The role of corporate science in technology competition and exploration

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Abstract

How does corporate science influence the technology search strategy of firms when technology competition intensifies? In this study, we examine the degree to which corporate science moderates the relationship between technology competition and technology exploration. Based on a sample of 2,752 U.S. public firms for the period between 1980 and 2015, we find that firms are more likely to reduce the level of technology exploration when they face increased technology competition from product market rivals. However, firms that invest in corporate science are less likely to pull back from technology exploration. Interestingly, this difference is apparent also for firms that use available scientific knowledge (as opposed to firms directly performing research), suggesting that division of innovative labor in research and development can be an effective way to promote technology exploration. Lastly, the findings indicate that the moderating effect of corporate science is less pronounced for firms participating in markets for technology, providing further evidence that the knowledge required to evaluate and apply unfamiliar technologies is a significant factor driving technology exploration when competition intensifies.

Keywords: corporate science, technology competition, technology exploration, markets for technology

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1 Introduction

The ability to respond to changes in the competitive environment is critical to firm performance (March, 1991). The recent rise in geopolitical tension between the United States and China along with the rise of China's technological capabilities has brought into question how adequately equipped U.S. firms are in maintaining their technology leadership.[1] This question is especially relevant today given that U.S. corporate expenditure in research, which in part enables firms to apply external knowledge to their inventions (Cockburn & Henderson, 1998; Cohen & Levinthal, 1989, 1990; Gambardella, 1992; Rosenberg, 1990), has declined significantly in the recent decades (Arora, Belenzon, & Patacconi, 2018; Mowery, 2009; Pisano, 2010). This decline may hinder firms from exploring unfamiliar technology areas when responding to competition and in turn may threaten the long-term survival of the firms.

Firms developing technological inventions engage broadly in either technology exploitation or exploration. Exploitation involves refining an existing technology or knowledge base to make improvements along an expected technological trajectory, whereas exploration is associated with a distant search in pursuit of a new technology or a drastic improvement of an existing technology (Cyert, March, et al., 1963; Fleming & Sorenson, 2004; He & Wong, 2004; Holmqvist, 2004; Levinthal & March, 1993; March, 1991; March & Simon, 1958; Martin & Mitchell, 1998; R. Nelson & Winter, 1982; Stuart & Podolny, 1996). Prior studies show that a balance between exploitation and exploration is essential for a long-term success of a firm (Eisenhardt & Martin, 2000; He & Wong, 2004; Katila & Ahuja, 2002; Lavie, Kang, & Rosenkopf, 2011; March, 1991; Teece, Pisano, & Shuen, 1997; Tushman & O'Reilly III, 1996). But, at the same time, studies also argue that the decision to pursue exploitation or exploration is likely to be contingent on a wide variety of internal and external factors, including firm structure, process, capability, and competition (He & Wong, 2004; Lavie et

[1] Instigated by geopolitical tension and a pursuit of technological supremacy, the U.S. recently has banned investment in China's next generation technologies including quantum computing, artificial intelligence, and advanced chip technology (Financial Times, August 9, 2023; The Wall Street Journal, August 10, 2023).

al., 2011; Luger, Raisch, & Schimmer, 2018; Posen & Levinthal, 2012; Morandi Stagni, Fosfuri, & Santaló, 2021; R. Nelson & Winter, 1982; Stieglitz, Knudsen, & Becker, 2016; Sidhu, Commandeur, & Volberda, 2007; Voss, Sirdeshmukh, & Voss, 2008; Winter & Szulanski, 2001).

Given the significant impact that competition can have on firm performance and the complexity involved in adjusting innovation strategy, various studies have examined the effect of competition on firms' technology search and resulting innovation outcomes (Aghion, Bergeaud, Lequien, Melitz, & Zuber, 2021; Aghion, Bloom, Blundell, Griffith, & Howitt, 2005; Arrow, 1962; Autor, Dorn, Hanson, Pisano, & Shu, 2020; Bloom, Draca, & Van Reenen, 2016; Dasgupta & Stiglitz, 1980; Morandi Stagni et al., 2021; Schumpeter, 1942; Shu & Steinwender, 2019). However, these studies use a high-level measure to examine how product market competition (e.g., import penetration, Lerner index) affects firms' technological response. To complement these studies, we instead focus on the technology-level competition among product market rivals in the U.S. and examine how the introduction of similar inventions by product market rivals influences the technology search strategy of the firms. Furthermore, we investigate how corporate science moderates this relationship, where corporate science refers to a direct engagement in research or use of available scientific knowledge.

To facilitate our analysis, we combine several datasets. We construct our sample based on 2,752 U.S. public firms by merging firm data extracted from the Duke Innovation & SCientific Enterprise Research Network (DISCERN) (Arora, Belenzon, & Sheer, 2021) with patents from Kogan, Papanikolaou, Seru, and Stoffman (2017), patent-pair textual similarity data from Arts, Hou, and Gomez (2021), and product market rivalry measure from Bloom, Schankerman, and Van Reenen (2013). We incorporate two measures of corporate science. A measure of direct engagement in research, i.e., number of scientific publications produced by a firm in a given year, is obtained from DISCERN, and the measure of use of scientific knowledge, i.e., number of patent citations to scientific articles, is obtained from Marx and Fuegi (2020). We use patent-pair textual similarity data combined with product market rivalry data to determine the intensity of technology competition for each patent-protected invention. The measure of technology exploration is constructed by computing the average share of citations made to patents in CPC section that a firm has never cited before. To mitigate potential endogeneity concerns, we also present estimates from an instrumental variable analysis using variation in state R&D tax credit (Bloom et al., 2013; Lucking, Bloom, & Van Reenen, 2018) as well as a panel event study exploiting a sharp increase in the number of inventions (i.e., an increase in technology competition) granted in a given CPC section.

The results show that, when firms face increased technology competition from product market rivals, they tend to reduce technology exploration while increasing technology exploitation. However, this relationship is weakened when firms engage in research – that is, firms engaging in research explore more unfamiliar technology areas in developing subsequent inventions relative to firms that do not. Furthermore, even after controlling for direct engagement in research, firms that use available scientific knowledge more frequently, as reflected in cumulative patent citations to scientific publications, also tend to explore more unfamiliar technology areas relative to firms that use scientific knowledge less frequently. Lastly, the results show that the moderating effect of corporate science is dampened when firms participate in markets for technology, providing further evidence that the knowledge required to evaluate and incorporate unfamiliar knowledge is a significant driver of technology exploration.

This study makes contributions to three broad streams of research. First, given the technological competition between the U.S. and china, several recent studies have looked at the effect of competition on firm innovation (Aghion et al., 2021, 2005; Autor et al., 2020; Bloom et al., 2016; Shu & Steinwender, 2019). While these studies focus on product market competition, this study looks specifically at the technology competition by product market rivals. The results show that firms engaging in research and firms using available scientific knowledge are more likely to engage in technology exploration in response to an increased level of technology competition.

Additionally, while prior studies argue that a balance between exploitation and exploration in technology search strategy is critical to the long-term performance of a firm, they also recognize that various internal and external factors can influence the direction of the search (He & Wong, 2004; Lavie et al., 2011; Luger et al., 2018; Posen & Levinthal, 2012; Morandi Stagni et al., 2021; R. Nelson & Winter, 1982; Stieglitz et al., 2016; Sidhu et al., 2007; Voss et al., 2008; Winter & Szulanski, 2001). However, broad empirical evidence on such contingent factors is scarce. This study shows that, at least for the U.S. public firms, corporate science is indeed a significant factor that influences the technology search strategy of the firms.

This study also speaks to the literature looking at the decline of U.S. corporate research expenditure and concerns around its potential effect on corporate innovation and global technology competition. There has been a certain level of pessimism about the technology leadership of the U.S. firms based on the apparent decline in their research expenditure along with the rise of China's investment in research and development. The findings from this study indicate that, while firms directly engaged in research do indeed pursue technology exploration at a higher rate, firms that use available scientific knowledge also do the same, suggesting that division of innovative labor in research and development could be an effective way to promote technology exploration.

2 Background and Hypotheses

2.1 Technology competition and search strategy

Technology exploitation and exploration are two different modes of search strategy that facilitate the development of inventions within firms (Cyert et al., 1963; Fleming & Sorenson, 2004; He & Wong, 2004; Holmqvist, 2004; Levinthal & March, 1993; March, 1991; March & Simon, 1958; Martin & Mitchell, 1998; R. Nelson & Winter, 1982; Stuart & Podolny, 1996).

In general, exploitation is associated with refining an existing technology or knowledge base to make improvements along an expected technological trajectory. Although the technological improvements made through exploitation can help firms to compete more effectively, they tend to be more incremental. Accordingly, exploitation involves less uncertainty and time. On the other hand, exploration involves a distant search in pursuit of a new technology or a drastic improvement of an existing technology. As a result, exploration can help firms to develop novel technologies that can make them substantially more competitive. However, technology development through exploration involves higher uncertainty and tends to be more time consuming and costly (McGrath, 2001; Kline & Rosenberg, 1986; Rosenberg, 1998; Schumpeter, 1942).

The divergent outcomes from these two search strategies create a theoretical tension when firms need to respond to an increased level of competition. Firms could quickly refine an existing technology (i.e., exploit) and deploy it in response to a competitive threat, but they might have to do so at the expense of developing a more significant technology (Fleming, 2001; March, 1991). On the other hand, firms could invest in finding a more radical solution (i.e., explore), but they might experience inferior short-term performance (Tushman & O'Reilly III, 1996; March, 1991). Furthermore, it is less certain that they will be able to find a viable solution to the competitive threat.

In a recent study, Morandi Stagni et al. (2021) provide insights into this tension by showing that, when competition threatens survival, firms are more likely to pursue technology exploitation to reduce their response time. Specifically, the authors report that competition from Chinese imports leads to U.S. manufacturing firms increasing technology exploitation while reducing technology exploration. They also show that a tighter financial situation at the time of increased competition is likely to push the firms to pursue technology exploitation even more intensely.

Similarly, we argue that a product market rival's introduction of an invention similar to that of a focal firm can be a significant threat to the focal firm's profitability. The extant literature provides rich insights into how capturing value from an invention can be affected by the existence of similar inventions (Arora & Ceccagnoli, 2006; Cohen, Nelson, & Walsh, 2000; Gans, Hsu, & Stern, 2002; Levin et al., 1987; Mansfield, 1986; Teece, 1986). For instance, Teece (1986) discusses how the share of the profits that an inventing firm can capture from its invention depends on the extent to which the invention by nature can be imitated by its rivals and whether there are mechanisms through which the inventing firm can prevent rivals from imitating (e.g., intellectual property rights). Thus, when a rival firm introduces an invention similar to that of a focal firm, the profitability of the focal firm is likely to be adversely affected. In turn, the focal firm is more likely to pursue technology exploitation over exploration to respond quickly.

Hypothesis 1. *When technology competition from product market rivals intensifies, firms are more likely to respond by exploiting familiar technologies than by exploring unfamiliar technologies.*

Firms are different in their ability to capture value from their inventions. Typically, large firms have commercialization capabilities that are superior to that of small firms and thus can capture more value from their inventions (Arora & Ceccagnoli, 2006; Arora, Cohen, Lee, & Sebastian, 2023; Gans et al., 2002; Lee, 2023; Teece, 1986). Given that threat to profitability is what pushes firms to pursue technology exploitation over exploration, firms that can capture more value from their inventions would be less sensitive to increased competition with respect to technology search strategy. Thus, we hypothesize that large firms would be impacted less by the potential threat that a rival technology poses to profitability.

Hypothesis 2. *The negative relationship between technology competition and technology exploration is weaker for large firms than for small firms.*

Additionally, when a firm is diversified across multiple technology areas, a competing technology in one area is not as likely to affect the company's overall profitability as it would when the firm is focused in a single technology area (Koren & Tenreyro, 2013). Thus, we expect that the effect of technology competition on the firm's technology search strategy would be weaker when a firm is diversified.

Hypothesis 3. *The negative relationship between technology competition and technology exploration is weaker for diversified firms than for focused firms.*

2.2 The role of corporate science in technology search strategy

The argument that firms need to balance exploitation and exploration in technology search is based broadly on the notion that an insufficient level of the former can lead to inferior competitive position in the current market and an insufficient level of the latter can lead to missing out on technological discoveries that could make the current technologies obsolete or create new market opportunities.[2] Despite this apparent need for a balance between the two technology search strategies, studies have acknowledged that they are likely to be driven by substantially different internal and external factors, such as firm structure, process, and capability (He & Wong, 2004; Lavie et al., 2011; Luger et al., 2018; Posen & Levinthal, 2012; Morandi Stagni et al., 2021; R. Nelson & Winter, 1982; Stieglitz et al., 2016; Sidhu et al., 2007; Voss et al., 2008; Winter & Szulanski, 2001). This implies that, when faced with increased competition, some firms might be better positioned to pursue one search strategy over the other depending on the internal and external conditions that the firms are operating under.

This study focuses on one such factor – that is, how corporate science influences the degree to which firms use unfamiliar technologies to develop inventions in response to increased competition. The emphasis on corporate science as a moderating factor is due to its close relationship with the firm's ability to develop inventions, which are understood in part as novel combinations or reconfiguration of both new and existing technological components

[2] March (1991) argues that "Adaptive systems that engage in exploration to the exclusion of exploitation are likely to find that they suffer the costs of experimentation without gaining many of its benefits[...] Conversely, systems that engage in exploitation to the exclusion of exploration are likely to find themselves trapped in suboptimal stable equilibria."

(Fleming, 2001; Henderson & Clark, 1990; R. R. Nelson & Winter, 1985; Schumpeter, 1939). Combined with the evidence that investment in corporate science has declined substantially in recent decades (Arora et al., 2018; Mowery, 2009; Pisano, 2010) and the concerns over potentially eroding technological leadership of U.S. firms, a systematic investigation into how corporate science moderates the relationship between technology search strategy and technology competition should be beneficial.

Firms invest in corporate science for different reasons. A primary reason for investing in corporate science is to apply the scientific discoveries to the development of downstream inventions (Arora et al., 2021; Kline & Rosenberg, 1986; R. R. Nelson, 1959). (Arora et al., 2021). Broadly, firms might invest in corporate science to gain a general understanding of a subject matter, or they might invest in corporate science to solve a specific problem (Arora & Gambardella, 1994; Mowery & Rosenberg, 1982; Rosenberg, 1990; Vincenti et al., 1990). Prior studies have shown that, in general, corporate science can reveal promising technological trajectories (Fleming & Sorenson, 2004; Gambardella, 1995; Rosenberg, 1990) and can enable firms to produce high quality inventions (Cockburn & Henderson, 1998; Fabrizio, 2009; Gittelman & Kogut, 2003; Simeth & Cincera, 2016).

Besides the benefits gained through the direct use of scientific discoveries, corporate science can also facilitate inventive activity in other important ways. In particular, by helping firms to gain the requisite knowledge, corporate science enables firms to evaluate and apply useful, external technologies when developing their own inventions (Cockburn & Henderson, 1998; Cohen & Levinthal, 1989, 1990; Gambardella, 1992; Rosenberg, 1990). Accordingly, when trying to incorporate unfamiliar technologies into their own inventions, firms that have accumulated a stock of background knowledge through corporate science would be better positioned to do so. In other words, firms investing in corporate science can reduce the time and cost required to explore unfamiliar technologies. Thus, we hypothesize that, when faced with an increased level of competition, firms that invest in corporate science are more likely to explore unfamiliar technology areas than firms that do not.

Hypothesis 4. *When technology competition from product market rivals intensifies, firms that invest in corporate science are more likely to respond by exploring unfamiliar technology areas than firms that do not engage in research.*

While corporate science facilitates technology exploration by providing knowledge needed to evaluate and apply unfamiliar technologies, there are other channels through which such knowledge can be acquired, notably markets for technology. When a technology market exists, participants of the market interact with one another and transfer knowledge about both familiar and unfamiliar technologies (Arora, Fosfuri, & Gambardella, 2001; Arora & Gambardella, 2010). Arora and Gambardella (2010) point out that transactions in markets for technology involve transfer of not only technologies themselves, but also related intellectual properties, know-hows, and services. Furthermore, Ceccagnoli and Jiang (2013) show that, even when potential buyers lack the requisite knowledge to understand unfamiliar technologies, suppliers' ability to transfer knowledge can facilitate technology adoption. Thus, although there are several factors (e.g., cognitive and contractual) that limit markets for technology (Arrow, 1962; Kogut & Zander, 1992; Rosenberg, 1998; Winter, 2009), firms that do participate in technology markets are more likely to pursue technology exploration than firms that do not in part due to the knowledge transfers that occur and help firms to evaluate and apply unfamiliar technologies. In other words, a technology market acts as an alternative channel through which firms can acquire knowledge about unfamiliar technologies and in turn can promote technology exploration. As a result, active participation in markets for technology would dampen the moderating effect of corporate science.

Hypothesis 5. *The moderating effect of corporate science on technology exploration is weakened when firms participate in markets for technology.*

3 Data and measures

To examine the relationship between technology competition and technology exploration, we construct a sample consisting of U.S. public firms extracted from Duke Innovation & SCientific Enterprise Research Network (DISCERN) (Arora et al., 2021). The firms in the sample have at least one year of positive R&D expenditure and produce at least one patent over the years 1980 through 2015. For patent-based measures, we use the patent data from Kogan et al. (2017) for application years 1980 through 2015.[3] We also add patent similarity data from Arts et al. (2021), which we use to determine similarity of patented technologies. To determine technology competition from rivals, we construct a Mahalanobis-based measure of product market rivalry as in Bloom et al. (2013) and use it to weight the similarity scores between technologies.[4]

We add patent attributes including patent family, application and grant date, and citation from Worldwide Patent Statistical Database (PATSTAT) maintained by the European Patent Office as well as technology class (i.e., Cooperative Patent Classification, or CPC) from PatentsView maintained by the United States Patent and Trademark Office (USPTO). Lastly, when multiple patents exist in a DOCDB simple patent family, we keep only the earliest patent to avoid double counting (European Patent Office, 2017; Lee, 2023; Morandi Stagni et al., 2021).[5] We aggregate the patent-level measures to the firm-year level by averaging their values across the inventions produced by a firm in a given year. The final sample consists of 32,467 firm-year observations covering years 1980 through 2015 and represents 2,752 U.S. public firms.

[3]We merge with patents from Kogan et al. (2017) to cover application years between 1980 and 2015 instead of grant years, which the DISCERN database uses. Because of the time lag that exists between application and grant date, using application dates from the DISCERN patents, which are based on patent grant years, can lead to measurement errors and omission of patents.

[4]The results presented in this study are robust to using only the similarity scores (without the product market rivalry weights).

[5]The results presented in this study are robust to using all patents.

3.1 Technology exploration

The dependent variable in our analysis is the degree to which a firm pursues technology exploration. We construct a measure of technology exploration based on patent citations made to prior patents in technology areas that a firm has never cited before. Accordingly, it is a degree to which the firm explores unfamiliar technologies in developing an invention. More specifically, we use the share of citations made to unfamiliar technologies, aggregated to the firm-year level by averaging the values across the inventions produced by a firm in a given year.[6] In other words, it is $Exp_{ij} = \frac{N_{ij}}{C_{ij}}$, where N_{ij} is the number of patents in unfamiliar technology areas that firm i cites in a given year t. C_{ij} is the total number of citations firm i makes in year t.

We also construct an alternative measure of technology exploration based on new technology combinations that a firm explores in a given year. A new technology combination is defined as a combination of technology areas that a firm has never cited prior to the focal year.[7] More formally, it is $ExpC_{ij} = \frac{NC_{ij}}{CC_{ij}}$, where NC_{ij} is the number of unfamiliar combination of technology areas that firm i cites in a given year t. CC_{ij} is the total number of combination of technology areas that firm i cites in year t.[8]

3.2 Technology competition

To measure the level of technology competition that firms face, we use patent similarity data from Arts et al. (2021) who use patent title, abstract, and claims to determine textual similarity of patent pairs. To further ensure that the similar technologies are from rival firms, we follow Bloom et al. (2013) to construct a Mahalanobis-normalized measure of

[6] We also show that the results are consistent when using log transformed number of citations (as opposed to shares). Table 2 reports the results.

[7] We do not use technology component combination measures introduced by Fleming (2001) as those measures are more appropriate for measuring the realized novelty of the inventions, and not the exploration activities of firms where firms seek out new knowledge to use.

[8] By definition, the main measure of technology exploration is a subset of this alternative measure as, when a firm incorporates a technology from a technology area that it has never explored, a combination using that technology area will be unfamiliar to the firm as well.

product market rivalry between firm pairs and use it to weight the similarity scores. In other words, a focal technology facing a similar technology will get a higher technology competition score if the similar technology is produced by a product market rival. We aggregate the resulting weighted scores to the firm-year level by computing the average across the inventions produced by a firm in a given year. To minimize endogeneity concerns, for each invention, we limit competing inventions that are disclosed within three years after the production of the focal invention.[9]

We also construct an alternative measure of technology competition by incorporating a measure of product market rivalry from Hoberg and Phillips (2016) in place of the measure from Bloom et al. (2013). Hoberg and Phillips (2016) use textual analysis of product descriptions in 10-K's of firms represented in Compustat to determine firm pairwise similarities. We use this measure to weight the technology similarity score as we do with the main measure.

3.3 Corporate science

To examine the moderating effect of corporate science on the relationship between technology competition and technology exploration, we obtain from DISCERN a measure of corporate science based on the cumulative number of scientific articles published by each firm in our sample (i.e., time-varying publication stock). To construct the measure, Arora et al. (2021) merge firms extracted from Compustat to research articles indexed by the Web of Science. They include articles in "Science Citation Index" and "Conference Proceedings Citation Index-Science" while excluding articles in social sciences, arts, and humanities.

As an alternative measure of corporate science, we compute based on Marx and Fuegi (2020) the cumulative number of research publications that firms cite on their patent documents. We aggregate the measure to the firm-year level by averaging the values across the inventions produced by a firm in a given year. Prior studies have shown that patent citations to scientific publications are much better at capturing knowledge flow from scientific

[9] The results are robust to using all similar inventions, including those published prior to the production of focal inventions.

discoveries to inventions than patent citations to other patents (Arora et al., 2021; Roach & Cohen, 2013). Furthermore, Bikard and Marx (2020) and Ahmadpoor and Jones (2017) provide evidence that most of the patent citations to scientific publications come from the inventors themselves.

3.4 Markets for technology

To test the hypothesis that an active market for technology facilitates acquisition of unfamiliar technologies (Hypothesis 5), we construct a time-varying firm-level measure of markets for technology. To do so, we first obtain the patent reassignment data from the USPTO and clean the data according to the method outlined by Serrano (2010). We then count the number of patent reassignments that occur within each technology area for a given year. Finally, we construct a firm-level measure of markets for technology by weighting the technology area-level measure with each firm's share of inventions in each of the technology areas.

3.5 Control variables

To control for the differences in key variables that could bias the results, we include firm annual sales, R&D stock, invention stock, publication stock, and technology diversification.

R&D stock controls for the scale of R&D operations across firms and is defined as the cumulative amount of R&D investment made by a firm over sample years depreciated by 15% annually.[10] Invention stock controls for the inventiveness of the firms and is defined as the cumulative number of patents produced by a firm over sample years depreciated by 15% annually.[11] publication stock controls for the degree to which firms are able to maintain requite knowledge to adopt external technology and is defined as the cumulative number of research articles published by a firm over sample years depreciated by 15% annually.[12]

Diversification controls for the range of technology areas within which firms invent

[10] $R\&D\ stock_{i,t} = 0.85 \times R\&D\ stock_{i,t-1} + R\&D\ expenditure_{i,t}$.

[11] $Invention\ stock_{i,t} = 0.85 \times Invention\ stock_{i,t-1} + Inventions\ produced_{i,t}$.

[12] $Publication\ stock_{i,t} = 0.85 \times Publication\ stock_{i,t-1} + Publications\ produced_{i,t}$.

and is constructed by counting the number of technology areas in which a firm patents throughout the entire sample period. We multiply the count measure by one minus Herfindahl–Hirschman Index across the technology areas to control for the possibility that patents are concentrated in certain technology areas.[13]

3.6 Summary statistics

Table 1 presents the summary statistics for the main variables used in our study. It shows that the average technology competition score for a firm across its inventions in a given year is approximately 337.6 with a standard deviation of 2,366. Furthermore, firms in general tend to exploit familiar technologies more than unfamiliar technologies when developing their inventions. The average share of citations made to unfamiliar technologies is 0.025 with a standard deviation of 0.105, which is about 0.164 cites to unfamiliar technologies. The firm-level measure of markets for technology has a mean of 1,099 with a standard deviation of 1,626.

We also report distributions for sales, R&D stock, invention stock, publication stock, and technology diversification as prior studies have shown that technology search strategies and invention outcomes of firms can be influenced by these variables (Arora et al., 2023; Lee, 2023; Morandi Stagni et al., 2021). In all of our regression analyses, we control for these variables. Also, given that the measures are skewed, we log transform them.

[Insert Table 1 here]

[13] $Diversification_{i,t} = Number\ of\ CPC\ subclasses_{i,t} \times HHI_{i,t}$, where $HHI_{i,t}$ is the Herfindahl–Hirschman Index across the CPC classes that the firm patents in for a given year.

4 Econometric analysis

4.1 Econometric specification

To examine the interplay between technology competition, technology search strategy, and corporate science, we estimate the following specification in a regression analysis:

$$Tech\ explore_{it} = \beta_1 Comp_{it-1} + \beta_2 Comp_{it-1} \times Sci_{it-1} + \beta_7 Res_{it-1} + \mathbf{Z}_{it-1}\boldsymbol{\gamma} + \boldsymbol{\sigma}_i + \boldsymbol{\tau}_t + \epsilon_{it} \quad (1)$$

$Tech\ explore_{it}$ is the average share of citations made by firm i in year t to prior-art patents in unfamiliar technology areas. $Comp_{it-1}$ is the average technology competition score for firm i's inventions in year $t-1$. Sci_{it-1} is the number of research articles produced (or alternatively the cumulative number of patent citations made to scientific publications) by firm i in year $t-1$. $\mathbf{Z}_{it-1}$ is a vector of firm-level controls including sales, R&D stock, invention stock, publication stock, and technology diversification in year $t-1$. $\boldsymbol{\sigma}_i$ and $\boldsymbol{\tau}_t$ are complete sets of dummies for firms and years, respectively. ϵ_{it} is an *iid* error term. Standard errors are clustered at the firm level.

The coefficient of interest is β_1 and β_2. Per Hypothesis 1, we expect β_1 <0, indicating that technology competition leads to reduced technology exploration. Per Hypotheses 2, 3, and 4, we expect β_2 >0, indicating that large firms, technologically diversified firms, and firms investing in corporate science, respectively, pursue more technology exploration when technology competition intensifies.

Lastly, per Hypothesis 5, we estimate the following specification. (We also use a split sample with firms actively participatining in markets for technology and those that do not.)

$$\begin{aligned} Tech\ explore_{it} = {} & \beta_1 Comp_{it-1} + \beta_2 Comp_{it-1} \times Sci_{it-1} + \beta_3 MFT_{it-1} \times Comp_{it-1} \times Sci_{it-1} \\ & + \beta_4 MFT_{it-1} \times Comp_{it-1} + \beta_5 MFT_{it-1} \times Comp_{it-1} + \beta_6 MFT_{it-1} \times Sci_{it-1} \\ & + \beta_7 Res_{it-1} + \beta_8 MFT_{it-1} + \mathbf{Z}_{it-1}\boldsymbol{\gamma} + \boldsymbol{\sigma}_i + \boldsymbol{\tau}_t + \epsilon_{it} \end{aligned} \quad (2)$$

MFT_{it-1} is a dummy variable taking a value of 1 for firms with a high level of MFT participation (i.e., top half of the MFT score distribution), and 0 otherwise. The coefficient of interest is β_3, and per Hypothesis 5, we expect $\beta_3 <0$, indicating that when firms participate in markets for technology, the moderating effect of research engagement is dampened.

4.1.1 Instrumental variable strategy

In the baseline regression analyses, we take advantage of the panel structure of our sample and include complete sets of firm and year dummies to control for unobserved heterogeneity across firms and years. Furthermore, we lag the main explanatory variable and control variables to mitigate potential concerns regarding reverse causality. Lastly, to mitigate potential endogeneity concerns, we determine the level of competition by including only the competing inventions disclosed after the focal invention has been developed and filed for a patent.

Even with these measures, it is possible that both increases in technology competition and technology exploitation are driven by time-varying, unobserved technology shocks, resulting in an upwards bias. For instance, a commercially promising scientific discovery may spur downstream inventive activity in a specific technology area. This increase in development effort would lead to an increased number of inventions in that technology area. At the same time, firms would be less likely to explore other technology areas as they focus on applying the scientific discovery to their inventions in that same technology area. Thus, such common technology shock would result in a positive correlation between technology competition and technology exploitation.

To mitigate such concern, we instrument technology competition with state-level R&D tax credits that vary across states and years (Arora et al., 2021; Bloom et al., 2013; Lucking et al., 2018). The tax credits lower the cost of inventive activity, but should not directly affect the level of technology exploitation or exploration firms pursue. In essence, using each firm's cost of R&D for each sample year obtained from Lucking et al. (2018), we regress the number of inventions produced by firms against this cost. We then predict the number of inventions developed by each firm in each year. Lastly, for each firm, we compute the average number of inventions produced by other firms weighted by the product market proximity. We use this predicted average number of rival inventions to instrument for the measure of technology competition.

4.2 Baseline analysis

Table 2 presents the analysis examining the direct relationship between technology competition and exploration. Column 1 reports the results from the baseline regression. To control for firm and year fixed effects, the specification includes a complete set of firm and year dummies. Column 2 adds sales to control for firm size, which could influence technology search strategy (Rosenberg, 1990), and column 3 adds R&D and invention stock to control for R&D scale and level of inventive activity. Column 4 adds publication stock that could influence the extent to which firms can absorb external knowledge (Cohen & Levinthal, 1990), and column 5 adds technology diversification to control for the scope of the existing technology areas that could influence the degree to which firms pursue technology exploration.

The general pattern across the columns shows that as technology competition intensifies, firms are less likely to pursue technology exploration. Specifically, doubling technology competition score is associated with 0.007 percentage point decline in the share of citations made to patents in unfamiliar technology areas, or approximately 28.3% at the sample mean.

Given that *technology exploration* is defined as the share of patent citations made to inventions in unfamiliar technology areas, it is not possible to determine whether technology exploration and exploitation increased or declined in absolute level. Thus, we run two more regressions using the number of citations made to patents in unfamiliar technology areas (column 6) and familiar technology areas (column 7). The results indicate that, when firms face increased competition, they reduce technology exploration (column 6), while increasing technology exploitation (column 7). More specifically, at the sample mean, doubling the level of *technology competition* is associated with 12% decline in technology exploration and

67% increase in technology exploitation.[14]

Lastly, columns 8 and 9 present results using an instrumental variable analysis. Column 8 reports the first stage results on the relationship between technology competition and aggregate rival inventions. As expected, the positive coefficient (statistically significant at the 1% level) indicates that 10% increase in aggregate rival inventions is associated with 8.9% increase in technology competition. This result is expected as firms operating in the same product market invent more, the number of similar inventions are likely to increase. F-statistic is 41, indicating a strong first-stage relationship.

Column 9 reports the second-stage results. Consistent with the OLS results, the negative coefficient (statistically significant at 1% level) indicates that increased technology competition leads to firms pulling back from technology exploration relative to technology exploitation. Specifically, the results show that a doubling of technology competition leads to 0.016 percentage point decline in the share of patent citations made to patents in unfamiliar technology areas, or 65% at the sample mean.

These findings are consistent with the notion that firms pull back from technology exploration when increased competition threatens their ability to capture profits from their inventions.

[Insert Table 2 here]

In Table 3, we explore the extent to which firm size (columns 1-3) and technology diversification (columns 4-6) of a firm moderate the relationship between technology competition and technology exploration. To the extent that firms pull back from technology exploration because of the threat to their profitability realized through their inventions, both firm size and technology diversification should weaken the technology competition-exploration relationship. Consistent with Hypothesis 2, the results in columns 1-3 show that when technology competition intensifies, large firms do not pull back from technology exploration as much

[14] We use share, instead of number, of patent citations made to unfamiliar technology areas throughout the rest of the study to avoid redundancy. The results are consistent even if we use number of patent citations made to unfamiliar and familiar technology areas.

as small firms. Specifically, 2SLS results in Column 3 indicate that larger firms pull back approximately 7.7% less from technology exploration than smaller firms.

Columns 4-6 provide evidence supporting Hypothesis 3, indicating that the relationship between technology competition and technology exploration is weakened when firms are technologically diversified across multiple technology areas. Specifically, 2SLS results in column 6 indicate that more diversified firms pull back from technology exploration 25% less than less diversified firms.

Together the findings from Tables 2 and 3 provide evidence that firms pull back from technology exploration when the expected profits from their inventions are lower due to similar inventions introduced by product market rivals.

[Insert Table 3 here]

4.3 Corporate science

In Table 4, we examine the extent to which the relationship between technology competition and technology exploration is moderated by corporate science (both direct engagement in research and use of available science). To do so, we first interact *technology competition* with a continuous measure of direct research engagement (i.e., time-varying publication stock) and a dummy variable indicating a high level of research engagement (i.e., firms in the top quartile of publication stock distribution) in columns 1 and 2, respectively.

Consistent with Hypothesis 2, the results in both columns 1 and 2 show a positive and statistically significant (at the 1% level) coefficient on the interaction term (0.002 and 0.008), indicating that the negative relationship between technology competition and technology exploration is weakened when firms conduct research. In other words, the results show that firms with a higher level of research engagement pull back less from technology exploration when technology competition intensifies. The 2SLS results in column 3 provide additional support, showing that firms engaging in more research pull back approximately 4.8% less from technology exploration than firms engaging in less research. These results are consistent with the interpretation that direct engagement in research allows firms to develop the capacity to evaluate and use unfamiliar technologies which they can harness when they face increased technology competition.

As an additional test, we examine whether frequent use of available scientific knowledge, as reflected in the cumulative number of patent citations made to scientific publications, also influences the degree to which firms pursue technology exploration when they face increased competition. To the extent that frequent use of scientific knowledge also equips firms with the requisite knowledge to explore unfamiliar technologies in response to increased competition, it should moderate the competition-exploration relationship in a way similar to direct research engagement. To investigate this notion, we interact *technology competition* with a continuous measure of cumulative number of patent citations made to scientific publications and a dummy variable indicating a high level of such citations (i.e., firms in the top quartile of the cumulative citation count distribution) in columns 4 and 5, respectively. We control for the number of scientific publications, a measure of direct research engagement, to disentangle the effect of the use of scientific knowledge from the effect of direct research engagement. 2SLS results in column 6 add further support, showing that firms using more scientific knowledge pull back approximately 4.2% less from technology exploration than firms using less scientific knowledge.

The findings indicate that, when technology competition intensifies, both firms engaging directly in research and firms using available scientific knowledge tend to pull back less from technology exploration relative to firms that do not. Notably, while prior studies have emphasized the importance of direct research engagement in absorbing external knowledge, this finding provides evidence that use of available scientific knowledge can have a similar effect.

[Insert Table 4 here]

4.4 Markets for technology

To further investigate the mechanism driving the effect of corporate science, we examine how corporate science is in turn conditioned by the existence of active markets for technology. To the extent that markets for technology facilitate the discovery and understanding of unfamiliar technologies, the moderating effect of corporate science should be weakened when firms actively participate in markets for technology (Hypothesis 5).

Table 5 presents results relating to markets for technology. Column 1 interacts technology competition with a continuous measure of markets for technology and a dummy variable for high research engagement (a three-way interaction). The negative coefficient on the three-way interaction (statistically significant at 5% level) indicates that, when the level of participation in MFT is higher, the moderating effect of research engagement is weakened by 11% relative to when the level is lower. Columns 2 and 3 present results from a split sample analysis with column 2 reporting low-MFT results and column 3 reporting high-MFT results. Consistent with column 1, the results show that, when the level of MFT is high, the effect of research engagement is less pronounced.

Columns 4-6 report results relating to cumulative use of scientific knowledge in place of direct research engagement. Column 4 is based on a three-way interaction, and columns 5 and 6 are based on split-sample analysis. The results are consistent with those in columns 1-3, showing that the moderating effect of cumulative use of scientific knowledge is weakened by 9% when the level of participation in MFT is high.

These findings are consistent with Hypothesis 5 and provide additional support that possessing the requisite knowledge is a significant driver of technology exploration, specifically when technology competition intensifies.

[Insert Table 5 here]

4.5 Robustness tests

To test the robustness of our findings, we conduct analyses relating to alternative measures of technology exploration and technology competition as well as analyses relating to core inventions and firm technology areas. We also present results from a panel event study exploiting sharp increases in the number of inventions produced in individual technology areas.

4.5.1 Alternative measure of technology exploration

To further examine how increased technology competition from product market rivals affects technology exploration, we test the robustness of the main finding using an alternative measure of technology exploration. The measure is based on a combination of technologies that firms explore rather than a single, new technology area.

Table 6 reports results relating to this analysis. The pattern of results are consistent with the main findings of the study. Column 1 shows that the alternative measure of technology exploration has a negative relationship with technology competition. Columns 2 and 3 continue to show that this relationship is weakened when the firm is large (column 2) or technologically diversified (column 3). Columns 4 and 5 provide additional support that firms investing more in corporate science, through direct engagement or by using scientific knowledge, are more likely to engage in technology exploration relative to firms that invest less. Lastly, columns 6 and 7 indicate that the moderating effect of corporate science is weaker when firms actively participate in markets for technology, suggesting that possession of requisite knowledge is a significant factor driving the relationship.

4.5.2 Alternative measure of technology competition

To ensure that our findings are not sensitive to how competition is defined, we reexamine the competition-technology exploration relationship using time-varying product market competition measure obtained from Hoberg and Phillips (2016). We use this alternative measure to weight the invention similarity scores as it was done for the main measure of competition. The alternative measure is based on the product descriptions in the 10-K's of the firms represented in Compustat and is computed as the sum of all pairwise textual similarity scores between the focal firm and all other firms.

Columns 1 and 2 of Table 7 present results based on this alternative measure. Consistent with the main findings, the results show that there is a negative relationship between technology competition and technology exploration and that this relationship is weakened for either firms directly engaged in research (column 1) or firms using available scientific knowledge (column 2).

4.5.3 Invention similarity score threshold

To determine whether two inventions are similar, our main analysis uses cosine similarity scores computed based on patent text (Arts et al., 2021). To ensure that the results are robust to using only highly similar inventions to define technology competition, we set the threshold to 75th percentile of the similarity score distribution across all pairs of inventions and designate two patents to be similar only if their similarity score is above the threshold.

Columns 3 and 4 of Table 7 report the results relating to this analysis. The results are consistent with the main findings, showing that both direct engagement in research (column 3) and use of scientific knowledge (column 4) weaken the negative relationship between technology competition and technology exploration.

4.5.4 Core inventions

Given that a firm can produce inventions in several technology areas outside of its core area, it may not be as sensitive to increased competition in non-core technology areas. Thus, we reexamine the relationship between technology competition and technology exploration as well as the moderating effect of research engagement only based on inventions in the core technology areas of firms. The core technology area of a firm is defined as the technology area (i.e., CPC section) in which the firm produces the highest number of inventions.

Columns 5 (direct research engagement) and 6 (use of scientific knowledge) of Table 7 show that the main findings hold even when using only the core inventions.

4.5.5 Firm-technology area-year level analysis

On the other hand, given that firms could have a focus in multiple technology areas, we rerun our analysis using a firm-technology area-year level sample. To do so, we re-compute the measure of technology competition and cites to research publications to be at the firm-technology area-year level. Columns 7 and 8 of Table 7 continue to show that the main findings hold even at the firm-technology area-year level.

[Insert Table 7 here]

4.5.6 Difference-in-differences models

In Appendix Section A.1, we present results from a panel event study exploiting sharp increases in the number of inventions produced by firms in individual technology areas during the sample period. The results are consistent with the main findings showing that a sharp increase in the number of inventions in a given technology area leads to a decline in technology exploration (Figure A1, Figure A2, Table A2). The results further show that this negative relationship is weakened when firms invest in corporate science (Figure A3, Figure A4, Table A2). Refer to Appendix Section A.1 for a more detailed discussion.

For completeness, we also look at two-way fixed effects model in Appendix Section A.2. Consistent with the main findings, the results in A3 indicate that technology competition results in firms pulling back from technology exploration (column 1) but that this relationship is weaker for firms engaging directly in research (columns 2 and 3) as well as firms using available scientific knowledge (columns 4 and 5).

5 Concluding remarks

In this study, we explore the degree to which corporate science facilitates technology exploration when firms face an increased level of technology competition from their product market rivals. To do so, we construct a measure of technology competition based on textual similarity of patent documents combined with data on product market rivals as well as a measure of technology exploration based on patent citations made to patents in unfamiliar technology classes. We also employ different measures of corporate science, reflecting the degree to which firms either directly engage in research or use available scientific knowledge. Robust to several alternative specifications and measures, the findings show that, on average, firms decrease the level of technology exploration when technology competition from product market rivals intensifies. However, firms that invest in a higher level of corporate science tend to pursue more technology exploration relative to firms that do not.

The recent rise in geopolitical tension between the United States and China has spurred discussions on whether U.S. firms can maintain its technology leadership. A part of the concern arising from these discussions is the fact that U.S. firms have withdrawn significantly from scientific research. However, the findings from this study suggest that direct engagement in scientific research may not be the only way to facilitate technology exploration of firms, but that use of available scientific knowledge also helps firms to explore distant technology areas when they face a competitive threat from similar technologies. The evidence suggests that, despite the concerns regarding the decline in research expenditure by U.S. firms, division of innovative labor in research and development between universities and firms could be an effective way to promote technology exploration. The findings also suggest that well-functioning markets for technology can serve as an alternative channel through which firms pursue technology exploration.

This study is subject to several limitations. While this study includes patented inventions from U.S. public firms, it excludes a large number of non-public and non-U.S firms that produce technological inventions. A future study could extend the sample to include non-public and non-U.S. firms and examine whether the findings of this study generalize to the representative sample.

Additionally, we use textual similarity of patent documents to determine the level of competition for each of the inventions included in our sample. While this measure does allow us to determine the similarity of the inventions at the technology level, it does not tell us the ways in which these inventions are incorporated into products. Understanding the level of significance that these inventions have at the product level could provide us with additional insights into how firms respond to competition involving their inventions.

Lastly, while we show that corporate science facilitates technology exploration, we do not explore the types of scientific knowledge that might be more useful in promoting technology exploration. Understanding the types of scientific knowledge that firms can benefit most from in pursuing a certain technology search strategy would help set policies that promote effective division of innovative labor in research and development with respect to technology exploration.

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Table 1: Summary statistics for main variables

	(1)	(2)	(3)	(4)	(5)	(6)
				Distribution		
VARIABLES	No. Obs	Mean	Std. Dev.	10th	50th	90th
Year	32,467	1,997	8.573	1,985	1,997	2,009
Technology competition	32,467	337.6	2,366	0.123	7.038	373.7
Number of cites to unfamiliar CPC	32,467	0.164	0.507	0	0	1
Share of cites to unfamiliar CPC	32,467	0.025	0.105	0	0	0.025
Markets for technology	32,467	1,199	1,626	0	710.5	3,109
Sales	32,407	3,289	14,126	8.915	259.9	6,049
R&D stock	32,466	589.5	2,876	1.524	41.05	836.5
Patent stock	32,466	168.2	804.4	1.614	13.41	300.9
Publication stock	32,466	107.3	586.7	0	3.222	116.1
Citations to research	32,467	685.2	3,994	0	17.4	996.4
Diversification	32,467	0.86	1.283	0	0	2.776

Notes: The table presents summary statistics for the main variables used in our study. *Year* is based on application year of patents. *Technology competition* is the degree of technology-level competition that firms face across its inventions in a given year. *Number of cites to unfamiliar CPC* is the average number of patent citations made to patents in CPC sections that the firm have never cited. *Share of cites to unfamiliar CPC* is the share of patent citations made to CPC sections that the firm has not cited before. *Market for technology* is the weighted average of the number of patent reassignments across technology areas, where the weight is the firms' expore to each of the technology areas.

Table 2: Technology competition and technology exploration

Dependent variable	Share of cites made to patents in unfamiliar technology area					log(1+Cites to unfam. tech. area)	log(1+Cites to fam. tech. area)	log(1+Tech. comp.)	Share of cites to unfam. tech area
								1st stage	2nd stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(1+Tech. competition)$_{t-1}$	-0.008**	-0.008**	-0.007**	-0.007**	-0.007**	-0.019**	0.107**		-0.016**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.012)		(0.006)
log(1+Rival inventions)$_{t-1}$								0.888**	
								(0.139)	
log(1+Sales)$_{t-1}$		0.001	0.002	0.001	0.002	0.014**	0.156**	0.032	0.002
		(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.014)	(0.019)	(0.001)
log(1+R&D stock)$_{t-1}$			0.001	-0.000	0.000	0.002	0.084**	0.088**	0.001
			(0.001)	(0.001)	(0.001)	(0.003)	(0.021)	(0.024)	(0.001)
log(1+Patent stock)$_{t-1}$			-0.003**	-0.005**	-0.004**	-0.051**	0.009	0.639**	0.002
			(0.001)	(0.001)	(0.001)	(0.004)	(0.021)	(0.026)	(0.004)
log(1+Publication stock)$_{t-1}$				0.004*	0.004*	0.004	-0.006	-0.030	0.003*
				(0.001)	(0.001)	(0.004)	(0.020)	(0.025)	(0.001)
log(1+Diversification)$_{t-1}$					-0.011**	-0.029**	0.601**	0.277**	-0.009**
					(0.002)	(0.005)	(0.027)	(0.023)	(0.002)
F-stats								41	
Firm dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Number of firms	2,752	2,752	2,752	2,752	2,752	2,752	2,752	2,752	2,752
Mean of DV	0.02	0.02	0.02	0.02	0.02	0.16	0.16	0.02	0.02
Observations	32,467	32,467	32,467	32,467	32,467	32,467	32,467	32,467	32,467
R-squared	0.18	0.18	0.18	0.18	0.19	0.18	0.81	0.25	0.00

Notes: The table presents results on the relationship between the technology competition and technology exploration. Robust standard errors in parentheses. ** p<0.01, * p<0.05.

Table 3: Firm size and technology diversification

Dependent variable	Share of cites made to patents in unfamiliar technology area					
	Firm size			Diversification		
			2nd stage			2nd stage
	(1)	(2)	(3)	(4)	(5)	(6)
log(1+Technology competition)$_{t-1}$	-0.013**	-0.009**	-0.026**	-0.010**	-0.010**	-0.016**
	(0.001)	(0.001)	(0.008)	(0.001)	(0.001)	(0.006)
log(1+Tech competition)$_{t-1}$ ×						
log(1+Sales)$_{t-1}$	0.001**		0.002**			
	(0.000)		(0.000)			
Dummy for a large firm$_{t-1}$		0.006**				
		(0.001)				
log(1+Technology diversification)$_{t-1}$				0.008**		0.004**
				(0.001)		(0.001)
Dummy for high diversification$_{t-1}$					0.007**	
					(0.001)	
log(1+Sales)$_{t-1}$	-0.005**	0.003**	-0.007**	0.002	0.002	0.002*
	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
log(1+R&D stock)$_{t-1}$	0.001	0.001	0.002	0.001	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
log(1+Patent stock)$_{t-1}$	-0.006**	-0.006**	-0.001	-0.006**	-0.007**	-0.000
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.004)
log(1+Publication stock)$_{t-1}$	0.002	0.003	0.002	0.002	0.003*	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(1+Diversification)$_{t-1}$	-0.012**	-0.012**	-0.010**	-0.063**	-0.006**	-0.035**
	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.007)
Dummy for a large firm$_{t-1}$		-0.044**				
		(0.007)				
Dummy for high diversification$_{t-1}$					-0.049**	
					(0.006)	
F-stats			21			20
Firm dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	Firm	Firm	Firm	Firm	Firm	Firm
Number of firms	2,752	2,752	2,752	2,752	2,752	2,752
Mean of DV	0.02	0.02	0.02	0.02	0.02	0.02
Observations	32,467	32,467	32,467	32,467	32,467	32,467
R-squared	0.19	0.19	0.00	0.19	0.19	0.01

Notes: The table presents the results on the extent to which firm size and technology diversification moderates the relationship between technology competition and technology exploration. *Dummy for a large firm* takes a value of 1 if a firm is in the top half of the sales distribution, 0 otherwise. *Dummy for high diversified* takes a value of 1 if a firm is in the top half of the diversification distribution. Robust standard errors in parentheses. ** p<0.01, * p<0.05.

Table 4: Corporate science and technology exploration

Dependent variable	Share of cites made to patents in unfamiliar technology area					
			2nd stage			2nd stage
	(1)	(2)	(3)	(4)	(5)	(6)
log(1+Technology competition)$_{t-1}$	-0.011**	-0.009**	-0.021**	-0.013**	-0.009**	-0.024**
	(0.001)	(0.001)	(0.007)	(0.001)	(0.001)	(0.006)
log(1+Tech competition)$_{t-1}$ ×						
log(1+Publication stock)$_{t-1}$	0.002**		0.001**			
	(0.000)		(0.000)			
Dummy for a high research engagement$_{t-1}$		0.008**				
		(0.001)				
log(1+Cumulative cites to science)$_{t-1}$				0.002**		0.001**
				(0.000)		(0.000)
Dummy for a high cites to research$_{t-1}$					0.009**	
					(0.001)	
log(1+Sales)$_{t-1}$	0.003*	0.002*	0.003*	0.002*	0.002	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(1+R&D stock)$_{t-1}$	0.001	0.001	0.002	0.002	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
log(1+Patent stock)$_{t-1}$	-0.006**	-0.005**	0.003	-0.006**	-0.005**	0.002
	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.003)
log(1+Publication stock)$_{t-1}$	-0.013**	0.002	-0.004	0.001	0.002	0.001
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
log(1+Diversification)$_{t-1}$	-0.011**	-0.011**	-0.008**	-0.010**	-0.011**	-0.008**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
log(1+Cumulative cites to pubs)$_{t-1}$				-0.016**		-0.007**
				(0.001)		(0.002)
Dummy for a high research engagement$_{t-1}$		-0.062**				
		(0.007)				
Dummy for a high cites to research$_{t-1}$					-0.063**	
					(0.007)	
F-stats			21			20
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	Firm	Firm	Firm	Firm	Firm	Firm
Number of firms	2,752	2,752	2,752	2,752	2,752	2,752
Mean of DV	0.02	0.02	0.02	0.02	0.02	0.02
Observations	32,467	32,467	32,467	32,467	32,467	32,467
R-squared	0.19	0.19	0.00	0.19	0.19	0.19

Notes: The table presents the results on the extent to which corporate science moderates the relationship between technology competition and technology exploration. Robust standard errors in parentheses. ** $p<0.01$, * $p<0.05$.

Table 5: Corporate science and markets for technology

Dependent variable	Share of cites made to patents in unfamiliar technology area					
	Publication stock			Cumul. num. of cites to research		
	Interaction	Low MFT	High MFT	Interaction	Low MFT	High MFT
	(1)	(2)	(3)	(4)	(5)	(6)
log(1+Tech competition)$_{t-1}$	-0.013**	-0.011**	-0.004**	-0.013**	-0.011**	-0.004**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
log(1+Tech competition)$_{t-1}$ ×						
Dummy for a high research engagement$_{t-1}$	0.009**	0.012**	0.002**			
	(0.002)	(0.001)	(0.001)			
Dummy for a high cites to research$_{t-1}$				0.011**	0.012**	0.002**
				(0.001)	(0.001)	(0.001)
log(1+Tech competition)$_{t-1}$ ×						
Dummy for high research engagement$_{t-1}$ ×						
Markets for technology$_{t-1}$	-0.001**					
	(0.000)					
Dummy for high cites to research$_{t-1}$ ×				-0.001**		
Markets for technology$_{t-1}$				(0.000)		
				(0.001)		
log(1+Sales)$_{t-1}$	0.003*	0.004*	0.001	0.002*	0.004*	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
log(1+R&D stock)$_{t-1}$	0.001	0.005	-0.000	0.001	0.004	-0.000
	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)
log(1+Patent stock)$_{t-1}$	-0.006**	-0.014**	-0.001	-0.006**	-0.014**	-0.001
	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)
log(1+Publication stock)$_{t-1}$	0.002	0.005	-0.000	0.002	0.005	-0.001
	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)
log(1+Diversification)$_{t-1}$	-0.010**	-0.016**	-0.005**	-0.010**	-0.016**	-0.004**
	(0.002)	(0.004)	(0.001)	(0.002)	(0.004)	(0.001)
Dummy for a high research engagement$_{t-1}$	-0.077**	-0.074**	-0.018**			
	(0.011)	(0.011)	(0.005)			
Dummy for a high cites to research$_{t-1}$				-0.079**	-0.075**	-0.020**
				(0.010)	(0.010)	(0.005)
Markets for technology$_{t-1}$ ×						
log(1+Tech competition)$_{t-1}$	0.001**			0.001**		
	(0.000)			(0.000)		
Dummy for a high research engagement$_{t-1}$	0.006**					
	(0.001)					
Dummy for a high cites to research$_{t-1}$				0.006**		
				(0.001)		
Markets for technology$_{t-1}$	-0.008**			-0.008**		
	(0.001)			(0.001)		
Firm dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	Firm	Firm	Firm	Firm	Firm	Firm
Number of firms	2,752	2,120	1,869	2,752	2,120	1,869
Mean of DV	0.02	0.04	0.01	0.02	0.04	0.01
Observations	32,467	15,987	15,867	32,467	15,987	15,867
R-squared	0.192	0.196	0.288	0.192	0.197	0.288

Notes: The table presents the results on the extent to which participation in markets for technology affects the moderating effect of corporate science and the use of available scientific knowledge. Robust standard errors in parentheses. ** p<0.01, * p<0.05.

Table 6: Unfamiliar technology combination

Dependent variable	Share of cites made to unfamiliar technology combination						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(1+Technology competition)$_{t-1}$	-0.012**	-0.013**	-0.013**	-0.014**	-0.016**	-0.013**	-0.013**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
log(1+Tech competition)$_{t-1}$ ×							
Dummy for a large firm$_{t-1}$		0.005**					
		(0.002)					
Dummy for a diversified firm$_{t-1}$			0.004*				
			(0.002)				
Dummy for a high research engagement$_{t-1}$				0.009**		0.001	
				(0.002)		(0.004)	
Dummy for a high cites to research$_{t-1}$					0.014**		0.007*
					(0.002)		(0.003)
log(1+Tech competition)$_{t-1}$ ×							
Dummy for high research engagement$_{t-1}$ ×							
Markets for technology$_{t-1}$						0.001*	
						(0.001)	
Dummy for high cites to research$_{t-1}$ ×							0.001*
Markets for technology$_{t-1}$		0.005**					(0.000)
		(0.002)					
log(1+Sales)$_{t-1}$	0.010**	0.011**	0.010**	0.011**	0.011**	0.011**	0.011**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log(1+R&D stock)$_{t-1}$	0.002	0.003	0.002	0.003	0.003	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log(1+Patent stock)$_{t-1}$	-0.030**	-0.030**	-0.031**	-0.031**	-0.030**	-0.033**	-0.032**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log(1+Publication stock)$_{t-1}$	0.001	-0.000	0.001	0.001	-0.001	0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
log(1+Diversification)$_{t-1}$	-0.013*	-0.012*	-0.004	-0.013*	-0.011*	-0.003	-0.001
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
log(1+Tech competition)$_{t-1}$ ×							
Markets for technology$_{t-1}$						0.001	0.001
						(0.001)	(0.001)
Dummy for a high research engagement$_{t-1}$							
Markets for technology$_{t-1}$						-0.005	
						(0.004)	
Dummy for high cites to research$_{t-1}$ ×							
Markets for technology$_{t-1}$							-0.004
							(0.004)
Markets for technology$_{t-1}$						-0.008**	-0.008**
						(0.002)	(0.002)
Dummy for a large firm$_{t-1}$		-0.049**					
		(0.016)					
Dummy for a diversified firm$_{t-1}$			-0.031*				
			(0.013)				
Dummy for a high research engagement$_{t-1}$				-0.074**		-0.032	
				(0.016)		(0.029)	
Dummy for a high cites to research$_{t-1}$					-0.127**		-0.099**
					(0.014)		(0.023)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Number of firms	2,752	2,752	2,752	2,752	2,752	2,752	2,752
Mean of DV	0.15	0.15	0.15	0.15	0.15	0.15	0.15
Observations	32,467	32,467	32,467	32,467	32,467	32,467	32,467
R-squared	0.21	0.21	0.21	0.21	0.21	0.21	0.21

Notes: The table presents results on the relationship between the technology competition and technology exploration. Robust standard errors in parentheses. ** p<0.01, * p<0.05.

Table 7: Other robustness tests

Dependent variable	Share of cites made to patents in unfamiliar technology area							
	Alt. measure of comp		75th %tile threshold		Core inventions		Firm-tech-year level	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(1+Technology competition)$_{t-1}$	-0.002**	-0.002**	-0.003**	-0.003**	-0.005**	-0.005**	-0.002**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
log(1+Technology competition)$_{t-1}$ ×								
Dummy for a high research engagement$_{t-1}$	0.004**		0.005**		0.006**		0.005**	
	(0.000)		(0.001)		(0.001)		(0.000)	
Dummy for a high research engagement$_{t-1}$		0.004**		0.005**		0.007**		0.004**
		(0.000)		(0.000)		(0.001)		(0.000)
log(1+Sales)$_{t-1}$	0.002*	0.002*	0.002	0.002	0.001	0.001	-0.002	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(1+R&D stock)$_{t-1}$	-0.000	-0.000	-0.000	0.000	0.000	0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(1+Patent stock)$_{t-1}$	-0.008**	-0.008**	-0.008**	-0.009**	-0.006**	-0.006**	-0.008**	-0.009**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(1+Publication stock)$_{t-1}$	0.003	0.003	0.004*	0.003*	0.002	0.002	0.003**	0.005**
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(1+Diversification)$_{t-1}$	-0.012**	-0.012**	-0.012**	-0.012**	-0.008**	-0.008**	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Dummy for a high research engagement$_{t-1}$	-0.029**		-0.023**		-0.049**		-0.018**	
	(0.004)		(0.004)		(0.006)		(0.004)	
Dummy for a high research engagement$_{t-1}$		-0.026**		-0.022**		-0.048**		-0.028**
		(0.003)		(0.004)		(0.007)		(0.003)
Firm dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Number of firms	2,752	2,752	2,752	2,752	2,454	2,454	2,796	2,796
Mean of DV	0.02	0.02	0.04	0.04	0.04	0.04	0.02	0.02
Observations	32,467	32,467	32,467	32,467	29,142	29,142	97,264	97,264
R-squared	0.19	0.19	0.18	0.19	0.19	0.19	0.26	0.26

Notes: The table presents results from various robustness tests relating to an alternative measure of competition (columns 1 and 2), textual similarity threshold (columns 3 and 4), core inventions (columns 5 and 6), and firm-technology class-year level (columns 7 and 8). Robust standard errors in parentheses. ** p<0.01, * p<0.05.

Appendix A Difference-in-Differences Model

A.1 Panel even study

In this section, we further address potential endogeneity concerns by employing a panel event study that allows us to examine the change in the level of technology exploration before and after a sharp increase in technology competition.

To construct the sample for the panel event study, we first compute the yearly changes in the number of inventions produced within each CPC section, which USPTO uses to group similar technologies together.[15] We aggregate this CPC section-year level measure to the firm-year level by weighting the changes by each firm's share of inventions in each of the CPC sections.

The treatment group for the panel event study consists of firms inventing in technology areas that experience a sharp increase in the number of inventions produced by all inventing firms. More specifically, we first compute yearly changes in the number of inventions for each technology area. This technology area-level measure is aggregated to the firm level by weighting the values by each firm's share of inventions in each of the technology areas for a given year. We designate the firm-year pairs that are in the top quartile of this measure as treated.

To account for the underlying propensity of firms to pursue technology exploration, for each treated observation, we find a control observation matched on industry (3-digit SIC) and year and with the smallest difference in sales, R&D stock, invention stock, publication stock, and cumulative citations to scientific publications – attributes that can potentially influence technology exploration. We perform our matching using Coarsened Exact Matching method (Iacus, King, & Porro, 2012).

Table A1 presents the mean comparison of the matched variables between treatment group and control group at the time of the treatment. The results show that there are no statistically significant differences between the treatment and control groups. However, to further mitigate potential concerns, we add these variables (log transformed) to the panel event study as controls.

Table A1: Mean comparison of matched variables between treatment and control group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mean comp.	Treated			Untreated		
VARIABLES	(3) minus (6)	No. firms	Mean	Std. Dev.	No. firms	Mean	Std. Dev.
Sales	1,137	385	2,820	14,141	378	1,684	5,485
R&D stock	210	385	557	3,648	378	347	1,443
Patent stock	6	385	116	579	378	110	456
Publication stock	14	385	54	248	378	40	131
Stock of cites to research	175	385	661	2,270	378	486	1,742

Notes: The table presents mean comparison between treated inventions and their matched firms. ** p<0.01, * p<0.05.

To examine the effect of a sharp increase in technology competition on the subsequent

[15] We use CPC section because CPC sections are the broadest categorization and thus moving across CPC sections should represent most distant technolog exploration. The results are consistent when we use CPC classes instead.

technology search strategies of firms, we estimate the following panel event study specification:

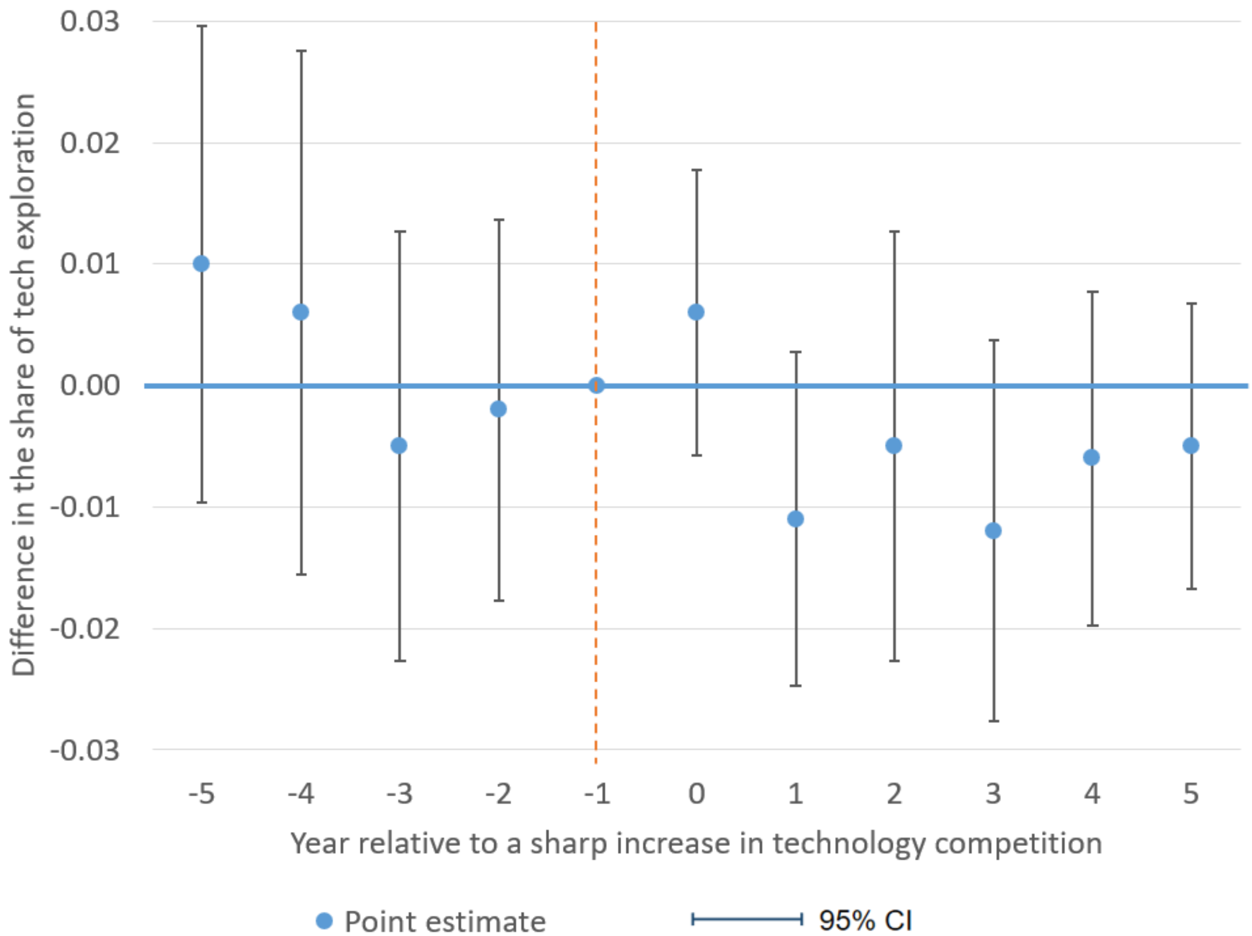
$$Tech\ explore_{it} = \sum_{j=1}^{5} \beta_j \left(Lead\ j\right)_{it} + \sum_{k=1}^{5} \gamma_k \left(Lag\ k\right)_{it} + X\prime_{it-1}\Gamma + \mu_i + \lambda_t + \varepsilon_{it} \qquad \text{(A.1)}$$

$(Lead\ j)_{it} = 1[t = Event_i - j]\ for\ j\ \in \{1, 2, 3, 4, 5\}$ and $(Lag\ k)_{it} = 1[t = Event_i + k]\ for\ k\ \in \{1, 2, 3, 4, 5\}$. $Event_i$ is the year in which a firm i experiences a sharp increase in the number of inventions in technology areas in which they invent. μ_i and λ_t are firm and year fixed effects, and $X\prime_{it-1}$ are time-varying, firm-level controls as specified in the baseline analysis. ε_{it} is the *iid* error term. Robust standard errors are clustered at the firm level.

Figure A1 presents results from the panel event study. (The regression results underlying the figure are reported in column 1 of Table A2.) The horizontal axis is the year relative to a sharp increase in technology competition, and the vertical axis is the difference in the share of citations made to patents in unfamiliar technology areas between the treated group and the control group relative to that of the reference year, marked by the vertical dotted line. Each solid vertical bar indicates a 95% confidence interval.

The figure shows that, although the apparent drop in the difference in the share of citations to patents in unfamiliar technology areas is not statistically significant at the 5% level, at the 10% significance level, the difference drops 12% compared to the reference year.

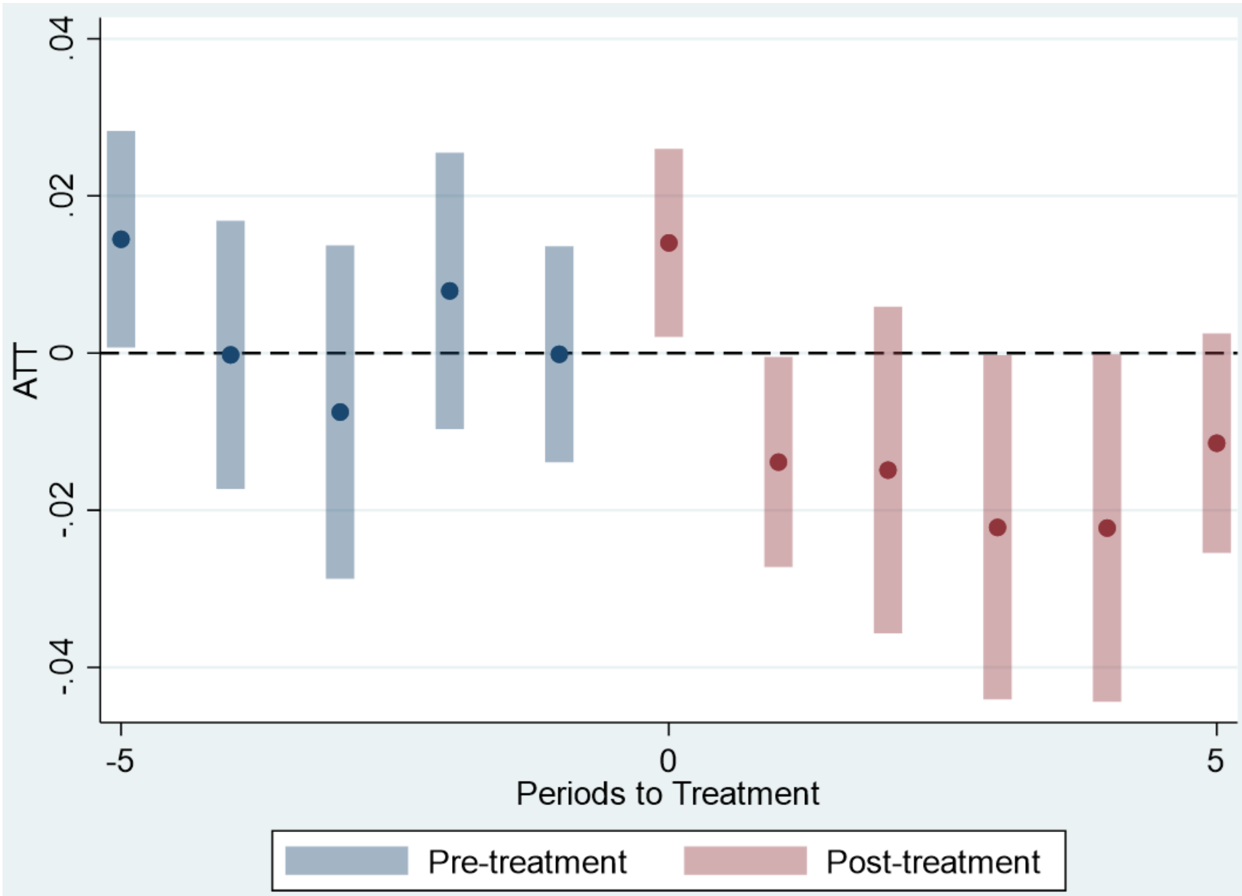
Figure A1: Panel event study - Technology exploration



Notes: The figure presents results from a panel event study regression, examining the effect of increased technology competition on technology exploration. X-axis represents years relative to a sharp increase in the technology competition, and Y-axis represents the difference in technology exploration (i.e., share of patent citations made to patents in unfamiliar technology areas) between treated and control groups relative to the reference year (year -1). The vertical lines represent 95% confidence interval.

Recent studies have shown that panel event studies can be biased when treatment effects are heterogeneous across time or firms as is the case in this study (De Chaisemartin & d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021). Thus, we further probe the results from the panel event study using a method proposed by Callaway and Sant'Anna (2021) that is robust to such biases. We replicate our analysis using the proposed method and present the results in Figure A2. The results show that the decline in technology exploration during the post-treatment period is statistically significant at the 5% level.

Figure A2: Panel event study - Callaway and Sant'Anna



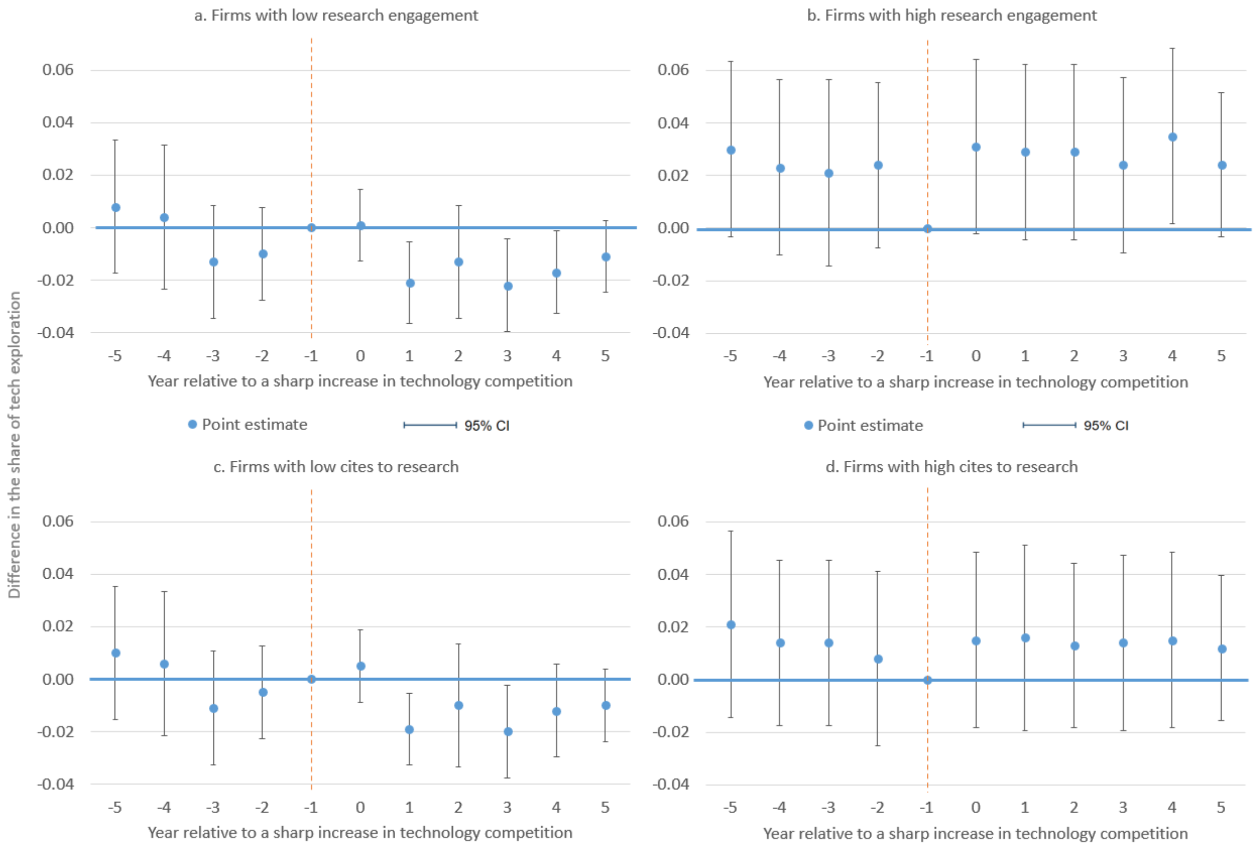
Notes: The figures present results from a panel event study regression, examining the effect of increased competition on technology exploration. To account for the potential bias arising from treatment heterogeneity across years and firms, the analysis utilizes the algorithm proposed by Callaway and Sant'Anna (2021) that accounts for such bias.

Turning to Figure A3, we examine the extent to which the drop in technology exploration differs between firms with a low level (Figure A3a) and a high level (Figure A3b) of research engagement. The regression results underlying the figures are reported in columns 2 and 3 of Table A2. The figures show that, in the pre-treatment years, there is no statistical difference in the share of citations made to patents in unfamiliar technology for both groups of firms. However, in the post-treatment years, the difference declines below that of the reference year only for the firms that have low research engagement. In fact, there is no apparent decline for firms with a high level of research engagement.

Figures A3c and A3d also report results based on use of science as an alternative measure of research engagement. The underlying regression results are presented in columns 4 and 5 of Table A2. The results continue to show that the decline in technology exploration is steeper for firms with a low use of science (Figure A3c) than firms with a high use science

(Figure A3d). Again, the drop in technology exploration for firms with a high use of science is not statistically different from 0.

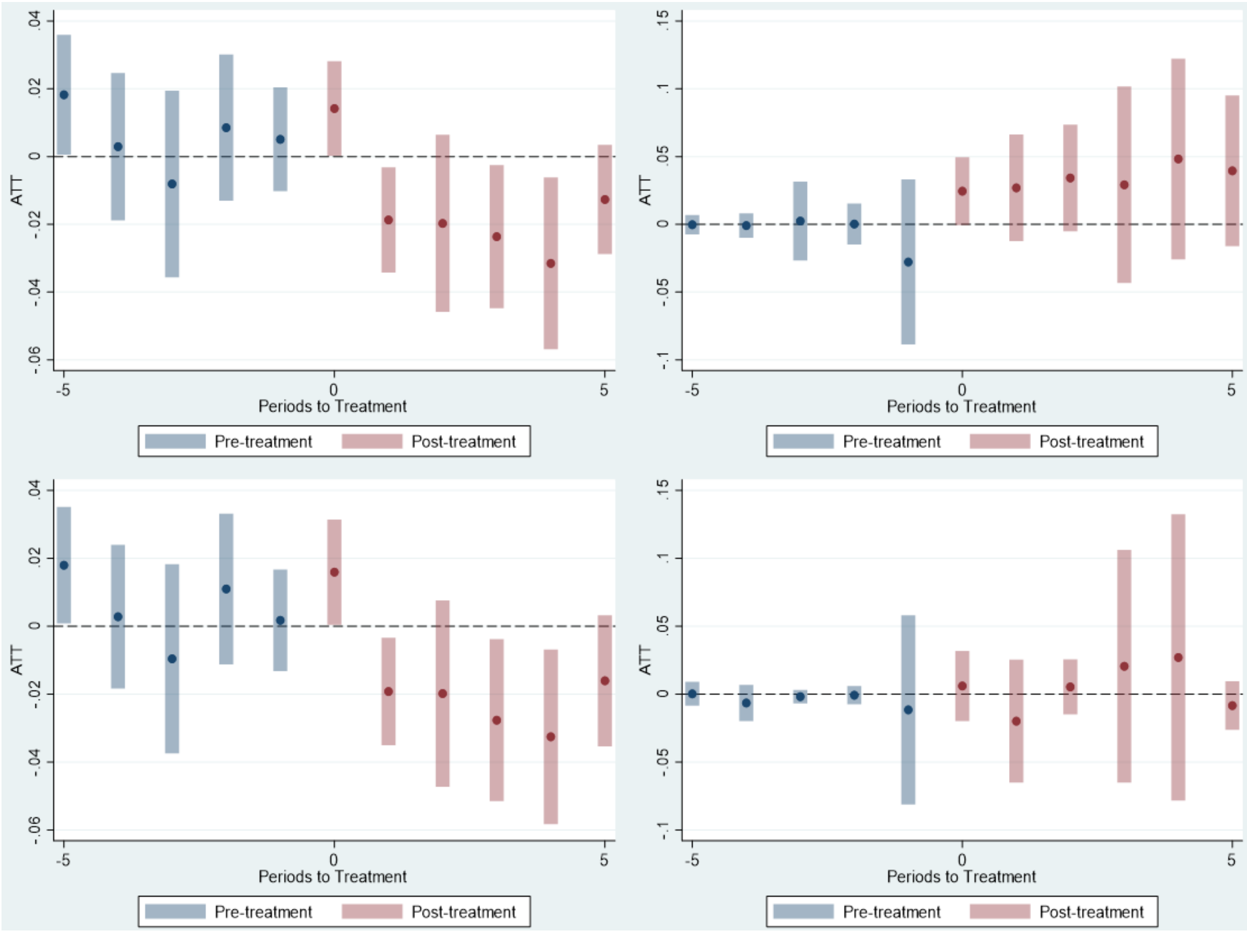
Figure A3: Panel event study - Low and high level of research engagement



Notes: The figure presents results from a panel event study regression, examining the effect of increased technology competition on technology exploration. Figure A3a and Figure A3b are for firms with a low and high level of research engagement, respectively. Figure A3c and Figure A3d are for firms with a low and high cumulative cites to research publications, respectively. X-axis represents years relative to a sharp increase in the technology competition, and Y-axis represents the difference in technology exploration (i.e., share of patent citations made to patents in unfamiliar technology areas) between treated and control groups relative to the reference year (year -1). The vertical lines represent 95% confidence interval.

The corresponding figures using the method proposed by Callaway and Sant'Anna (2021) are reported in Figure A4. The results are consistent with those from the baseline panel event study. These results provide additional support for Hypothesis 4.

Figure A4: Low and high level of research engagement - Callaway and Sant'Anna



Notes: The figure presents the results from a panel event study regression, examining the moderating effect of research engagement on the relationship between technology competition and technology exploration. To account for the potential bias arising from treatment heterogeneity across years and firms, the analysis utilizes the algorithm proposed by Callaway and Sant'Anna (2021) that accounts for such bias. Figure A3a and Figure A3b are for firms with a low and high level of research engagement, respectively. Figure A3c and Figure A3d are for firms with a low and high level of research engagement, respectively.

Table A2: Technology search strategy - Panel event study

Dependent variable	Share of cites made to patents in unfamiliar technology area				
	Full sample	Low research engagement	High research engagement	Low cites to research	High cites to research
	(1)	(2)	(3)	(4)	(5)
Lead 5	0.010	0.008	0.030	0.010	0.021
	(0.010)	(0.013)	(0.017)	(0.013)	(0.018)
Lead 4	0.006	0.004	0.023	0.006	0.014
	(0.011)	(0.014)	(0.017)	(0.014)	(0.016)
Lead 3	-0.005	-0.013	0.021	-0.011	0.014
	(0.009)	(0.011)	(0.018)	(0.011)	(0.016)
Lead 2	-0.002	-0.010	0.024	-0.005	0.008
	(0.008)	(0.009)	(0.016)	(0.009)	(0.017)
Lead 0	0.006	0.001	0.031	0.005	0.015
	(0.006)	(0.007)	(0.017)	(0.007)	(0.017)
Lag 1	-0.011	-0.021**	0.029	-0.019**	0.016
	(0.007)	(0.008)	(0.017)	(0.007)	(0.018)
Lag 2	-0.005	-0.013	0.029	-0.010	0.013
	(0.009)	(0.011)	(0.017)	(0.012)	(0.016)
Lag 3	-0.012	-0.022*	0.024	-0.020*	0.014
	(0.008)	(0.009)	(0.017)	(0.009)	(0.017)
Lag 4	-0.006	-0.017*	0.035*	-0.012	0.015
	(0.007)	(0.008)	(0.017)	(0.009)	(0.017)
Lag 5	-0.005	-0.011	0.024	-0.010	0.012
	(0.006)	(0.007)	(0.014)	(0.007)	(0.014)
log(1+Sales)$_{t-1}$	0.000	0.000	0.002	0.001	-0.001
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)
log(1+R&D stock)$_{t-1}$	-0.007*	-0.008*	-0.007	-0.007	-0.009
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
log(1+Patent stock)$_{t-1}$	-0.002	-0.005	0.009*	-0.005	0.005
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
log(1+Publication stock)$_{t-1}$	0.004	0.005	0.002	0.004	0.002
	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)
log(1+Diversification)$_{t-1}$	-0.005	-0.004	-0.008	-0.002	-0.010
	(0.003)	(0.004)	(0.005)	(0.003)	(0.005)
Firm dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
SE Clustered	Firm	Firm	Firm	Firm	Firm
Observations	3,912	2,748	1,164	2,174	828
R-squared	0.10	0.10	0.14	0.12	0.09

Notes: The table presents the panel event results on the moderating effect of research engagement and use of scientific knowledge on the relationship between technology competition and technology exploration. Robust standard errors in parentheses. ** p<0.01, * p<0.05.

A.2 Two-way fixed effects model

Table A3: Two-way fixed effects model

Dependent variable	Share of cites made to patents in unfamiliar technology area				
	Interaction	Low research engagement	High research engagement	Low cites to research	High cites to research
	(1)	(2)	(3)	(4)	(5)
Treated × Post	-0.010*	-0.014**	0.008	-0.014*	0.003
	(0.004)	(0.006)	(0.005)	(0.005)	(0.004)
Treated	0.003	0.004	-0.005	0.004	-0.002
	(0.004)	(0.007)	(0.003)	(0.006)	(0.003)
Post	0.010*	0.015*	-0.004	0.014*	-0.002
	(0.004)	(0.007)	(0.004)	(0.006)	(0.004)
log(1+Sales)$_{t-1}$	0.001	0.002	0.001	0.003	-0.000
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
log(1+R&D stock)$_{t-1}$	-0.006	-0.007	-0.007	-0.005	-0.009
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
log(1+Patent stock)$_{t-1}$	-0.002	-0.004	0.008*	-0.005	0.005
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
log(1+Publication stock)$_{t-1}$	0.003	0.006	0.002	0.003	0.003
	(0.002)	(0.004)	(0.005)	(0.003)	(0.005)
log(1+Diversification)$_{t-1}$	-0.006*	-0.005	-0.008	-0.005	-0.007
	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)
Firm dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
SE Clustered	Firm	Firm	Firm	Firm	Firm
Number of firms	733	641	203	591	206
Mean of DV	0.014	0.017	0.004	0.017	0.005
Observations	6,615	4,952	1,663	4,969	1,646
R-squared	0.14	0.14	0.16	0.14	0.16

Notes: The table presents the results from two-way fixed effects model examining the moderating effect of research engagement on the relationship between technology competition and technology exploration. Robust standard errors in parentheses. ** $p<0.01$, * $p<0.05$.