# Scientific Talent and Firm Growth: Evidence from Scientific Breakthroughs

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This paper investigates the impact of corporate scientists on firm growth following scientific breakthroughs. Utilizing a bibliographic database of 258 million papers and a text-embedding tool, I develop a measure of corporate scientific human capital. By analyzing three major university-driven scientific breakthroughs, I find that firms with core technologies related to these breakthroughs perform better afterward. The impact is more pronounced for firms with substantial pre-existing scientific human capital. Corporate scientists add value through knowledge transfer, leading to more patents, higher-impact patents, and earlier adoption of related science post-breakthrough. This study highlights the crucial role of corporate scientists in bridging basic science with industrial innovation in an economy increasingly relying on intangible assets and human capital.

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## 1. Introduction

Technological innovation is a crucial driver of long-term growth and value creation (Aghion and Howitt, 1990; Kogan et al., 2017; Babina et al., 2024), while the generation of new scientific knowledge is a fundamental source of novel ideas for industrial innovation (Sorenson and Fleming, 2004; Ahmadpoor and Jones, 2017; Krieger, Schnitzer, and Watzinger, 2022). In the current U.S. innovation ecosystem, universities have emerged as the primary contributors to basic science. Firms, meanwhile, have reduced their investment in internal research (Arora, Belenzon, and Sheer, 2021; Arora et al., 2021), concentrating instead on the development and commercialization of scientific discoveries derived from publicly funded research. Although this approach may efficiently reduce the high uncertainty and prolonged timelines associated with conducting internal research, it compromises the firm's ability to absorb and apply knowledge generated by academics (Cockburn and Henderson, 1998; Rosenberg, 1990). This absorption process is typically facilitated by the presence of corporate scientists. A failure to effectively integrate new scientific knowledge into the innovation process in a timely manner can cause firms to fall behind their competitors, particularly in the wake of scientific breakthroughs (Cohen and Levinthal, 1989). As a result, the impact of corporate investment in scientific human capital on firm value within the modern innovation landscape remains a topic of great interest to both scholars and policymakers.

Despite its importance, very few studies have comprehensively examined how corporate investment in scientific human capital (hereafter SHC) drives firm growth. One reason for this gap is that measuring corporate SHC[1] is difficult. To address this challenge, I leverage a bibliographic database and a text-embedding language processing tool to construct a measure of SHC for public firms in the U.S. I then investigate whether SHC significantly contributes

[1] Recent studies have assessed corporate investment in scientific research using publication data or Census data (e.g., Arora et al., 2021; Arora, Belenzon, and Sheer, 2021; Mezzanotti and Simcoe, 2023). I take a further step by identifying corporate scientists and measuring scientific human capital, which facilitates the tracking of publication and patent activities of corporate scientists.

to firm value and innovation in the context of scientific breakthroughs, and, if so, how it influences firm outcomes.

The impact of corporate investment in SHC on firm value is shaped by the interplay of two opposing forces. On the one hand, corporate scientists with high absorptive capacity can drive the development of novel and disruptive products (Cohen and Levinthal, 1989; Rosenberg, 1990; Sorenson and Fleming, 2004). Onboarding prestigious scientists can also enhance a firm's reputation, signaling high product quality to investors and customers (Hicks, 1995; Polidoro Jr and Theeke, 2012). On the other hand, maintaining those scientists' absorptive capacity requires a publishing culture that allows them to stay connected with the academic community (Hicks, 1995; Sauermann and Roach, 2014; Ahmed, 2022), which in turn risks the leaking of proprietary information to rivals (Arrow, 1972; Arora, Belenzon, and Sheer, 2021). Furthermore, internal research conducted by corporate scientists is often associated with significant uncertainty and high costs. That being said, when unexpected scientific breakthroughs in public research arise, firms with more SHC have a significant advantage in the race to efficiently integrate this knowledge into corporate innovation processes. This can lead to a significant boost in the returns on such investments.

To study how value is created through the accrual of corporate SHC in the context of scientific breakthroughs, I first construct a measure of corporate SHC. From the *OpenAlex* database[2] of more than 258 million scientific publications, I collect papers published by corporate scientists along with their affiliations. Corporate scientists are defined as those who have published academic articles affiliated with a company. The primary scientific human capital used in the analysis is derived from the historical publication records of employees affiliated with a firm. It is constructed as follows: first, the annual publication stock is obtained by counting the total number of scientific papers published by all employees affiliated with firm $i$ in year $t$; second, the scientific human capital measure SHC is calculated

[2]OpenAlex offers an increasingly widely used industry-standard scientific knowledge base, covering a comprehensive set of internationally published academic papers up to 2024. See `https://docs.openalex.org/`.

by averaging the annual publication stock within the window $[-3, -1]$ years prior to the breakthrough year.[3]

Next, I utilize exogenous shocks from discoveries in public science within a stacked difference-in-differences framework. This approach allows me to capitalize on positive shocks to the innovation opportunities offered to corporate scientists, highlighting their role in driving firm value. The exogenous shocks include three major twenty-first-century university-driven scientific breakthroughs: the Human Genome Project; Deep Learning; and Gene Editing. These events were selected based on an editorial article in *Nature*[4] magazine, which highlights the most groundbreaking scientific innovations of the 21st century so far. These three scientific breakthroughs, originating from academia, are largely unforeseen by companies, thus presenting increased positive innovation and investment opportunities for affected firms while having no immediate impact on unaffected companies.

I then sort firms into treated and control groups based on their exposure to a significant scientific breakthrough. To measure the level of impact, I assess the most valuable patents of each company in the three years before the breakthrough, following the method employed by Kogan et al. (2017). Patent relevance to the breakthrough is determined by utilizing a text-embedding tool to calculate the cosine similarity between patent abstracts and the breakthrough's representative paper. A company's relevance is the average similarity score of its valuable patents. Firms in the top 20% are classified as treated, while the rest are controls. Using a stacked difference-in-differences approach, I find that treated firms exhibit significantly better operating profitability and increased sales in the five years post-breakthrough compared to control firms. For instance, treated firms' operating profitability increases by 2.7 percentage points more than control firms. Pre-trend tests show no significant

[3]To test robustness, two additional measures are developed using publications by corporate scientists affiliated with the firm six to eight years before the shock, or considering in addition the closeness of scientists' expertise to the breakthrough, assessed using textual information from publication abstracts and the abstract of the paper signifying the breakthrough.

[4]See https://www.nature.com/articles/d41586-023-04021-2.

pre-existing trends, confirming the positive impact of the breakthroughs on relevant firms.

After identifying the affected firms, I examine the core question: What role does scientific human capital play in driving innovation and long-term growth among these firms? I hypothesize that a treated firm's performance will be superior when it possesses a higher level of SHC prior to a scientific breakthrough in question. This prediction is grounded in the notion that firms with greater SHC possess a significantly higher absorptive capacity for the cutting-edge knowledge embedded in these breakthroughs (Rosenberg, 1990; Cockburn and Henderson, 1998), allowing them to transfer this knowledge to their products more efficiently.

In a stacked triple difference-in-differences setting, the findings reveal that firms with higher levels of SHC experience 5.86% higher operating profitability and a 32% increase in market value in the five years following scientific breakthroughs compared to other firms. The results remain robust with the inclusion of control variables, firm-event and year-event fixed effects. To further mitigate the concern that significant differences might exist in firm characteristics between those with high scientific human capital and those with low scientific human capital, I conduct the analysis using a propensity-score-matched sample. In this analysis, I match a treated firm with high SHC to a treated firm with low SHC and a control firm within the same industry, based on a number of corporate characteristics. The findings in this matched sample are consistent with those from the overall sample, suggesting that the measure of SHC is unlikely to be confounded by other observable firm characteristics. These results demonstrate the critical role of corporate scientific human capital in driving firm growth following scientific breakthroughs.

Next, I conduct several tests to examine the channels through which scientific human capital impacts post-breakthrough firm value. The first is the *knowledge transfer* effect, wherein companies with high SHC absorb new knowledge relatively quickly (Cohen and Levinthal, 1989; Rosenberg, 1990). Scientists in these companies are expected to engage in more patenting activities and collaborate with inventors, fostering new ideas and producing impactful patents. My findings provide strong support for this channel. First, I show that treated firms with high SHC have a higher proportion of scientist-inventors among their patents, produce higher quality patents, and are more likely to be among the first to cite knowledge related to scientific breakthroughs. Further analysis at the patent level reveals that patents involving scientist-inventors in these firms are of higher quality compared to those filed by peer firms. Second, aided by ChatGPT, I find that patents produced by these firms are more closely related to the scientific knowledge underlying the breakthroughs and are more aligned with their products. Third, I demonstrate that firms with a substantial stock of scientific human capital publish more impactful papers after the scientific breakthrough than their peer firms, indicating a faster accumulation of SHC and an enhanced absorptive capacity for the new scientific knowledge embedded in these breakthroughs. These results provide evidence of the crucial role corporate scientists play in increasing firm value by facilitating the transfer of scientific knowledge into the innovation process.

The second channel is the attraction effect for star scientists. According to anecdotal evidence and findings in the literature (Hicks, 1995; Sauermann and Roach, 2014; Ahmed, 2022), support for publication is a crucial factor influencing a scientist's decisions to join a company. A firm's stock of SHC can thus serve as a proxy for its culture of supporting scientific publications and internal research. Consequently, I hypothesize that companies with a higher SHC are more attractive to star scientists. My results confirm this hypothesis, revealing that treated firms with higher levels of SHC prior to scientific breakthroughs attract more star scientists post-breakthrough than their peer firms. Further analysis at the patent level reveals that, following scientific breakthroughs, patents involving star scientists are of higher quality than those involving non-star scientists in affected firms with substantial scientific human capital. This attraction effect complements the knowledge transfer effect, further enhancing a firm's capacity to absorb and translate new scientific knowledge into superior innovation outcomes.

The study contributes to three strands of literature. First, I build on the growing literature on labor and finance, particularly those studies that seek to understand the impact of labor on firm performance and policies.[5] For example, Shen (2021) utilizes the friction of skilled labor mobility during the green card application process to study the effect of skilled labor mobility on firm valuation. Previous studies have shown that the demand for human capital is a significant factor in firms' acquisition strategies (Tate and Yang, 2024; Chen, Gao, and Ma, 2021). I complement this line of research by focusing on a category of highly skilled employees that are becoming increasingly important to firm success yet remain unexplored: corporate scientists. By constructing a firm-level SHC measure and tracking corporate scientists' publication and patenting activities, I provide supporting evidence that corporate scientists can significantly enhance firm value by absorbing new knowledge from scientific breakthroughs and translating it into innovative products. My findings align with those of Israelsen and Yonker (2017), who use disclosures of "key man life insurance" to measure firms' exposure to key human capital risk. They find that key employees are four times more likely to hold PhD degrees than top managers, and that firms with key human capital tend to be more innovative. I complement their findings by providing additional evidence on the channels through which key employees have an impact.

Second, this paper contributes to the understanding of corporate innovation in an economy increasingly reliant on human capital and intangible assets (Peters and Taylor, 2017; Corrado and Hulten, 2010). Prior research has explored the relationship between various managerial and inventor-level characteristics and firm innovation (Aghion, Van Reenen, and Zingales, 2013; Acemoglu, Akcigit, and Celik, 2022; Fitzgerald and Liu, 2020; Li and Wang, 2023). However, this study differs by focusing specifically on corporate scientists and examining their role in driving innovation, particularly in the context of scientific breakthroughs, through

[5]For example, Acharya, Baghai, and Subramanian (2014); Agrawal, Hacamo, and Hu (2021); Belo, Lin, and Bazdresch (2014); Belo et al. (2017); Chen, Gao, and Ma (2021); Eisfeldt and Papanikolaou (2013); Fedyk and Hodson (2023); Israelsen and Yonker (2017); Mueller, Ouimet, and Simintzi (2017); Serfling (2016); Tate and Yang (2024).

which their contributions are most prominently realized. Furthermore, this research adds to the literature on the effects of corporate culture on innovation by providing evidence that a culture supportive of corporate research and scientific publication enhances corporate innovation, especially during periods of scientific breakthrough.

Finally, this paper introduces a novel dataset of scientific talents in corporations. Using a bibliographic database and textual analysis to identify corporate scientists and connect their publications with scientific breakthroughs, I propose a new measure of scientific human capital. Previous studies have used bibliometric data to measure corporate investment in research (Arora, Belenzon, and Sheer, 2021; Arora et al., 2021), and link university publications with patenting (Babina et al., 2023; Myers and Lanahan, 2022). A closely related recent study (Arora et al., 2023) constructs a measure of firms' exposure to public science by connecting university publications and firm publications. My study complements this literature in several key aspects. First, my research focuses on highlighting the role of corporate scientists in driving firm growth in response to unexpected scientific breakthroughs. Second, I concentrate on prominent scientific advancements in the 21st century, which create positive shocks to the innovation opportunities offered to corporate scientists. Third, tracking the patents and publications of corporate scientists allows me to examine the channel through which they advance firm growth, value, and innovation.

## 2. Empirical strategy and data

### 2.1. Scientific breakthrough

Studying the role of scientific human capital in propelling firm growth at the time of scientific breakthroughs requires the identification of shocks to firms' exposure to these breakthroughs. I select the most impactful scientific breakthroughs of the past twenty-five years as ranked by *Nature*.[6] The article refers to the most extraordinary instances of scientific

[6] See https://www.nature.com/articles/d41586-023-04021-2.

disruption since 2000, including the Human Genome Project, the discovery of the Higgs boson, gene editing and CRISPR technology, the first detection of gravitational waves, and AI and machine learning. Among these scientific breakthrough events, the discovery of the Higgs boson and the detection of gravitational waves belong to the field of theoretical physics and do not have a direct impact on industrial innovation on a large scale. Therefore, for the purposes of my study, I retain only the Human Genome Project, gene editing and CRISPR technology, and AI and machine learning as scientific breakthrough shocks. In addition, all three were initiated by researchers in public research institutions instead of the private sector. They can thus serve as a exogenous shock to firms as firms cannot predict the timing of the breakthrough *ex ante*.

I define the breakthrough year of each event as the year the paper that signifies that breakthrough was published. According to *Nature*, the achievements of the Human Genome Project are embodied by the paper titled "Initial sequencing and analysis of the human genome" published in *Science* in 2001, a landmark study that presented the draft sequence of the human genome, organized by the International Human Genome Sequencing Consortium. The development of deep learning and neural networks was announced by the paper "A fast learning algorithm for deep belief nets," published in *Neural Computation* in 2006 by one of the so-called "Godfathers of AI," Geoffrey E. Hinton and co-authors. This paper was seen as a breakthrough that rekindled interest in neural nets and started the movement of "deep learning."[7] The third event, the development of gene editing technology, was introduced in a paper titled "A Programmable Dual-RNA–Guided DNA Endonuclease in Adaptive Bacterial Immunity," published in *Science* in 2012. Two co-authors of the paper, Jennifer Doudna and Emmanuelle Charpentier, were awarded the Nobel Prize in 2020 for their extraordinary contributions, particularly in recognition of the CRISPR-Cas9 system's potential as a programmable tool for precise gene editing with wide applications in medicine and agriculture.

[7] See https://www.skynettoday.com/overviews/neural-net-history.

## 2.2. Identification strategy

My identification strategy exploits the unpredictable nature of scientific discovery, particularly of those breakthroughs that have a significant impact on industrial innovation. Firms, especially those that rely on the development of scientific advancements, can benefit immensely from the emergence of new technology, which can increase productivity or spur the innovation of new products. Even though firms may have some awareness of ongoing scientific developments, predicting the exact timing of a scientific revolution is still challenging. Therefore, I consider these three academic discoveries—the Human Genome Project, deep learning and neural networks, and gene editing and CRISPR technology—as exogenous shocks for existing publicly listed corporations.

Given that the three events occurred in different years, I first use a stacked difference-in-differences design following Gormley and Matsa (2011), which compares treated firms that operate in areas closely related to the forthcoming (but as yet unknown) scientific breakthrough with control firms that operate in less-related areas before the breakthrough year. To reduce the estimation bias caused by noisy control firms, I only use control firms that have never been classified as treated firms for any of the three events, following the literature (Baker, Larcker, and Wang, 2022; Gormley and Matsa, 2011). After classifying treated and control firms, I run the following stacked difference-in-differences regression:[8]

$$Y_{i,c,t} = \beta_0 + \beta_1 \cdot \textit{Exposure to Sci-Breakthrough}_{j,c,t} + \alpha_{i,c} + \theta_{t,c} + \epsilon_{i,j,c,t}, \qquad (1)$$

where $Y$ is one of the firm outcome variables of interest for firm $i$ and year $t$, and *Exposure to Sci-Breakthrough* is an indicator that equals 1 if firm $i$ is classified as a treated firm in

[8]I intentionally exclude firm-level covariates from the regressions because these variables are likely influenced by the shocks associated with scientific breakthroughs. Including them could confound the estimates of the *Exposure to Sci-Breakthrough*. This approach aligns with the methodology employed in the literature (e.g., Gormley and Matsa (2011)). The results are robust when pre-breakthrough accounting variables are included in the regressions.

event cohort $c$ in year $t$, and zero otherwise. I examine a window of five years before and after the breakthrough year $[-5, 5]$. The firm outcome variables include measures of firm performance, *Operating Profitability*, and *Sales*. To account for fixed differences between firms across events, I incorporate the firm-event fixed effect, denoted as $\alpha_{i,c}$. Year-event fixed effects are also included to control for any secular time trends, denoted as $\theta_{t,c}$. Standard errors are clustered at the industry level to address the potential covariance among firm-level variables over time within the same three-digit SIC code.

Next, I examine my core research question: the role played by scientific human capital in the face of scientific breakthroughs. Since they have the absorptive capability and first-mover advantage in transferring new technology into their product and process innovations (Rosenberg, 1990; Arora, Belenzon, and Dionisi, 2023), firms that invest more in basic science research can reap greater benefits from largely unexpected scientific breakthroughs. Thus, firms with more in-house SHC prior to the breakthrough-shock should benefit more from it. I run the following stacked triple difference-in-differences regression to test this hypothesis, including an interaction term between the high scientific human capital indicator *HighSHC* and the *Exposure to Sci-Breakthrough*:

$$\begin{aligned} Y_{i,c,t} = \beta_0 + &+ \beta_1 \textit{Exposure to Sci-Breakthrough}_{c,t} \cdot \textit{HighSHC}_{i,c,t-3:t-1} \\ &+ \beta_2 \textit{Exposure to Sci-Breakthrough}_{c,t} + \alpha_{i,c} + \theta_{t,c} + \epsilon_{i,c,t} \end{aligned} \tag{2}$$

Where $Y_{i,c,t}$ includes an array of firm-level outcome variables of interest. $\textit{HighSHC}_{i,c,t-3:t-1}$ indicates whether firm $i$ belongs to the group with high scientific human capital. I measure scientific human capital *SHC* based on the publication stock of employees who were hired by firm $i$ between years $t-3$ and $t-1$. The firm-event fixed effects, denoted as $\alpha_{i,c}$, and the year-event fixed effects, denoted as $\theta_{t,c}$, are also included. Standard errors are clustered at the industry level to address the potential covariance among firm-level variables over time within the same three-digit SIC code. More details about the *SHC* measure can be found in section 2.3.1.

### 2.3. Data and variable construction

**Treated and control firms.** Firms without any patents filed during the sample period are excluded from the analysis. A firm is classified as a treated firm if its core patents, ranking in the top 10 by market value during the period $[t-3, t-1]$ centered around the breakthrough year, exhibit high textual similarity to scientific breakthroughs, placing it in the top 20% of all firms with patents filed during this time window. Control firms include those that fall within the remaining 80%. To mitigate the estimation bias caused by noisy control firms (Baker, Larcker, and Wang, 2022), I only retain control firms that have never been classified as treated firms in any of the three events. To obtain the textual similarity between two texts, I utilize the text embedding feature of the natural language processing tool *Instructor-xl*,[9] which can convert text to a vector. Then I calculate the cosine similarity between the vector embedding of each selected patent abstract and the text describing the content of the scientific breakthrough. The firm-level technological similarity in each event is obtained by taking the average of the patent similarity scores of the selected representative patents for firm $i$ as shown below:

$$\begin{aligned}&\text{Technology Similarity}_{i,c}\\ &= \frac{1}{N}\sum_{t=-3}^{-1} \text{cosine similarity between patent}_{i,c,t} \text{ and scientific breakthrough}_c,\end{aligned}$$

where $N = \max[30,\ \text{Total number of patents filed by firm } i \text{ during } [-3,-1]]$, and $\text{Patent}_{i,c,t}$ refer to patents filed by firm $i$ in year $t$ which fall within the three years $[-3,-1]$ prior to the occurrence year of scientific breakthrough $c$ and rank in the top 10 in market value among

[9] *Instructor-xl* an instruction-finetuned text embedding model that generates embeddings suited for any task—such as classification, retrieval, clustering, or text evaluation—and across diverse domains, including science and finance, by simply providing the task instruction, without the need for further fine-tuning. For more information, please refer to https://instructor-embedding.github.io/.

all patents filed by firm $i$ in the same year.

Figure 1 illustrates the ratio of firms classified as treated within each industry, with the ratio exceeding 10%. As shown, the industries most affected by the Human Genome Project event include Drugs, Healthcare, Business Services, and Laboratory Equipment, with nearly 60% of firms in the Drugs industry classified as treated. For the deep learning breakthrough event, the most impacted industries are Healthcare, Business Services, Computer Software, Electronics and Equipment, and Finance. The gene editing event most notably affects the Agriculture, Healthcare, and Drugs industries. Overall, the industry classifications generally align with expectations regarding the relative impact of all three scientific breakthroughs.

**Scientific publication data.** The publication data used in this study is downloaded from the website OpenAlex, a non-profit organization that collects and publishes the entire database of research papers, book chapters, and other publications covering the whole world (Priem, Piwowar, and Orr, 2022). I retain journal articles and proceeding articles that have at least one author affiliated with a company in the U.S. and were published between 1996 and 2017, as 1996 is the fifth year before the first breakthrough event and 2017 is the fifth year after the last breakthrough event. In order to match firms covered by the OpenAlex database with those covered by the Compustat database, I conduct a name match between the names on the publication affiliations and U.S. publicly listed firms. Authors' affiliations, however, are sometimes not listed under the parent firm's name. In addition, ownership changes can affect the actual parent firm to which a firm belongs. To increase the accuracy of matching between the two databases, I use the data covering the subsidiary-parent relation and ownership relationships of U.S. public firms shared by Arora, Belenzon, and Sheer (2021). In this way, I obtain a dataset of U.S. firm names with Compustat identifiers, including all the corresponding subsidiaries and acquired firms. Finally, I conduct the name match between the affiliation names from the OpenAlex database and U.S. public firms (including historical parent firm names and all subsidiary and acquired firm names) and set a threshold of 70 to keep likely successful matches. I classify those with a score of 100 as successful matches. For those below 100 and above 70, I manually check if they are a successful match. My final sample includes about 1,386 firms that have published at least one paper between 1996 and 2017, comparable to the publishing firms identified in Arora, Belenzon, and Sheer (2021).

**2.3.1. Publication-based measure.** To measure scientific human capital prior to each breakthrough event, I first construct a dataset that tracks the employment history of publishing employees. An author affiliated with a firm who publishes a paper in a given year is considered an employee of that firm for that year. It is acknowledged that publishing employees may not publish annually. It is assumed that an employee does not leave the firm during years without a publication, provided the author does not publish with another firm in the interim. If an author publishes for a different firm, the first year of publication for that new firm is considered the year of departure from the previous firm. Subsequently, I collect the employment records of individuals hired by a firm and gather their historical publications up to the year preceding the breakthrough. Then I calculate the annual publication stock using the total number of scientific papers published by all employees affiliated with firm $i$ in year $t$ until year $t$. The measure of scientific human capital *SHC* is defined as the average of the annual publication stock within the window $[-3, -1]$ prior to the breakthrough year. This is the main measure I use throughout the analysis. I also construct other scientific human capital measures based on a window outside of my sample period and a relevant scientific human capital measure based on the relevance of scientists' expertise to a breakthrough using textual information in publication abstracts and abstracts of scientific papers. For a more detailed description, see Appendix A.

To evaluate the impact of a paper, I create a measure termed *Impactful Paper*. This measure relies on a field classification indicator provided by OpenAlex, which utilizes a state-of-the-art natural language model to classify papers under 252 subfields and 4,516 topics. A paper is classified as impactful if it ranks among the top 5% in terms of citations received within five years of publication, relative to papers in the same subfield published in the same year.

The *Impactful Paper* variable is also used to identify star scientists. A scientist is classified as a *Star Scientist* if more than 50 percent of the papers they have published before a given year $t$ are categorized under *Impactful Paper*.

**Patent data.** The patent data utilized in this study is sourced from PatentsView, a comprehensive patent database that offers detailed records for approximately seven million patents. This dataset is extracted from the bulk data files of the United States Patent and Trademark Office (USPTO). It encompasses a range of information including patent application dates, grant dates, inventors, assignees, textual content of patents, citations of prior art, and technology classifications, from 1976 to the present. Disambiguation algorithms are employed to assign unique identifiers to patent inventors and assignees, thereby facilitating the tracking of inventors' activities and employment history over time. The Patent-CRSP matching methodology adheres to the approach outlined in Stoffman, Woeppel, and Yavuz (2022). Patent abstract information is employed to assess firms' exposure to scientific breakthroughs and the extent to which their patents rely on scientific knowledge embedded in these breakthroughs. Additionally, citations of prior art are utilized to construct an annual citation network among patents, which is subsequently used to develop an impactful patent identifier.

**2.3.2. Patent quantity and quality measure.** The measure of patent quantity, *Patent Count*, is calculated as the sum of patents granted to firm $i$ in year $t$. To assess patent quality, I employ several proxies. The first proxy, *Citations*, is the sum of citations received by all patents filed by firm $i$ prior to year $t$. The second proxy, *Patent Value*, is the average patent value, as defined by Kogan et al. (2017), for all patents granted in year $t$. The third proxy, *Impactful Patent Count*, is the number of impactful patents granted to a firm in a given year.

An impactful patent is defined as one that ranks in the top 5% in terms of forward citations received within five years of being granted, relative to patents filed in the same year.

**2.3.3. Patent reliance on science measure.** To evaluate the relationship between patents and scientific knowledge, I utilize three variables: *scienceRelevance_Cites*, *firstToCiteScience*, and *scienceRelevance_Gpt4o*. The first two variables are derived from citations of scientific papers within patents. The measure *scienceRelevance_Cites* is defined as the total number of patents granted to a firm in a given year that cite relevant scientific papers, weighted by the number of cited papers. *firstToCiteScience* is calculated as the number of patents that are among the first to cite these relevant scientific papers. A paper is considered relevant if it is listed in the breakthrough paper's citations and was published after 1996, or if it directly cites the breakthrough paper. A patent is classified as among the first to cite a relevant scientific paper if it cites the paper within the first three years of its publication. The patent-to-paper citation data is sourced from Marx and Fuegi (2020, 2022)[10].

The third measure, *scienceRelevance_Gpt4o*, is derived with the assistance of a generative AI tool. Leveraging the capabilities of generative AI in text summarization and classification, models such as ChatGPT have increasingly been employed in finance literature to extract information from large-scale text data (Eisfeldt, Schubert, and Zhang, 2023; Jha et al., 2024; Kim, Muhn, and Nikolaev, 2024), such as corporate disclosures. *scienceRelevance_Gpt4o* is designed to assess the extent to which patents depend on scientific knowledge based on the content of the patent abstract. For instance, in the context of deep learning, I utilize the state-of-the-art generative AI model GPT-4o mini developed by OpenAI. For each patent abstract and its assignee firm's name, the following prompt is used:

*"Based on the given patent abstract and its assignee firm's name, please answer the following questions successively. Q1. Does the patent rely on the knowledge of machine learning? Answer choices: Heavily, Mildly, NA. Q2. How important is the patent for the*

[10] See https://relianceonscience.org/patent-to-paper-citations

*products of the assignee firm? Answer choices: Super, Mild, Little. Q3. Briefly explain your choice to Q1 and Q2 in less than 50 words."*

Responses are manually reviewed to ensure reliability, and the prompt is adjusted accordingly. For each patent, responses to Q1 are scored as 1 (Heavily), 0 (Mildly), or 0 (NA), and responses to Q2 are scored as 1 (Super), 0 (Mild), or 0 (Little). The final score for each patent is calculated by multiplying the score from Q1 by the score from Q2. The firm-level measure *scienceRelevance_Gpt4o* is obtained by summing the final scores for all patents within the firm for each year.

**2.3.4. Other Firm-Level Variables.** Firm outcome and control variables are obtained from Compustat. The firm performance outcome variables examined include *Operating Profitability*, *Sales*, and *Market Value*. *Operating Profitability* is calculated by dividing operating income before depreciation (Compustat item *oibdp*) by total assets (*at*). *Market Value* is derived by subtracting the book value of common equity (*ceq*) from total assets (*at*) and adding the market value of common equity, which is computed as the product of the closing price ($prcc_c$) and the number of shares outstanding (*csho*).

### 2.4. Summary Statistics

After excluding firms without at least one observation in both the pre-event and post-event periods, the final sample comprises 38,588 observations covering 2,244 firms across the three events. Panel A of Table 1 presents the descriptive statistics for the main variables used in the analysis. Panel B illustrates the distribution of treated and control firms for each event. Across the three events, the ratio of treated firms to control firms is approximately 20%. Panel C displays the proportion of publishing and non-publishing firms within the treated and control groups. Approximately 40% of treated firms publish papers, compared to 26% of control firms. Both groups exhibit a significant proportion of firms that have published at least one paper.

[Insert Table 1 Here]

# 3. Scientific human capital, scientific breakthrough, and firm performance

Product innovation is an important driver of firm growth. Innovative ideas typically rely on either the redeployment of existing knowledge or the exploration of new knowledge. Existing knowledge is public and accessible to all; it can be difficult to distinguish a firm's products from those of its competitors when they are drawing from the same pool of data and ideas. By contrast, new knowledge represents an opportunity for firms to pioneer entirely new concepts and develop more disruptive and revolutionary products (Ahmadpoor and Jones, 2017; Krieger, Schnitzer, and Watzinger, 2022). The ability to absorb and convert new knowledge into novel products is thus crucial for firm growth. A key measure of a firm's capacity to absorb new knowledge is the stock of scientific human capital, particularly in areas with intensive scientific knowledge. This section leverages three significant scientific revolutions of the 21st century—the Human Genome Project, deep learning and neural networks, and gene editing technology—to examine the impact of investment in scientific human capital on firm growth during these breakthrough periods.

## 3.1. Scientific breakthrough and firm performance

Before examining the role of scientific human capital, I first assess whether these breakthroughs yield opportunities for firms operating in relevant areas and quantify the overall effect of the three scientific breakthroughs on firm performance. I perform the regression analysis using the stacked difference-in-differences setting as specified in equation (1), with results presented in Table 2. The explanatory variables include *Operating Profitability*, *Sales*, and *Market Value*. It is anticipated that affected firms' performance will improve post-breakthrough due to the rollout of innovative products and increased productivity resulting from the opportunities associated with new knowledge.

Table 2 displays the results for firm performance. Columns (1), (3), and (5) control for firm fixed effects and year fixed effects, while columns (2), (4), and (6) include firm-event and year-event fixed effects. The coefficients on *Exposure to Sci-Breakthrough* indicate that treated firms experience approximate 2.7% higher *Operating Profitability* following the scientific breakthrough compared to control firms. This magnitude is significant given that the mean *Operating Profitability* is around 2.9%. Furthermore, the difference in *Sales* between treated and control firms becomes more pronounced in the five years following the scientific breakthrough. Specifically, firms operating in areas related to the breakthrough exhibit an 13% higher sales compared to firms in unrelated areas. However, there is no significant difference in *Market Value* between treated firms and control firms around scientific breakthroughs. This leads us to conjecture whether investors identify firms that will benefit from new opportunities in the long run as a subset of all firms impacted by scientific breakthroughs. The results in Table 2 suggest that firms engaged in fields related to scientific breakthroughs generally achieve superior operating profitability and sales due to the new opportunities provided by these advancements. However, the financial market does not capture the positive information for all impacted firms.

One potential concern is that firms in related areas might experience other growth opportunities unrelated to the scientific breakthrough, which could confound the observed results. To address this, I test for pre-trends in the differences between treated and control firms prior to the scientific breakthrough. Specifically, I test the following specifications:

$$\begin{aligned} Y_{i,c,t} = {} & \beta_0 + \beta_1 \cdot \text{Pre1Treated}_{i,c} + \beta_2 \cdot \text{Pre2Treated}_{i,c} + \beta_3 \cdot \text{Pre3Treated}_{i,c} + \beta_4 \cdot \text{Pre4Treated}_{i,c} \\ & + \beta_5 \cdot \text{EventYearTreated}_{i,c} + \beta_6 \cdot \text{Post1Treated}_{i,c} + \beta_7 \cdot \text{Post2Treated}_{i,c} \\ & + \beta_8 \cdot \text{Post3Treated}_{i,c} + \beta_9 \cdot \text{Post4Treated}_{i,c} + \beta_{10} \cdot \text{Post5Treated}_{i,c} \\ & + \alpha_{i,c} + \theta_{t,c} + \epsilon_{i,c,t}, \end{aligned} \tag{3}$$

where $Y_{i,c,t}$ includes an array of firm-level variables of interest. $\text{Pre1Treated}_{i,c}$ to $\text{Pre4Treated}_{i,c}$ are dummy variables that are equal to one for treated firm $i$ of event $c$ for the first to fourth year before a scientific breakthrough occurs and zero otherwise. $\text{EventYearTreated}_{i,c}$ is a dummy variable that is equal to one for treated firm $i$ of event $c$ for the occurrence year of a scientific breakthrough and zero otherwise. $\text{Post1Treated}_{i,c}$ to $\text{Post5Treated}_{i,c}$ are dummy variables that are equal to one for treated firm $i$ of event $c$ for the first five years after a scientific breakthrough occurs and zero otherwise. The firm-event fixed effects, denoted as $\alpha_{i,c}$, and the year-event fixed effects, denoted as $\theta_{t,c}$, are included. Standard errors are clustered at the industry level.

Figure 2 illustrates the difference in *Operating Profitability* and *Sales* between treated firms and control firms over the [-5, 5] window surrounding a scientific breakthrough event. Subfigure (a) indicates that, in the years prior to the event, the differences in *Operating Profitability* between the two groups remain stable and statistically insignificant, suggesting the absence of clear pre-trends. However, subsequent to the scientific breakthrough, the differences between treated and control firms become positive and statistically significant. Subfigure (b) demonstrates that, in the three years preceding the event, the differences in *Sales* between the two groups remain stable. Following the scientific breakthrough, however, the differences between treated and control firms increase substantially and are statistically significant.

The results presented in Table 2 and depicted in Figure 2 support the hypothesis that firms operating in areas related to scientific breakthroughs achieve higher profits and sales compared to control firms when these breakthroughs occur. This evidence suggests that scientific breakthroughs act as positive shocks to firms operating within overlapping technological fields.

[Insert Table 2 Here]

[Insert Figure 2 Here]

### 3.2. Does Scientific Human Capital play a role?

Next, I examine the role of scientific human capital (SHC) in facilitating knowledge transfer and the creation of high-quality innovations in response to scientific breakthroughs. Scientific breakthroughs often introduce cutting-edge knowledge, yet it can be challenging for firms to absorb and incorporate that knowledge into new products. Engagement in basic scientific research enhances a firm's absorptive capacity, enabling it to better integrate new knowledge into its innovation processes (Rosenberg, 1990; Cockburn and Henderson, 1998). Consequently, I predict that firms with a higher stock of related SHC will benefit more from scientific breakthroughs over the subsequent five years compared to firms with a lower stock of SHC. To test this prediction, I include an interaction term between *Exposure to Sci-Breakthrough* and the scientific human capital measure *SHC* in a stacked triple difference-in-differences regression, as outlined in equation (2). Given that the SHC measure may be highly correlated with firm size—larger firms are generally believed to have more resources and a greater ability to diversify the risks associated with investment in basic science research —I control for the potential confounding effect of firm size by including an interaction term between firm size in the year prior to the breakthrough and the *Exposure to Sci-Breakthrough* variable.

Table 3 presents the results on firm performance, with dependent variables including *Operating Profitability*, *Sales*, and *Market Value*. The scientific human capital measure (*SHC*) takes the value of one if a firm ranks in the top 10% among all firms in a scientific breakthrough cohort, and zero otherwise. In columns (1), (3), and (5), I control for firm fixed effects and year fixed effects to account for unobserved firm characteristics and time-series trends in firm outcomes. In columns (2), (4), and (6), I include event-firm and event-year fixed effects to control for unobserved firm characteristics specific to each event and any secular time trends. The coefficients remain stable across different fixed effect specifications. The interaction between *SHC* and *Exposure to Sci-Breakthrough* is positive and significant at the 5% level in all columns. The magnitude of the effect is substantial. For instance, compared to their peers, treated firms with high *SHC* experience 5.86% higher operating profitability and a 32% increase in market value within the five years following the scientific breakthrough. These results hold with alternative scientific human capital measures, which are reported in Appendix B. These results indicate that treated firms with a greater stock of scientific human capital exhibit significantly higher growth and profitability over the five years following a relevant scientific breakthrough, relative to both treated firms with lower scientific human capital and all control firms. The results of *Market Value* also demonstrate that the financial market can capture the positive information associated with scientific breakthroughs in firms possessing high scientific human capital.

[Insert Table 3 Here]

**The pre-trend of the effect of scientific human capital.** To further demonstrate that scientific breakthroughs provide unique opportunities for corporate scientists to leverage their knowledge and integrate it into the innovation process, it is necessary to address the hypothetical pre-trend in the differences in operating profitability and market valuation between treated firms with high *SHC* and their peers. Specifically, if the difference in profitability between treated firms with high *SHC* and their peers exhibits a distinct pre-trend prior to the breakthrough year and does not show an upward jump around the breakthrough year, it would undermine the argument that scientific human capital plays a critical role in driving firm growth post-breakthrough. This is because the role of corporate scientists, who serve as a bridge between cutting-edge scientific knowledge and industry innovation, should be most evident when new scientific knowledge becomes available for exploitation.

To test the pre-trend, I plot the average difference in market value between firms with high *SHC* and those with low *SHC* within both the treated and control groups over the [-5, 5] window surrounding the three scientific breakthroughs. This is illustrated in subfigures (a) and (b) in Figure 3, along with 95% confidence intervals.

As illustrated in subfigure (a), there is no pre-trend in *Market Value* between treated firms with high *SHC* and those with low *SHC*, as the coefficients for the pre-trend dummies remain stable and statistically insignificant. A noticeable increase occurs at year zero, the breakthrough year, with positive coefficients for the post-trend dummies. Following the breakthrough, treated firms with high *SHC* tend to experience a more substantial increase in *Market Value* compared to their treated firms with low *SHC*. This difference persists through the fifth year. For comparison, subfigure (b) displays the pre-trend pattern for the control group. There is no discernible difference in *Market Value* around the breakthrough year between control firms with high *SHC* and those with low *SHC*.

The patterns in Figure 3 reinforce the argument that, when scientific breakthroughs occur, investments in scientific human capital yield substantial rewards and create significant growth opportunities for impacted firms.

[Insert Figure 3 Here]

## 4. What role does scientific human capital play?

The previous section establishes that firms with more scientific human capital in related areas derive greater benefits from scientific breakthroughs. In this section, I explore the specific role of scientists in treated firms in driving innovation and growth.

### 4.1. Knowledge transfer channel

The three events I examine are science-intensive and demand advanced knowledge and skills to keep pace with the latest academic findings and translate them into products. Firms with a higher stock of relevant scientific human capital at the time of these breakthroughs are better positioned to rapidly absorb new knowledge and capitalize on first-mover advantages in the development of innovative products.

**4.1.1. Patent Quantity and Quality.** If scientists serve as intermediaries between academic knowledge and industrial innovation, one would expect to observe enhanced innovation outcomes for firms possessing greater scientific human capital. To assess patent outcomes, multiple metrics are employed, including *Patent Count*, *Citations*, *Patent Value*, and *Impactful Patent Count*.

Table 4 presents the results. Given the skewed and truncated nature of patent count and citation measures, poisson regression is employed for the analysis of these variables. Across all specifications in Table 4, the coefficient of the interaction term between *Exposure to Sci-Breakthrough* and *SHC* is positive and statistically significant, even after accounting for various fixed effects and control variables. The magnitude of the effect is substantial. For instance, firms exposed to scientific breakthroughs and possessing high scientific human capital exhibit a 47% increase in the rate of patent count and a 27% increase in patent value over the subsequent five years compared to their peer firms.

To test the pre-trend, I plot the average difference in the number of *Impactful Patent* between firms with high *SHC* and those with low SHC within both the treated and control groups over the [-5, 5] window surrounding the three scientific breakthroughs. This is illustrated in subfigures (a) and (b) in Figure 4, along with 95% confidence intervals.

As shown in subfigure (a), there is no pre-trend in the number of *Impactful Patent* granted between treated firms with high *SHC* and those with low *SHC*, as indicated by the stability of the pre-trend dummy coefficients. A notable increase occurs in the breakthrough year, with positive coefficients for the post-trend dummies. After the breakthrough, firms with high *SHC* generally experience a more substantial rise in the number of *Impactful Patent* compared to their peers, with this difference persisting up to the fifth year. In contrast, subfigure (b) shows the pre-trend pattern for the control group, highlighting the difference in *Impactful Patent* between control firms with high *SHC* and those with low *SHC*, with no significant jump around the breakthrough year.

These findings provide further evidence that enhanced innovation outcomes can be a significant driver of firm growth for those firms with substantial scientific human capital.

[Insert Table 4 Here]

[Insert Figure 4 Here]

**4.1.2. Scientist engagement in patenting activities.** When innovation opportunities emerge from scientific breakthroughs, corporate scientists play a critical role in translating academic knowledge into firm-level product innovation. Consequently, I anticipate that these scientists will increase their engagement in patenting activities following scientific breakthroughs in firms with high *SHC*, compared to firms with low *SHC* and control firms.

To assess scientist engagement in patenting activities, I conduct a name-matching process between author names in the OpenAlex database and inventor names in the USPTO patent database. I first construct a dataset of inventor employment history using the filing year and assignee firm information, with the earliest (latest) patent filed by an inventor indicating the first (last) year of employment at the firm. Similarly, I compile a dataset of scientist employment history using publication years to determine the first and last year of employment.

Groups of inventors who file patents in a given year and scientists employed by the same firm in that year are identified within the matched sample used in previous analyses. The fuzzy similarity score between inventor and scientist names in each group is calculated, retaining matches with a score of 80 or above, using the commonly employed name-matching package, *fuzzywuzzy*. Matches with a score of 100 are considered successful by default; for scores below 100, manual verification is conducted to confirm successful matches.

A firm-level measure, the *Scientist-Inventor Ratio*, is derived by averaging the scientist-inventor ratio across all patents granted to a firm in a given year. Table 5 presents the results where *Scientist-Inventor Ratio* serves as the dependent variable. The hypothesis is tested using a triple-stacked difference-in-differences approach as specified in equation (2).

The interaction term between *Exposure to Sci-Breakthrough* and *SHC* consistently shows a positive coefficient across specifications. Firms with higher stock of scientific human capital exhibit a 2% higher *Scientist-Inventor Ratio* compared to peer firms. This magnitude is significant given that the mean *Scientist-Inventor Ratio* is approximately 1.4%.

[Insert Table 5 Here]

To further demonstrate the quality of patents involving scientists after scientific breakthroughs, I conduct a patent-level analysis to determine whether such patents exhibit superior innovation quality. This analysis employs a quadruple difference-in-differences framework, incorporating the interaction between *Exposure to Sci-Breakthrough* × *SHC* and the *Scientist* variable, which indicates scientist involvement. The dependent variables include various patent quality measures: the log of forward citations received within five years of a patent's grant (*Forward Cites*), forward citations adjusted by overall citations within the same CPC class and year (*FW Cites Adj*), and the dummy variable *IsImpactfulPatent*, which indicates whether a patent is impactful.

Table 6 presents the results. The coefficient for the term *Exposure to Sci-Breakthrough* × *SHC* × *Scientist* is positive and significant across all columns, with patent class fixed effects as well as firm and year fixed effects. The magnitude of the effect is also substantial. For instance, scientists-inventors in firms affected by scientific breakthroughs who possess high pre-existing SHC are 4% more likely to produce high-impact patents. This suggests that patents with scientist involvement display enhanced quality in treated firms with high scientific human capital after the scientific breakthroughs.

[Insert Table 6 Here]

These findings align with the hypothesis that firms with greater scientific human capital demonstrate higher engagement of scientists in patenting activities, providing direct evidence of the knowledge transfer channel.

**4.1.3. Patent Reliance on Science.** Another approach to evaluate whether firms with greater *SHC* excel in integrating new knowledge from scientific breakthroughs into their product innovation is to assess the extent to which their patents rely on science. Firms with substantial SHC are also expected to have a first-mover advantage in absorbing new knowledge. Therefore, I examine the following hypotheses: 1) Firms with higher *SHC* are more likely to have a greater number of patents that cite related scientific papers; 2) Firms with higher *SHC* are more likely to have a greater number of patents that are among the first to cite related scientific papers; and 3) Firms with higher *SHC* are more likely to produce patents that demonstrate a greater reliance on the scientific knowledge derived from scientific breakthroughs.

Table 7 presents the results related to these hypotheses. The dependent variables *scienceRelevance_Cites* and *firstToCiteScience* assess a firm's ability to integrate scientific knowledge into its innovation processes based on citations to related scientific papers in patents. By contrast, the dependent variable *scienceRelevance_Gpt4o* serves as a textual-based proxy that measures the relatedness between a firm's patent portfolio in a given year and the scientific knowledge tied to a specific breakthrough event. The results in columns (1) to (6) show that treated firms with higher *SHC* produce patents more closely related to new scientific knowledge from breakthroughs and do so more quickly than their peers. This is evidenced by the positive and statistically significant coefficients on *Exposure to Sci-Breakthrough* $\times$ *SHC* in all specifications. These findings further support the knowledge transfer channel, highlighting how scientists facilitate the application of scientific knowledge in the corporate innovation process.

[Insert Table 7 Here]

**4.1.4. Accumulation of scientific human capital.** A firm that prioritizes basic science encourages its corporate scientists to publish research, which is crucial for their ongoing accumulation of scientific human capital. Publications not only reflect the personal reputation of scientists but also serve as a measure of their ability to absorb cutting-edge knowledge. Given that scientific breakthroughs create opportunities to explore new areas, corporate scientists are likely to publish more impactful papers following these breakthroughs, which represent an enhancement in scientific human capital beneficial to the firm. Consequently, I expect that treated firms with higher levels of scientific human capital will produce more impactful papers compared to their peers.

Table 8 presents the results. The variables *Number of Impactful Papers* and *Percentage of Impactful Papers* serve as proxies for the overall quality of a firm's publications. The coefficients align with our expectations, revealing a positive and significant interaction between *Exposure to Sci-Breakthrough* and *SHC*. Treated firms are observed to publish approximately 12% more impactful papers than their peer firms in the five years following a scientific breakthrough. This supports the notion that firms with a greater stock of scientific human capital demonstrate a more pronounced enhancement in their ability to absorb scientific knowledge compared to peer firms.

[Insert Table 8 Here]

### 4.2. Attracting star scientists

Another channel through which investment in scientific human capital can contribute to firm growth is by enhancing the firm's ability to attract distinguished scientists and inventors, owing to its reputation. Firms that cultivate a robust culture that is supportive of basic science and academic publishing are likely to gain a significant advantage in recruiting star scientists in fields related to scientific breakthroughs (Hicks, 1995; Ahmed, 2022). I thus hypothesize that firms with greater investments in scientific human capital prior to a breakthrough are better positioned to attract star scientists.

Table 9 presents results testing this hypothesis. The dependent variables include *Number* *of Scientists* and *Number of Star Scientists*. Columns (1) and (2) show a positive coefficient for the interaction term between *Exposure to Sci-Breakthrough* and *SHC*. Columns (3) and (4) demonstrate that firms with a high stock of scientific human capital are more likely to hire star scientists, as indicated by the positive and statistically significant coefficient for the interaction term. Specifically, firms with greater SHC hire 0.8 more star scientists than their peer firms in the five years following a scientific breakthrough. This effect is notable given that the mean number of star scientists among all firms is 1.1.

The results in Table 9 indicate that firms with higher levels of scientific human capital are more successful in recruiting scientists, particularly distinguished scientists, compared to their peers. This may further enhance their absorptive capacity for cutting-edge scientific knowledge.

[Insert Table 9 Here]

To further demonstrate the role of star scientists in enhancing firm value and innovation, I examine whether star scientists produce higher-quality patents than non-star scientists following scientific breakthroughs. Table 10 presents the coefficients from patent-level regressions assessing patent quality measures using the interaction term $Star \times Post$ in a difference-in-differences framework, applied to a subsample of treated firms with high scientific human capital ($SHC$). Here, *Star* indicates the involvement of a star scientist in a patent, while *Post* is a dummy variable for the period after scientific breakthroughs, and zero otherwise. The dependent variables include the patent quality measures *Forward Cites*, *FW Cites Adj*, and the dummy *IsImpactfulPatent*. All specifications include patent class fixed effects, defined by the three-digit patent CPC class. The positive significance of the $Star \times Post$ interaction term across all specifications indicates that patents involving star scientists exhibit higher quality compared to those involving only non-star scientists in treated firms with high scientific human capital after scientific breakthroughs. Specifically, patents involving star scientists are 4% more likely to achieve high impact than those involving only non-star scientists in these firms following scientific breakthroughs.

These results, along with those in Table 9, support the notion that firms with high scientific human capital are better positioned to hire top scientists after breakthroughs, who in turn are crucial in producing impactful patents.

[Insert Table 10 Here]

## 4.3. Robustness

**4.3.1. Propensity Score Matching.** Previous findings demonstrate the influence of SHC on firm growth and innovation following scientific breakthroughs. To address concerns about potential differences in firm characteristics between those with high and low SHC, I perform the analysis using a propensity-score-matched sample. In the breakthrough year, I sort the sample into three groups: Group 1 consists of treated firms with high SHC, Group 2 includes treated firms with low SHC, and Group 3 comprises all control firms not affected by the scientific breakthroughs.

I then construct a sample that includes firms from these three groups in the breakthrough years and estimate a logit regression with *Treated* as the dependent variable and a set of pre-event firm characteristics as independent variables. The set of control variables includes firm size (*Size*), *Leverage*, *Book-to-Market* ratio, and firm industry (based on the Fama-French 48 industry classification). I obtain the predicted probabilities from the logit model. For each firm in Group 1, I match it to a firm in Group 2 with the closest propensity score. The same procedure is then applied to match firms in Group 1 to firms in Group 3. This approach generates a sample comprising a treated group with high *SHC*, a matched treated group with low *SHC*, and a matched control group, with firms in these groups exhibiting similar characteristics.

Panel A and Panel B in Table 11 present the pre-event variable averages for the treated group with high *SHC*, and the treated group with the control group, as well as the differences in means for each variable and the corresponding t-statistics, respectively. The results indicate no significant differences in typical pre-event firm-level characteristics between each sample pair.

Panels C and D in Table 11 confirm that the baseline results hold within this matched sample. Treated firms with high *SHC* experience significantly higher growth and profitability and better innovation outcomes compared to their matched peers in the five years following a scientific breakthrough.

[Insert Table 11 Here]

**4.3.2. Alternative Scientific Human Capital Measures.** The primary measure of scientific human capital, *SHC*, is based on the stock of publications by scientists' employees in the window $[-3, -1]$ prior to the scientific breakthrough year. To test robustness, I construct two alternative measures of *SHC*. *HighSHC_Far* is a dummy variable indicating whether the stock of publications in the window $[-8, -6]$ prior to the breakthrough year is high. *HighSHC_Relevant* is a dummy variable indicating whether a firm possesses high relevant scientific human capital, measured in the window $[-3, -1]$ relative to the event year. Further details about these two measures are provided in Appendix A. The results are consistent with those from the main *SHC* measure, suggesting that scientific human capital is a long-term investment reflecting a firm's culture of supporting internal research. Additionally, unreported results show that relevant scientific human capital *SHC_Relevant* provides stronger support for the channels documented using general *SHC*, indicating that *HighSHC_Relevant* more accurately captures a firm's capacity to absorb knowledge from related scientific breakthroughs.

## 5. Conclusion

In this study, I investigate how scientific human capital enhances value creation among publicly listed companies in the context of emerging scientific breakthroughs. I utilize three prominent scientific breakthroughs originating from universities in the 21st century—the Human Genome Project, deep learning and neural networks, and gene editing—as exogenous shocks to firms operating in related fields. This provides a unique setting to examine the role of scientific human capital in driving firm growth, as these breakthrough events serve as unexpected shocks that offer new sources of scientific knowledge that require academic expertise to be effectively absorbed and integrated into the innovation process.

I demonstrate that firms experiencing these scientific breakthroughs and possessing higher levels of scientific human capital exhibit greater improvements in operating performance and market valuation compared to both peer firms with lower levels of scientific human capital as well as those unaffected by the breakthroughs.

Further analyses of the role of scientific human capital reinforces the knowledge transfer channel, whereby corporate scientists absorb new knowledge from scientific breakthroughs and integrate it into the innovation process. My findings regarding innovation output support the knowledge transfer channel. Specifically, for firms with higher stocks of scientific human capital, I observe: (1) increased engagement of corporate scientists in patenting activities, (2) higher quality of innovation, and (3) a faster incorporation of scientific knowledge into patents within the five years following scientific breakthroughs.

Additionally, my results indicate that firms with higher stocks of scientific human capital are more successful in attracting star scientists in the five years following scientific breakthroughs. This finding complements the knowledge transfer channel, as the influx of star scientists further enhances the firm's capacity to integrate cutting-edge scientific knowledge into the innovation process.

My findings underscore the critical role of corporate scientists in advancing firm innovation in response to scientific breakthroughs and have significant implications for corporate investment in research and development. Given the ongoing trend of specialization between universities, who focus on basic research, and firms, who commercialize this research, the role of corporate scientists is particularly significant. They bridge the gap by translating scientific discoveries from academic institutions into product innovations within the private sector. The evidence presented in this study highlights and expands our understanding of this bridging role.

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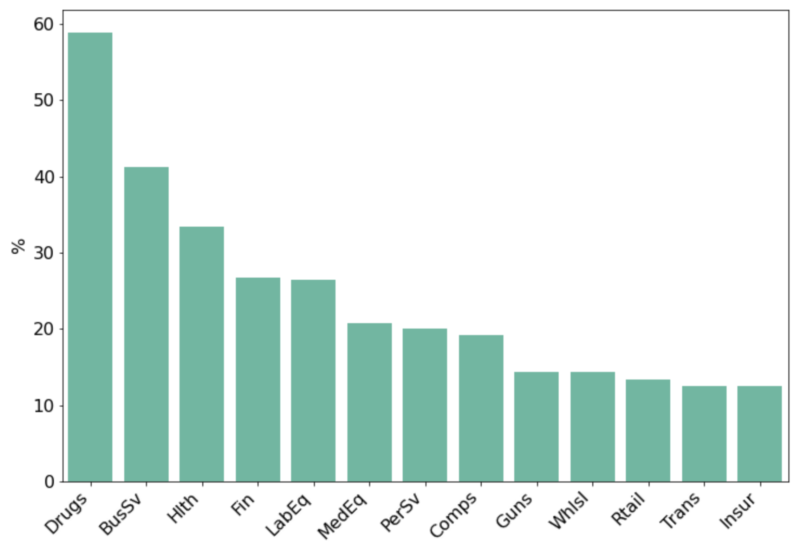
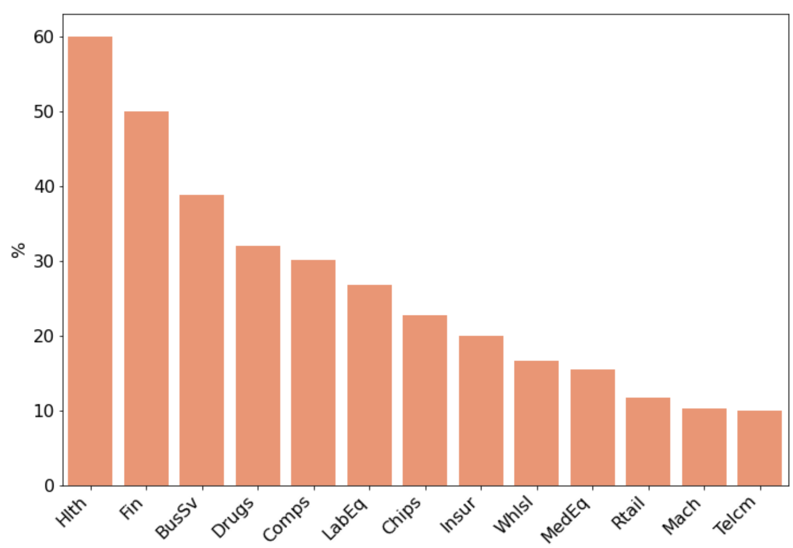
**Figure 1.** Affected sectors in three scientific breakthroughs

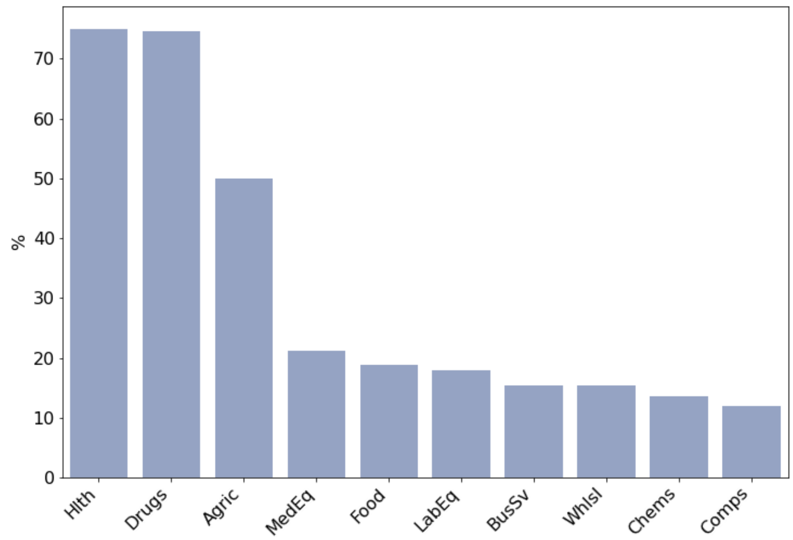
This figure illustrates the sectors most impacted by each scientific breakthrough. I calculate the fraction of firms classified as treated firms within each sector, using the Fama-French 48 industry classification approach. Subfigures (a), (b), and (c) depict sectors where this fraction exceeds 10% for the three breakthrough events: the Human Genome Project, Deep Learning, and Gene Editing, respectively. Subfigure (d) consolidates the sectors most affected across all three breakthrough events into a single plot.



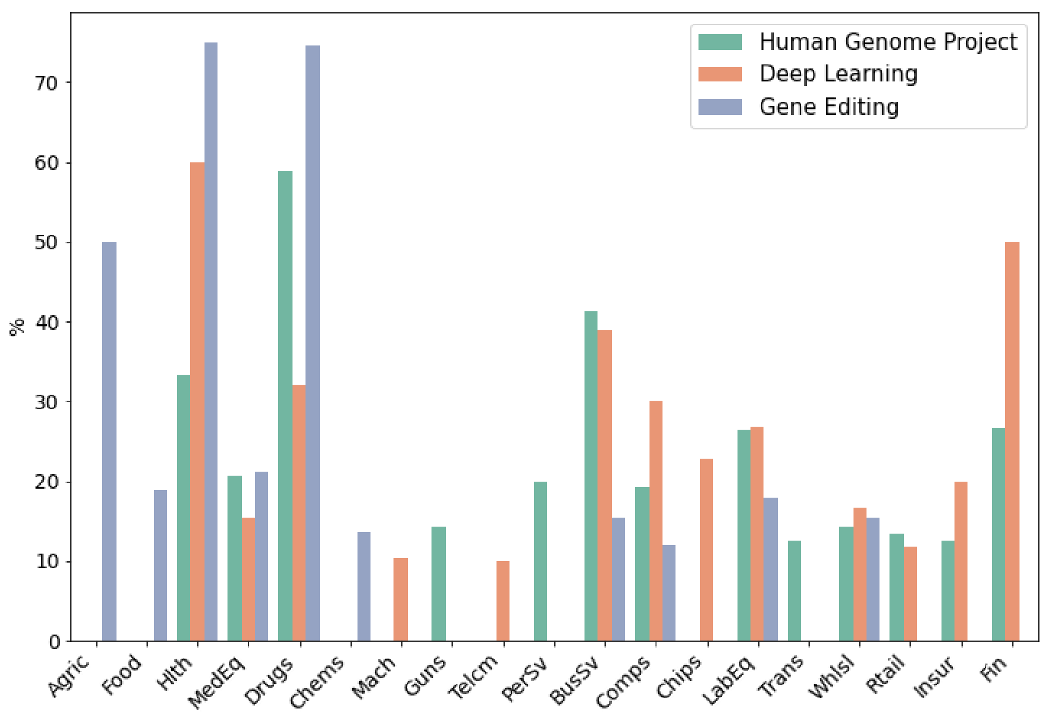

**(a)** Human Genome Project




**(b)** Deep Learning



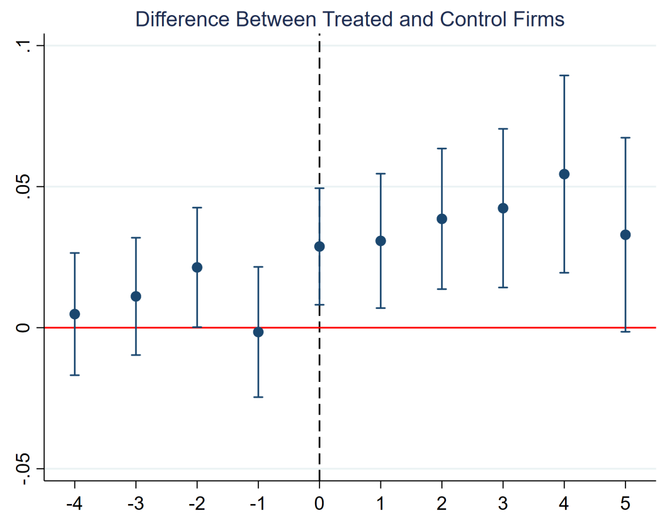

**(c)** Gene Editing



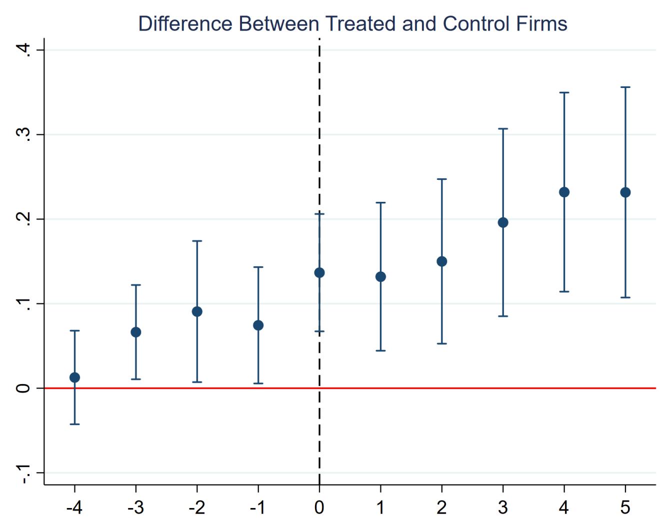

**(d)** Combined

**Figure 2.** Testing for pre-trends: Profitability and Sales

This figure plots difference-in-difference estimates of the effects of scientific breakthroughs on firm performance, *Operating Profitability* and *Sales*. Firms without any patents filed during the sample period are excluded from the analysis. Treated firms are those ranked in the top 20% based on the similarity of their core area to a scientific breakthrough, while control firms are in the remaining 80%. I include data from an 11-year window centered on the year in which the representative paper of a scientific breakthrough is published. The coefficients are estimated using OLS and include fixed effects for Firm × Event, and Year × Event, as described in Section 3.1. The vertical lines represent 95% confidence intervals. Variables are defined in Appendix A.



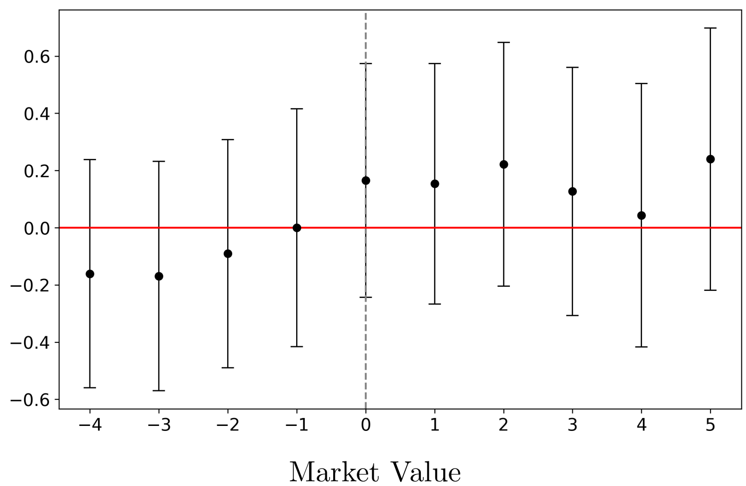

**(a)** Operating Profitability



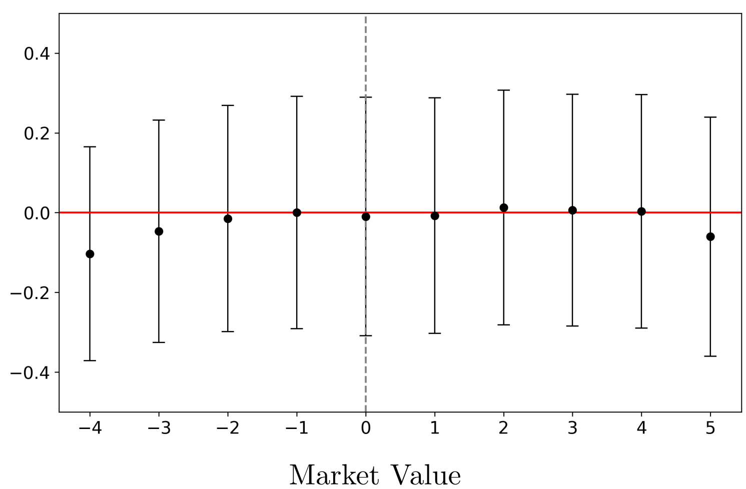

**(b)** Sales

**Figure 3.** Testing for pre-trends in Market Value: High vs. Low *SHC*

This figure plots estimates of the effects of scientific human capital *HighSHC* on firm valuation *Market Value* within treated firms (subfigure (a)) and control firms (subfigure (b)), respectively. Firms without any patents filed during the sample period are excluded from the analysis. Treated firms are those ranked in the top 20% based on the similarity of their core area to a scientific breakthrough, while control firms are in the remaining 80%. *HighSHC* is a dummy variable that indicates whether a firm possesses high scientific human capital prior to scientific breakthroughs. I include data from an 11-year window centered on the year in which the representative paper of a scientific breakthrough is published. The vertical lines represent 95% confidence intervals. Variables are defined in Appendix A.



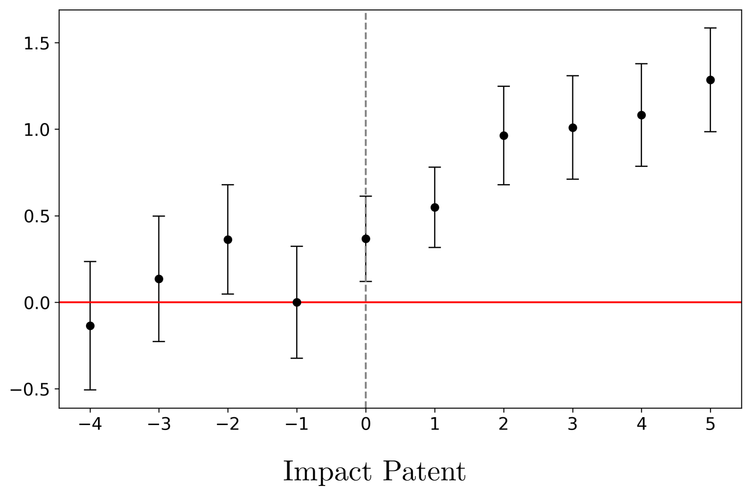

(a) Treated Firms: Difference Between High vs. Low *SHC*



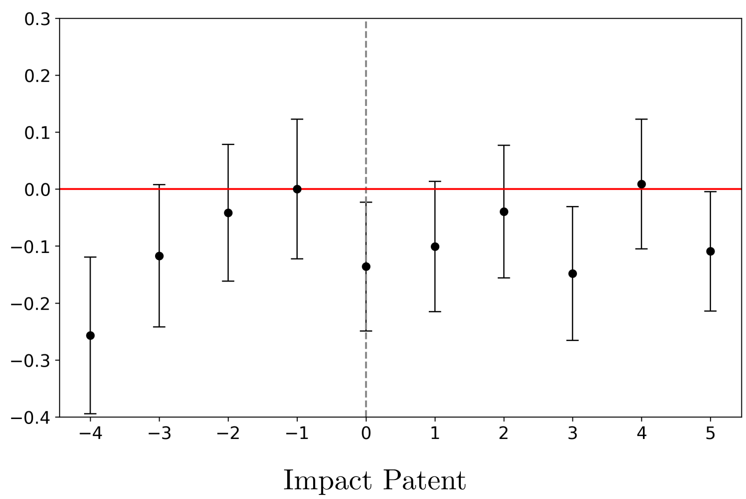

(b) Control Firms: Difference Between High vs. Low *SHC*

**Figure 4.** Testing for pre-trends in Impactful Patent: High vs. Low *SHC*

This figure plots estimates of the effects of scientific human capital *HighSHC* on innovation quality *Impactful Patent Count* within treated firms (subfigure (a)) and control firms (subfigure (b)), respectively. Firms without any patents filed during the sample period are excluded from the analysis. Treated firms are those ranked in the top 20% based on the similarity of their core area to a scientific breakthrough, while control firms are in the remaining 80%. *HighSHC* is a dummy variable that indicates whether a firm possesses high scientific human capital prior to scientific breakthroughs. I include data from an 11-year window centered on the year in which the representative paper of a scientific breakthrough is published. The coefficient on *Impactful Patent Count* is estimated using Poisson regression. The vertical lines represent 95% confidence intervals. Variables are defined in Appendix A.




(a) Treated Firms: Difference Between High vs. Low *SHC*




(b) Control Firms: Difference Between High vs. Low *SHC*

**Table 1.** Summary statistics

Panel A summarizes the descriptive statistics of the key variables used in the analysis. Firms without any patents filed during the sample period are excluded. The sample contains 38,588 firm-year observations, representing 2,244 firms between 1996 and 2017. Panel B reports the number of treated firms and the number of control firms in each breakthrough event. Treated firms are those ranked in the top 20% based on the similarity of their core area to a scientific breakthrough, while control firms are in the remaining 80%. The three scientific breakthrough events include Human Genome Project in 2001, Deep Learning in 2006, and Gene Editing in 2012. Details about scientific breakthrough events are described in section 2.3.1. Panel C reports the number of publishing firms and non-publishing firms in the treated group and control group. Variables are defined in Appendix A.

*Panel A: Summary statistics for key variables*

| | N | Mean | SD | p10 | Median | p90 |
|---|---|---|---|---|---|---|
| *Size* ($M) | 38,588 | 5,973.464 | 21,618.943 | 27 | 395 | 10,820 |
| *Operating Profitability* | 38,588 | 0.029 | 0.278 | -0.254 | 0.103 | 0.221 |
| *Sales* ($M) | 38,588 | 4,524.69 | 14,390.67 | 14 | 424 | 9,545 |
| *Market Value* ($M) | 38,588 | 12,435.574 | 43,781.163 | 61 | 931 | 24,162 |
| *Patent Count* | 38,588 | 28.501 | 109.123 | 0 | 2 | 47 |
| *Citation* | 38,588 | 415.111 | 1779.702 | 0 | 17 | 570 |
| *Impactful Patent Count* | 38,588 | 0.405 | 2.314 | 0 | 0 | 1 |
| *Patent Value* ($M) | 38,588 | 1.097 | 1.226 | 0 | 0.732 | 2.903 |
| *Number of Scientists* | 38,588 | 15.080 | 72.358 | 0 | 0 | 19 |
| *Number of Star Scientists* | 38,588 | 1.111 | 7.684 | 0 | 0 | 1 |
| *Scientist-Inventor Ratio* | 38,588 | 0.014 | 0.071 | 0 | 0 | 0 |
| *Number of Impactful Papers* | 38,588 | 4.911 | 47.478 | 0 | 0 | 3 |
| *Percentage of Impactful Papers* | 38,588 | 0.158 | 0.871 | 0 | 0 | 0.438 |
| *scienceRelevance_Cites* | 38,588 | 0.102 | 1.686 | 0 | 0 | 0 |
| *firstToCiteScience* | 38,588 | 0.055 | 0.852 | 0 | 0 | 0 |
| *scienceRelevance_Gpt4o* | 38,588 | 0.041 | 0.687 | 0 | 0 | 0 |
| *HighSHC* | 38,588 | 0.118 | 0.323 | 0 | 0 | 1 |

*(continued)*

*Panel B: The number of treated firms and control firms in each event year*

| Event Year | Scientific Breakthrough | No. of treated firms | No. of control firms |
|---|---|---|---|
| 2001 | Human Genome Project | 273 | 1207 |
| 2006 | Deep Learning and Neural Networks | 242 | 1059 |
| 2012 | Gene Editing | 191 | 866 |

*Panel C: The number of publishing firms and non-publishing firms in each event year*

| | Publish | | Do not Publish | | Total | |
|---|---|---|---|---|---|---|
| | Count | % | Count | % | Count | % |
| Treated | 285 | 40% | 421 | 60% | 706 | 100% |
| Control | 823 | 26% | 2309 | 74% | 3132 | 100% |

**Table 2.** Scientific Breakthrough and Firm Performance

This table reports the results from the regression that examines the firm performance after scientific breakthroughs in a stacked difference-in-difference framework. The classification of treated and control firms is described in section 2.3. *Exposure to SciBreak* is a dummy variable that is equal to one for treated firm-year observations in the 5 years after a scientific breakthrough and zero otherwise. The dependent variables include *Operating Profitability*, *Sales* and *Market Value*. In columns (1), (3) and (5), I control for firm fixed effects and year fixed effects, In columns (2), (4) and (6), I control for firm × event and year × event fixed effects. Standard errors are clustered at the industry level. t-statistics are presented in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Variables are defined in Appendix A.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Operating Profitability* | | *Sales* | | *Market Value* | |
| *Exposure to SciBreak* | 0.0273*** | 0.0277*** | 0.114*** | 0.124*** | 0.0169 | 0.0249 |
| | (3.58) | (3.88) | (3.86) | (3.53) | (0.45) | (0.60) |
| | | | | | | |
| Firm × Event FE | No | Yes | No | Yes | No | Yes |
| Year × Event FE | No | Yes | No | Yes | No | Yes |
| Firm FE | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | No | Yes | No | Yes | No |
| R-squared | 0.699 | 0.734 | 0.952 | 0.965 | 0.939 | 0.952 |
| Observations | 38,588 | 38,588 | 38,588 | 38,588 | 38,588 | 38,588 |

**Table 3.** Triple-difference Estimates of the Effect of SHC on Firm Performance

This table reports the results from the regression that examines the effect of pre-existing scientific human capital on firm performance following scientific breakthroughs, utilizing a stacked triple difference-in-differences framework. The classification of treated and control firms is described in section 2.3. *Exposure to SciBreak* × *HighSHC* is a dummy variable that is equal to one for treated firm-year observations with high scientific human capital *SHC* in the 5 years after a scientific breakthrough and zero otherwise. The dependent variables include *Operating Profitability*, *Sales* and *Market Value*. In columns (1), (3) and (5), I control for firm fixed effects and year fixed effects, In columns (2), (4) and (6), I control for firm × event and year × event fixed effects. Controls include the interaction term between pre-event *Size* × *Exposure to SciBreak*. Standard errors are clustered at the industry level. t-statistics are presented in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Variables are defined in Appendix A.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Operating Profitability* | | *Sales* | | *Market Value* | |
| *Exposure to SciBreak × HighSHC* | 0.0536*** | 0.0586*** | 0.172*** | 0.173** | 0.305*** | 0.279*** |
| | (3.43) | (3.38) | (2.68) | (1.97) | (4.40) | (3.54) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm × Event FE | No | Yes | No | Yes | No | Yes |
| Year × Event FE | No | Yes | No | Yes | No | Yes |
| Firm FE | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | No | Yes | No | Yes | No |
| R-squared | 0.702 | 0.734 | 0.954 | 0.965 | 0.940 | 0.952 |
| Observations | 38,588 | 38,588 | 38,588 | 38,588 | 38,588 | 38,588 |

**Table 4.** Triple-difference Estimates of the Effect of SHC on Firm Innovation

This table reports the results from the regression that examines the effect of pre-existing scientific human capital on firm innovation outcomes following scientific breakthroughs, utilizing a stacked triple difference-in-differences framework. The classification of treated and control firms is described in section 2.3. *Exposure to SciBreak* × *HighSHC* is a dummy variable that is equal to one for treated firm-year observations with high scientific human capital *SHC* in the 5 years after a scientific breakthrough and zero otherwise. The dependent variables include *Patent Count*, *Citation*, *Impactful Patent Count* and *Patent Value*. Poisson regressions are used to estimate the effects on *Patent Count*, *Citations*, and *Impactful Patent Count*. In columns (1), (3), (5), and (7), I control for firm fixed effects and year fixed effects, In columns (2), (4), (6) and (8), I control for firm × event and year × event fixed effects. Controls include the interaction term between pre-event *Size* × *Exposure to SciBreak*. Standard errors are clustered at the industry level. t-statistics are presented in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Variables are defined in Appendix A.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *Patent Count* | | *Citations* | | *Impactful Patent Count* | | *Patent Value* | |
| *Exposure to SciBreak* × *HighSHC* | 0.401** | 0.386** | 0.534*** | 0.531*** | 0.755** | 0.673** | 0.464*** | 0.458*** |
| | (2.00) | (2.03) | (2.97) | (2.93) | (2.50) | (2.26) | (5.37) | (5.16) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm × Event FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Year × Event FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Firm FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | No | Yes | No | Yes | No | Yes | No |
| R-squared | | | | | | | 0.708 | 0.745 |
| Observations | 38,419 | 38,167 | 37,993 | 37,701 | 15,680 | 12,834 | 38,588 | 38,588 |

**Table 5.** Triple-difference Estimates of the Effect of SHC on Scientist Patenting

This table reports the results from the regression that examines scientist engagement in patenting following scientific breakthroughs, utilizing a stacked triple difference-in-differences framework. The classification of treated and control firms is described in section 2.3. *Exposure to SciBreak* × *HighSHC* is a dummy variable that is equal to one for treated firm-year observations with high scientific human capital *SHC* in the 5 years after a scientific breakthrough and zero otherwise. The dependent variable is the *Scientist-Inventor Ratio*, which represents the average proportion of scientist inventors in a firm's patent portfolio. In column (1), I control for firm fixed effects and year fixed effects. In column (2), I control for firm × event and year × event fixed effects. Controls include the interaction term between pre-event *Size* × *Exposure to SciBreak*. Standard errors are clustered at the industry level. t-statistics are presented in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Variables are defined in Appendix A.

| | (1) | (2) |
|---|---|---|
| | *Scientist-Inventor Ratio* | |
| *Exposure to SciBreak* × *HighSHC* | 0.0182*** | 0.0199*** |
| | (3.13) | (3.78) |
| | | |
| Controls | Yes | Yes |
| Firm × Event FE | No | Yes |
| Year × Event FE | No | Yes |
| Firm FE | Yes | No |
| Year FE | Yes | No |
| R-squared | 0.528 | 0.556 |
| Observations | 38,588 | 38,588 |

**Table 6.** Quadruple-difference Estimates of Scientist Involvement on Patent Quality

This table reports the results from the regression that examines the effect of scientist involvement on patent quality after scientific breakthroughs in a stacked quadruple difference-in-difference framework. *Scientist* is an indicator of whether a patent contains a scientist inventor. *Exposure to SciBreak* × *HighSHC* is a dummy variable that is equal to one for treated firm-year observations with high scientific human capital *SHC* in the 5 years after a scientific breakthrough and zero otherwise. The dependent variables include the log number of forward citations received within five years of a patent's grant, *Forward Cites*, the forward citations received in the five years post-grant, adjusted by the overall citations received within the same CPC class and granted in the same year, *FWCitesAdj*, and the dummy variable *IsImpactfulPatent*, which indicates whether a patent is impactful, and zero otherwise. I include class fixed effects in all specifications, where class represents the three-digit patent CPC class. Controls include the interaction term between pre-event *Size* × *Exposure to SciBreak*. Standard errors are clustered at the industry level. t-statistics are presented in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Variables are defined in Appendix A.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Forward Cites* | | *FW Cites Adj* | | *IsImpactfulPatent* | |
| *Exposure to SciBreak* × *HighSHC* | 0.250*** | 0.145** | 0.873** | 0.542** | 0.0513*** | 0.0445** |
| × Scientist | (2.87) | (2.58) | (2.55) | (1.99) | (2.70) | (2.49) |
| *Exposure to SciBreak* × *HighSHC* | -0.107 | 0.00122 | -0.357 | 0.000466 | -0.00364 | 0.00470 |
| | (-1.30) | (0.02) | (-1.29) | (0.00) | (-0.30) | (0.40) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm × Event FE | No | Yes | No | Yes | No | Yes |
| Year × Event FE | No | Yes | No | Yes | No | Yes |
| Class × Event FE | No | Yes | No | Yes | No | Yes |
| Class × Year FE | No | Yes | No | Yes | No | Yes |
| Firm FE | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | No | Yes | No | Yes | No |
| Class FE | Yes | No | Yes | No | Yes | No |
| R-squared | 0.112 | 0.143 | 0.094 | 0.120 | 0.052 | 0.069 |
| Observations | 771,154 | 770,961 | 771,154 | 770,961 | 771,154 | 770,961 |

**Table 7.** Triple-difference Estimates of the Effect of SHC on Patent Reliance on Science

This table reports the results from the regression that examines the level of reliance on science in firm patents after scientific breakthroughs, using a stacked triple difference-in-difference framework. The classification of treated and control firms is described in section 2.3. *Exposure to SciBreak* × *HighSHC* is a dummy variable that is equal to one for treated firm-year observations with high scientific human capital *SHC* in the 5 years after a scientific breakthrough and zero otherwise. The dependent variables include patent quality measures, *scienceRelevance_Cites*, *firstToCiteScience* and *scienceRelevance_Gpt4o*. In columns (1), (3) and (5), I control for firm fixed effects and year fixed effects, in Column (2), (4) and (6), I control for firm × event and year × event fixed effects. Controls include the interaction term between pre-event *Size* × *Exposure to SciBreak*. Standard errors are clustered at the industry level. t-statistics are presented in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Variables are defined in Appendix A.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *scienceRelevance_Cites* | | *firstToCiteScience* | | *scienceRelevance_Gpt4o* | |
| *Exposure to SciBreak* | 0.0867*** | 0.0677*** | 0.0454*** | 0.0338** | 0.172** | 0.173** |
| × *HighSHC* | (3.29) | (2.85) | (2.75) | (2.01) | (2.00) | (2.23) |
| | | | | | | |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm × Event FE | No | Yes | No | Yes | No | Yes |
| Year × Event FE | No | Yes | No | Yes | No | Yes |
| Firm FE | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | No | Yes | No | Yes | No |
| R-squared | 0.474 | 0.669 | 0.433 | 0.620 | 0.348 | 0.703 |
| Observations | 38,588 | 38,588 | 38,588 | 38,588 | 38,588 | 38,588 |

**Table 8.** Triple-difference Estimates of the Effect of SHC on Corporate Publication

This table reports the results from the regression that examines the firm publication after scientific breakthroughs in a stacked triple difference-in-difference framework. The classification of treated and control firms is described in section 2.3. *Exposure to SciBreak* × *HighSHC* is a dummy variable that is equal to one for treated firm-year observations with high scientific human capital *SHC* in the 5 years after a scientific breakthrough and zero otherwise. The dependent variables include *Number of Impactful Papers* and *Percentage of Impactful Papers*. In columns (1) and (3), I control for firm fixed effects and year fixed effects, in Column (2) and (4), I control for firm × event and year × event fixed effects. Standard errors are clustered at the industry level. Controls include the interaction term between pre-event *Size* × *Exposure to SciBreak*. t-statistics are presented in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Variables are defined in Appendix A.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *Number of Impactful Papers* | | *Percentage of Impactful Papers* | |
| *Exposure to SciBreak* × *HighSHC* | 0.0944** | 0.115*** | 0.0604** | 0.0760** |
| | (2.15) | (2.66) | (2.42) | (2.50) |
| Controls | Yes | Yes | Yes | Yes |
| Firm × Event FE | No | Yes | No | Yes |
| Year × Event FE | No | Yes | No | Yes |
| Firm FE | Yes | No | Yes | No |
| Year FE | Yes | No | Yes | No |
| R-squared | 0.951 | 0.976 | 0.711 | 0.761 |
| Observations | 38,588 | 38,588 | 38,588 | 38,588 |

**Table 9.** Triple-difference Estimates of the Effect of SHC on New Scientist Hiring

This table reports the results from the regression that examines the recruitment of scientists after scientific breakthroughs in a stacked triple difference-in-difference framework. The classification of treated and control firms is described in section 2.3. *Exposure to SciBreak* $\times$ *HighSHC* is a dummy variable that is equal to one for treated firm-year observations with high scientific human capital *SHC* in the 5 years after a scientific breakthrough and zero otherwise. The dependent variables include *Number of Scientists* and *Number of Star Scientists*. In columns (1) and (3), I control for firm fixed effects and year fixed effects, in Column (2) and (4), I control for firm $\times$ event and year $\times$ event fixed effects. Controls include the interaction term between pre-event *Size* $\times$ *Exposure to SciBreak*. Standard errors are clustered at the industry level. t-statistics are presented in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Variables are defined in Appendix A.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *Number of Scientists* | | *Number of Star Scientists* | |
| *Exposure to SciBreak* $\times$ *HighSHC* | 9.223** | 9.538** | 0.830** | 0.913** |
| | (2.31) | (2.30) | (2.25) | (2.20) |
| Controls | Yes | Yes | Yes | Yes |
| Firm $\times$ Event FE | No | Yes | No | Yes |
| Year $\times$ Event FE | No | Yes | No | Yes |
| Firm FE | Yes | No | Yes | No |
| Year FE | Yes | No | Yes | No |
| R-squared | 0.916 | 0.944 | 0.901 | 0.928 |
| Observations | 38,588 | 38,588 | 38,588 | 38,588 |

**Table 10.** The Effect of Star Scientist on Patent Quality Following Scientific Breakthroughs

This table reports the results from the regression that examines the effect of star scientist involvement on patent quality around scientific breakthroughs in a subsample comprising treated firms with high scientific human capital *SHC*. The classification of treated and control firms is described in section 2.3. *Star* is an indicator of whether a star scientist is involved in a patent, while *Post* is a dummy variable indicating the period after scientific breakthroughs, and zero otherwise. The dependent variables include the log number of forward citations received within five years of a patent's grant, *Forward Cites*, the forward citations received in the five years post-grant, adjusted by the overall citations received within the same CPC class and granted in the same year, *FWCitesAdj*, and the dummy variable *IsImpactfulPatent*, which indicates whether a patent is impactful, and zero otherwise. I include class fixed effects in all specifications, where class represents the three-digit patent CPC class. Controls include the interaction term between pre-event *Size* × *Post*. Standard errors are clustered at the industry level. t-statistics are presented in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Variables are defined in Appendix A.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Forward Cites* | | *FW Cites Adj* | | *IsImpactfulPatent* | |
| *Star* × *Post* | 0.118* | 0.159** | 0.609*** | 0.609** | 0.0435** | 0.0423** |
| | (1.80) | (2.12) | (3.02) | (2.30) | (2.28) | (2.16) |
| *Star* | 0.0238 | -0.00465 | -0.0239 | 0.0236 | -0.00568 | -0.00154 |
| | (0.58) | (-0.11) | (-0.16) | (0.16) | (-0.33) | (-0.10) |
| *Post* | -0.365 | | -0.800 | | -0.0684 | |
| | (-1.65) | | (-0.98) | | (-1.24) | |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm × Event FE | No | Yes | No | Yes | No | Yes |
| Year × Event FE | No | Yes | No | Yes | No | Yes |
| Class × Event FE | No | Yes | No | Yes | No | Yes |
| Class × Year FE | No | Yes | No | Yes | No | Yes |
| Firm FE | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | No | Yes | No | Yes | No |
| Class FE | Yes | No | Yes | No | Yes | No |
| R-squared | 0.170 | 0.212 | 0.129 | 0.183 | 0.087 | 0.141 |
| Observations | 11,726 | 11,616 | 11,726 | 11,616 | 11,726 | 11,616 |

**Table 11.** Triple-difference Estimates: Propensity Score Matching

This table reports the results from the regression that examines the impact of scientific human capital (*SHC*) on firm performance following scientific breakthroughs, employing a propensity score matching approach. The classification of treated and control firms is outlined in section 2.3. In the breakthrough year, I divided the sample into three groups: Group 1 consists of treated firms with high *SHC*, Group 2 includes treated firms with low *SHC*, and Group 3 comprises all control firms unaffected by the scientific breakthroughs. A matching treated group with low *SHC* and a matching control group were then constructed using nearest-neighbor propensity-score matching based on *Size*, *Book-to-Market*, *Leverage*, and industry, applying a 0.2 caliper. Panel A reports pre-event variable averages for the treated group with high *SHC* and the treated group with low *SHC*, along with the differences in means for each variable and the corresponding $t$-statistics from T-tests. Panel B presents pre-event variable averages for the treated group with high *SHC* and the control group, as well as the differences in means for each variable and the corresponding $t$-statistics from T-tests. Panels C and D report the results from the baseline regressions on firm performance and innovation, respectively, using the propensity score matched sample. Poisson regressions are used to estimate the effects on *Patent Count*, *Citations*, and *Impactful Patent Count*. Controls include the interaction term between pre-event *Size* $\times$ *Exposure to SciBreak*. Standard errors are clustered at the industry level. t-statistics are presented in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Variables are defined in Appendix A.

*Panel A: Differences between Treated Firms with High SHC and Treated Firms with Low SHC*

| Variable | Treated with High SHC | Treated without Low SHC | Difference | $t$-statistics | $p$-Value |
|---|---|---|---|---|---|
| *Log Size* | 5.490 | 5.156 | 0.334 | 1.786 | 0.075 |
| *Log Sales* | 4.638 | 4.290 | 0.349 | 1.406 | 0.161 |
| *Book-to-Market* | 0.321 | 0.301 | 0.020 | 0.702 | 0.483 |
| *Leverage* | 0.066 | 0.059 | 0.007 | 0.694 | 0.488 |
| *Tangibility* | 0.132 | 0.117 | 0.016 | 1.376 | 0.170 |

*Panel B: Differences between Treated Firms with High SHC and Control Firms*

| Variable | Treated with High SHC | Control Group | Difference | $t$-statistics | $p$-Value |
|---|---|---|---|---|---|
| *Log Size* | 5.490 | 5.470 | 0.021 | 0.107 | 0.915 |
| *Log Sales* | 4.638 | 4.895 | -0.256 | -1.049 | 0.295 |
| *Book-to-Market* | 0.321 | 0.268 | 0.053 | 2.212 | 0.027 |
| *Leverage* | 0.066 | 0.063 | 0.003 | 0.328 | 0.743 |
| *Tangibility* | 0.132 | 0.140 | -0.008 | -0.661 | 0.509 |

*(continued)*

*Panel C: Triple-difference estimates of Firm Performance with Propensity Score Matching Approach*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Operating Profitability* | | *Sales* | | *Market Value* | |
| *Exposure to SciBreak × HighSHC* | 0.0380** | 0.0427*** | 0.113** | 0.130*** | 0.173*** | 0.178*** |
| | (2.60) | (2.77) | (2.23) | (2.69) | (3.39) | (3.19) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm × Event FE | No | Yes | No | Yes | No | Yes |
| Year × Event FE | No | Yes | No | Yes | No | Yes |
| Firm FE | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | No | Yes | No | Yes | No |
| R-squared | 0.651 | 0.672 | 0.931 | 0.944 | 0.910 | 0.927 |
| Observations | 6,823 | 6,823 | 6,823 | 6,823 | 6,823 | 6,823 |

*Panel D: Triple-difference estimates of Firm Innovation with Propensity Score Matching Approach*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *Patent Count* | | *Citations* | | *Impactful Patent Count* | | *Patent Value* | |
| *Exposure to SciBreak × HighSHC* | 0.462** | 0.454** | 0.449*** | 0.453*** | 0.919*** | 0.874*** | 0.109* | 0.134** |
| | (2.46) | (2.35) | (3.17) | (3.22) | (3.65) | (3.39) | (1.94) | (2.55) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm × Event FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Year × Event FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Firm FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | No | Yes | No | Yes | No | Yes | No |
| R-squared | | | | | | | 0.759 | 0.786 |
| Observations | 6,805 | 6,805 | 6,710 | 6,710 | 2,592 | 2,319 | 6,823 | 6,823 |

## Appendix A: Definitions of Variables

| Variable | Definition |
|---|---|
| *firstToCiteScience* | The total number of patents granted to firm $i$ in year $t$ that are among the first to cite scientific papers. A patent is considered among the first to cite a related scientific paper if it references the paper within three years of its publication. A paper is classified as related if it is cited in a breakthrough paper published after 1996 or if it cites a breakthrough paper. |
| *Forward Cites* | The logarithm of one plus the forward citations received by a patent in the five years post-grant. |
| *FW Cites Adj* | The forward citations received by a patent in the five years post-grant, adjusted for the overall citations received within the same CPC class and granted in the same year. |
| *HighSHC* | A dummy variable that equals 1 if the firm ranks in the top 10% in terms of scientific human capital measure *SHC* in a scientific breakthrough event, and 0 otherwise. |
| *HighSHC_Far* | A dummy variable that equals 1 if the firm ranks in the top 10% in terms of scientific human capital measure *SHC_Far* in a scientific breakthrough event and 0 otherwise. |
| *HighSHC_Relevant* | A dummy variable that equals 1 if the firm ranks in the top 10% in terms of the scientific human capital measure *SHC_Relevant*, and 0 otherwise. |
| *Impactful Paper* | A paper is classified as an impactful paper if it ranks among the top 5% in terms of citations received within five years of publication, relative to other papers in the same subfield published in the same year. The subfield classification is determined according to the bibliometric database OpenAlex. |
| *IsImpactfulPatent* | A dummy variable indicating whetehr a patent is an impactful patent. A patent is classified as an impactful patent if it ranks in the top 5% in terms of forward citations received within five years of being granted, relative to other patents filed in the same year. |
| *Impactful Patent Count* | The number of impactful patents granted to a firm in a given year. |
| *Market Value* | Equal to the total assets (*at*), subtract the book value of common equity (*ceq*) and add the market value of common equity (calculated as $prcc_c$ times *csho*). The analysis uses the value in logarithmic format, with 1 added. |
| *Number of Impactful Papers* | The number of impactful papers published by a firm in a given year. The logarithm of one plus the value is used in the analysis. |
| *Number of Scientists* | An employee is identified as a scientist of firm $i$ in year $t$ if the individual has published papers affiliated with firm $i$ in year $t$, or if the individual has published papers both before and after year $t$. *Number of Scientists* is the sum of all scientists in firm $i$ in year $t$. |
| *Number of Star Scientists* | A scientist is classified as a star scientist if more than 50% of the papers they have published before year $t$ are classified as Impactful Paper. |

*(continued)*

| **Variable** | **Definition** |
|---|---|
| *Operating Profitability* | Divide the operating income before depreciation (Compustat item *oibdp*) by total assets (*at*). |
| *Patent Count* | The number of patents granted to firm $i$ in year $t$. |
| *Percentage of Impactful Papers* | The ratio of *Number of Impactful Papers* to the total number of papers published by a firm in a given year. |
| *Post* | A dummy variable indicating the post-breakthrough period. |
| *Sales* | The logarithm of 1 plus the Compustat item *Sales* for firm $i$ in year $t$. |
| *Scientist* | A dummy variable indicating whether an inventor is classified as a scientist. The method for identifying scientist inventors is detailed in Section 4.1.2. |
| *Star* | A dummy variable indicating whether a scientist is classified as a star scientist, defined as one whose Impactful Papers constitute more than 50% of their publications before year $t$. |
| *scienceRelevance_Cites* | Defined as the total number of patents granted to a firm in a given year that cite related scientific papers, weighted by the number of cited papers per patent. |
| *scienceRelevance_Gpt4o* | A textual-based measure of a patent reliance on science as described in section 2.3.3. |
| *SHC* | The general scientific human capital measure. It is constructed as follows: 1. Obtain the annual publication stock using the total number of scientific papers published by all employees (affiliated with firm $i$ in year $t$) until year $t$. 2. The *SHC* is obtained by taking the average of the annual publication stock within the window $[-3, -1]$ centered on the breakthrough year. |
| *SHC_Far* | *SHC_Far* is obtained by taking the average of the annual publication stock within the window $[-8, -6]$ centered on the breakthrough year. |
| *SHC_Relevant* | It is constructed as follows: 1. Obtain expertise similarity to a breakthrough at the employee level using the maximum similarity score between the abstracts of an employee's historical publication and the abstract of the breakthrough paper. 2. The annual publication relevance score is obtained by taking the average expertise similarity among the top three employees affiliated with firm $i$ in year $t$ based on expertise similarity. 3. *SHC_Relevant* is computed by taking the average of the annual publication relevance score within the window $[-3, -1]$ centered on the breakthrough year. |
| *Scientist-Inventor Ratio* | The average scientist-inventor ratio among all patents granted to a firm in a year. The scientist-inventors are identified by conducting the name match between inventor names and author names for the same firm in a year, as described in section 4.1.1. |
| *Size* | Total book assets (Compustat item *at*) of firm $i$ in year $t$. The logarithm of one plus the value is used in the analysis. |

# Appendix B: Additional Results

**Table B.1.** Alternative SHC Measures

This table reports the results from the regression that examines the firm operating performance after scientific breakthroughs in a stacked triple difference-in-difference framework. *HighSHC_Far* is a dummy variable that indicates whether a firm is endowed with high scientific human capital measured in a window $[-8, -6]$ relative to the event year, and zero otherwise. *HighSHC_Relevant* is a dummy variable that indicates whether a firm is endowed with high relevant scientific human capital measured in a window $[-3, -1]$ relative to the event year, and zero otherwise. The dependent variables include *Operating Profitability*, *Sales* and *Market Value*. In columns (1), (3) and (5), I control for firm fixed effects and year fixed effects, In columns (2), (4) and (6), I control for firm × event and year × event fixed effects. Controls include the interaction term between pre-event *Size* × *Exposure to SciBreak*. Standard errors are clustered at the industry level. t-statistics are presented in parentheses. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Variables are defined in Appendix A.

*Panel A: Scientific human capital based on early years*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Operating Profitability* | | *Sales* | | *Market Value* | |
| *Exposure to SciBreak* × | 0.0530** | 0.0526** | 0.316*** | 0.262*** | 0.321*** | 0.270*** |
| *HighSHC_Far* | (2.41) | (2.07) | (4.13) | (3.22) | (4.52) | (3.76) |
| | | | | | | |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm × Event FE | No | Yes | No | Yes | No | Yes |
| Year × Event FE | No | Yes | No | Yes | No | Yes |
| Firm FE | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | No | Yes | No | Yes | No |
| R-squared | 0.702 | 0.734 | 0.954 | 0.965 | 0.940 | 0.952 |
| Observations | 38,588 | 38,588 | 38,588 | 38,588 | 38,588 | 38,588 |

*Panel B: Scientific human capital based on expertise similarity to scientific breakthroughs*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Operating Profitability* | | *Sales* | | *Market Value* | |
| *Exposure to SciBreak* × | 0.0519*** | 0.0548*** | 0.173*** | 0.116* | 0.336*** | 0.284*** |
| *HighSHC_Relevant* | (3.51) | (3.31) | (2.82) | (1.90) | (4.35) | (3.72) |
| | | | | | | |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm × Event FE | No | Yes | No | Yes | No | Yes |
| Year × Event FE | No | Yes | No | Yes | No | Yes |
| Firm FE | Yes | No | Yes | No | Yes | No |
| Year FE | Yes | No | Yes | No | Yes | No |
| R-squared | 0.702 | 0.734 | 0.954 | 0.965 | 0.940 | 0.952 |
| Observations | 38,588 | 38,588 | 38,588 | 38,588 | 38,588 | 38,588 |