instead. The results from inventor networks also demonstrate the importance of communication and collaboration, which entail the exposure of firms to new and different talent. Lastly, the heterogeneous impacts depending on the city size and location serve as cautious reminders to the government that growing inequality could impact innovation by concentrating innovation in certain agglomerated areas instead of taking advantage of the unique aspects that numerous different geographical locations can offer.

Nonetheless, there are some limitations of this study. First, we recognize that the control and treatment groups are imperfect; while the East Asian countries share a handful of similarities, many differences exist. Future studies could do sample matching to allow the control and treatment groups to better align before the shock. Second, we took the trade-off of using the internationally recognized U.S. patent base, USPTO, instead of the Chinese patent base, Chinese National Intellectual Property Administration (CNIPA). We chose not to use the Chinese patent base mainly because of logistical obstacles, such as the fact that many Chinese patents are not publicly available and existing data require significant work to clean. This decision to focus on patents from the USPTO risks capturing only a portion of the true impacts of the Trump shock, as in some rare cases, some Chinese inventors may have decided to stop filing patents in the USPTO despite the benefits of filing in a well-recognized office to expand the patent's power. There are opportunities for future studies to explore the Chinese patent base and patent data from other databases, such as the European Patent Office (EPO). Lastly, future studies could add more information about specific firm-level characteristics and related heterogeneous effects, such as firms' amount of resources available and whether firms are state-owned enterprises.

7. Conclusion

Innovation is the engine of economic growth; literature has timelessly proven this. There have been studies on the factors contributing to innovation, including knowledge diffusion and transaction cost. However, few past studies have accounted for the coexistence of these two seemingly contradictory theories, and even fewer have considered the impact of politics. This study uses recent empirical evidence to provide a new perspective on political tension and innovation. By analyzing patents from USPTO, we find that on all three levels — the patent, inventor, and firm — China has produced higher patent quality and quantity, as well as demonstrated greater search distance compared to the nearby regions of the control group, including Singapore, Japan, Taiwan, and South Korea. We also observed three trends of heterogeneity across the results:

1. Innovation efficacy depended heavily on the field of research, with semiconductors and electricity being prioritized by China;

2. Larger inventor networks led to more innovative output;

3. The geographical location of being in an urban city in southern China contributed to more valuable inventions.

These results contribute to literature regarding knowledge diffusion, transaction cost, and their coexistence. Our analysis also guides policymakers to caution about the inadvertent economic implications of political actions. The impacts of the Trump shock have been more complex than individuals may have thought; this research has again demonstrated that global politics and economies are not simply predictable pieces but instead intricate cogs in a societal machine transforming in multidimensional ways. Moving forward, more studies can focus on the growing interconnectedness between politics and innovation, the Trump shock’s long-term impacts, and China’s unforeseen responses.

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Acknowledgment

Topic Origin

As a competitive debater, I have always been keen on following the news. Though I was young when I experienced it, I would always remember the watershed election of Trump in 2016. I was instantly drawn to the deeper implications of an election upset for the U.S. and the rest of the world. I was also never a student who conformed to rigid boundaries and subjects. In this case, I believed in transcending the divisions between politics and economics to examine the impacts of foreign political policies on the heart of China's economy: innovation. My interest furthered when I discovered controversial debates among academia regarding the benefits and drawbacks of Trump's policies on the China’s economy.

Research Background

It has been well-established that innovation is crucial to economic growth, and numerous inputs affect innovation, including politics. The Trump shock welcomed a host of changes, including immigration restrictions, the trade war, and unprecedented actions restricting Chinese firms and researchers from U.S. technology. From a cursory first glimpse, these actions seemed to hamper Chinese innovation by limiting China's access to resources. However, closer scrutiny of Trump's impacts revealed a dilemma: knowledge diffusion suggests that Chinese innovation was hurt, whereas transaction cost economics proposes that China improved its internal innovative output. This disagreement was an interesting source of curiosity and warranted further investigation.

Research Process

I began the research process by reviewing the most well-recognized academic literature on politics and innovation. From these readings, I familiarized myself with the typical kinds of methodology, jargon, and data sources utilized. After extensive reading and guidance from Dr. Lang, I gained a better understanding of the knowledge diffusion framework and transaction cost economics, as well as the context of the Trump election and the Trump administration's specific subsequent actions.

Following this, I drew inspiration from similar well-recognized academic papers studying innovation. After brainstorming, Dr. Lang and I decided on a differences-in-differences regression model with the control group as nearby regions similar to China, including Singapore, Japan, Taiwan, and South Korea. Next, I downloaded patent data from PatentsView, the official website of the United States Patent and Trademark Office. With assistance from Dr. Lang, I began re-applying my previously learned C++ coding language experience to Stata. I accomplished the tasks of data cleaning, constructing dependent variables, and model construction. Although I met various logistical challenges along the way, Dr. Lang taught me the necessary skills in cleaning and constructing variables from data specific to our situation.

At the same time, I dived into literature exploring the possibilities of heterogeneity across characteristics of inventors and geographic locations. Following these discoveries, I constructed control variables and moderators. With help from Dr. Lang, I established robustness checks for the regression analysis, learned to export the tables, and received guidance on proper economic research conventions.

Lastly, I wish to thank Dr. Lang for his support. All errors are mine. I express my gratitude to the S.T. Yau Science Award committee for this unforgettable experience of research offered to high schoolers.