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RESEARCH ARTICLE

Shadow of the great firewall: The impact of Google blockade on innovation in China

Yanfeng Zheng | **Qinyu (Ryan) Wang**

Faculty of Business and Economics, University of Hong Kong, Pokfulam, Hong Kong

Correspondence
Yanfeng Zheng, Faculty of Business and Economics, University of Hong Kong, Pokfulam, Hong Kong.
Email: yz2010@hku.hk

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Abstract

Research summary: Building on the search-based view of innovation, we develop a framework regarding how Google guides innovative search behavior. We exploit an exogenous shock, China's unexpected blockade of Google in 2014, and adopt a difference-in-differences approach with a matched sample of patents from China and nearby regions to test our predictions. Our analyses show that the blockade negatively affected inventors in China to search distantly in technological and cognitive spaces compared to those in the control group who were presumably unaffected by the event. The impact was less severe for inventors with larger collaboration networks but became more pronounced in technological fields proximate to science. Our findings contribute to innovative search literature and highlight the theoretical and practical importance of Internet technologies in developing valuable inventions.

Managerial summary: Inventors nowadays depend heavily on Internet search to access information and knowledge. They therefore become vulnerable to barriers imposed on their online search. In this study, we find that China's unexpected blockade of Google and its affiliated services altered the searching behavior of inventors in China such that they became less able to seek distant knowledge. This impact was further contingent on the availability of offline knowledge channels and the reliance of each technological field on science. We also find that the economic value of their inventions decreased due to the blockade. Our findings reveal a neglected but consequential aspect of Internet censorship beyond the commonly found media effect and offer important implications to practitioners and policymakers.

KEYWORDS

Google, innovation, recombinant search, distant search, Internet censorship

1 | INTRODUCTION

On June 1, 2014, millions of Internet users in China were suddenly unable to access Google, the world's leading search engine. Any visit from China to the search engine or its affiliated services resulted in a domain error. Although it was speculated as only a temporary one, the blockade has lasted more than 5 years and continues today (Google, 2019). While some expect that it perhaps impacted only public opinions because direct access to scientific and technological information through specific websites or databases remained unaffected, others speculate that such an event could be consequential for innovation since Google was once widely used by scientists and researchers in China to seek business information and scientific knowledge (Qiu, 2010).

From a conceptual perspective, prior studies largely view the Internet and related technologies as tools that reduce the cost of information access or interpersonal coordination (Ding, Levin, Stephan, & Winkler, 2010). Such a conceptualization, however, cannot adequately explain why the loss of Google mattered so much since the knowledge contents were still available online and all coordination tools such as video calls remained intact or even improved. For example, our analyses reveal that the economic value of inventions from China dropped by around 8% or USD57K after the event compared to those from nearby unaffected regions. Together, it is conceptually intriguing and practically meaningful to examine why and how the unexpected blockade of Google in China affected the knowledge seeking behavior of inventors in China and their innovative outcome.

Building on the insights gathered from the search-based view of innovation and cognitive psychology studies on the Internet, we develop a conceptual framework of Google-enabled online search. We contend that Google and its affiliated services both extend human memory and enhance the ability of inventors to access, digest, and assimilate unfamiliar and unnoticeable knowledge. It therefore helps inventors to overcome the local search tendency, extending their search distance in technological and cognitive spaces. We further argue that this online knowledge channel and traditional offline channels such as inventor collaboration networks are substitutes, such that offline channels can compensate for the unavailability of Google. In addition, the effect of online search becomes more pronounced in technological fields that are proximate to science since Google-enabled search is particularly helpful for inventors to seek and apply scientific knowledge to guide their distant search in these fields.

Exploiting China's unexpected blockade of Google in 2014, we test our predictions using patents as innovation outcomes with a difference-in-differences (DiD) approach. We also match patents from inventors in China with those from a control group of inventors in Japan, South Korea, Taiwan, Hong Kong, and Singapore using coarsened exact matching (CEM) to strengthen causal inferences. Our analyses reveal that inventors in China experienced significant decreases in both technological and cognitive search distances after the blockade. The negative impact was less severe for those inventors with larger collaboration networks but became more pronounced in science-proximate fields, consistent with our conceptual framework. Overall, we show that Google and its affiliated services subtly assist inventors in knowledge seeking beyond a mere cost reduction effect.

Our paper makes several contributions. First, we contribute to the search-based view of innovation by elaborating on the role of advanced search tools such as Google. Unlike previous studies that proposed a positive impact of the Internet from the perspective of information access and cost reduction (Ding et al., 2010), we show that Internet tools and technologies can have a more nuanced impact on inventors' behavior. Theorizing two major functions of Google-enabled online search—a gigantic knowledge indexing and an intelligent knowledge retrieval system, we find that this online channel enables inventors to search for more distant and unnoticeable knowledge. By revealing the importance of Internet technologies for distant search and its boundary conditions, our study thus connects and contributes to the literature that mainly focused on offline solutions to mitigate the local search trap (Rosenkopf & Almeida, 2003; Singh & Fleming, 2010).

Second, this study also contributes to the broader knowledge production literature. Indeed, this literature has recognized the importance of developing knowledge systems enabled by modern information technologies or the importance of accessing the Internet. For example, a few studies used small-scale surveys to examine the performance benefits of implementing corporate knowledge management systems (Gray, Parise, & Iyer, 2011; Kim, Mukhopadhyay, & Kraut, 2016). This strand of work nevertheless suffered from endogeneity or reverse causality concerns since building a knowledge management system is often not an exogenous decision but confounds with factors such as employees' innovative performance. Exploiting a nearly perfect exogenous shock, our study thus contributes to this dialogue by providing a more rigorous design and hence stronger causal inferences.

Third, our study enriches the literature on Internet censorship with unique policy implications. For a fast-growing country like China, blocking Google, the world's leading search engine, helps its regime to influence the beliefs and attitudes of its residents (Chen & Yang, 2019), but such extreme Internet censorship may backfire on its another ambition to achieve global leadership in technology and innovation. We show with compelling evidence that blocking Google had real economic consequences beyond mere media effects. The blockade hampered distant search for inventors and systematically weakened the innovation capacity that China is striving to cultivate. The dual effect on media control and innovation therefore calls for practitioners to deal with the impact and for policymakers to carefully and holistically examine their Internet policies.

2 | THE BLOCKADE OF GOOGLE

Google's formal operations in China began in 2006. Leveraging its extensive webpage coverage, advanced algorithms, and rich operation experience, Google expanded rapidly and became widely used by scientists and inventors in China to access business information and scientific knowledge (Qiu, 2010). In 2010, Google ceased operating in China because it refused to accept the censorship intervention from the Chinese government. However, inventors in China were still able to access Google since the company redirected all search requests from China to its Hong Kong site (Tan & Tan, 2012). Google then experienced two temporary blockades in 2012, both of which lasted only a few hours. This situation continued until June 1, 2014 when all direct visits from China to Google services worldwide were suddenly blocked (Google, 2019). The blockade came with no prior notice, and no reasonable explanation was ever given regarding how exactly this decision was made. It was particularly surprising because Google had formally exited the China market 4 years ago and made no further confrontation since then. Although at the time it was speculated that this blockade would again be temporary, it has lasted more than 5 years and remains in force as of today.

Google is one of the most advanced and integrated online search tools. It handles more than 90% of search requests worldwide and covers content in over 100 languages. Its market leadership rests squarely on its competence in several upstream technologies such as webpage crawling, language processing, information indexing, data storage, and information retrieval. The company has over 11,000 US patents on information storage and retrieval, 50% more than Microsoft, which owns the second largest search engine, Bing. Such patents are extremely important for search engines and illustrate Google's technological dominance. Along with its core search engine, Google also developed supplementary services such as Google Patents, Google Translate, and Google Scholar, which are valuable for professionals or inventors to access high-quality technological and scientific knowledge.

Google can be conceptualized as a map encompassing the metaknowledge of “where to find what” for Internet users (Sparrow, Liu, & Wegner, 2011). On the one hand, it continuously stores and updates directories and indexes to a gigantic volume of knowledge contents, and therefore functions as an external transactive memory for its users. On the other hand, its relevancy and ranking algorithms, building on technologies such as natural language processing and neural networks, enable even nonexpert users to query these contents in an easy and efficient way. In this regard, Google is also an intelligent knowledge retrieval system. The combination of these two functions equips its users with the metaknowledge, or a higher-order map, of the Internet.

The importance of Google in China, particularly for knowledge workers, was evident. In a 2010 *Nature* survey of approximately 800 scientists in China, virtually all responded that they depended on Google to search for academic papers and the latest news. Eighty percent of respondents believed that losing Google would “somewhat or significantly” hamper their research (Qiu, 2010). In addition, an annual survey by the European Union Chamber of Commerce in China found that 31% of corporate respondents were unable to properly seek information and engage in R&D due to China's Internet censorship (European business in China: Business confidence survey, 2018). Our interviews with engineers and scientists from leading technology firms and research universities in China also suggested that Google was indeed the major portal for them to seek both industry news and domain-specific knowledge whenever it was available.

All the evidence above suggests that blocking Google may cause a substantial disruption for researchers and inventors in China. We consider this exogenous shock as a golden opportunity to examine the role of Google-enabled online search in facilitating innovation. In the next section, we develop a conceptual framework regarding online search vis Google and formally hypothesize how the blockade of Google affects innovation in China.

3 | HYPOTHESES DEVELOPMENT

Innovation is cumulative and its development requires intense search over existing knowledge within one discipline or across disciplines (Dosi & Nelson, 2010). The search-based view of innovation thus regards search as the key determinant of innovation outcomes (Fleming, 2001; Katila & Ahuja, 2002; Nelson & Winter, 1982). One notable feature of search, however, is the localization tendency well documented in the literature (Fleming, 2001; Stuart & Podolny, 1996). It refers to the observation that firms and individuals tend to search around their existing expertise or prominent knowledge elements, leading to a path-dependent innovation trajectory. At the firm level, this tendency is rooted in the rigidity of organizational routines and structures (Leonard-Barton, 1992). At the individual level, the prevalence of local search is mainly due to limited attention and bounded rationality (Arts & Fleming, 2018). Although local search has the advantage of efficiency, scholars agree that both firms and individuals need to increase their search distance to avoid the "local search trap" (Laursen, 2012; Wagner, Hoisl, & Thoma, 2014).

Given the importance of distant knowledge, prior studies have examined solutions to overcome the local search tendency. The majority of those solutions concentrated on firm-level strategies such as interfirm alliances and employee hiring (Jain, 2016; Rosenkopf & Almeida, 2003; Tzabbar, 2009). They paid insufficient attention to how individuals extend their search distance with some exceptions. For example, some scholars have examined how individuals can extend search distance and recombine new knowledge elements via social ties (McFadyen, Semadeni, & Cannella Jr, 2009; Singh & Fleming, 2010). Other scholars have proposed that scientific knowledge can serve as a valuable guide or "map" for inventors to establish connections between distant knowledge elements (Arts & Fleming, 2018; Fleming & Sorenson, 2004). Despite these offline solutions, the literature has largely neglected the impact of modern Internet technologies on innovative search, a topic becoming imperative given that knowledge workers are increasingly reliant on online channels such as Google to seek and digest knowledge.

Psychology research has documented how the Internet and Google affect human behavior by influencing memory and cognition processes. The Internet as a knowledge repository serves as an external transactive memory for individuals (Sparrow et al., 2011), while Google creates and maintains directories for this gigantic collection of contents. With Google, people have lower rates recalling the information itself but higher rates recalling where to access it. The Internet and Google together offload information from human memory to external data storage facilities, which in turn prevents memory distortions (Ward, 2013). In addition to the role of transactive memory, Google also functions as an intelligent enabler of knowledge retrieval. It has iteratively encoded search heuristics from knowledgeable users through technologies such as natural language processing and neural networks. It enables users to retrieve knowledge with sufficient depth and breadth using simple queries, which reduces the need for specific expertise (Jansen & Spink, 2006). Overall, Google-enabled online search can substantially change how knowledge is remembered and retrieved.

Building on the search-based view of innovation and psychological studies about the Internet, we posit that Google helps inventors to overcome the tendency to focus on familiar and visible knowledge elements by increasing their search distance both technologically and cognitively. Consequently, we predict that the unexpected blocking of Google affects inventors in China by reducing their search distance.

4 | TECHNOLOGICAL DISTANCE

Technological distance refers to the extent of search among distant disciplines and technological fields. The benefits of seeking knowledge from distant fields have been recognized in the literature. Exploring technologically distant knowledge leads to psychological refreshment and new combinatory opportunities. Technologically distant search is often explorative in nature and stimulates the serendipitous arrival of novel ideas rather than incremental improvements. It therefore increases the likelihood of developing breakthrough innovation (Arts & Fleming, 2018).

The lack of prior experience and heuristics in technologically distant search can, however, lead to two problems that obstruct inventors' pursuit of distant knowledge. First, the huge volume of existing knowledge creates information overload and makes identification of relevant information challenging, especially for knowledge distant from one's expertise (Eppler & Mengis, 2004). When information overload occurs, distant search usually fails and ends up with a narrow focus on familiar elements (Piezunka & Dahlander, 2015). Second, technological distance reduces the usefulness of one's absorptive capacity and increases the difficulty of knowledge interpretation and recombination (Cohen & Levinthal, 1990). Distant fields usually include many knowledge elements that are new to one's knowledge network. The lack of mental linkages between existing and new knowledge elements causes difficulties in assimilating distant knowledge (Bower & Hilgard, 1981).

Search through Google can mitigate these problems. First, the well-trained algorithms in Google's quality search engine encode search heuristics of experienced users through the iterative analyses of their past search logs, real clicks, and the relational structure of webpages that store useful and relevant knowledge. These algorithms simplify user queries for knowledge retrieval and lower the prerequisite of expertise. Therefore, inventors can use these tools to explore and identify important information from distant fields in which they have less expertise. Second, search through Google usually yields rich contextual information such as forum discussions (e.g., Stack Overflow) or videos (e.g., YouTube). These informal knowledge sources, which often include tacit understandings of a topic, are valuable for novices to digest and assimilate distant knowledge. Such a combination of various types of knowledge sources is unusual for offline channels or specialized databases.

Given the technological dominance of Google and its irreplaceable role in facilitating knowledge identification and absorption, we expect that China's blockade of Google in 2014 would undermine the ability of inventors to carry out technologically distant search. They would often have to resort to more domain-specific sources (e.g., the Web of Science database or major patent office websites) that favor local search. Thus, we hypothesize the following:

Hypothesis (H1). *After China's unexpected blockade of Google, inventors in China experienced a decrease in technological search distance compared to inventors in unaffected regions.*

4.1 | Cognitive distance

Cognitive distance is the extent of search among knowledge that is not noticeable to inventors. Psychology research has convincingly shown that people exhibit biases when acquiring and processing information (Kahneman, Slovic, & Tversky, 1982). They disproportionately consider information and knowledge that is temporally proximate or cognitively prominent because such information is more salient in their cognitive space. In line with these arguments, studies have found that scientists and inventors are more likely to cite prior knowledge created by high-status firms or researchers (Paruchuri & Eisenman, 2012; Podolny & Stuart, 1995). Cognitively local searching eventually leads to the over-exploitation of recent and visible knowledge and the under-exploration of less visible knowledge, leaving room for cognitively distant search (Nerkar, 2003). Searching less visible knowledge can also avoid the redundancy of information and offer valuable new perspectives.

To increase cognitive distance, inventors must overcome recency and salience biases, and Google-enabled online search can be extremely useful. First, as a gigantic external transactive memory, Google enables users to greatly expand their memory capacity and access a much wider spectrum of knowledge (Sparrow et al., 2011). It offloads and shifts the information and cognitive burden from individuals to the Internet (Ward, 2013) and thus reduces the use of cognitive shortcuts that lead to biases (Reyes, Thompson, & Bower, 1980). Studies have found that doctoral students include more references and the age distribution of the references shifts toward older publications over time with the extensive use of search engines (Varshney, 2012). Second, Google also helps inventors to avoid considering only high-profile information. Although popularity is one ranking metric in Google, it is counterbalanced by many other factors such as content relevance. Using natural language processing techniques such as Google BERT, the search engine assigns a weight of relevance when making suggestions based on the similarity between user queries and webpage content. For example, researchers can easily find unpublished yet relevant working papers in Google Scholar and relevant contextual information such as presentation slides. Searching for such unnoticeable knowledge via other channels is usually challenging and unsystematic, if not entirely impossible.

In summary, given the importance of Google-enabled online search in shaping memory and assisting knowledge retrieval, we expect that the blockade of Google in China will lead to difficulties in cognitively distant search for inventors. We therefore hypothesize the following:

Hypothesis (H2). *After China's unexpected blockade of Google, inventors in China experienced a decrease in cognitive search distance compared to inventors in unaffected regions.*

Thus far, we have argued that the unexpected blockade of Google can systematically shape the search behavior of inventors in China such that they became less able to search distant knowledge in technological and cognitive spaces. The literature on innovative search has also suggested two important boundary conditions that are worth further exploration. First, social collaboration networks can also serve as transactive memories for individuals to access distant knowledge (Brandon & Hollingshead, 2004; McFadyen et al., 2009). It is thus theoretically intriguing to examine whether this offline channel substitutes or complements the online channel. Second, scholars have found that science can infuse theories into the search process for inventors (Fleming & Sorenson, 2004). Given Google's critical importance for inventors in some fields such as biotechnologies to keep abreast of scientific knowledge, exploring heterogeneities across fields in terms of their proximity to science can enrich our understanding of the intricate relationship between Google-enabled online search and innovation. Thus, we develop hypotheses regarding these two important boundary conditions derived from this literature: inventor network and proximity to science.

4.2 | Inventor network

The literature on innovative search has introduced several knowledge channels for developing innovation. At the inventor level, social collaboration networks have received the most research attention (Singh, Kryscynski, Li, & Gopal, 2016). Inventors are often socially connected with each other through joint work. Social connections facilitate knowledge transfer between inventors and allow inventors to learn about different perspectives and knowledge elements. Studies have found that occupying a central position in a network increases an inventor's innovation performance by enabling him or her to access broader information flows (Paruchuri & Awate, 2017; Perry-Smith, 2006) and learn both new knowledge elements and tacit know-how (Singh et al., 2016). Overall, this literature suggests that inventor networks are an important channel for accessing innovation-related knowledge.

In this study, we argue that social search through inventor collaboration networks and Google-enabled online search are substitutes, as a large social network can compensate for the loss of search distance caused by the blocking of Google. This substitution effect manifests in two ways. First, a large collaboration network can also function as a transactive memory for inventors to deploy (Brandon & Hollingshead, 2004). Past collaboration can help inventors to develop metaknowledge of "who knows what" (Argote, 2012), enabling them to precisely locate the right expertise and extend the effective memory capacity. Second, socialization with collaborators facilitates knowledge retrieval in a similar way to Google. Through interactive communication, a knowledgeable collaborator can help identify relevant and sometimes omitted knowledge elements from a rough description of the underlying problem and provide contextual information to facilitate absorption. Therefore, an inventor can retrieve distant and less noticeable knowledge through socialization, even if he or she has little expertise in a specific field or has not been aware of such knowledge. Thus, we expect that a large network can compensate for the reduction of search distance caused by the unavailability of Google. We therefore hypothesize the following:

Hypothesis (H3). *The impact of China's unexpected blockade of Google on technological and cognitive search distances was less negative for inventors with larger collaboration networks.*

4.3 | Proximity to science

Science has played an increasingly important role in developing commercial innovation (Roach & Cohen, 2013). It is conceptualized as a "map" for the underlying technological landscape (Fleming & Sorenson, 2004). A scientific approach fundamentally shapes how inventors understand technological problems and how they search for solutions. Inventors equipped with advanced scientific knowledge can increase their search distance by viewing a technological landscape as if from an oblique hyperplane (Evans, 2010), as fundamental scientific principles often cut across many seemingly unrelated technological fields and guide inventors to search for knowledge elements compatible with these principles, even by unknown creators. In contrast, those who are not able to access scientific knowledge are more likely to fall into the local search trap when navigating a rugged technological landscape (Fleming & Sorenson, 2004). In addition, scientific knowledge about the technological landscape also motivates inventors to continue searching when they face failures, and this motivation effect is particularly profound when they attempt to explore distant fields or unpopular knowledge in which failures are much more common. Overall, scientific knowledge encourages distant search and reduces the reliance on experience that is often associated with the localization bias.

Researchers in science-intensive fields nowadays are heavily reliant on Internet services such as Google Scholar when seeking scientific knowledge (Van Noorden, 2014). Such tools integrate scientific publications from various sources and often include unpublished working papers in a user-friendly way. The dissemination of scientific knowledge is thus facilitated through these online tools (Evans, 2008). Moreover, the rich and complementary sources of information rendered by a quality search engine through relevancy algorithms can offer contextual information about scientific discoveries, which is extremely useful in connecting science with practical problems. For example, a vivid YouTube video explaining the features of graphene, a breakthrough finding in material science, can significantly enhance inventors' understanding and motivate them to search novel solutions in various fields. Thus, Google-enabled online search is essential in technological fields that rely on science to search for distant knowledge elements. We expect that China's unexpected blockade of Google will lead to a greater decrease in search distance for inventions in fields closely related to science. Thus, we hypothesize the following:

Hypothesis (H4). *The impact of China's unexpected blockade of Google on technological and cognitive search distances became more negative in technological fields that are proximate to science.*

Figure 1 provides a summary of our conceptual framework.

5 | METHOD

5.1 | Data and sample

We chose the United States Patent and Trademark Office (USPTO) as our main source of data. First, the United States offers the most attractive market for inventors worldwide to obtain patent protection, and inventors from China proactively file high-quality patents in the United States to boost their competitiveness. Thus, patents granted by the USPTO to Chinese inventors provide a good representation of China's innovation capacity (Hu & Mathews, 2008). Second,

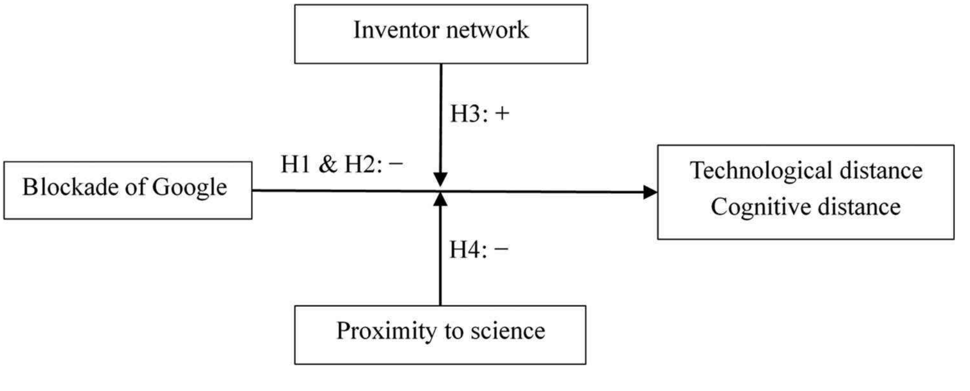

FIGURE 1 Summary of the conceptual framework

unlike China's domestic patent office or the European Patent Office, which are less strict in their demands for applicants to submit prior art, the USPTO requires applicants to include all relevant prior art or backward citations in their applications (Hall, Jaffe, & Trajtenberg, 2005). Failure to do so may result in delays in granting or rejection. This institutional feature helps us to more accurately identify inventors' search behavior, which is central to our framework. Last, the literature on innovation has extensively used patent and citation records from the USPTO when investigating topics such as knowledge diffusion (Jaffe, Trajtenberg, & Henderson, 1993; Singh & Marx, 2013). Although USPTO patent data have its weaknesses such as only partially capturing the actual knowledge flows (Roach & Cohen, 2013), researchers still use them due to their remarkable coverage, scale, and transparency.

We first obtained all patents granted by the USPTO with priority dates1 between June 1, 2013 and June 1, 2015, a two-year window surrounding the blockade event. We chose a two-year window for three reasons. First, it should not be too short because time was required for the effect of the event to be reflected in invention outputs. Second, it should not be too long to avoid confounding events. Last, our window ended on June 1, 2015 to allow sufficient time for patent applications to be granted. We extracted a total of 442,705 patents from the USPTO.

To draw reasonable causal inferences, we took a DiD approach by constructing a control group of patents filed by comparable inventors who were not affected by the event. We selected our control group from nearby East Asian regions that are culturally, economically, and geographically proximate to China. We chose patents filed by inventors in Japan, South Korea, Taiwan, Hong Kong, and Singapore as the control group. Compared to European countries or the United States, innovation activities in these countries or “regions” are more similar to those in China, and Google is the primary online search channel in these regions. We used inventor locations to identify the geographic origin of an invention (Jaffe et al., 1993). To avoid the confounding effect of international collaboration, we excluded all cross-country teams. One lakh and fifty thousand and sixty-three patents were thus identified as developed by inventors residing in China and the five control regions.

Some patent applications filed during the research window are still under examination, which could lead to the concern that patents before and after the event may have different characteristics due to truncation. Our DiD approach mitigated this to a great extent, but we further enhanced the comparability between pre- and post-event samples by focusing on only patents granted within 4.5 years after their priority dates, or the lag between June 2015 and November 2019. After applying this restriction, our sample included 117,905 observations.

We took a CEM approach to match each treatment patent with a control patent (Arts & Fleming, 2018). CEM matches samples based on *ex ante* criteria, effectively minimizing heterogeneities between the observations in the treatment and control groups and therefore strengthening causal inferences (Iacus, King, & Porro, 2012). The treatment and control patents were one-to-one matched according to the following criteria. First, we required that both patents were in the same International Patent Classification (IPC) class to ensure technological comparability. Second, their priority dates fell in the same year and quarter to control for the time effect. Third, we also matched the inventor team size with five bins (i.e. 1, 2, 3, 4, or >5) because a large team can possibly search broadly for distant knowledge. Last, we required that their assignee type was the same (i.e., individual, university, or business) because different types of

[1]Priority date is the date of the first patent application worldwide for a patent family. In our context, this date is preferred to the U.S. filing date because it better captures the timing of knowledge creation, as non-U.S. applicants usually first apply in their home patent offices before filing the same inventions with the USPTO.

TABLE 1 *T*-tests in the overall sample and the CEM-matched sample

	Mean		Difference	*SE*	Observations
	China	Non-China			
Panel A: Overall sample					
Blockade of Google	0.506	0.564	−0.058***	0.004	117,905
Business assignee	0.940	0.881	0.060***	0.002	117,905
Individual assignee	0.023	0.035	−0.012***	0.001	117,905
University assignee	0.037	0.084	−0.047***	0.002	117,905
Inventors	2.707	2.892	−0.185***	0.016	117,905
IPC subclasses	1.857	1.927	−0.070***	0.009	117,905
Total number of patents	15,567	102,338			
IPC classes covered	113	122			
Panel B: CEM-matched sample					
Blockade of Google	0.568	0.568	0.000	0.005	29,290
Business assignee	0.912	0.912	0.000	0.003	29,290
Individual assignee	0.065	0.065	0.000	0.003	29,290
University assignee	0.023	0.023	0.000	0.002	29,290
Inventors	2.787	2.830	−0.043†	0.023	29,290
IPC subclasses	1.942	1.924	0.018	0.013	29,290
Total number of patents	14,645	14,645			
IPC classes covered	98	98			

†$p < .1$, ***$p < .001$.

assignees usually exhibit different search behavior. This procedure yielded 29,290 matched patents with 14,645 in each group. Table 1 shows the key statistics of the treatment and control groups both before and after matching.

5.2 | Dependent variables

We used the backward citations of a focal patent to construct the two search distance variables. For US patents, both applicants and examiners will add backward citations to relevant prior art during the patent examination. These citations are regarded as valuable indicators of knowledge flows (Jaffe, Trajtenberg, & Fogarty, 2000) and are widely used by researchers to examine inventor search behavior (Nerkar, 2003; Paruchuri & Awate, 2017; Sorenson, Rivkin, & Fleming, 2006). Since examiner-added citations may introduce noises when tracking innovative search (Alcacer & Gittelman, 2006), we opted to construct our search distance variables using only applicant-added citations to accurately capture inventors' search behavior.

5.2.1 | Technological distance

Technological distance captures how widely one explores distant knowledge fields for an invention (Katila & Ahuja, 2002). Building on this notion, we measured this variable in two steps. First, we measured the pairwise knowledge distance between two fields by calculating the likelihood of a citation from one field to the other. Denoting knowledge fields with IPC subclasses, we followed George, Kotha, and Zheng (2008) to generate a cross-citation matrix based on patents from the past 5 years. Each matrix entry $C_t^{A \to B}$ represented the proportion of citations made by patents in subclass A to those in subclass B. For example, if 30% of all citations made by patents in subclass A pointed to patents in subclass B, the cross-citation index $C_t^{A \to B}$ was 0.3. In addition, $C_t^{A \to B}$ could differ from $C_t^{B \to A}$ because search can be unidirectional. For example, it is common for inventors in the semiconductor sector to search for knowledge concerning basic materials, but the opposite is less common. We then adjusted $C_t^{A \to B}$ by the base rate of B being cited in a random search (C_t^B) (Uzzi, Mukherjee, Stringer, & Jones, 2013). C_t^B was the proportion of citations received by patents in B among all citations. The knowledge proximity from A to B was calculated as:

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

Knowledge proximity measured how much the actual citation rate from A to B exceeded that of a random search. Knowledge distance was then one minus the knowledge proximity:

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

Second, for each citation made by the focal patent i, we calculated the citation-dyad level distance as the distance from the focal patent's field to that of the cited patent. The citation–dyad distance was then aggregated across all backward citations (Set Γ) to derive the technological search distance of the focal patent:

$$Technological\ distance_i = \sum\nolimits_{j \in \Gamma} Knowledge\ distance^{i \to j}.$$

We used the natural log of this variable to account for its skewness in actual estimations.

5.2.2 | Cognitive distance

Cognitive distance refers to the extent to which inventors searched for knowledge with low visibility. To construct this variable, we first calculated the knowledge visibility of each backward citation. Knowledge visibility refers to the prominence of a knowledge item when searched for, and it is positively associated with its temporal proximity and creator's prominence (Nerkar, 2003; Paruchuri & Eisenman, 2012; Simcoe & Waguespack, 2011). We therefore measured visibility for each cited patent j based temporal and assignee visibility.

Temporal visibility refers to the recency of cited knowledge. First, for each cited patent j, we calculated the time lag from its last use to the time point when the focal search took place. We used the date of last use rather than the date of creation in the calculation of the time lag because the former has a better fit with human cognition. For example, an old yet still frequently cited paper (e.g., a classical theoretical paper) still has high visibility to researchers.

Assignee visibility measured the prominence of the knowledge creator. It was calculated as one divided by the ranking of the cited patent j's assignee in j's field, based on the patent count in the past 5 years. The assignee's visibility was thus field-specific and positively related to its exposure in the technological field. For example, a firm specializing in 5G is highly visible in the telecommunications sector but maybe unknown to chemical firms.

Temporal visibility and assignee visibility were then standardized and summed to derive the overall visibility of j. Its cognitive distance was calculated as the reciprocal of its visibility. Next, the citation dyad cognitive distance was aggregated across all backward citations (Set Γ) to derive the value of cognitive search distance for the focal patent:

$$Cognitive\ distance_i = \sum_{j \in \Gamma} \frac{1}{Temporal\ visibility_j + Assignee\ visibility_j}.$$

5.3 | Independent variables

The independent variables in our study were *China*, an indicator equal to one for those patents developed by inventors residing in China, and *blockade of Google*, an indicator equal to one for patents whose priority dates were after June 1, 2014.

5.4 | Moderators

5.4.1 | Inventor network

This moderating variable measured the size of the social collaboration network accessible to the inventor team. Studies have shown that both direct and indirect ties can serve as sources of knowledge (Singh et al., 2016), so our measure of the inventor network considered both ties. This variable was calculated as

$$Inventor\ network_{t-5,t} = \ln(direct\ ties_{t-5,t} + 0.5\ indirect\ ties_{t-5,t}),$$

where $direct\ ties_{t-5,\ t}$ was the number of direct collaborators with the focal team members within the past 5 years and $indirect\ ties_{t-5,\ t}$ was the number of second-degree ties to the team members. In the calculation, we assigned a 0.5 discount to the indirect ties because they were relatively remote and were weaker information channels than the direct ties. We also used the log transformation to account for the skewness of the network size.

5.4.2 | Proximity to science

This variable captured the proximity of a technological field to science. We inferred a field's proximity to science from backward citations made by all patents in the field to scientific

[2]We thank an anonymous reviewer for suggesting this extremely valuable and publicly available dataset.

publications. We identified these citations using the dataset constructed by Marx and Fuegi (2019), who established approximately 16 million linkages from patent citations to non-patent literature.2 We then developed our measure of proximity to science in two steps, inspired by Ahmadpoor and Jones (2017).

First, we constructed a citation network using all patent citations including patent-to-patent and patent-to-paper citations. We regarded patent-to-paper citations as linkages that spanned the "invention-science" boundary. The distance to science for each patent was calculated as the minimum degree of ties that can connect the patent with a scientific publication. For example, a patent that made direct boundary-spanning citations to science had a distance–to-science score of 1. For a patent that had no direct citations to scientific papers but had cited another patent with a distance of 1, we coded its distance to science as 2. We continued this iterative coding up to the 10th degree and assigned the distance of 10 to all the remaining patents.

Second, we took the average distance to science for all patents in each IPC class. We then measured a field's proximity to science as 10 minus the field's average distance to science, so that a higher value represented a closer link to science. In our sample, the field with the highest score was C12, which involved biochemistry and genetic engineering (proximity to science = 8.635), and field B43, which referred to stationery products, appeared to be farthest from science (proximity to science = 4.837).

5.5 | Control variables

All estimation models included fixed effects for regions and primary IPC classes to account for time-invariant regional and technological field heterogeneities. We also added time-variant control variables at the region, assignee, and patent levels.

At the regional level, the scale and growth of the domestic economy may affect the direction and intensity of innovation. We therefore controlled for regional quarterly *GDP level* and *GDP growth rate*. In addition, as we examined innovation activities through patents filed in the United States, regional trade and capital flows from and to the United States may impact inventors. We thus controlled for the quarterly *import from US*, *export to US*, *FDI from US* and *FDI to US* for each region.

At the assignee level, we first controlled for assignee types. Unlike university assignees that generally cite scientific papers, for-profit firms are market-driven with stronger incentives to search for trendy or novel elements. The search behavior of individual assignees may be narrow due to resource constraints. We thus classified assignees into three categories: *individual*, *university*, and *business assignees*. In addition, as large MNCs have established many research subsidiaries in the East Asian regions, the impact of blocking Google may differ for these R&D facilities due to their cross-country nature. We therefore added *foreign assignee* to indicate whether a focal patent belonged to a foreign firm. Last, we added an assignee's *US patenting experience*, measured by the log number of its US patents in the past 5 years, to control for factors associated with increasing experience in filing US patents.

At the patent level, we first controlled for the number of *inventors* because differences in team size are often associated with differences in search behavior (Singh & Fleming, 2010). Therefore, the reliance on online search and Google may differ across teams. We also included the number of *IPC subclasses* to control for the technological breadth of the focal patent.

5.6 | Estimation

We adopted the CEM to construct comparable treatment and control groups and used the DiD approach to test our hypotheses. Our dependent variables were all continuous. We therefore used the OLS regression with region and IPC class fixed effects. In addition, standard errors were clustered at the region level.

Our main variable of interest was the interaction term *China X blockade of Google*. The coefficients of this interaction should be interpreted on a relative basis. They indicate the changes in dependent variables for inventors in China compared to those in the control regions after China's unexpected blockade of Google.

6 | RESULTS

Table 2 reports the summary statistics for the variables in the matched sample. Table 3 shows the estimated impact of blocking Google on search distance of inventors. The coefficients of

TABLE 2 Summary statistics

	Mean	*SD*	Min	Max
Technological distance	1.486	0.983	0.000	7.011
Cognitive distance	1.257	1.519	0.000	26.888
GDP level[a]	1.255	0.192	1.026	1.606
GDP growth rate	4.697	2.901	−0.948	7.927
Import from US[b]	21.850	10.053	5.537	39.160
Export to US[b]	70.512	47.740	1.139	128.200
FDI from US[b]	1.192	3.487	−14.280	7.312
FDI to US[b]	3.579	5.918	−1.435	28.020
Individual assignee	0.023	0.149	0.000	1.000
University assignee	0.065	0.247	0.000	1.000
Foreign assignee	0.113	0.316	0.000	1.000
US patenting experience	5.994	2.945	0.000	10.330
Inventors	2.808	1.958	1.000	29.000
IPC subclasses	1.933	1.087	1.000	13.000
Inventor network	4.520	2.522	0.000	9.472
Proximity to science[c]	7.128	0.518	4.837	8.635
Blockade of Google	0.568	0.495	0.000	1.000
China	0.500	0.500	0.000	1.000

Note: n = 29,290.
[a]GDP level was standardized by the real GDP in 2011 Q1 for each region.
[b]Import/export and FDI were measured in US$ billion.
[c]Proximity to science measured a technological field's reliance on science as knowledge inputs and a value of 7.128 means that, on average, patents in the field connect to scientific publications through 2.872 (10–7.128) degrees of citation links.

TABLE 3 Effects of blocking Google on search distance variables

Model	(1)	(2)	(3)	(4)
Dependent variables	Technological distance	Technological distance	Cognitive distance	Cognitive distance
Region-level controls				
GDP level	0.220	0.110	0.147	0.378
	(0.469)	(0.117)	(0.543)	(0.220)
GDP growth rate	−3.264	−1.323	−0.118	0.243
	(0.007)	(0.061)	(0.865)	(0.504)
Import from US	−6.911	−7.076	−0.405	−5.860
	(0.057)	(0.000)	(0.880)	(0.080)
Export to US	−0.971	0.338	−2.850	−2.149
	(0.684)	(0.429)	(0.278)	(0.428)
FDI from US	−1.957	−0.612	4.581	6.410
	(0.417)	(0.720)	(0.141)	(0.004)
FDI to US	−1.830	1.014	4.359	6.600
	(0.040)	(0.204)	(0.192)	(0.012)
Assignee-level controls				
Individual assignee	−0.304	−0.306	−0.197	−0.198
	(0.001)	(0.001)	(0.129)	(0.128)
University assignee	−0.283	−0.282	−0.016	−0.016
	(0.034)	(0.035)	(0.897)	(0.901)
Foreign assignee	−0.246	−0.247	−0.084	−0.086
	(0.054)	(0.053)	(0.001)	(0.001)
US patenting experience	0.050	0.050	−0.017	−0.017
	(0.029)	(0.030)	(0.550)	(0.555)
Patent-level controls				
Inventors	0.048	0.048	0.008	0.008
	(0.001)	(0.001)	(0.657)	(0.659)
IPC subclasses	0.139	0.138	0.019	0.018
	(0.000)	(0.000)	(0.270)	(0.279)
Independent variables				
Blockade of Google		0.121		0.059
		(0.025)		(0.091)
China		**−0.135**		**−0.144**
X blockade of Google		**(0.016)**		**(0.002)**
IPC class FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Observations	29,290	29,290	29,290	29,290
R-squared	0.154	0.155	0.096	0.096

Notes: p-values in parentheses. Standard errors were clustered at the region level.

control variables generally meet our expectations. For example, individual and university assignees are associated with a stronger local search tendency than business assignees. These results are consistent with what prior studies found (Bessen, 2008). The coefficients of *US patenting experience* indicate that more experienced inventors appeared to be capable of incorporating more technologically distant knowledge. At the patent level, the coefficients of both inventor team size and the number of IPC subclasses are positively associated with search distance, also compatible with earlier findings (Arts & Veugelers, 2014; Singh & Fleming, 2010).

Models 1 and 2 in Table 3 show the impact of blocking Google on technological and cognitive search distances, respectively. The coefficients of the interaction term *China X blockade of Google* are negative for both distance dimensions (technological distance: $\beta = -0.135$, $p < .05$; cognitive distance: $\beta = -0.144$, $p < .01$), thus supporting and . The magnitude of these coefficients is also significant. Compared to the mean values, the blockade of Google caused a drop of 9.1% in technological distance and 11.5% in cognitive distance. In other words, compared to those in nearby regions, inventors in China became more localized in terms of their knowledge seeking after Google was blocked in China.

Table 4 provides estimates of the moderating effects. Panel A shows the estimation results for , which proposes that inventor social networks can compensate for the unavailability of Google. The three-way interaction does exhibit positive signs for both dimensions of distance (e.g., for technological distance, $\beta = 0.010$, $p < .01$). These results suggest that offline knowledge channels in the form of inventor networks can serve as a substitute for Google-enabled online search and can thus offset the decline in search distance caused by the blockade. Panel B shows the estimation results for H4. The results show that inventors in science-proximate fields suffered more from the blockade such that they searched less knowledge from distant fields (technological distance as the DV: $\beta = -0.022$, $p < .01$) and less noticeable sources (cognitive distance as the DV: $\beta = -0.125$, $p < 0.1$) after the event. Overall, tests of the moderating effects show supportive evidence to our framework.

6.1 | Robustness checks

We conducted several robustness tests to validate our findings. First, the secretive blockade of Google may coincide with a trend that Chinese inventors increasingly became hostile toward the United States. Our findings could therefore be driven by an observed shift in the patenting behavior of Chinese inventors (i.e., they became hesitant to file high-quality patents in the United States). To assess this possibility, we conducted a thorough review of public news and government documents for the period 2013–2016 and found no supporting evidence. Contrary to this speculation, the Chinese government actively encouraged firms to develop high-quality inventions, and pursuing global IP protection remained a priority for leading technology firms in China. For example, Huawei, one of China's leading technology companies, continually increased its patent applications worldwide over the past 10 years. Moreover, we quantitatively examined and compared in Figure 2 the number of patent applications from inventors in China and those in the control regions at the USPTO. We found no evidence that patent applications from China decreased after the event, thus refuting the hostile attitude explanation.

Another possible explanation for our findings is a pre-event trend of Chinese inventors being less innovative (Hu, Zhang, & Zhao, 2017). We evaluated this possibility with two approaches. First, we performed de-trend analyses using the linear de-trend method (Jermann & Quadrini, 2012). Specifically, we regressed all dependent variables on calendar days t ($t = 0$

TABLE 4 Moderating effects of inventor network and proximity to science

Model	**(1)**	**(2)**
Dependent variables	Technological distance	Cognitive distance
Panel A: Inventor network as a moderator		
Blockade of Google	0.081	0.195
	(0.143)	(0.032)
China	**−0.197**	**−0.356**
X blockade of Google	**(0.006)**	**(0.002)**
Inventor network	0.018	−0.037
	(0.118)	(0.099)
China X	0.010	0.040
Inventor network	(0.302)	(0.148)
Blockade of Google X	0.010	−0.032
Inventor network	(0.015)	(0.021)
China X blockade of Google X	**0.010**	**0.046**
Inventor network	**(0.006)**	**(0.003)**
Controls	YES	YES
IPC class FE	YES	YES
Region FE	YES	YES
Observations	29,290	29,290
R-squared	0.161	0.099
Panel B: Proximity to science as a moderator[a]		
Blockade of Google	−0.347	−1.535
	(0.002)	(0.025)
China	**0.116**	**0.793**
X blockade of Google	**(0.161)**	**(0.152)**
China X	0.024	0.140
Proximity to science	(0.366)	(0.118)
Blockade of Google X	0.055	0.221
Proximity to science	(0.000)	(0.015)
China X blockade of Google X	**−0.022**	**−0.125**
Proximity to science	**(0.008)**	**(0.087)**
Controls	YES	YES
IPC class FE	YES	YES
Region FE	YES	YES
Observations	29,290	29,290
R-squared	0.157	0.098

Notes: p-values in parentheses. Standard errors were clustered at the region level.
[a]Proximity to science was omitted because it has not within-class variation and all the models have included IPC class fixed effects.

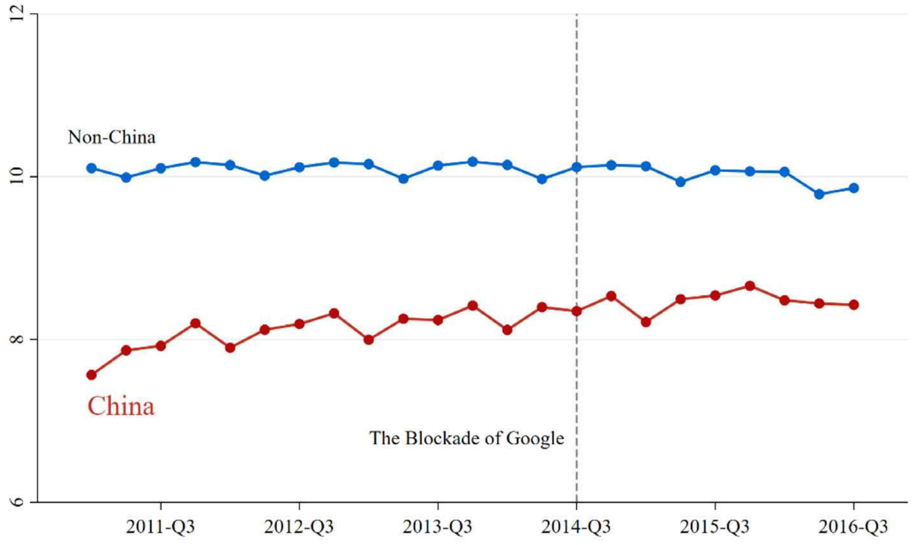

FIGURE 2 The log number of patent applications from China and the control regions [Color figure can be viewed at wileyonlinelibrary.com]

for January 1, 2009) and the interactions of region dummies with t for the period 2009–2013 to estimate any pre-existing general and region-specific trends. We then used the estimated coefficients to predict dependent variables for the sample period and took the residuals that cannot be explained by trends as our new dependent variables for the DiD analyses. Panel A of Table 5 reports the results. The coefficients of the interaction term remain negative in all the models. The other approach was to perform placebo tests. If a pre-event decreasing trend did exist, the DiD estimates with an earlier pseudo-event should yield results similar to those reported in Table 3. We conducted placebo tests with two pseudo blockade dates. One was June 1, 2013, exactly 1 year prior to the actual event while the other was March 23, 2010, the date when Google formally ceased its operations in China. The results are reported in Panel B and C of Table 5. The results suggest that China was actually on a rising trend prior to the blockade compared to nearby regions, confirming our earlier qualitative findings. Together, the above results indicate that our findings were unlikely driven by a pre-event trend.

Third, studies have suggested that applicants may supply citations for strategic reasons such that they intentionally omit some prior art in their favor (Lampe, 2012). In this scenario, examiner-added citations may mitigate this bias. We performed a test to check whether the examiner-to-applicant citation ratio increased after the blockade. As expected, this ratio indeed increased for patents from China compared to those in the control group after the event. We also re-estimated the parameters with both distance variables constructed on the pooling of applicant- and examiner-added citations. Panel D of Table 5 shows the results. The estimates of the key interaction term were still negative and but less significant than those reported in Table 3 (technological distance: $\beta = -0.052$, $p < .05$; cognitive distance: $\beta = -0.063$, $p < .05$). These findings suggest that inventors in China encountered difficulties in searching for relevant prior art. Examiners can provide complementary but incomplete search, a result compatible with prior studies on examiner behavior (Frakes & Wasserman, 2017).

Fourth, inventor network was measured as the number of direct and indirect ties in the main analyses. However, the social network literature has shown that people tend to socialize

TABLE 5 Results of robustness checks

Model	**(1)**	**(2)**
Dependent variables	Technological distance	Cognitive distance
Panel A: De-trend analyses		
Blockade of Google	0.088	0.133
	(0.184)	(0.014)
China	**−0.055**	**−0.110**
X blockade of Google	**(0.035)**	**(0.061)**
Controls & FEs	Yes	Yes
Observations	29,290	29,290
R-squared	0.149	0.083
Panel B: Treating June 1, 2013 as the pseudo-blockade date		
Pseudo blockade	−0.026	0.020
	(0.037)	(0.398)
China	**0.142**	**0.066**
X pseudo blockade	**(0.001)**	**(0.088)**
Controls & FEs	Yes	Yes
Observations	23,370	23,370
R-squared	0.142	0.085
Panel C: Treating march 23, 2010 as the pseudo-blockade date		
Pseudo blockade	0.032	0.081
	(0.566)	(0.173)
China	**0.084**	**0.062**
X pseudo blockade	**(0.057)**	**(0.268)**
Controls & FEs	Yes	Yes
Observations	10,836	10,836
R-squared	0.251	0.105
Panel D: DVs building on both applicant- and examiner-citations		
Blockade of Google	0.056	0.012
	(0.004)	(0.257)
China	**−0.052**	**−0.063**
X blockade of Google	**(0.032)**	**(0.012)**
Controls & FEs	Yes	Yes
Observations	29,290	29,290
R-squared	0.158	0.106
Panel E: Diversity-adjusted inventor network as a moderator		
Blockade of Google	0.080	0.296
	(0.253)	(0.039)
China	**−0.208**	**−0.464**
X blockade of Google	**(0.015)**	**(0.005)**

TABLE 5 (Continued)

Inventor network	0.019	−0.044
	(0.103)	(0.082)
China	0.010	0.046
X inventor network	(0.332)	(0.147)
Blockade of Google	0.007	−0.040
X inventor network	(0.172)	(0.036)
China X blockade of Google	**0.011**	**0.053**
X inventor network	**(0.043)**	**(0.010)**
Controls & FEs	Yes	Yes
Observations	29,290	29,290
R-squared	0.160	0.100
Panel F: International team as a moderator		
Blockade of Google	0.612	0.194
	(0.000)	(0.043)
China	**−0.596**	**−0.252**
X blockade of Google	**(0.000)**	**(0.015)**
International team	−0.153	−0.366
	(0.016)	(0.113)
China X	0.372	0.377
International team	(0.009)	(0.126)
Blockade of Google X	−0.563	−0.113
International team	(0.000)	(0.181)
China X blockade of Google X	**0.586**	**0.215**
International team	**(0.000)**	**(0.029)**
Controls & FEs	Yes	Yes
Observations	35,876	35,876
R-squared	0.126	0.087

Notes: *p*-values in parentheses. Standard errors were clustered at the region level.

with similar others, leading to homophily in their networks (McPherson, Smith-Lovin, & Cook, 2001). A large collaboration network may not provide the necessary diversity of knowledge. We therefore conducted a robustness check using a diversity-adjusted measure of inventor network. Specifically, we counted the distinct IPC subclasses in which collaborators of the focal team members had invention experience and took the natural log of this count. We report the results in Panel E of Table 5. Our findings remain qualitatively the same with this diversity-adjusted social network measure.

Fifth, if the effect and mechanisms proposed in this study are valid, inventors outside of China should be unaffected by the blockade and could thus share their findings with collaborators in China. Therefore, cross-country teams should be less affected. We thus examined whether collaboration with inventors outside of China can mitigate the negative impact. We carried out a round of similar analyses with an expanded sample including those cross-country inventor teams. The results in Panel F of Table 5 support the prediction of an offsetting effect of international collaboration (e.g., the coefficient of the three-way interaction term for technological distance: $\beta = 0.586$, $p < .01$). Teams with foreign members showed significantly less decrease in their search distance compared to domestic teams.

Last,3 we checked the robustness of our findings by varying the event window size. In addition to our reported 2-year event window (1 year before and 1 year after), we repeated the same analyses with event windows of 1 year and 3 years. While the results for the three-year window remain similar to those in Table 3 (e.g., the coefficient of the interaction term for technological distance: $\beta = -0.097$, $p < .05$), the coefficients for the one-year window exhibit less significant effects. These results suggest that a shorter event window is perhaps inappropriate for our study because the impact took time to be reflected in innovation outputs. The three-year window results, however, suggest that the effect of the blockade on innovation in China can last over a long-time horizon. Thus, the blockade may cast a long shadow over China's innovation system, rather than causing a brief disruption.

6.2 | Supplementary analysis

In the above analyses, we show that the blockade of Google subtly changed the search behavior of inventors in China such that their knowledge seeking pattern became more localized. At last, it is theoretically and practically intriguing to explore whether this shift eventually impaired the economic value of their invention outputs.

Existing research has found a positive relationship between search distance and the value or impact of innovation (Jeppesen & Lakhani, 2010; Kok, Faems, & de Faria, 2018; Phene, Fladmoe-Lindquist, & Marsh, 2006). Huawei is a case in point. As an aspiring player in technological competition, it frequently searches for distant knowledge through both online and offline channels when developing cutting-edge technologies. In 2008, its researchers found a working paper by a Turkish mathematician who proposed a novel data-coding scheme. Following the paper and broadening search among numerous sources, Huawei was then able to develop a series of valuable inventions, which became the foundation for the next generation of telecommunication technology or commonly titled 5G (Ren, 2019). Therefore, we expect that the blockade of Google would undermine the economic value of inventions created by inventors in China due to reduced search distance.

To test this prediction, we measured invention economic value with the valuation dataset provided by Bureau van Dijk (BvD), a data analytics company owned by Moody's, who estimates a patent's dollar value from technical, market, and legal dimensions based on multiple triangulated datasets such as patent litigations and company information. Using this valuation. We find that the coefficient of *China X blockade of Google* is negative ($\beta = -0.081$, $p < .05$).4 It shows that after the blockade, inventors in China generated inventions of lower value compared to their counterparts in nearby regions that were presumably unaffected by the event.

[3]We have carried out a few other robustness checks but not reported here to save space. For example, we did not find a change in team size for inventors from China; our results were robust to a citation-adjusted scale-free DV measurement; adding a control variable of the time lag between the event date and patent filing date did not alter our key findings.

[4]The full results of this analysis and other supplementary analyses are available from the authors upon request. The authors are also willing to provide results of all other unreported robustness checks and figures such as changes in DVs prior and after the event.

Compared to those in the control group, the value of patents from China dropped by 8.1% after the event, which translates to a loss of roughly 57 k USD per patent. Overall, we find a real and profound impact of blocking Google on China's innovation capacity.

7 | DISCUSSION

Search is essential for innovation, and online search has become almost indispensable. However, little is known about how Internet technologies such as Google search affect the searching behavior of inventors and their innovation outcomes. In this study, we develop a framework for Google-enabled online search and find that after China's blocking Google, inventors located in China experienced a subtle decrease in technological and cognitive search distances compared to those in nearby countries or "regions." In other words, what inventors in China missed out was not a random draw from a large pool, but rather predictable from our framework. We also find that the impact was heterogeneous. Inventors with larger collaboration networks were less affected by the blockade, but it had a greater impact in technological fields proximate to science. Moreover, we find in a supplementary analysis that blocking Google eventually led to an unintended but non-negligible loss in the economic value of inventions for firms and inventors in China compared to those from the control group.

Our study makes a few important contributions. First, we contribute to the search-based view of innovation by examining the role of advanced online tools such as Google in overcoming the tendency for local search. The literature focusing on search distance has mainly considered offline knowledge channels, perhaps because the prevalence of Google search is often taken for granted by researchers. Although some scholars have alluded to the importance of online search (Wagner et al., 2014) or considered online channels simply as tools to reduce the cost of information access (Ding et al., 2010), few studies examine and test how exactly advanced Internet tools such as Google shape the behavior of inventors. Our study shows that search via Google enables inventors to overcome the local search bias. We also find a substitution effect between offline channels such as inventor networks and online search engines, which resonates with the finding that the availability of Internet tools benefits researchers in non-elite universities more than those in elite institutions (Ding et al., 2010). The importance of Google is also found to be heterogeneous across technological fields, and those proximate to science suffered more. This finding implies that cutting off an important online channel to science can have a ripple effect on technological innovation, echoing and extending an emerging literature on how scientific knowledge facilitates innovation (Fleming & Sorenson, 2004). Our study therefore makes a novel contribution to the search-based view of innovation and enriches the understanding of how Google-enabled online search can be instrumental in developing innovation.

Second, we add to the knowledge management and economics of information access literatures by offering compelling evidence that access to Google, a "huge catalogue" of existing knowledge elements and a "smart librarian" providing guidance, is beneficial for innovation. In previous studies, when examining how the development of digital knowledge systems facilitates innovation, it is challenging to disentangle whether the development decision is totally exogenous or is due to employees' requests (Kim et al., 2016). Similarly, the early finding that the diffusion of online access boosts scientific productivity faced the same endogeneity concern for the same reason that connection to the Internet is not a random decision but subject to factors such as the research potential of target institutions. As a comparison, China's decision to block

Google is characterized by its nearly perfect exogeneity, and thus enables us to mitigate the endogeneity concern previously encountered.

Third, our study offers a new perspective on the academic debate about Internet censorship. The focus has typically been on how governments practice media controls (Lorentzen, 2014) or how Internet censorship affects personal attitudes or beliefs (Chen & Yang, 2019). Our study broadens this literature by revealing the real economic consequences of such an Internet policy. Unlike the censorship of specific content providers such as Instagram or the *New York Times* examined in previous studies, we consider Google, which is a fundamental and intelligent portal for the Internet in the age of information explosion. Our findings suggest that other than influencing political beliefs, blocking the leading search engine can backfire on the innovation capacity of the regime. Therefore, policymakers should examine the blockade more holistically and consider actions that can mitigate its negative impact (e.g., the recently disclosed Dragonfly project), to balance economic goals and political ambitions.

Some limitations of this study are worth noting. First, our search distance variables were based on patent citations, which can capture only a portion of the information and knowledge that inventors search for. Patent citations can also be subject to strategic hiding by applicants (Lampe, 2012). Future studies could examine whether searching for broader sources of information was also affected. Second, one should be aware that Google-enabled online search has its own weakness. For example, it may bias toward contents in English and other major languages (Evans & Aceves, 2016). Besides, it may deliver user-specific results over time. It will be intriguing for future studies to examine possible dark sides of over-reliance on Google or other similar tools. Third, the availability of anti-blocking tools such as virtual private networks (VPNs) may introduce noise into our estimation. Moreover, inventors in China could switch to other search engines such as Baidu.com. Therefore, it cannot be assumed that Google was completely blocked and had no substitute in China. However, the existence of VPNs and alternative search engines actually biases our results toward zero instead of confounding our estimates. Put differently, the effect size that we discovered is conservative rather than inflated. Future studies equipped with more accurate Internet traffic data or novel research designs can reassess the effect size.

Our study opens doors for many future studies in several directions. First, future researchers can carry out lab experiments to uncover subtle causal mechanisms. For example, one can disentangle the disruption effect from the ignorance effect by comparing people's responses in situations between being deprived of Google from heavy users and providing it to first-time users (Chen & Yang, 2019). If the impact was mainly caused by the disruption effect on heavy Google users, one can also explore whether blocking other popular search engines would have the same impact. Second, China's blocking of Google is not the only institutional force shaping Internet usage. Laws and policies that regulate or intervene with firm activities in the virtual world have emerged rapidly—Net Neutrality, the General Data Protection Regulation, and China's Internet Security Law, just to name a few. With firms' increasing involvement in online communities, future research can offer fruitful strategic implications by examining those institutions and their impacts. Last, we find that the blockade of Google impeded searching for distant knowledge. Future studies may explore whether inventions from China became somehow detached from the rest of the world since they essentially drew information from a different information pool. If it is the case, one can further investigate the long-term impact of the event such as will China's blockade of Google also affect knowledge creation in other countries, or will China become more self-sustainable in terms of knowledge production and even introduce more technological diversity to the global technological landscape?

8 | CONCLUSION

Innovation is critically dependent on search. This notion has been well articulated by scholars from various fields and various offline search channels have been examined thoroughly in the literature. However, the effect of advanced online tools such as Google on innovation is not well understood, partly because researchers tend to take for granted the proliferation of Google search. We examine the unexpected blocking of Google in China and discover that losing access to a powerful search engine can lead inventors in China to narrow their search and ultimately produce less valuable inventions. Our study contributes to the search-based view of innovation and highlights the importance of Internet technologies in developing high-quality innovation. The subtle effects and long-term implications of the blockade warrant further research.

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