Bridging Research(R) and Development(D): The Strategic Role of Scientists on the Board*

Ronald W. Masulis, Elvira Sojli, Wing Wah Tham, Yufeng Yao

July 23, 2024

Abstract

Recent trends show US firms reducing their investments in scientific research while relying increasingly on scientific breakthroughs for patent development. This shift raises a critical question: How do firms access scientific ideas to fuel their innovations? Our study examines the role of top decision-makers in firms, specifically Scientific Directors (SciDs), defined as outside directors with scientific expertise, in bridging the gap between scientific research and patent development. These SciDs are increasingly prevalent, especially in firms whose patents depend heavily on basic scientific research. We find a positive relationship between the influence of SciDs' publications on a firm's innovation activity and the quality of its patents. Utilizing deep learning techniques, we categorize patents based on the SciDs' areas of expertise, revealing that firms produce high-quality patents in fields where SciDs are actively conducting research. We also provide evidence that SciDs contribute to developing a firm's innovation talent by tapping their professional networks to help connect top-tier inventors. To address endogeneity concerns, we explore the impacts of scientific breakthroughs due to the Human Genome Project. We observe an increase in both the numbers and economic benefits of SciDs at pharmaceutical firms, highlighting their pivotal role in transforming basic science into patented innovations.

Keywords: Scientific Directors, Corporate innovation, Deep Learning, Scientific non-patent literature citation, Inventors

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*All authors at University of New South Wales. Contact: ron.masulis@unsw.edu.au (Masulis), e.sojli@unsw.edu.au (Sojli), w.tham@unsw.edu.au (Tham), yufeng.yao1@unsw.edu.au (Yao). We are grateful to Wesley Deng, Jinzhao Du, Ron Giammarino, Zonghe Guo, Amy Kwan, Domenic McEwan (Discussant), Raphael Park, Gordon Phillips, Roham Rezaei, Janghoon Shon, Jenny Tak, participants at the AFBC 2023, and seminar attendees at the University of New South Wales, University of Massachusetts Amherst, Fordham University, Victoria University of Wellington, and University of Auckland for their valuable feedback and insights.

The shift in corporate innovation strategies since the 1980s has raised concerns about the efficiency of the new innovation ecosystems (Gordon, 2016; Arora et al., 2018; Akcigit et al., 2020). For example, many large firms have closed their corporate labs, reduced their investments in scientific research, and are increasingly relying on external sources of scientific knowledge. This shift has diminished these firms' capacity to identify promising scientific ideas for innovations.

Despite increased research funding in this century, the current American innovation ecosystem has produced relatively few technological innovations capable of driving growth comparable to the 'golden age,' when many innovations stemmed from basic scientific research, such as transistors, plastics, and synthetic fibers. Additionally, the inability to convert basic science into patented innovation results in serious social opportunity losses (Arora et al., 2020). For example, this gap may cause government-funded scientific breakthroughs to remain uncommercialized, thereby reducing the efficiency of government investments.

As firms cut investments in internal scientific research, a critical question emerges: how can they effectively bridge the growing gap between external scientific research and patent innovation? Several obstacles, including rising research costs and managerial short-termism, could enlarge the gap between scientific research and firms' patented innovation (Arora et al., 2018, 2020). We argue that scientists serving as board members could overcome these obstacles through their scientific expertise and influence over the firm's innovation strategy. In this study, we investigate the role of these key decision-makers, specifically outside directors with doctorate degrees or scientific publications, whom we refer to as Scientific Directors (SciD), in bridging this critical gap.

In recent years, the marginal costs of corporate research have typically increased, often rapidly, due to the rising level of existing scientific knowledge. Also, recruiting top scientists is expensive, as they require salary premiums and costly research laboratories. These factors can often seriously constrain firms' ability to conduct internal research. Satell (2016) suggests that firms can identify promising scientific ideas by tracking scientific breakthroughs in the public research arena. SciDs can be the link, serving as boardroom advisors on basic science, as they are able to identify key scientific breakthroughs for the firm and influence the direction of the firm's long-term innovation strategies. SciDs can also help firms minimize research costs by helping recruit talented scientists from their professional networks, as SciDs often work at leading research institutes with a rich supply of young scientists.

Empirically, we test these channels by investigating how SciD affects a firm's innovation outputs through their scientific expertise and professional networks. Although the previous literature often overlooks the advisory role of directors given that it is difficult to observe and is closely intertwined with their monitoring role, the importance of their advice to management is increasingly recognized, as highlighted in recent years by the frequency with which boards of directors exhibit more diversified skill sets that include scientific expertise. For instance, the percentage of firms with science and technology board committees has doubled in the past five years (SpencerStuart, 2023). To evaluate whether SciDs can shape a firm's innovation strategy as advisors on the board, we compile a novel dataset that includes the publication records by subject area of each SciD alongside detailed information on the firm's patent filings. We construct two dynamic measures of SciD's expertise that track not only the SciD's time-varying scientific expertise, but also the relevance of this expertise for the technologies described in a firm's patent filings.

Our first measure of SciD expertise captures the direct influence of a SicD's publications on a firm's patents, which is the portion of the firm's patents referencing a SciD's publications over the total number of firm patents since SciD joined the board. The scientific citations of a firm's patents reflect knowledge transfers from the SciD, which supports an invention that clearly builds on the director's scientific knowledge.

There may be concerns that the correlation observed above arises due to endogenous decisions surrounding director turnover events, see Fee et al. (2013). To address this concern, we exploit within firm-SciD pair variation using a director $\times$ firm fixed effect analysis. This specification is attractive because it allows us to assess how a corporate's innovations change over time with the dynamics of a SciD's influence, holding a firm-director match constant. As a result, we can overcome an important inference challenge that affects existing studies, which use director-fixed effects as proxies for time-invariant director attributes. Our results suggest that taking into account a firm's changing technologies and the SciD's changing expertise can provide new insights, for example, in how firms exhibit improved innovation performance when the scientific works of SciDs become more influential or relevant to the firm's currently used technology.

Relying only on direct citations to SciD's publications could be overly conservative. A SciD's expertise can also influence a firm's innovation in areas that, while not directly cited, are still highly relevant to the firm's patent technologies. To address the limitation of our first SciD's influence measure, we use a Large Language Model (LLM) to categorize patents into subject areas that may benefit the focal patent's development. The LLM that we use is the BERT model, a transformer model developed by Google AI in 2018. We fine-tuned the BERT model on over 340,000 abstracts of publications and patents labeled with their scientific subject areas. Next, we use this fine-tuned model to categorize patents into all relevant, non-mutually exclusive scientific subject areas, including Biochemistry, Chemistry, Computer Science, Engineering, Materials Science, Medicine, Pharmacology, and Physics.

Patents with LLM-assigned subject areas allow us to link the expertise of each SciD to the scientific basis of their patents. We measure the scientific expertise of a SciD by examining their recent publications over the prior three years. The recent publications provide a more current and relevant assessment of a SciD's expertise. Moreover, the outcome variables we measure include both the quality and quantity of patents associated with each of a SciD's areas of expertise. Our empirical evidence suggests that in areas where the SciD has recently published more papers or received more citations, the firm produces a higher quantity of patents, and these patents are of better quality.

We argue that our two measures of a SciD's technical expertise are superior to the measures used in the existing corporate governance literature. The existing literature relies on static measures such as corporate director experience (Masulis et al., 2012; Chen et al., 2020), professional career experience (Burak Güner et al., 2008; Huang et al., 2014; Dass et al., 2013), or educational qualifications (Field et al., 2013) to capture an individual director's expertise. However, these commonly used measures are very noisy and implicitly assume a director's expertise remains constant over time and that a homogeneous level of director expertise exists across the same expertise category. In contrast, our measures account for changes in a director's expertise over time and they recognize that different directors possess varying levels of relevant expertise.

Regarding the SciD network channel, we investigate whether a SciD can reduce a firm's asymmetric information problem concerning its hiring of an inventor of unknown ability by tapping into the SciD's professional network. We refer to this hiring as SciD-affiliated network hiring. Using a network comprising over 1 million people and 20 million connections among scientific authors and inventors, we construct the inner communities of each SciD. These inner communities consist of co-authors and co-inventors who connect more closely with SciDs than with others within the social network.

We investigate a SciD's role in enhancing the human capital of a firm through the firm's hiring of inventors who are in a SciD's inner community. On average, SciD-affiliated inventors hired by a firm are more productive with better innovation outcomes than are other inventors within the SciD's community, i.e., suggesting that a SciD recommends high-quality candidates in their social community to join their firms. Furthermore, the SciD-affiliated inventors continue to outperform the same cohort of non-affiliated inventors after joining the firm, suggesting that SciDs also help with affiliated inventor retention. Our findings are new to the literature and reflect how a SciD's network can provide valuable soft information about potential scientific hires as well as exploit their social connections to help recruit these inventors to the firm, utilize their expertise better, and retain them for longer once they join the firm.

One possible alternative explanation for the positive correlation between firm innovation outcomes and the presence of SciDs at the firm is an endogenous matching of firms and SciDs based on unobservable characteristics that are associated with successful innovation. It is plausible that firms achieving successful innovation actively establish connections with universities and professors, which in turn increases the likelihood of having SciDs on their boards. To address these concerns, we adopt a strategy that utilizes a scientific breakthrough as an exogenous source of variation in board structure to estimate the economic benefits that SciDs contribute to firms.

In our study, we focus on a major scientific breakthrough achieved in the late 20th and early 21st centuries as a result of the US and UK government-funded research project, the Human Genome Project (HGP). HGP is an international scientific research project aimed at identifying, mapping, and sequencing human genes, thus relaxing technology constraints and opening new possibilities in gene therapy. Despite the scientific advances, firms still face challenges in effectively translating basic scientific discoveries into commercialized therapies.

SciDs can serve as valuable advisors to firms, helping them to understand scientific discoveries, identify feasible commercial opportunities, and navigate the complexities of translating basic research into profitable commercial applications. We investigate the potential rise in economic benefits of qualified SciDs following the completion and publication of the HGP findings, which we use as an exogenous shock to the board structure.

We find that following the HGP shock, firms operating in industries able to commercialize genetics knowledge show a higher propensity to appoint SciDs to their boards. This includes both SciDs in general and SciDs with genetics expertise. Our empirical finding is consistent with the prediction of Garlappi et al. (2017) by showing that firms appoint more SciDs who share the same belief and can accurately evaluate the risk of the project when facing investment opportunities. Post-shock, these firms experience significant improvements in their long-term R&D activities relative to firms in the control group. The strength of our empirical design lies in the premise that the technological progress resulting from the HGP shock exogenously raises the demand for SciDs which is attributable to their increased value to pharmaceutical firms' applied research activities. By utilizing this exogenous shock, we can attribute the observed changes in board composition and subsequent R&D improvements to the specific influence of SciDs. Moreover, the results are robust to a matched sample based on firm size, ROA, annual stock return, and patent innovation activities measured just prior to the shock.

To further strengthen our identification strategy, we exploit the exogenous variation in the local supply of SciD candidates as an instrumental variable (IV) to predict a SciD's presence on a firm's board. The local supply of SciD candidates is measured by the number of SciDs at firms that are headquartered within 100 miles of the focal firm's headquarters, excluding potentially competing firms with the same industry (SIC4) code.

In the first stage analysis, we find a strong and statistically significant relationship between the supply of local SciD candidates and the presence of SciDs on a firm's board. We find that firms located in areas with a larger supply of nearby SciDs have a higher proportion of SciDs on their boards. This finding shows that our IV satisfies the relevance condition. To further support the validity of our IV, we argue that the headquarters location is selected early in a firm's life based on economic considerations separate from the local SciD supply, and thus, it can be treated as exogenously determined for our purposes. This exogeneity condition is particularly the case after controlling for the local supply of scientists, which includes the number of tenured assistant, associate, and full professors at nearby universities.

The location of a firm headquarters is also unlikely to affect innovation outputs directly. Therefore, the local supply of SciD candidates can be considered a valid instrument for the presence of SciDs on boards. The second stage analysis shows that firms predicted to have a larger share of SciDs on their board have better innovation results compared to similar firms within the same industry. By employing an IV approach, we estimate the Local Average Treatment Effect (LATE), which quantifies how the appointment of a new SciD to a firm's board results in a change in patent innovation. Compared to our previous analysis of HGP, the IV estimation provides us with more general as well as strong evidence of a causal effect of SciDs on firm innovation.

Managerial short-termism could also be a possible alternative reason for firms to cut internal research investments (Arora et al., 2018; Marginson and McAulay, 2008). Scientific research often requires long gestation periods and lacks frequent, easily interpreted milestones, making it challenging for non-expert investors to evaluate research progress. This uncertainty over scientific research investment could pressure managers with generalist boards to pursue short-term profits. However, SciDs are well-positioned to serve as effective evaluators of ongoing scientific research and also to potentially mitigate investor concerns. In this study, we explore the relationship between stock performance and the presence of SciDs in the boardroom, examining how their expertise might influence investor's investment decisions and firm valuation.

We investigate the shareholder assessments of SciDs embedded in firm stock price changes. We specifically focus on market reactions to announcements of SciD appointments and departures. This is a useful metric since market reactions to appointment events are forward-looking assessments and should generally reflect the expected marginal value of the services that appointed SciDs provide to the firm. If SciD can serve as a reliable evaluator of basic science, investors should positively react to their appointments. Our results show an average positive market reaction to SciD appointments. After controlling for various firm and director characteristics, we find a statistically significant 0.5% higher three-day cumulative abnormal returns (CAR[0, +2]) for SciD appointments compared to non-SciD appointments within the same sample of firms.

We also examine exogenous director departures due to deaths. These events are particularly informative because the market reactions to these generally unexpected departures from the board should reflect investor assessments of the expected decline in firm value resulting primarily from the firm's loss of these SciDs' services. To capture the differential economic benefits of SciDs, we compare the average stock price reactions to death announcements of SciDs to those of non-SciDs. If SciDs are particularly valuable, then we should observe more negative announcement effects on their deaths. We find an average -2.05% CAR[0, +2] for announcements of SciD deaths compared to an average 0.16% CAR[0, +2] for non-SciD deaths, where this difference in market reactions is statistically significant. The positive market reaction to SciD appointments combined with the negative market reaction to SciD deaths indicates that the market recognizes the value of SciDs.

As additional evidence of SciD benefits, we examine the relation between SciDs and long-term firm valuation. For this purpose, we employ the average Tobin's Q over the subsequent five years to measure long-term firm valuation, given the long-term nature of basic science research. Our analysis finds that firms having SciDs are associated with higher firm valuation compared to firms without SciDs that are within the same industry. Our analysis documents that within an industry, there is a positive relationship between SciDs and Tobin's Q, underscoring the significant long-term benefits of having SciDs on board for a firm's market valuation.

Lastly, the reasons behind SciD appointments could also help us to understand the value of

SciD. We propose that the likelihood of having SciDs on the board depends on how much the firm's technology relies on fundamental science. To gauge the reliance on fundamental science, we calculate the ratio of patents that heavily rely on fundamental science to the total number of firm patents over the prior three years. Patents that rely heavily on fundamental science are classified as those patents that reference more scientific publications than the 75th percentile value of the scientific citation distribution within their technology class and grant year. Our findings show that firms relying more on fundamental science are not only more inclined to appoint SciDs, but also to appoint SciDs whose expertise overlaps with scientific knowledge referenced by the firm's recent patents. Additionally, we observe a positive correlation between the presence of relevant SciDs and a firm's reliance on fundamental science.

Despite our best attempt to establish the value-enhancing impact of SciDs, we cannot fully rule out the possibility that some of our results could be partially driven by endogenous firm-director matching, such as boards choosing certain directors because of their particular attributes. Nevertheless, both the influence of SciD with particular scientific expertise on a firm's innovation outcomes and SciD-network hiring suggest that SciDs possess valuable skill sets and professional networks that are important for a firm's strategic innovation and inventor hiring decisions, which represent several important novel contributions of our paper.

Two groups of directors who overlap with SciDs and who are naturally connected to firm innovation activities are inventor-directors and academic-directors. Compared to inventor-directors, SciDs are more commonly found on boards, and they have three times the representation of inventor-directors, while half of the inventor-directors have scientific publications (making them SciDs as well). Also, inventor-directors typically focus on a firm's patent innovation that may not be useful in identifying promising scientific ideas for a firm's long-term innovation strategy. In addition, focusing only on academic-directors neglects the fact that industry practitioners working for non-universities, including government, corporations, and research institutions, also engage in basic scientific research and often publish academic papers. In fact, only 30% of SciDs are drawn from academia, with the remainder being primarily industry practitioners, some of whom also have remarkable publication records. For example, John Palmour, a non-university affiliated SciD, has an impressive record of 266 scientific publications. Such industry practitioners are also particularly valuable to study because they bring more practical experience to the commercialization of scientific research.

Our paper makes several contributions to the existing literature. Firstly, our paper is related to the literature on scientific research and innovation. The previous literature has established the link between scientific research and successful innovation, highlighting the role of scientific knowledge in driving innovation activities and enhancing innovation efficiency (Nelson, 1959; Kline and Rosenberg, 2009; David et al., 1994; Fleming and Sorenson, 2004; Griliches, 1986; Arora et al., 2021). However, a noticeable trend has emerged since the 1980s, with firms reducing investments in research, closing research labs, and publishing fewer scientific papers. This raises a critical question: if firms are cutting back on internal research activities, where are they finding their innovative ideas? Our study contributes to this literature by introducing a new channel through which basic scientific research is connected to firm innovation. Specifically, by having SciDs with cutting-edge scientific knowledge on the board, firms can benefit from these SciDs' expertise and understanding of the latest scientific advances and insights into how to effectively utilize scientific research to fuel the firm's long-term innovations. In addition, SciDs provide help in selecting and hiring particularly talented inventors from their professional networks, and then assist the firm in retaining these valuable employees. Besides, we highlight the increased economic benefits of having SciDs following scientific breakthroughs, such as the Human Genome Project.

Second, our novel method of mapping patents based on their underlying scientific knowledge offers new insights into how scientific research influences patented innovations. A primary challenge in understanding the impact of scientific research on innovations is establishing a connection between scientific research and patents. Initially, research in this area was not scalable due to the complexity of scientific knowledge and focused solely on knowledge from a single scientific field or the innovations of firms within a single industry (e.g., Henderson and Cockburn, 1994; Zucker and Darby, 1996; Zucker et al., 1998). More recent studies utilize scientific non-patent literature citations in patents to link scientific knowledge to specific technologies (e.g., Ahmadpoor and Jones, 2017; Arora et al., 2021; Marx and Fuegi, 2020). Scientific non-patent literature citations underestimate the broader impact of scientific research, as patents only need to cite the scientific knowledge that directly influences the underlying inventions. The basic science could serve as a more fundamental stepping stone for subsequent innovations across disparate technological domains. For instance, while Artificial Intelligence (AI) originated as a scientific breakthrough in computer science, the technology of AI now influences nearly all industries. Our novel research method leverages the deep learning model's contextual understanding capabilities to first comprehend the various categories of scientific knowledge embedded in scientific publications and then link them to the specific types of scientific knowledge upon which these patents are based.

Third, we document new evidence on the advisory role of outside directors by specifically examining the impact of SciDs on corporate innovation activities, thus helping to disentangle directors' monitoring and advisory functions. Unlike previous studies that often measure director expertise by an indicator variable, our novel dataset enables us to investigate the heterogeneity of director expertise. Importantly, we demonstrate that this heterogeneity in SciD expertise matters for corporate innovation. For instance, a SciD's contributions to corporate innovation activities vary, depending on their recent publication activities and their relevance to a firm's current stream of patents. While some recent studies have examined the role of academic directors (Francis et al., 2015; Pang et al., 2020; Xie et al., 2021), SciDs include not only academic-directors (making up 30% of SciDs), but also industry practitioners. The inclusion of these industry practitioners in our study is particularly salient because they bring not only scientific knowledge but also practical experience needed to commercialize scientific research.

Last, Our paper contributes to the existing literature on boards of directors by introducing the Human Genome Project as a novel exogenous shock to board structure. In contrast to prior research, which focuses on the change in board structure due to exogenous director turnover events (Nguyen and Nielsen, 2010; Masulis et al., 2022), regulatory changes such as the introduction of the Sarbanes-Oxley Act, the granting of Permanent Normal Trade Relations to China (Linck et al., 2008; Guo and Masulis, 2015; Balsmeier et al., 2017; Chen et al., 2020), or variations in the local supply of director candidates near a firm headquarters (Knyazeva et al., 2013), our work shows that scientific breakthroughs with potentially important commercialization opportunities also enhance the economic benefits that firms realize from appointing directors with related scientific expertise. In addition, scientific breakthroughs, as well as the resulting emergence of new products, serve as particularly useful exogenous shocks for examining corporate demand for the advisory services of outside directors. Given the inherent complexity of such technology shocks, firms are more likely to prioritize the need for a scientific director's advisory services over her management monitoring ability. Also, we document the strategic practice of appointing new directors with specific expertise as part of a firm's group of strategies used to address potential technological changes.

1 Data and Method

Our core dataset consists of information on firms' innovation, board membership, directors' scientific profiles and patent portfolios. For each firm-year in the sample, we collect the financial characteristics, innovation output and board of directors' identities. We collect directors' names, classifications (inside or outside), employment, educational credentials, scientific publications, and patents to examine the relation between a firm's innovation and directors' scientific knowledge. Our combined data are from six sources: (i) BoardEx provides board composition and director profiles; (ii) The CRSP and Compustat Merged data (CCM) provide firm stock and accounting information; (iii) Scopus provides author profiles and scientific publications; (iv) United States Patent and Trademark Office (USPTO) PatentView provides patents and patent citations; (v) Marx and Fuegi (2020) provides patents' Non-Patent Literature (NLP) citations; (vi) Kogan et al. (2017) provides data on patent market values. All variable definitions are provided in Table A1.

Our sample starts with the entire set of firms covered in both BoardEx and CCM from 1996 to 2018, which includes 92,876 firm-year observations and 8,104 firms. We exclude 24,187 firm-year observations from financial firms (SIC 6000-6999) and regulated utilities (SIC4900-4999) and 165 firm-year observations with missing or 0 total assets. Our final sample consists of 68,524 firm-year observations, 6,098 firms and 39,283 unique outside directors. Note that outside directors can be on multiple boards. Table A2 provides the sample characteristics.

1.1 Innovation data

We use three patent datasets taken from: PatentView, Kogan et al. (2017), and Marx and Fuegi (2020). The PatentView data provides the micro-records for all patents granted by the USPTO from 1976 to 2020.[1] We collect information on the patent number, application year, grant year, citations, technology class, assignees, and inventors for each patent from the 2021 April version of the PatentView dataset. We map patents to publicly listed firms and obtain patent market values from the Kogan et al. (2017) data. Patents cite not only other patents, but also scientific publications, government reports, technology reports and other product reports, which are all defined as non-patent literature (NPL). A special subset of the NPL is the Scientific Non-Patent Literature (SNPL), which are scientific publications that are cited by patents. SNPL is very informative about the scientific foundation that a patent is based on. Marx and Fuegi (2020) map the patents' NPL citations to scientific publications and provides information related to the SNPL, such as the author names, DOI and the scientific journal name. This data allows us to map each patent's SNPL to the associated scientific publications, that serve as the scientific foundation of the patent.

1.2 Scientific knowledge data

We collect the outside directors' scientific profiles from the Scopus database (Rose and Kitchin, 2019). We use Scopus as our primary source of scientific information for two key reasons. Firstly, the Scopus database has comprehensive coverage of publications (Singh et al., 2021), encompassing high-quality articles from peer-reviewed academic journals. The comprehensive coverage and high-quality articles allow us to identify successful scientists and identifying their range of expertise, and their network of coauthors. Secondly, Scopus provides an author-level data structure, enabling us to construct an individual scientific profile for each director.

The scientific knowledge data consists of the authors' personal information, scientific impact, active subject areas, and publication details such as title, DOI and publication year. To construct our sample, we match all the firm's outside directors to their author profiles in Scopus. The matching process involves a two-step procedure. First, we match the outside directors with authors based on their full names. Then, we compare the employment history of outside directors to the affiliation history of all possible matched authors identified in the first step. The two-step procedure defines the correct link between authors and outside directors, considering both name similarities and overlapping employment histories.

We query the authors' profiles for each outside director using their surname, middle name, and first name. The Scopus query formats are the following:

- Directors without the middle name: "AUTHLAST (surname) and AUTHFIRST (first name)"
- Directors with the middle name: "AUTHLAST (surname) and AUTHFIRST (first name and

[1]As is the convention in this literature, we focus on Utility patents.

middle name initial)"

The second query format utilizes the middle name initial instead of the full middle name to maximize potential matches. Scopus employs a "contain" algorithm in the query process, meaning that Scopus returns all possible search results that contain the input of the query. For instance, a SciD named "Stephen William" in BoardEx might be listed as "Stephen W" in Scopus. Notably, Scopus does not return "Stephen W" as a possible match for the query "Stephen William" because "Stephen W" does not contain "Stephen William". We collect all possible matched author profiles for each director from Scopus. However, depending only on names to link authors with directors can be inaccurate because many directors can have the same names as multiple Scopus authors, even if they're not familially related. As an illustrative example, a director named "Ning Li" matched with over a thousand author profiles in Scopus.

As a result, we implement a second layer of identification to ensure accurate matching. We exploit affiliation and employment information in Scopus and BoardEx to establish accurate links between directors and authors. More specifically, a valid link is established when the employment history of directors in BoardEx overlaps with the affiliation history of authors in Scopus. For example, director Michael Stuart Brown has worked for UT Southwestern since 1976. Author Michael Stuart Brown is affiliated with UT Southwestern as an author. In this case, the director and author, Michael Stuart Brown, are presumed to be the same person due to the overlap between their publication affiliation history and employment history.

Next, we verify the directors who link to more than one author's profile. More specifically, if Scopus has only one profile for each author, the matching relationship between the director and author should be one-to-one. However, some directors link to multiple author profiles for two reasons. First, Scopus may create multiple profiles for a single author, and these authors usually have a primary profile and minor profiles in Scopus. The primary profile of the author has a relatively complete publication and affiliation history compared to the minor profile. We aggregate directors' primary and minor profiles to complete the scientific profile. Second, there are director mismatches with some authors' minor profiles due to incomplete affiliation information in the author's minor profiles or data errors in Scopus. We manually remove the mismatched profiles according to publication information when SciDs are linked to more than one author profile. First, suppose the SciD's CV is available. In that case, we compare publications in Scopus profiles to the author's CV and retain the author's profile with the same publications listed in the author's CV. Second, for SciDs who do not have CVs, we compare the subject areas in their minor profile to the SciD's subject areas in their primary profile or information online.

We collect all the Scopus publication IDs under the linked author profile and query publication information via Scopus. Publication information includes title, year, citations until 2021, co-authors, journal name and DOI. Our final publication dataset consists of 274,790 publications by 3,586 SciDs. Journal articles constitute the largest proportion of all publications, representing 74.19% of them, followed by conference papers and reviews, which account for 9.02% and 6.64%, respectively. The top three scientific areas having scientific publications in our sample are biochemistry (9.65%), molecular biology (8.58%), and oncology (7.02%).

1.3 Network analysis and professional community construction

We construct a SciD's professional network to investigate the relation between firm value and the SciD's network. Our measure of the SciD professional network combines the SciDs, co-inventors and co-authors of the SciD, and other inventors at the same firm, which includes around one million nodes (people) in the network. Nodes (people) connect through invention and publication activities, and the strengths of connections are determined by the number of patents, publications or both between nodes. The network is measured as of December 2021.

To construct the inventor-scientist network, we map the patent profiles of SciDs and their co-authors. More specifically, for those authors who are also inventors, we combine their publication and patent profiles together. For example, individual A has publication and patent profiles due to his/her patenting and publication activity. Suppose we do not aggregate the patent and publication profiles. In that case, our network will treat author A and inventor A as two different individuals and create two network nodes for the same individual, resulting in double-counting.

We use a two-step procedure to identify the patent profiles associated with each scientific author who is also an inventor. In the first step, we identify all inventors with names similar to the Scopus authors in our sample. In the person name-matching process, we map the last name between an inventor and an author, allowing for just one permissible spelling error. Subsequently, within each matched last name between inventors and authors, we refine the match according to their first and middle names. For this purpose, we employ a fuzzy matching algorithm designed to recognize variations in first and middle names. We consider variants of the focal names as similar names, and the specific variant formats include the following:

- "First name" + "middle name" matches to "First name" + "middle name initial" e.g., "Frank Graham" matches to "Frank G"
- "First name" + "two middle names" matches to "First name" + "middle name and middle name initial" e.g., "Frank Graham Smith" matches to "Frank Graham S" and "Frank GS"
- "First name" matches to known"Nicknames" associated with this given name, e.g., "Robert" matches to "Rob"

Our next step is to compare the patent assignee history to the publication affiliation history for each pair of similar inventor and author names. The patent assignee refers to the organization or individual holding the ownership rights to the patent and is normally the inventor's employer. We establish the links between authors and inventors when inventors have similar names and overlapping employment histories with the authors. For example, if inventor A shares a similar name with author A, and inventor A has a patent with company ABC, while author A published a paper affiliated with company ABC, We establish a match between inventor A and author A due to their similar names and shared employment history.

Our network has two special characteristics: first, the network is large, containing over 1 million nodes; second, the network has numerous inner communities, suggesting a group of nodes are closely connected within the group, but these nodes are isolated from other nodes within the network. For example, authors within a specific field frequently collaborate with others in the same research field, thus forming inner communities based on their common research interests. The study of inner community structure is important as the inner community allows us to identify the groups of individuals collaborating closely with each other and who know each other very well as inner community members. We use the inner communities to identify the group of authors who work closely with a SciD and assume that the SciD knows these authors well. For example, the researchers in a SciD's inner communities could include their co-authors, co-inventors, mentors or PhD students. We use the Louvain community detection algorithm of Blondel et al. (2008) to extract the inner community structure of the network. The Louvain algorithm allows us to detect the inner community of individuals based on their innovation and publication activities. For example, Inventor C works with two scientists, A and B. Inventor C has 20 papers with Scientist A, but one paper with Scientist B. Inventor C has a closer relationship with Scientist A than with Scientist B. The Louvain algorithm will cluster Inventor C and Scientist A in the same community. A detailed explanation of the Louvain algorithm is in Appendix A. We chose the Louvain algorithm given its speed in detecting communities in large networks, making it the most suitable choice for our large network.

1.4 Variables construction

We use the following firm characteristics for our sample of S&P 1500 firms: size, capital expenditures (CAPEX), Research and Development (R&D) expenses, firm age, annual stock returns, and Tobin's q. Size is the logarithm of the firm's total assets. Firm age is the natural logarithm of a firm's age measured as the difference between the current year and the first year the firm appears in CCM. CAPEX and R&D are scaled by total assets. All variable definitions are provided in Table A1.

1.4.1 SciD and SciD's influence

SciDs are outside directors who publish at least one scientific paper or have an advanced degree, such as a PhD, Doctor of Medicine, or Doctor of Science. For outside directors where no employment or education is reported in BoardEx, we check if these directors have doctor or professor titles such as "Doctor", "Professor," and "Professor Doctor" in their full names. Our sample has 6,236 SciDs, where 38% of these SciDs have Doctorate degrees and zero publications.

We present the SciD characteristics in Panel A of Table 2. On average, SciDs have authored 46 scientific publications, received an average of 3,337 citations, and had an average H-index of

12 over their careers as of year 2021. The H-index, measuring scientific influence, is defined as the maximum value of h such that the author has published at least h papers, each cited at least h times. The SciD with the most publications is Homer Neal, a particle physicist and notable figure in U.S. scientific policy as a member of the National Science Board of the National Science Foundation. Eric Lander is the SciD with the most citations, and he was a leader of the human genome project and a former Science Advisor to the President. American geneticist Michael S Brown is the SciD with the highest H-index who won the Nobel Prize in Physiology/Medicine in 1985.

Examining our SciD pool further, we find that it includes some of the top scientists in the world, such as 22 Nobel laureates in physiology or medicine, physics, economic sciences, and chemistry. The field with the most Nobel laureates in our sample is physiology/medicine. Also, 142 SciDs won at least one prestigious research award in science or technology. For example, SciD Robert Langer won the Wolf Prize. Robert Kahn and Vint Cerf won the Turing Award. 85 SciDs are also US National Academy members. Of our SciD sample, 27% are full professors (excluding non-academic professors like professors of practice) at a university. 5% of the SciDs hold or have held an academic position (assistant professor to full professor) at Ivy League Universities.

We classify the primary subject area of SciDs based on the 2-digit Scopus subject area where SciDs publish the most papers (based on rank ordering). Figure 1 illustrates the primary subject areas of 3,502 SciDs with available publication and subject area information. At the macro level, subject area classifications encompass life and health science, physical science, and general social science. The majority of SciDs specialize in life and health science, comprising 52% of this sample. Following this, physical science and social science account for 30% and 18% of the sample, respectively. Within the life and health science areas, the top three micro subject areas are medicine, biochemistry, and pharmacology, accounting for 32%, 15%, and 2% of SciDs, respectively. In the Physical science area, engineering, computer science and physics are the top three micro subject areas, comprising 15%, 5% and 2% of the SciD sample, respectively. For the general social science category, the leading micro subject areas of the SciD sample are business (10%), social science (4%), and economics (2%), respectively. We use the terms $SciD_{\mathrm{i,t}}$ and $SciD\ share_{\mathrm{i,t}}$ to refer to SciDs at firm i for a given year t. $SciD_{\mathrm{i,t}}$ is an indicator variable equal to 1 if firm $\mathtt{i}$ has at least one SciD on the board at year $\mathtt{t}$, and 0 otherwise. $SciD\ share_{\mathrm{i,t}}$ is the ratio of the number of SciDs to the total number of directors in firm $\mathtt{i}$ in year $\mathtt{t}$.

Furthermore, we gauge a SciD's influence on a firm's patents by assessing the Scientific Non-Patent Literature (SNPL) citations of these patents. The SNPL citations listed in a patent represent the prior knowledge in academic journals on which the patent is built. For each patent, we gather its SNPL citations from patent documents and link SNPL citations to SciDs' publications using the DOI of each publication. We identify firm patents that reference SciD's publications while the SciD is on a firm's board, labeling these patents as SciD-influenced patents (SciDIP). SciDIP presents a group of firm patents that can be directly influenced by the scientific work of the SciD. We then employ SciDIP to quantify the SciD's innovation influence at the firm, SciD, and year levels, which is the cumulative number of SciDIPs divided by the cumulative number of patents awarded to the firm. The cumulative number of SciDIPs allows us the measure how a SciD's influence on the firm's patents varies as of the year that the SciD joined the board. The SciD influence is calculated by the following formula:

$$\mathrm{SciD\ influence}_{\mathrm{i,d,t}} = \frac{\mathrm{Cum\ \#SciDIP}_{\mathrm{i,d,[t-n,t]}}}{\mathrm{Cum\ \#Patents}_{\mathrm{i,[t-n,t]}}} \tag{1}$$

We use the cumulative number of SciDIP and patents up to the focal year as a SciD's influence measure. This influence measure remains constant in all the years when the firm is not filing new patents, and the measure builds on a director's prior knowledge and expertise. The influence measure suggests that SciD's scientific works influence more of a firm's innovation activity when the firm has proportionally more patents that cite SciD's publications. For example, SciD Michael Brown joined Regeneron Pharmaceuticals in 1991. Regeneron Pharmaceuticals' patents gradually cite more of Michael Brown's scientific publications. Michael Brown's influence rises as the share of Regeneron Pharmaceuticals' patents that cite Michael Brown's scientific works scaled by the firm's total number of patents grows.

1.5 Deep learning method using SciBERT

Apart from the influence of SciDs, their level of expertise also plays a critical role in a firm's innovation activity. We measure the expertise of SciDs by considering the number of recent publications they have authored and the number of citations that their publications have received. It's important to note that even among SciDs specializing in the same subject areas, their levels of expertise can vary significantly. The number of publications and the number of citations received by a SciD's work serve as a measure of the director's knowledge and expertise. SciDs who publish more papers or whose papers receive more citations are generally considered to possess a higher degree of expertise. It is also important to acknowledge that successful researchers may have expertise across a range of subject areas, and it is unrealistic to assume that a SciD is equally specialized in all the areas they have published in. Therefore, our approach focuses on measuring expertise at the subject area level. Furthermore, the expertise of a SciD in a specific scientific subject area should only affect those firms' patents that can utilize knowledge from this area. To accurately map the firm's patents to the SciD's subject areas, we use the Large Language Model (LLM) of deep learning.

1.5.1 LLM: BERT

Mapping patents to scientific subject areas requires a deep understanding of knowledge in various scientific areas. LLMs are trained using a large amount of text from diversified sources. Google AI has an LLM, which is called the Bidirectional Encoder Representations from Transformers(BERT) model. The BERT model is a pre-trained model on Toronto BookCorpus and Wikipedia for two tasks, which are Masked Language Modeling (MLM) and Next Sentence Prediction (NSP). In the MLM task, the model randomly masks a percentage of words in a sentence and then predicts the masked words using the unmasked words in the sentence. The MLM task helps the model to understand the bidirectional context of a sentence, which is key to grasping the meaning of words in contexts. For the NSP tasks, the model selects a a pair of sentences and needs to predict whether the second sentence is a subsequent sentence of the first sentence. NSP trains the model to understand the relationship between sentences, which is key to understanding the paragraph.

1.5.2 Training the model and performance

Our labeled dataset includes 340,000 abstracts of SciD's publications and patents. We first define the target subject areas for patents. We selected 8 primary subject areas of the labeled sample: Biochemistry, Chemistry, Computer Science, Engineering, Materials Science, Medicine, Pharmacology, and Physics. These 8 subject areas comprise 90% of the abstracts in the labeled sample. Following the best deep learning conventions, we split our labeled dataset into 80% for training, 10% for validation, and 10% for testing. The validation dataset is used during training to monitor the training process, while the test dataset, which is never used during training, serves to evaluate the model's performance. After we trained the model using the training dataset, we evaluated our model using the test dataset. To evaluate our model, we use three conventional scores in the machine learning literature, which are precision, recall and f1 score. Our model achieves weighted average values of precision, recall, and F1-scores of 0.79, 0.75, and 0.77, respectively. Detailed performance metrics for each subject are provided in Table A4. Understanding scientific knowledge across multiple subject areas is inherently complex and challenging, posing significant difficulties even for expert human analysts due to the vast and diverse nature of scientific information. For more complex tasks, lower performance of the model is expected. For example, Guzman and Li (2023) uses machine learning to predict the early-stage success of startups and achieves a similar performance to our model. We further validated our model by investigating the extent to which mutually cited patents originate from the same scientific subject areas. Our findings show that 82% of the mutually cited belong to the same scientific subject areas.

To measure the expertise of SciDs, we analyze their publications at the subject areas level and align their expertise with patent' scientific subject areas assigned by our deep learning model. It is also important to recognize that SciDs' expertise can change over time, especially if they start publishing in new areas or stop publishing in some of their older research areas. To account for this, we concentrate on SciDs' publications over the past three years, which provides a more current and relevant assessment of their expertise. We construct our expertise at the firm $\mathtt{i}$ and the subject area $\mathtt{s}$ level with a three-year rolling window, which is the average number of publications or publication citations per SciD $\mathtt{d}$ of firm $\mathtt{i}$ in the subject area $\mathtt{s}$. We employ a log transformation due to the skewed distribution of the variable. The formulas for the expertise variables are as follows:

$$\text{Expertise(pub)}_{\mathrm{i,s,t}} = \text{Log}(1+\text{Avg}(\text{No.pub}_{\mathrm{i,d,s,[t-3,t]}})) \tag{2}$$

$$\text{Expertise(cites)}_{\mathrm{i,s,t}} = \text{Log}(1+\text{Avg}(\text{No.Cites}_{\mathrm{i,d,s,[t-3,t]}})) \tag{3}$$

1.6 Innovation variables

We assess firm innovation output using the total number of patents, average adjusted citations, average market value of patents, total number of breakthrough patents and total number of fundamental patents. The market value of patents is derived from the cumulative abnormal return around the publication date of the patent grant, see Kogan et al. (2017) for more details. Breakthrough patents are defined as patents in the top 10% of patent citations within the same technology class (IPC4) and year (see, Balsmeier et al., 2017). In addition to these conventional innovation measurements, we introduce a novel measurement called fundamental patents. Fundamental patents are patents based on fundamental scientific research, which in turn serve as the fundamental knowledge base for subsequent patents. There are two conditions for patents to be classified as fundamental patents. First, the patent must cite at least one scientific publication. Scientific research commonly refers to the underpinning scientific idea or process that is the basis for the innovation (Arora et al., 2021). The first condition ensures that patents are closely tied to fundamental knowledge, enhancing their significance in technology development. Secondly, the patent should receive more citations than the 75th percentile value within the patent distribution for the same technology class and year. A high volume of patent citations signifies the fundamental nature of patents within a specific technology domain.

Furthermore, we assess the value of fundamental patents by comparing the market value, generality and originality to other patents within the same firm, technology class and grant year. We find that fundamental patents exhibit a larger market value, serve as the generalized knowledge base for subsequent patents, and embody original ideas derived from a diversified range of specialized knowledge. Specifically, Table A5 shows that fundamental patents exhibit a 3% higher market value compared to their counterparts within the same firm, technology class and grant year. The generality index of a patent captures the range of technology classes of subsequent patents that cite a focal patent. A patent with a high generality index is a patent cited by patents from a wide range of technology classes (Hall and Trajtenberg, 2004). We find fundamental patents demonstrate a 13.3% greater generality compared to other patents in the same firm, technology class and grant year, suggesting that fundamental patents play a pivotal role as the knowledge foundation of other patents from a diverse range of technology classes. Moreover, the originality of a patent represents the diversity of technology classes on which a patent relies. Innovations that rely on technologies from a wider range of technology classes are likely to be original (Trajtenberg et al., 1997). We find that the originality of fundamental patents is 1.5% higher than that of other patents within the same firm, technology class and year, suggesting that fundamental patents draw upon a broader range of technology classes and are a wellspring of innovative ideas that transcend traditional boundaries.

We define $Patents_{t+1,t+n}$ as firm i's total number of patents filed (and eventually granted) from year $t+1$ up to year $t+n$ to create a forward looking innovation metric. For example, $Patents_{t+1,t+5}$ in 1990 is equal to No. patents_{1991} + No. patents_{1992} + No. patents_{1993} + No. patents_{1994} + No. patents_{1995}. *Avg. Adj.* $Cites_{t+1,t+n}$ is firm i's average adjusted citations per patent received for the firm's patents filed (and eventually granted) from year $t+1$ up to year $t+n$. The adjusted citations are citations scaled by technology class and grant year fixed effects to address the truncation issue associated with patent data, following Hall et al. (2001). All patent citations are counted as of December 2021. *Avg.* $Value_{t+1,t+n}$ is the natural logarithm of firm i's average market value (Kogan et al., 2017) of patents filed (and eventually granted) from year $t+1$ up to year $t+n$. *Breakthrough* $patents_{t+1,t+n}$ are firm i's patents ranked in the 90th percentile of filed patent citations (and eventually granted) from year $t+1$ up to year $t+n$. *Fundamental* $patents_{t+1,t+n}$ are firm i's total number of fundamental patents filed (and eventually granted) from year $t+1$ up to year $t+n$. All the patents map to the firm's yearly innovation output based on the patent's application year, not the year when the patent is granted, although all of these patent applications are granted.

Firm technologies exhibit varying degrees of reliance on scientific knowledge, a reliance that can be attributed to factors such as their products, industry, and stage of development. For example, the younger firms' patents tend to rely more on scientific knowledge (Howell et al., 2020). To assess the degree of reliance on fundamental science in firms' patent portfolios, we first classify patents that exhibit a strong reliance on science as those patents referencing more scientific publications than the 75th percentile of the patent distribution for the same technology class and grant year. Notably, some patents demonstrate minimal reliance on fundamental science in certain technology classes and years, resulting in the 75th percentile value of the patents taking on a value of zero. In such cases, we categorize all patents within technology classes where the 75th percentile values are zero as patents that do not rely on fundamental science.

To aggregate the level of reliance on fundamental science to the firm level, we calculate the proportion of patents that heavily rely on fundamental science over the total number of patents within the firm's portfolio over the past three years using the following formula:

$$\text{Reliance on Fundamental Science}_{i,t} = \frac{\text{No. patents heavily rely on fundamental science}_{i,[t-3,t]}}{\text{No. patents}_{i,[t-3,t]}} \tag{4}$$

For firms holding patents, approximately 73% have at least one patent that relies heavily on fundamental science. On average, patents that rely heavily on fundamental science make up about 26% of the firm's patent portfolio. When examining a patent's reliance on fundamental science across different Fama-French 12 classifications in figure 2, we find energy is at the top, with 36% of its patents relying heavily on science, followed closely by healthcare at 34% and business equipment at 33%. The chemicals industry also has over 30% of patents relying heavily on fundamental science. Turning to the frequency of SciDs by industry, we see that the healthcare, business equipment, and chemicals industries are the top three, with the highest percentage of SciD among their outside directors. Furthermore, the pie charts in figure 2 present the dominant subject areas of the publications cited by the patents in the energy, healthcare, and business equipment industries. We assess the subject areas using 4-digit Scopus subject areas. We prefer the 4-digit Scopus subject areas over 2-digit because the 4-digit level is a more refined classification level, offering more descriptive detail. Furthermore, patents within the same industry tend to focus on publications from only a few 2-digit Scopus subject areas. For example, the majority of patents in the business equipment industry rely on publications in computer sciences and engineering under the 2-digit Scopus subject areas. In the energy sector, key subject areas include chemistry, energy engineering, power technology, materials chemistry, geochemistry, and petrology. In the healthcare industry, the top three subject areas are biochemistry, molecular biology, and cell biology. Meanwhile, patents in the business equipment industry often cite scientific publications in electrical and electronic engineering, software and computer networks, and communications.

1.7 Descriptive statistics

Table A2 presents the characteristics of our sample firms. On average, our sample firms exhibit a 21% leverage ratio, log(sales) of 5.56, return on assets of 4%, annual stock market return of 13%, a 2.21 Tobin's q, a 2% free cash flow relative to total assets, R&D expenditures of 10% of total assets, CAPEX of 5% of total assets, and PPE of 25% of total assets. Table A3 presents the number of outside directors, SciDs and the board's share of SciDs from 1996 to 2018. In our sample, there are 39,283 unique outside directors and 6,236 SciDs. The typical firm in our sample has, on average, a board with 18% SciDs.

Table 1 presents a comparison between firms with and without SciDs on their boards based on firm fundamentals, valuation, and growth characteristics. The sample is divided based on whether firms have at least one SciD during the sample period. Throughout the sample period, there are 20,460 firm-year observations without SciDs and 48,064 firm-year observations with at least one SciD. The average number of SciDs per firm-year observation is 1.37. Firms with SciDs, on average, are larger (in total assets), have higher Tobin's q, and have greater growth in total assets and sales. These firms also have lower leverage, hold more cash, spend more on R&D and have more significant valuations, highlighting their economic importance.

In Panel B of Table 2, we describe the differences between SciDs and non-SciDs regarding their education, experience, age, and tenure. SciDs are more likely to be inventors, but less likely to hold professional degrees such as JD and MBA or have experience in finance and executive roles than is observed for non-SciDs, suggesting that SciDs have different skill sets and provide different types of expertise than non-SciDs. Specifically, most SciDs specialize in basic sciences such as medicine, biochemistry and engineering. These basic science areas are innovation-related areas with more granted patents. Conversely, non-SciDs typically have generalized management skills for corporate operations such as finance, management and law. Additionally, SciDs are also older, have longer tenure on the board, and are less likely to be executives at other firms or be affiliated directors compared to non-SciDs.

In our sample, 2,199 outside directors are inventors (i.e., invent at least one patent), including 1,097 scientific inventor directors and 1,102 non-scientific inventor directors. Panel C of Table 2 presents the patent portfolios of inventor directors, separately for SciDs and non-SciDs. On average, scientific inventor directors outperform non-scientific inventor directors in both the quality and quantity of their patent portfolios. More specifically, scientific inventor directors have more patents with more adjusted citations, larger scope, and larger generality and originality than non-scientific inventor directors, and these differences are statistically significant.

2 Empirical results

2.1 SciD presence and the reliance on science

We start our analysis by investigating the reasons behind firms appointing SciDs. SciD is a special subset of outside directors. Unlike conventional outside directors, SciDs may lack significant operations experience, political connections, or business strategy experience, but the standout characteristic of SciDs is their scientific expertise. Basic science research serves as a wellspring of innovative ideas and plays a pivotal role in fostering innovation (Arora et al., 2021). SciDs are typically prestigious scientists at the forefront of developing cutting-edge research and have the ability to identify promising cutting-edge scientific discoveries for future innovation development, thus acting as a bridge between fundamental science and practical innovations.

We argue that the benefits for a firm to have SciDs will vary based on the firm's innovation activity and its capacity to leverage fundamental science. In industries with lower levels of innovation, such as retail, real estate, and tobacco, the benefits of appointing SciDs may be limited, primarily because firms in these industries often do not actively seek to undertake innovation activities. Moreover, when a firm operates in an innovative industry, but it lacks the capability to leverage fundamental science, such as a software firm, appointing SciDs may not result in significant benefits, as these firms cannot utilize the scientific expertise of SciDs effectively. Therefore, we predict that innovative firms, especially those firms that heavily rely on fundamental science for their innovations, are more likely to realize significant benefits from the expertise of SciDs and, consequently, they are more likely to appoint SciDs as advisors.

We empirically test whether SciDs are more likely to be present in a firm relying heavily on fundamental science. To gauge the extent of a firm's reliance on scientific knowledge for its patents, we employ a novel measurement, $\text{Reliance on Fundamental Science}_{i,t}$, which represents the proportion of a firm's patents that heavily rely on fundamental science over its total number of patents measured over a three-year rolling window, as described in Equation 4 of Section 1.6. We measure the presence of SciD using several alternative variables. First, the indicator variable for the appointment event of a SciD in year t+1, which is equal to 1 if the firm appoints a SciD to its board in the following year and is 0 otherwise. We also classify a relevant SciD as a SciD whose expertise overlaps with at least one of the top three subject areas of the publications most frequently referenced by a firm's patents over the past three years. An indicator variable for a relevant SciD appointment equals 1 if the firm appoints a relevant SciD to its board in the following year and is 0 otherwise. One limitation of this indicator is that firms could replace a SciD with another SciD so that the number of SciD stays constant after the appointment event. Therefore, we also measure the presence of SciDs by counting both general SciDs and relevant SciDs (with expertise in the subject areas related to the firm's technology) at year t+1. The regression model is expressed as follows:

$$\text{SciD appointment/presence}_{i,t+1} = \alpha_0 + \alpha_i + \alpha_t + \beta_1 \text{Reliance on Fundamental Science}_{i,t} + X'_{i,t}\lambda + e_{i,t} \quad (5)$$

where SciD appointment/presence$_{i,t+1}$ are measures of SciD appointments/presence on the board of firm i at year t+1; X represents the vector of the firm control variables: size, R&D, CAPEX, firm age, annual returns, leverage, indicators for board independence and a scientific CEO, as well as number of new patents, PPE and Cash; and α_i and α_t are firm and year fixed effects, respectively. The standard errors in table 3 are clustered at the 4-digit industry level. Columns 1 and 2 are estimated using a Probit model. Columns 3 and 4 are estimated using Poisson regressions.

Columns 1 and 2 of table 3 show that a firm's predicted likelihood of appointing SciDs and relevant SciDs rises when firms rely more on fundamental science. More specifically, column 1 presents the Probit model estimate on the indicator variable for a SciD appointment at year t+1, given a firm's level of reliance on fundamental science in its prior patents. The coefficient of β_1 is 0.196, and it is statistically significant at the 1% level. In column 2, the coefficient is 0.865 and statistically significant at the 1% level, indicating that the predicted likelihood of appointing a relevant SciD rises as firms increase their reliance on fundamental science. In column 3, the dependent variable is the number of SciDs at the firm in year $t+1$, and while the coefficient estimate is positive, it is statistically insignificant. Column 3 suggests that the number of SciDs on the board remains constant even if the likelihood of appointing a SciD increases. This could be indicative of firms being more likely to replace one SciD with another SciD. Column 4 presents Poisson regression estimates of the number of relevant SciDs conditional on the firm's reliance on fundamental science. β_1 of column 4 is 1.507 and statistically significantly different from zero at 1% level, suggesting that when firms increasingly rely on fundamental science, they have 4.51($e^{1.507}$) times more relevant SciDs on the board. The combined insights of columns 3 and 4 suggest that firms are more likely to appoint relevant SciDs over non-relevant SciDs when these firms rely more heavily on fundamental science. These findings in table 4 underscore the strong connection between a firm's reliance on fundamental science in its patents and the likelihood of a SciD's presence on the board, particularly SciDs with expertise in relevant subject areas related to the firm's technology.

2.2 SciDs and firm innovation

The relation between SciDs and firm innovation remains an open question. We expect a positive correlation between SciDs and long-term innovation performance due to their scientific expertise and superior advisory capabilities. SciDs leverage their ability to deeply comprehend the implications of a firm's innovations. The deep understanding of the firm's innovation allows SciDs to offer not just technical insights but also macro-level guidance, facilitating the strategic and commercial exploitation of groundbreaking discoveries for long-term success. Moreover, the integrity of SciDs, stemming from the value of a scientist's reputation, is a key factor ensuring that SciDs provide honest and insightful advice on a firm's research progress. SciDs' esteemed scientific backgrounds contribute to a level of credibility and trust that shareholders value. There are two anecdote examples. First, John Baxter, serving as a SciD on the board of Bionovo, while also being a member of the U.S. National Academy of Sciences, exemplifies the benefits of such directors. The CEO of Bionovo has highlighted John Baxter's role in helping the firm to advance clinical trial programs using his experience in transforming his scientific discoveries into successful therapies (PRNewswire, 2008). Another example is Robert Langer, who is a SciD of multiple firms and one of three living people who have received the U.S. National Medal of Science and the National Medal of Technology and Innovation. Robert Langer highlighted the pivotal role of a scientist's expertise in managing a firm's research progress, identifying breakthroughs in basic science, and connecting the firm with capable scientists (Langer, 2016).

We measure long-term innovation outputs using the number of patents, average adjusted patent cites, average patent market value, number of breakthrough patents and number of fundamental patents measured over the following three years. The main explanatory variable is a SciD indicator, which is equal to one if the firm's board has at least one SciD and is zero otherwise. Besides controlling for firm characteristics, we also include indicators for scientific CEOs, who might produce similar benefits and board independence in these regressions to separate the effects of having one or more SciDs from the effects of having a scientific CEO and an independent board (Balsmeier et al., 2017). Our regressions have the following form:

$$\text{Innovation output}_{i,[t+1,t+3]} = \alpha_0 + \alpha_j + \alpha_t + \beta_1 \text{SciD}_{i,t} + \lambda X'_{i,t} + e_{i,t}, \tag{6}$$

where Innovation output$_{i,[t+1,t+3]}$ is the innovation output for firm i from year 1 to year 3; X represents the vector of firm control variables: size, R&D, CAPEX, firm age, annual returns, leverage, board independence, and the indicator for a scientific CEO[2]; and α_j and α_t are SIC 4-digit industry fixed effects and year-fixed effects, respectively. The standard errors in the odd columns 1, 3, 5, 7 and 9 of table 4 are clustered at the firm level. The standard errors in the even columns 2, 4, 6, 8 and 10 of table 4 are clustered at the SIC 4-digit industry level.

[2]Results are robust when controlling for the scientific expertise of other executives, such as the Chief Technology Officer(CTO), Chief Scientific Officer(CSO) and Chief Medical Officer(CMO).

Ideally, employing regression models with firm fixed effects is preferred because it enables us to observe how a specific firm's outcomes evolve with and without SciDs. However, Table A3 shows the share of SciDs to outside directors has remained relatively stable over the years. Consequently, our key explanatory variable $\mathrm{SciD}_{i,t}$ lacks sufficient time series variation to support the inclusion of firm fixed effects. As an alternative, we use industry-fixed effects to compare the long-term values of firms with SciDs to other firms without SciDs within the same industry.

Panel A of table 4 presents OLS regressions of the natural logarithm of one plus innovation output on the presence of one or more SciDs. Panel B of table 4 reports Poisson regressions when the dependent variable is a count measure such as a firm's number of patents, citations, breakthrough patents and fundamental patents (columns 1, 2, 3, 4, 7, 8, 9, and 10) (Cohn et al., 2022) and OLS regressions when the dependent variable represents non-count data such as the natural logarithm of the average market value of a firm's patents (columns 5 and 6).

In Panel A of table 4, the results indicate that firms with SciDs demonstrate superior long-term innovation performance in terms of quantity and quality of patents compared to other firms within the same industry without SciDs. Columns 1 and 2 focus on the relationship between SciDs and the number of patents, and show a significantly positive coefficient of 0.176, regardless of the clustering choice used for the standard errors, suggesting that firms with SciDs have 17.6% more patents than other firms in the same industry without SciDs. Moving to the average adjusted citations per patent (columns 3 and 4), the coefficients are statistically significant regardless of the choice of clustering method used to estimate the standard errors. The SciD coefficient is 0.029 in columns 3 and 4, indicating that firms with SciDs on the board experience 2.9% higher average adjusted cites per patent over the next 3 years compared to similar firms in the same industry without SciDs. Columns 5 and 6 examine the average value per patent over the next three years, and these estimates show that firms with SciDs have 5.6% greater average value per patent than other firms in the same industry without SciDs. Columns 7 and 8 reveal that firms with SciDs produce more breakthrough patents over the next three years, with β_1 equal to 0.093, which is statistically significant. Finally, the coefficients in columns 9 and 10 are 0.088 and statistically significant, regardless of the clustering method used to estimate the standard errors. This result indicates that firms with SciDs generate 8.8% more fundamental patents compared to similar firms in the same industry.

In panel B of table 4, we present Poisson regressions showing that over the next three years, firms with SciDs generate more patents, larger average adjusted cites per patent and more breakthrough patents and fundamental patents than other firms in the same industry. Using the number of patents over the next three years as the dependent variable in column 1, the SciD estimate β_1 equals 0.320 and is statistically significant, which suggests that firms with SciDs have 1.38 ($e^{0.320}$) times more patents over the next three years than other firms in the same industry. Regarding average adjusted cites over the next three years, the coefficients in columns 3 and 4 are positive and statistically significant at the 1% level, regardless of the clustering method used for the standard errors. Columns 3 and 4 show that firms with SciDs have 1.16 ($e^{0.149}$) times more average citations than other firms in the same industry, after controlling for firm characteristics. Columns 7 and 8 present Poisson regression estimates of how SciDs are positively associated with the number of breakthrough patents, with coefficients of 0.328 that are statistically significant. Columns 7 and 8 suggest that firms with SciDs have 1.39 ($e^{0.328}$) times more breakthrough patents than other firms in the same industry. Lastly, the coefficient estimates in columns 9 and 10 equal 0.378 and are statistically significant, suggesting that firms with SciDs on the board produce 1.46($e^{0.378}$) times more fundamental patents than other firms in the same industry. In summary, the results in Table 4 suggest that firms with SciDs are associated with more productive innovation than other firms in the same industry without SciDs.

3 Endogenous director appointments

Appointments of SciDs by innovative firms are endogenously chosen. This endogenous selection process for SciDs means that they may not positively affect firm innovation, but instead, they are sitting on the boards of innovative firms because these firms' decision makers know these scientists from prior professional collaborations. For example, innovative firms may have stronger connections to universities and SciDs than other firms because innovative firms are likely to collaborate with university researchers through grants.

In this section, we address the endogeneity issue by using the local SciD supply as an instrumental variable that captures director preferences for serving on local boards and exogenous shocks due to technological breakthroughs such as the human genome project.

3.1 Local SciD supply

This section investigates the relation between the share of SciDs on boards and innovation outputs using the Local SciD supply (Local SciD supply) as an Instrumental Variable (IV). Following Knyazeva et al. (2013), the Local SciD supply is the logarithm of one plus the number of SciDs in firms headquartered within 100 miles of the focal firm's headquarters, excluding firms in the same four-digit SIC (SIC4) industry. As Knyazeva et al. (2013) suggest, we exclude firms in the same four-digit SIC industry because executives of close competitors are unlikely to appoint the focal firm's board due to competition concerns and anti-trust legal liability. Additionally, we exclude firms located in Alaska and Hawaii, comprising only a handful of observations. We further exclude large firms with a size larger than 75th percentile of the size distribution of all our sample firms per year, as local director markets are less likely to be a binding constraint for these larger firms who can attract directors more easily given their high visibility. We exclude small firms with total assets less than $20 million since, on average, these smaller firms are less attractive to potential directors. We calculate the distance between firms by using the Great Circle Distance. The inputs of Earth's Great Circle Distance (EGCD) are the longitudes and latitudes of two locations. The output of

EGCD is the distance between two locations in miles. The firm's headquarters zip codes are from Compustat. We use the U.S. Census Gazetteer to find the longitudes and latitudes of each firm's location that correspond to the location centroid of its zip code. Additionally, SciD may be located in areas with a rich supply of scientists who could help advance the firm's innovation activities. Thus, it is important to control for the local supply of scientists near the firms. We proxy the local supply of scientists using the logarithm of one plus the number of tenured assistant/associate/full professors (including professors who are on the tenure track) in universities located within 100 miles of the firm's headquarters.

It is essential to assess the validity of the IV's relevance condition and the exclusion restriction. With respect to the relevance condition, a qualified SciD has substantial demands on his/her time because he or she is commonly an executive at another firm or otherwise can have a full-time public or private sector job. Locally available SciDs are generally in short supply and thus represent a scarce human resource for a firm. Firms often rely on SciDs to advise them on their major innovative projects. In such cases, the firm could demand substantial time and energy from a SciD to provide the firm with valuable feedback on their innovation investments, potentially on a frequent basis. Given these expected demands, local directorships are more likely to be attractive to SciD candidates since they minimize the time needed to attend board meetings.

Empirically, the first stage regression (Column 1 of Table 5) shows a positive coefficient on the local SciD supply, which is statistically different from zero at 5%. This suggests that the share of SciDs on the board increases by 0.005 points as the local SciD supply increases by 1%. The F statistic is 39.65, which is greater than 10, supporting the relevance of the IV. Since the headquarters location is generally selected early in a firm's life, we treat it as exogenously determined for our analysis. The location of the firm headquarters is also unlikely to affect innovation outputs directly, especially after controlling for the supply of local scientists. Thus, we argue that the Local SciD supply only affects innovation output through the share of SciDs on a board. We conclude that the IV meets the relevance and exclusion conditions.

The first stage regression estimates the relation between SciDs' share of the board and the Local SciD supply, which is specified as follows:

$$\text{SciD share}_{i,t} = \alpha_0 + \beta_1 \text{Local SciD supply}_{i,t} + \lambda X'_{i,t} + \alpha_j + \alpha_t + e_{i,t}, \tag{7}$$

where *SciD share*$_{i,t}$ is the ratio of the number of SciDs to the total number of directors at firm i in year t. In the second stage, we regress future innovation outputs on the predicted share of SciDs based on the fitted value of the local SciD supply, denoted with a hat, which is specified as:

$$\text{Innovation output}_{i,[t+1,t+3]} = \alpha_0 + \beta_1 \widehat{\text{SciD share}}_{i,t} + \lambda X'_{i,t} + \alpha_j + \alpha_t + e_{i,t}, \tag{8}$$

where *Innovation output*$_{i,[t+1,t+3]}$ is the natural logarithm of one plus the innovation output of firm i over the years 1 through 3; X is a vector of the following firm control variables: size, CAPEX, RD, age, annual return, leverage, board size, board independence, an indicator for a scientific CEO and local scientists supply; while α_j and α_t are three-digit SIC industry and year fixed effects.

Table 5 shows that the fitted values of the SciD share are positively related to the number of new patents, the average market value of the new patents, the number of new breakthrough patents and fundamental patents. The IV estimates should be interpreted as Local Average Treatment Effects (LATE). Firms with a greater local SciD supply tend to appoint more SciDs, and these treated firms with more SciDs produce more patents, a larger average market value per patent and more fundamental patents within the same industry. More specifically, the dependent variable in column 2 is the natural logarithm of one plus the number of patents measured over the next 3 years. The coefficient in column 2 is 12.488 and statistically significant. Column 2 shows that for a 1% increase in the number of local SciD candidates near the focal firm, the treated focal firm experiences a 6.244% (0.005×12.488×100) increase in the number of patents for the next years 3 within the same industry. In column 3, the dependent variable is the average adjusted cites, and the coefficient is positive but not statistically significant. Column 4 presents a second-stage regression of the natural logarithm of one plus the average patent value over the next three years on the fitted value of the SciD share.

Examining Table 5 further, we see in column 4 that the coefficient of the average value of patents is 7.730 and statistically significant, suggesting that for a 1% increase in the number of local SciDs near the focal firm, the average market value of patents is 3.87% (0.005×7.730×100) larger than for other firms in the same industry. Examining the number of breakthrough patents, the β of coefficient in column 5 is positive and statistically significant at 10%, suggesting that for a 1% increase in the local SciD supply, the treated firms produce 2.872% (0.005×5.743×100) more breakthrough patents than other similar firms in the same industry. The number of fundamental patents is positively associated with the supply of local SciD candidates, shown by the β_1 estimate in column 6, of 5.87, which is statistically significant. Column 6 suggests that over the next 3 years, a 1% increase in the number of local SciD candidates near the focal firm leads to 3.84% (0.005×7.681×100) more fundamental patents for firms with a greater SciD supply than for other firms in the same industry respectively. Overall, the focal firms hire more SciDs for their boards of directors due to a greater supply of local SciD candidates. These SciD-appointing firms experience better innovation performance based on multiple metrics than other firms in the same industry.

3.2 Human genome project

We next examine whether a positive technological shock results in an increase in a firm's demand for SciDs, attributed to the enhanced value provided by SciD. In this experiment, we begin by assuming that a positive technology shock will increase the value to the firm of having SciDs as board members, who are either generally conversant with the technology being shocked or have expertise in this technology. This shock should increase the economic benefit of the SciD and a firm's demand for these SciDs. This can be because these SciD can help guide the firm's new investments in the shock-affected technology and help recruit relevant experts due to their professional connections with these scientists. It can also be because these SciDs can provide valuable guidance to the firm's technology investments, advising both the board and senior executives about which internal projects or acquisition targets are most promising with regard to the shocked technology.

For our experiment, we are going to focus on a technology shock associated with the Human Genome Project (HGP), which is an international scientific research project launched in 1990 with the aim of identifying, mapping, and sequencing all the genes of the human genome. The project freely published all its data related to the human genome, which was eagerly seized upon by pharmaceutical firms seeking to develop innovative drugs or devices with the help of this human genome map. Highlighting its economic value, some firms were known to have paid significant amounts of money to obtain privately patented human genome data prior to the HGP's data release date to gain a competitive advantage in the human genome drug market (Williams, 2013).

Thus, we utilize the HGP as an exogenous shock to the demand for SciDs due to their increased expected value to firms in the genetics-related industry. We investigate whether firms in industries that benefit from HGP appoint more SciDs and subsequently produce more patents after the publication of the HGP findings. We define our genetics-related industries as firms in industries that can convert human genome data into commercialized devices or products. Specifically, the genetics-related industries include the drugs and pharmaceutical products (13) and lab equipment (37) industries identified from the Fama-French 48 industry classification. We include the lab equipment industry because they produce DNA and protein detection equipment and DNA-sequencing machines. Our analysis is based on the event year 2001, when the full draft of the sequence and initial analysis of the HGP became publicly available. We hypothesize that the economic benefits of having a SciD increase after the public release of the HGP findings, consequently leading to greater demand for SciDs by firms in genetics-related industries. It is important to note that, in our analysis of HGP, we do not claim the causal effect of SciD on innovation output. Instead, our focus is on the causal effect of a major exogenous technology breakthrough on the economic benefit of having a SciD on the board and the subsequent firm demand for SciD.

We first investigate whether firms in genetics-related industries are more likely to hire SciDs or SciDs with genetics expertise, which we hereafter denoted as genetics SciDs, following the public release of the HGP results, due to the increased economic benefit associated with having a SciD. The first stage regression equation is specified as follows:

$$\text{SciD/genetics SciD share}_{i,t} = \alpha_i + \alpha_t + \beta \text{genetics industry}_i * \text{Post2001}_t + \lambda X'_{i,t} + +e_{i,t} \tag{9}$$

where *SciD/genetics SciD share*$_{i,t}$ is the ratio of the number of SciDs/genetics SciDs to the total number of directors at firm i in year t; X is a vector of the following firm control variables: size, R&D, CAPEX, age, annual returns, leverage, and board independence and scientific CEO indicators; α_i and α_t are firm and year fixed effects. All standard errors are clustered at the 4-digit industry level.

Panel A of table 6 shows firms in the genetics-related industries hired more SciDs or genetics SciDs to their boards after 2001. Column 1 presents OLS regression of SciD share against the interaction between *genetics industries* and *post2001*. The coefficient in column 1 is 0.024 and statistically significant at the 5% level, suggesting that firms in the genetics-related industry have 2.4% more SciDs than firms in other non-genetics industries after the HGP shock. Additionally, figure 3 presents the time trend in the board's share of SciDs before and after 2001 and indicates no pre-trend in the two years prior to the HGP treatment year. Column 2 evaluates the effect of HGP on the share of genetics SciDs on the board. The coefficient in column 2 is 0.019 and statistically significant at the 1% level, suggesting that firms in the genetics-related industry have 1.9% more genetics SciDs than other firms after the HGP shock, as predicted.

We further test whether these firms experience better innovation outcomes. Columns 4, 5, 7 and 8 use Poisson regressions, given the dependent variables are count measures. Column 3 reports OLS regression estimates for the logarithm of the non-count dependent variables. Our regressions take the following form:

$$\text{Innovation output}_{i,t+1} = \alpha_i + \alpha_t + \beta \text{genetics industry}_i * \text{Post2001}_t + \lambda X'_{i,t} + +e_{i,t} \qquad (10)$$

where the dependent variable *Innovation output*$_{i,t+1}$ is the innovation output of firm i in year $t+1$; X is a vector of firm control variables that are the same as control variables in regression 11; α_i and α_t are firm and year fixed effects. All standard errors are clustered at the 4-digit industry level.

Panel A of table 6 shows that firms in the genetics-related industries produce fewer patents but are of higher quality than firms in other non-genetics industries after 2001. The dependent variable in column 3 is the natural logarithm of the average value of patents in the next year. Column 3 reports OLS estimates of the logarithm of the average value of patents on the interaction between *genetics industry* and *post2001*. The coefficient in column 3 is 0.204 and statistically significant at 5%, suggesting that firms in the genetics-related industry have a 20.4% larger average value per patent than firms in other industries after 2001. The dependent variable of column 4 is the average adjusted cites for the next year. The coefficient in column 4 is 0.136, which is statistically significant at the 10% level, indicating that firms in the genetics industry have 1.15($e^{0.136}$) times the average adjusted citations per patent than firms in other industries after 2001. Column 5 investigates the effect of the HGP shock on the number of patents in the next year. Interestingly, column 5 shows firms in the genetics industry have 0.57($e^{-0.561}$) times fewer patents than firms in other industries after 2001. The fall in patents could be due to firms in the genetics-related industries changing their areas of technological focus and thus, patenting less in their previously important technology areas in the short run. The dependent variable in column 7 is the number of breakthrough patents measured at the 99th percentile (top 1 percentile) in the next year. The coefficient in column 7 is statistically significant at the 5% level, suggesting that firms in the genetics-related industry have 1.98 ($e^{0.684}$) times more breakthrough patents measured at the 99th percentile level than other firms after 2001.

The covariate imbalance between firms in the genetics industry and firms in non-genetics industries can potentially bias any comparisons and inferences we make. Thus, we estimate a propensity score matching model to create a control group of comparable firms with similar characteristics. The covariates that we use are the following firm characteristics up to the event year 2001: firm size, ROA, annual return, and the number of patents. It is important to note that matching on patent activities can minimize the concerns that firms with better innovation ability are more likely to hire SciDs. Table A7 shows that the differences in the covariates of treatment and control groups are statistically insignificant after matching.

Panel B of table 6 presents an analysis of the matched samples. We find that our results are similar to Panel A of table 6. More specifically, the dependent variables in columns 1 and 2 are the shares of SciDs and genetics SciDs on the board. The coefficients of columns 1 and 2 are 0.025 and 0.019, respectively, and are statistically significant at the 5% and 1% level, suggesting that firms in genetics-related industries hire more SciDs and genetics SciDs than similar firms in other industries after the 2001 HGP shock. Regarding innovation outputs, all the key coefficients in columns 3, 4, 5 and 7 are statistically significant. Column 3 presents the OLS regression of the average patent value against the interaction of *Treatment* and *post2001*. The coefficient of the interaction term is 0.255, suggesting that firms in the genetics industry have a 25.5% larger average patent value per patent than similar firms in other industries after 2001. The dependent variable in column 4 is the average adjusted cites. The coefficient of the interaction term is 0.150, suggesting that firms in the genetics-related industry have 1.16($e^{0.150}$) times more average adjusted cites per patent than similar firms in other industries after the 2001 HGP shock. Column 5 presents evidence that firms in the genetics-related industry have 0.61($e^{-0.487}$) times few patents than similar firms in other industries. Regarding breakthrough patents at 90% in column 6, the coefficient is negative but not statistically significant. Column 7 shows that genetics industry firms have 1.82($e^{0.598}$) times more breakthrough patents at 99% than similar firms in other industries after the HGP shock.

Overall, we find that firms in the industry that can leverage genetics knowledge are more likely post-2001 to hire SciDs than similar firms in other industries. We also find firms in the genetics-related industry are associated with a larger average value and more adjusted cites to their patents and a greater number of breakthrough patents (99) post-2001, indicating more valuable innovations than otherwise similar firms in non-genetics industries. Thus, our evidence is consistent with a positive technology shock raising the value of SciDs, which in turn raises their frequency on boards of the shocked industry. However, this evidence is inconsistent with a reverse causality story that greater innovation outputs lead to the appointment of more SciDs.

4 Channels: SciD knowledge and professional networks

In this section, we explore the channels through which SciDs enhance firm value, focusing on two key characteristics: their scientific knowledge and professional networks. Firstly, we gauge the influence of SciDs on firm patents and examine the relation between their influence on firm patents and the efficiency of firm innovation in Section 4.1. Additionally, in Section 4.2, we assess the relation between firm innovation and the expertise level of SciDs, measured through their recent publication activities. Finally, we investigate SciDs' role in the recruitment and retention of inventors for the firm by leveraging their professional networks in Section 4.3.

4.1 SciD influence on a firm's patents

This section investigates the relation between a SciD's influence on firm patents and the quality and quantity of the firm's innovation output. As presented in Section 1.4.1, a SciD's influence is measured by the firm's cumulative number of patents that cite the SciD's work over the cumulative number of patents awarded to the firm. The increasing influence of SciDs on a firm's patent applications emphasises the advisory role of SciDs in the firm's innovation process, given that the scientific work of the SciD can directly influence the firm's inventors. Also, the greater influence of a SciD suggests that the SciD's expertise is more relevant to the technology underlying the firm's patents.

Our data is at the firm, SciD and year level, and it allows us to include firm×director fixed effects. The firm×director fixed effect exploits the fact that the SciDs' influence can vary over time, so that within firm-director pairs can arguably change their effects on a firm's innovation outcomes given exogenous shocks. More specifically, including firm×director fixed effects eliminates several types of confounding events on a firm's innovation output, such as an innovative firm endogenously appointing a more influential SciD. The inclusion of firm×director fixed effects allows us to capture the time series variation in a SciD's influence within a specific firm-SciD pair. The firm×director fixed effects facilitate an examination of the correlation between shifts in a SciD's influence and the corresponding changes in innovation output. In contrast, firm and director fixed effects only capture the time-invariant associations of a director and a firm on a firm's innovation activity, such as director quality or firm culture. Our regression equations take the following form:

$$\text{Innovation output}_{i,d,[t+1,t+n]} = \alpha_0 + \beta \text{SciD's influence}_{i,d,t} + \alpha_{i,d} + \alpha_t + X'_{i,t}\lambda + e_{i,t}, \tag{11}$$

where *Innovation output*$_{i,d,[t+1,t+n]}$ is the innovation output of firm i given SciD d is on the board for years 1 through n; X is a vector of the following firm control variables: size, R&D, CAPEX, age, annual returns, leverage, board independence, and the indicator for a scientific CEO; while $\alpha_{i,d}$ and α_t are firm×director and year fixed effects. All standard errors are clustered at the 4-digit industry level.

Panel A of table 7 presents OLS regression estimates of the natural logarithm of one plus innovation output against a SciD's influence on a firm's future patents. Panel B of table 7 reports Poisson regression estimates for count measure dependent variables (Cohn et al., 2022) and OLS regression estimates for the logarithm of non-count dependent variables. The number of patents, citations and the number of breakthrough patents are all count variables, and we estimate their relation to the SciD's influence using Poisson regressions in Panel B of table 7 (columns 1,2,3,4,7 and 8). We use OLS regressions to estimate the coefficient of the SciD influence against the natural logarithm of the average market value of a firm's patents in Panel B of table 7 (columns 5 and 6).

Panel A of table 7 shows firms produce higher-quality innovation output when the SciDs have a greater influence on a firm's patent innovation activity. The dependent variables in columns 3 and 4 are the average adjusted cites over the next 3 and 5 years. The coefficients of columns 3 and 4 are 0.387 and 0.215 respectively, and are statistically significant at the 1% level, suggesting that firms receive 38.7% and 21.5% more average adjusted citations over the following 3 and 5 years respectively, when a SciD's influence increases by one unit. For the average value of patents, the coefficients in columns 5 and 6 are 0.385 and 0.384, which are significantly different from zero at the 1% level, indicating that firms have 38.5% and 38.4% larger average market value for their patents over the next 3 and 5 years respectively when a SciD's influence increases by one unit. Last but not least, columns 7 and 8 report the number of breakthrough patents over the next 3 and 5 years as dependent variables. The β_1 coefficients of columns 7 and 8 are 0.688 and 0.946 respectively, and are statistically significant at the 1% level, suggesting that firms have 68.8% and 94.6% more breakthrough patents over the next 3 and 5 years respectively when a SciD's influence increases by one unit.

Panel B of table 7 shows that a firm's patents receive more adjusted citations and have larger market value when a SciD's scientific works have a larger influence on a firm's patent innovation. Column 3 presents the Poisson regression estimates of the average adjusted citations over the next 3 years against the influence of SciDs. The coefficient of a SciD's influence is 0.348 and statistically significant at 1%, suggesting that firms receive 1.41 ($e^{0.348}$) times more average adjusted citations per patent over the next 3 years when a SciD's influence increases by one unit. The dependent variables in Columns 5 and 6 are the average market values of patents in the next 3 and 5 years. The coefficients of SciD's influence in columns 5 and 6 are 0.439 and 0.515 respectively, which are statistically significant at the 1% level, suggesting that firms have, on average, 43.9% and 51.5% larger market values per patent over the next 3 and 5 years respectively, when a SciD's influence increases by one unit.

4.2 SciD expertise and a firm's innovation activity

In Section 4.1, we assess the SciD's influence on the firm's patents by examining the firm's patents that directly reference the scientific works of a SciD. However, there are two limitations to this measurement of a SciD's influence. First, relying only on direct citations to SciD's publications may be overly conservative when determining the connection between a firm's patents and the expertise and influence of a SciD. The firm's innovation may also be influenced by a SciD's expertise when the firm's patent is based on knowledge from the same areas where SciDs are actively involved in research. Secondly, the influence of SciDs provides limited insights into their recent scientific expertise. For instance, SciDs might begin working on new areas of research that are beneficial to a firm's innovation, but these publications in these novel research domains may not be directly cited by the firm's patents due to the lag between scientific research publications and patent applications (Ahmadpoor and Jones, 2017). To address these two limitations, we construct a dataset that operates at the firm, scientific subject area, and year. In this dataset, we identify the patent's scientific subject area using the deep learning method as described in Section 1.5. We also match the firm's patent output to a SciD's publication activities according to the subject areas of the firm patents and the SciD's publications over 3 prior years. The analysis allows us to evaluate the impact of a SciD's expertise on the patents that benefit from this knowledge, even if these patents do not directly cite the publications of a SciD. Also, we can investigate the effect of the firm's innovation activities on the SciD's recent research activities. Our regressions have the following form:

$$\text{Innovation output}_{i,s,[t+1,t+3]} = \alpha_0 + \alpha_i + \alpha_t + \alpha_s + \beta_1 \text{Expertise}_{i,s,[t-3,t]} + \lambda X'_{i,s,t} + e_{i,s,t} \tag{12}$$

We have two types of expertise measures as described in Section 1.5. First, $\text{Expertise(pub)}_{i,s,[t-3,t]}$ is the logarithm of one plus the average number of publications in the subject area that the SciDs authored in the past three years. Second, $\text{Expertise(cites)}_{i,s,[t-3,t]}$ is the logarithm of one plus the average number of publication citations in the subject area that the SciDs authored in the past three years. We further match the SciD's expertise to the firm's innovation output according to their subject areas. $\text{Innovation output}_{i,s,[t+1,t+3]}$ is the innovation output in subject area s for firm i over years 1 through 3; X represents the vector of firm control variables that follow: size, R&D, CAPEX, firm age, annual returns, leverage, board independence, and the indicator for a scientific CEO; while α_i,α_s and α_t represent firm, subject area and year fixed effects, respectively. The standard errors are clustered at the 4-digit industry level.

In table 8, all columns except 5 and 6 use Poisson regressions due to the count-dependent variables involved. Columns 5 and 6 present OLS regressions of the logarithm of average market values of patents on SciD expertise. Columns 1 and 2 of table 8 show that the firm produces more patents in the subject areas where a SciD has more publications or receives more publication citations. More specifically, the coefficient of column 1 is 0.472 and statistically significant, suggesting that the firm is associated with 1.603($e^{0.472}$) times more patents in the subject areas where the SciDs publish more. The coefficient of column 2 is 0.170 and statistically significant at the 1% level, suggesting that the firm is associated with 1.185($e^{0.170}$) times more patents in the subject areas where the SciDs receive more publication citations. Regarding a firm's average adjusted cites per patent reported in columns 3 and 4, the coefficients of expertise, whether measured by publications or citations, are positive and statistically significant at the 1% level. Columns 3 and 4 suggest that a firm respectively receives 1.162($e^{0.150}$) and 1.056($e^{0.054}$) times more average adjusted cites per patent in the subject areas where the SciD publishes more papers and receives more citations. Column 5 suggests that the SciD's expertise positively correlated with the average market value of the patent. The β_1 estimates of Expertise(pub)$_{i,s,[t-3,t]}$ and Expertise(cites)$_{i,s,[t-3,t]}$ are 0.032 and is statistically significant at the 5% level. Columns 7 and 8 suggest that firms are associated with 1.664 ($e^{0.509}$) and 1.206 ($e^{0.187}$) times more breakthrough patents in the subject areas when the SciDs publish 1% more publications and receive 1% more citations respectively. Lastly, we observe that firms produce more fundamental patents in subject areas where the SciDs have an increased level of expertise. The β_1 estimates in columns 9 and 10 are 0.572 and 0.193, and they are statistically significant, suggesting that the firm produces 1.772 ($e^{0.572}$) and 1.212 ($e^{0.193}$) more fundamental patents in the subject areas where SciDs publish more papers and receive more citations respectively.

4.3 SciD professional networks

While we find the valuable scientific expertise that SciDs bring to firm innovation through their pivotal advisory roles, another valuable resource of SciDs can be their extensive scientific networks. Given that many SciDs are affiliated with universities and laboratories, which are places that have a larger supply of scientists and inventors. SciDs are well-connected and knowledgeable about many highly qualified and productive inventors in the field. Furthermore, SciDs, particularly those who also serve as professors, are not only close to the supply of scientists and inventors, but they also play a role in the training and guidance of junior scientists and inventors as part of their university duties. Consequently, it is reasonable to expect that SciDs can leverage the resources of their social networks to help the firms where they are board members to recruit promising inventors who could potentially lead some of the firm's research projects.

To test the proposition that SciDs help a firm recruit talented inventors, we first form inner communities of SciDs with extensive professional networks that encompass SciDs, inventors affiliated with their firms, and co-authors and co-inventors of SciDs. The inner community of a SciD comprises scientists and inventors who collaborate closely with SciDs through publication and patent collaborations. A scientist (inventor) becomes a member of the SciD's community only when this scientist (inventor) has a closer working relationship with the SciD, demonstrated by having a significant number of co-authorships and successful patent collaborations compared to other scientists (inventors) in the network. The SciD's inner communities represent this SciD's important professional relationships. The inner communities of SciDs allow us to classify groups of scientists (inventors) who closely collaborate with SciDs on a yearly basis. We assume SciDs are familiar with scientists (inventors) in their corresponding communities. Within the communities associated with each SciD, we additionally categorize inventors into two groups: those affiliated with the SciD's firm (SciD-affiliated inventors) and those with other affiliations (Non SciD-affiliated inventors). The SciD-affiliated inventors are defined as those inventors who are in a SciD's community and who also work for the firm where the SciD sits on the board. Non SciD-affiliated inventors are inventors who are in the communities of a SciD, but do not work at the SciD's firm.

We conjecture that SciDs actively select the most productive inventors from their inner communities, introduce them to the firm, and support their recruitment. Subsequently, these SciD-affiliated inventors joined the firm and became some of the most productive inventors. We assume that SciD-affiliated inventors are particularly likely to be introduced by SciDs, considering that SciDs are familiar with these inventors and that these inventors also share closer working relationships with these SciDs.

We first investigate whether SciDs can identify more productive inventors in their community. To achieve this, we compare the innovation performance of the SciD-affiliated inventors to that of other inventors within the SciD community. Given that we assume the SciD-affiliated inventors are inventors being introduced to the firm by the SciD. If the SciD-affiliated inventors have higher productivity compared to other inventors within the SciD community, we infer that the SciD possesses the ability to identify productive inventors from within their community. It is important to note that inventors in SciDs' communities include individuals not only employed by the firms, but also those employed at universities, government, and private firms. Therefore, we estimate the following regression model, where we ignore the firm characteristics:

$$\text{Quality of Patent Portfolio}_{f,q,t} = \alpha_0 + \alpha_{q,t} + \beta\text{SciD-affiliated inventors}_{f,t} + \lambda X'_{i,t} + +e_{i,t} \quad (13)$$

where Quality of Patent Portfolio$_{f,q,t}$ is the quality metric for the patent portfolio of inventor f in community q and year t. The quality of the patent portfolio includes the average and maximum values of patent claims, adjusted citations, the count of breakthrough patents, and the proportion of breakthrough patents relative to the total number of patents in the portfolio. The "SciD-affiliated inventors" is an indicator variable equal to one if the inventor is a SciD-affiliated inventor and is zero otherwise. X is a vector of control variables that include a female indicator and inventor experience. All regressions include community×year fixed effects, $\alpha_{q,t}$. We include community×year fixed effects because network communities are dynamic structures that can change substantially over time. We can compare an inventor's productivity within a community and year using community×year fixed effects. Standard errors are clustered at the individual inventor level. We employ Poisson regression due to the count nature of dependent variables.

Table 9 indicates that SciD-affiliated inventors surpass the productivity of inventors within the SciD community across various metrics, including claims, citations, and the number of breakthrough patents. We first assess the average and maximum patent claims of these inventors' patent portfolios in columns 1 and 4. The patent's claim defines the scope of patent protection. The patent with larger claims has a wide scope of patent protection. The respective coefficients are 0.028 and 0.063 in columns 1 and 4, both statistically significant. These coefficient estimates suggest that SciD-affiliated inventors have 1.02($e^{0.028}$) times and 1.07 ($e^{0.063}$) times more average and maximum claims respectively than inventors within the SciD community. Regarding the average and maximum adjusted cites of these patent portfolios, SciD-affiliated inventors have 1.07 ($e^{0.063}$) times more average adjusted cites and 1.10 ($e^{0.098}$) more maximum adjusted cites than other inventors in the same SciD community. Lastly, SciD-affiliated inventors demonstrate a 1.02 ($e^{0.024}$) times larger share of breakthrough patents and 1.06 ($e^{0.06}$) times more breakthrough patents compared to other inventors within the SciD community. In sum, Table 9 shows that SciD-affiliated inventors are more productive than other inventors in the SciD communities. This suggests that SciDs can effectively identify the productive inventors within their communities and help recruit them to the firms where they are board members.

We next assess whether SciD-affiliated inventors can continuously be productive after joining the SciD's firm. The analysis involves the comparison of performance between SciD-affiliated inventors and other inventors in the firm where the SciD holds a board position, but who are not in the SciD community. We run an inventor, firm and year level regression of patent quality against a SciD-affiliated inventors indicator with firm, year, and cohort fixed effects and standard errors clustered at the inventor level. We define a cohort as a group of individuals entering the firm in the same year. Firm fixed effects allow for a comparison of inventors within the same firm, while cohort fixed effects facilitate comparisons among inventors who joined the firm in the same year. We use a Poisson regression model for dependent variables that are count variables and an OLS regression model for non-count data dependent variables.

$$\text{Quality of Patent Portfolio}_{i,f,c,t} = \alpha_0+\alpha_i+\alpha_t+\alpha_c+\beta_1\text{SciD-affiliated inventors}_{i,f,c,t}+\lambda X'_{i,f,c,t}+e_{i,f,c,t} \tag{14}$$

where Quality of Patent $\text{Portfolio}_{i,f,c,t}$ is the quality of the patent portfolio for inventor f in firm i, cohort c and year t. The quality of the patent portfolio includes the average and maximum values of patent claims, adjusted citations, the market value of patents, the count of breakthrough patents, and the proportion of breakthrough patents relative to the total number of patents in the portfolio. For non-count dependent variables (average and maximum market value of patents), we apply a log transformation, which is the logarithm of the average and maximum market value of patents.

The key explanatory variable is "SciD-affiliated inventors", an indicator variable that equals 1 if the inventor is a SciD-affiliated inventor. X is a vector of firm characteristics: size, CAPEX, RD, age, annual return, ROA, sales, PPE, and inventor characteristics: a female indicator and experience. It is important to note inventors in a SciD firm may not necessarily work closely with SciD or be part of the SciD's community. However, these inventors could still benefit from being in the community of SciDs at other firms. To isolate the effect of the scientific community, we include "Inventor in other com", an indicator variable equal to one if the inventor is in the community of SciDs at other firms and is zero otherwise. All regression includes firm, year, and cohort fixed effects.

Table 10 demonstrates that inventors in both of their SciD communities and firms exhibit higher productivity compared to other inventors who are not in their SciD communities within the same firm and cohort. Specifically, inventors who actively collaborate with their SciDs or establish connections with individuals closely associated with their SciDs demonstrate superior performance compared to other inventors within the firm. The dependent variables in columns 1 and 5 are the average and maximum claims of inventors' patent portfolios. The coefficients in columns 1 and 5 are 0.053 and 0.141, respectively and are statistically significantly different from zero, suggesting that SciD-affiliated inventors have 1.05($e^{0.053}$) and 1.15($e^{0.141}$) times more average and maximum patent claims than other inventors within the same firm and employee cohort.

Regarding an inventor's average and maximum adjusted cites, the respective coefficients in columns 2 and 6 are 0.173 and 0.336, which are again statistically significant. The column 2 and 6 coefficient estimates imply that the patent portfolios of SciD-affiliated inventors received 1.19 ($e^{0.173}$) times more average adjusted cites and 1.40 ($e^{0.336}$) times more maximum adjusted cites than other inventors within the same firm and employee cohort. Columns 3 and 7 show the OLS regression models of the average and maximum patent values. SciD-affiliated inventors have lower average patent values, but larger maximum values. Finally, the dependent variables in columns 4 and 8 are the share of breakthrough patents and the total number of breakthrough patents in the inventors' patent portfolios. The coefficients in columns 4 and 8 are statistically significant, indicating that the patent portfolios of SciD-affiliated inventors have 1.26 ($e^{0.230}$) times greater share of breakthrough patents and 1.59 ($e^{0.463}$) more breakthrough patents than is found in the patent portfolios of non SciD-affiliated inventors. Thus, Table 10 shows the firm's inventors who work closely with their SciDs are more productive inventors within the firm and cohort.

In summary, both table 9 and table 10 indicate that SciD-affiliated inventors exhibit higher productivity compared to other inventors within the SciD community, and these SciD-affiliated inventors maintain their high productivity levels after joining the firm. This suggests that SciDs can identify high-quality inventors from their scientific communities, potentially helping to recruit such inventors to the firms where they serve on the boards. Notably, we cannot claim our evidence documents the causal effects of its SciDs in terms of the firms' talent-hiring because we cannot observe the firm's choice set of talented inventor candidates or the inventor's choice set of potential employers.

5 Shareholder Assessments of SciDs

Investment in scientific research often involves long periods of research and the absence of frequent, clear milestones, which can be challenging for non-expert investors to assess the research progress. The ambiguity of scientific research may force managers to focus on short-term gains and underinvest in scientific research (Garlappi et al., 2017). However, SciDs are well-positioned to effectively evaluate ongoing scientific research and address investor concerns. Our study investigates how the presence of SciDs on the board affects stock performance, exploring their potential to influence investor decisions and the overall valuation of the firm.

We investigate how the stock market reacts to SciD appointment news. These stock market reactions are informative because they reflect investors' ex-ante assessment of the economic benefit of a newly appointed SciD to the firm. Positive market reactions reflect a positive assessment of the effect of the newly appointed SciD on the firm from her expected advisory and monitoring activities.

Following recent literature (Chen et al., 2020; Fahlenbrach et al., 2017), we use the 8-K filing dates as director appointment announcement dates obtained from the Director and Officer Changes table of the Audit Analytics database. Our sample starts with 12,581 director appointments, of which 2,364 are SciD appointments. We exclude appointment events when multiple new directors are jointly announced, comprising 3,020 events. We further exclude 1,511 Non-SciD appointments and 246 SciD appointments that occur plus and minus 5 trading days of either quarterly earnings or M&A announcements. Nearly all the outside board appointments over our sample period are independent directors, so in our subsequent analysis, we restrict ourselves to independent directors. Our final sample consists of 7,804 independent director appointments, including 1,238 SciD appointments.

We assess the market reaction to appointment events by calculating Cumulative Abnormal Returns (CARs) in various event windows, including 5-day CAR[-2,2], 3-day CAR[0,2] and 2-day CAR[0,1]. We calculate CARs using market-adjusted returns, defined as the difference between the stock's return and CRSP value-weighted index return.[3] Panel A of Table 11 shows that investors react positively to SciD appointments, where all these announcement CARs are positive and significantly different from zero. The 5-day CAR[-2,2] has the largest CAR at 62 basis points, the 3-day CAR[0,2] is 56 basis points, and the 2-day CAR[0,1] is 31 basis points.

The positive market reactions to SciD appointments could be the result of most SciDs being independent directors. Thus, the positive market reaction could simply capture the expected monitoring benefits of independent directors. If this is the case, then the market should react similarly to the appointments of scientific and non-scientific independent directors. To evaluate the added value of SciDs, we compare the appointment returns of SciDs to a relatively comparable group of non-SciDs. In panel B of Table 11, we match SciDs and non-SciDs based on general firm and director characteristics. Results in Table 1 reveal significant differences between firms with and without SciDs, such as larger total assets and lower ROA for firms with SciDs. Also, table 2 shows that SciDs are older, remain on the board longer and are less likely to have finance or executive experience. Thus, the covariate imbalance across these firms and director characteristics may affect our comparisons between SciD and non-SciD appointment returns. To address this concern, we use propensity score matching to create a non-SciD control group with similar firm and director characteristics.[4] The covariates considered are the following firm and director characteristics in year $t-1$: firm size, ROA, director's age, tenure, and indicators for whether the director graduated from an Ivy League university, and whether the director has experience in finance or as a corporate

[3]Results remain qualitatively similar when using the equally-weighted index return and are available from the authors on request.

[4]While we could control for these differences in an OLS regression framework, this approach assumes specific functional forms of the relationships to the announcement returns (e.g. linearity) and may be erroneous.

executive. Table A6 shows that the differences in the covariates of treatment and control groups are statistically insignificant after matching.

Panel B of Table 11 reveals a preference among investors for the appointment of SciDs over non-SciDs. The average 5-day CAR[-2,2] for SciD appointments is greater than non-SciD appointments by 89 basis points, and the difference is statistically significant. Similarly, the median 5-day CAR[-2,2] for SciD appointments is greater than that for non-SciD appointments by 52 basis points, and the difference is statistically significant. Additionally, the average 3-day CAR[0,2] of SciD appointments is 62 basis points, which is 67 basis points greater than non-SciD appointments, where the difference is also statistically significant. Likewise, the difference in median 3-day CAR[0,2] between SciD and non-SciD appointments is 23 basis points and is statistically significant.

Of course, the unobserved heterogeneity among firms may affect the market reaction to SciD appointments. For example, some firms may need independent directors to monitor firms because of serious agency problems that these firms are confronting. By coincidence, these firms could also appoint the most SciDs, resulting in a larger announcement return for SciD appointments compared to non-SciD appointments. To control for time invariant unobserved heterogeneity, we use an OLS regression model with firm fixed effects to compare scientific and non-scientific independent director appointment returns within the same firm. We then estimate regressions of SciD and non-Scid appointments by the same firm using the following model:

$$\mathrm{CAR}_{d,i,t} = \alpha_0 + \alpha_i + \alpha_t + \beta_1 \mathrm{SciD}_{i,d,t} + F'_{i,t-1}\lambda + D'_{i,t-1}\gamma + e_{d,i,t} \tag{15}$$

where $\mathsf{CAR}_{i,t}$ is the 2(3)-day CAR[0,1(2)] for firm i and year t that appoint an independent director d. *F* is a vector of the following firm characteristics: firm size, R&D, CAPEX, age, annual returns, ROA, PPE and sales. *D* is a vector of the following director characteristics: director age, tenure, and indicators for Ivy League graduates and directors with executive experience or finance experience. Regressions include firm and year-fixed effects, α_i and α_t. All standard errors are clustered at the 4-digit industry level.

Firm fixed effects (α_i) allow us to compare the appointment returns of SciDs to other non-SciDs within the same firm. Additionally, we also use director characteristics (D) and firm characteristics (F) to control for an array of observable characteristics. β_1 represents the difference in appointment returns between SciDs and other non-SciDs within the same firms, controlling for firm and director characteristics. Panel C of Table 11 shows the appointment returns of SciDs are greater than non-SciDs. More specifically, columns 1 and 2 indicate that the average CAR[0,1] of SciD appointments is 4 basis points larger than that of non-SciD appointments, and the difference is statistically significant, regardless of whether we include firm characteristics. In column 3, after controlling for firm and director characteristics, SciD appointment returns are 3 basis points higher than those of non-SciD, and the difference is statistically significant. Moving to columns 4, 5, and 6, which use CAR[0,2] as the dependent variable, the coefficients of β_1 are 0.005 and statistically significant, whether or not we control for firm and director characteristics.

We next investigate announcement returns around director deaths. Director death events are more informative than director appointment events because these deaths are outside the control of the firm and generally are unexpected and occur randomly. Another advantage of studying director deaths over director appointments is that the market reaction to death events reflects the loss of the expected benefits associated with this specific director. Directors normally sit on a firm's board for years and then leave the board suddenly due to deaths. Investors are likely to have a much more accurate evaluation of the benefits of these directors, given the sizable track record they have. Thus, the market reactions to director deaths should be more informative about the value of a director to the firm.

We collect the outside director death events from the Audit Analytics database. Following by (Masulis et al., 2022), we use the earliest news releases of outside director deaths as the event date. We find 34 SciD death events and 203 non-SciD death events. The average three-day CAR[0,2] after a SciD's death is -2.05% and statistically significant at the 5% level. The average 3-day CAR[0,2] of a non-SciD's death is 0.16% and statistically insignificant. The difference in the departure announcement returns between scientific and non-SciDs is -2.21% and statistically significant at the 5% level. Additionally, we employ propensity score matching to create a non-SciD control group with similar firm and director characteristics. The matching firm and director characteristics in year $t-1$ include size, ROA, and indicator variables for executive, finance experience, and independent director. The differences in the CAR[0,2] between SciD and Non-SciD is -2.97% and statistically significant at the 10% level.

6 Long-Term Firm Valuation

While the announcement returns of director appointments and deaths suggest that shareholders view SciDs as enhancing firm value, a more comprehensive evaluation involves assessing the long-term performance of these firms. We propose that SciDs can contribute to long-term firm valuation, given the long-term nature of firm innovation activity.

We use Tobin's q to measure firm value (e.g., Arora et al., 2021; Gompers et al., 2003; Morck et al., 1988, among many others). Long-term firm values are calculated from a firm's Tobin's q averaged over the next n years. We investigate the relation between SciDs and firm value using the following panel regression:

$$\text{Avg Tobin's } q_{i,[t+1,t+n]} = \alpha_0 + \alpha_j + \alpha_t + \beta_1 \text{SciD}_{i,t} + X'_{i,t}\lambda + e_{i,t}, \tag{16}$$

where Avg Tobin's $q_{i,[t+1,t+n]}$ is the natural logarithm of the average Tobin's q of firm i from year 1 to year n. $\text{SciD}_{i,t}$ is an indicator variable equal to one if the firm has at least one SciD on the board for the full year t and is otherwise 0. X is a vector of firm control variables: size, R&D, CAPEX, firm age, annual returns, leverage, board independence, and the indicator for a scientific CEO. Regressions include SIC 4-digit industry and year-fixed effects, α_j and α_t. All standard errors are clustered at the 4-digit industry level.

Table 12 shows that firms with SciDs have superior long-term firm valuations than firms without SciDs within the same 4-digit industry. More specifically, the β_1 in column 1 is 0.034 and is significantly greater than zero, suggesting that over the next 2 years, firms with SciDs have a 3.4% larger firm valuation relative to other firms in the same industry lacking SciDs. Column 2 presents the relation between SciD and the firm valuation in the next three years and shows that firms with SciDs are associated with 3.1% larger firm valuation for the next three years compared to other firms within the same industry without SciDs. In column 3, the results reveal a 2.8% larger firm valuation associated with firms having SciDs over the subsequent three years relative to other firms within the same industry without SciDs. Moving to column 4, which uses Tobin's q averaged over the next 5 years, the coefficient indicates a 2.6% greater firm valuation over the following three years for firms with SciDs compared to other firms within the same industry without SciDs.

7 Conclusion

This paper provides novel evidence on the advisory role of directors, exploring how outside directors can enhance a firm's value through specialised expertise. Scientific Directors (SciD), who are outside directors with scientific knowledge, add value to a firm by advising a firm on its R&D programs and commercialization of its outstanding intellectual property. The positive market reactions to SciD appointments and the negative market reactions to SciD deaths underscore the valuation benefits of SciDs from a shareholder's viewpoint. We further evaluate the long-term firm valuation impact of SciDs using Tobin's Q as a forward looking measure. It reveals a positive association between firms with SciDs and long-term valuations compared to similar firms without SciDs within the same industry.

Moreover, we find that firms with SciDs are more productive in terms of innovation than other similar firms without SciDs in the same industry. We address the concern about the endogenous nature of director appointments using the local supply of SciD candidates as an IV to predict SciDs and separately use the Human Genome Project as an exogenous shock that raises the economic benefits of SciDs. Using 2SLS regressions, we find that firms have more SciDs on the board due to the larger local supply of SciD candidates, and these firms have more SciDs on their boards and they have better innovation outcomes than other firms in the same industry. Additionally, firms in the genetics-related industry hire more SciDs to their boards after the 2001 HGP shock compared to similar firms in other industries.

SciDs directly contribute to a firm's innovation activities by directly using their scientific expertise. More specifically, firms with SciDs experience an improvement in innovation output, and this improvement is greater as the scientific works of SciDs influence an increasing portion of a firm's patents. Besides, firms produce a greater number of patents, and these patents are of higher quality in the subject areas where a SciD has recently published more papers or received more citations, which we use to proxy for a SciD's current research focus.

Finally, we exploit the network community detection method in network analysis to map out the network associated with each SciD. Our network analysis only counts the layer-1 connections containing one million nodes that include the co-authors and co-inventors of SciDs and the SciD firms' other inventors. We also define the inner community of a SciD as the group of inventors who work closely with SciD. We conjecture that SciDs endogenously introduce productive inventors from their research community to the firms where they serve on the board and help the firm recruit and retain this scientific talent.

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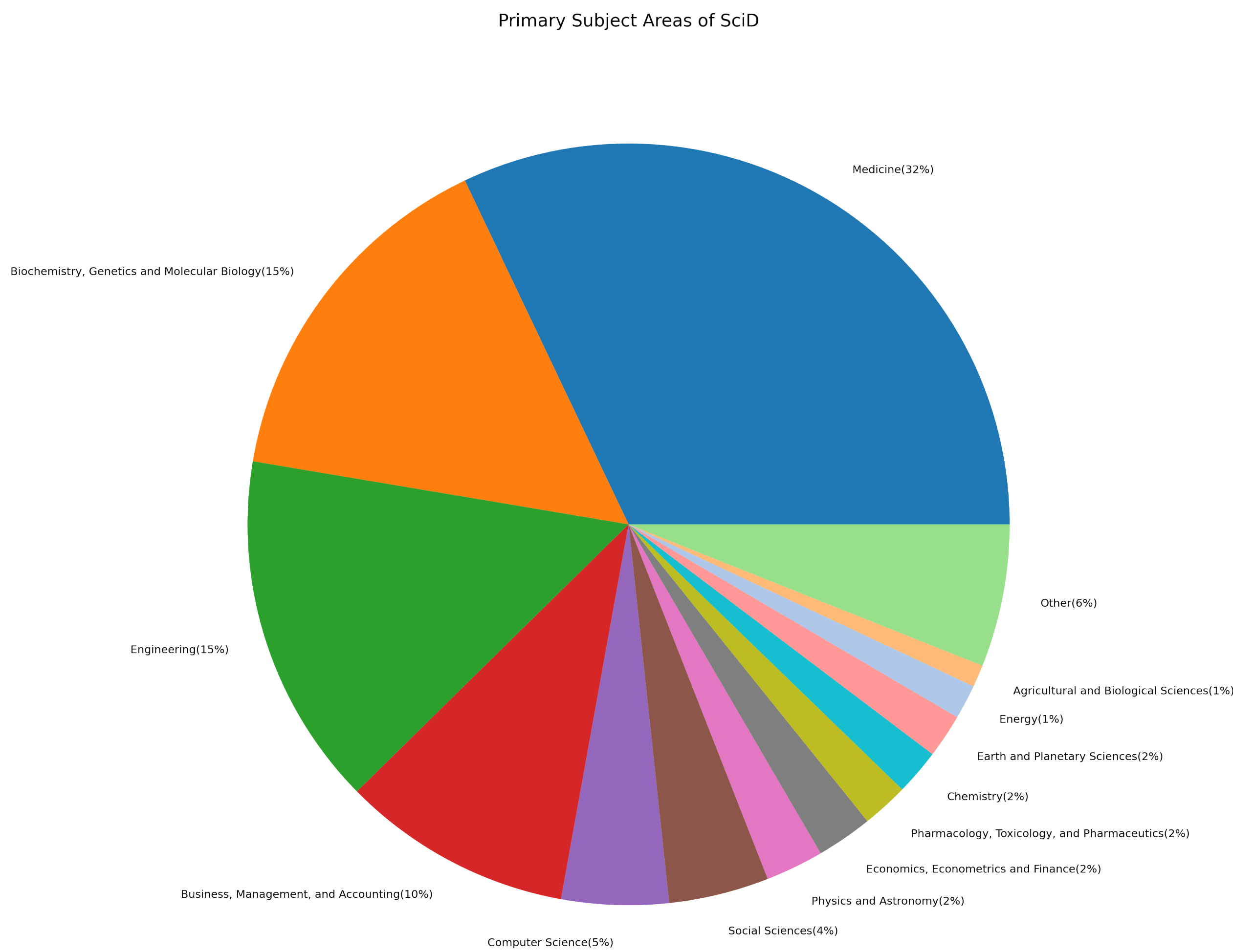

Figure 1

The pie chart illustrates the primary subject areas of SciD, defined as the 2-digit Scopus subject area where SciDs publish most frequently. The chart is based on a sample of 3,502 SciDs with publication records and subject area information available. The percentages of SciDs in specific subject areas are shown in parentheses. Subject areas comprising less than 1% are grouped under "Other", which are Arts and Humanities (0.86%), Immunology and Microbiology (0.86%), Materials Science (0.83%), Chemical Engineering (0.73%), Neuroscience (0.57%), Environmental Science (0.43%), Psychology (0.43%), Nursing (0.40%), Dentistry (0.29%), Decision Sciences (0.26%), Mathematics (0.26%), Veterinary(0.09%) and Health Professions (0.06%)

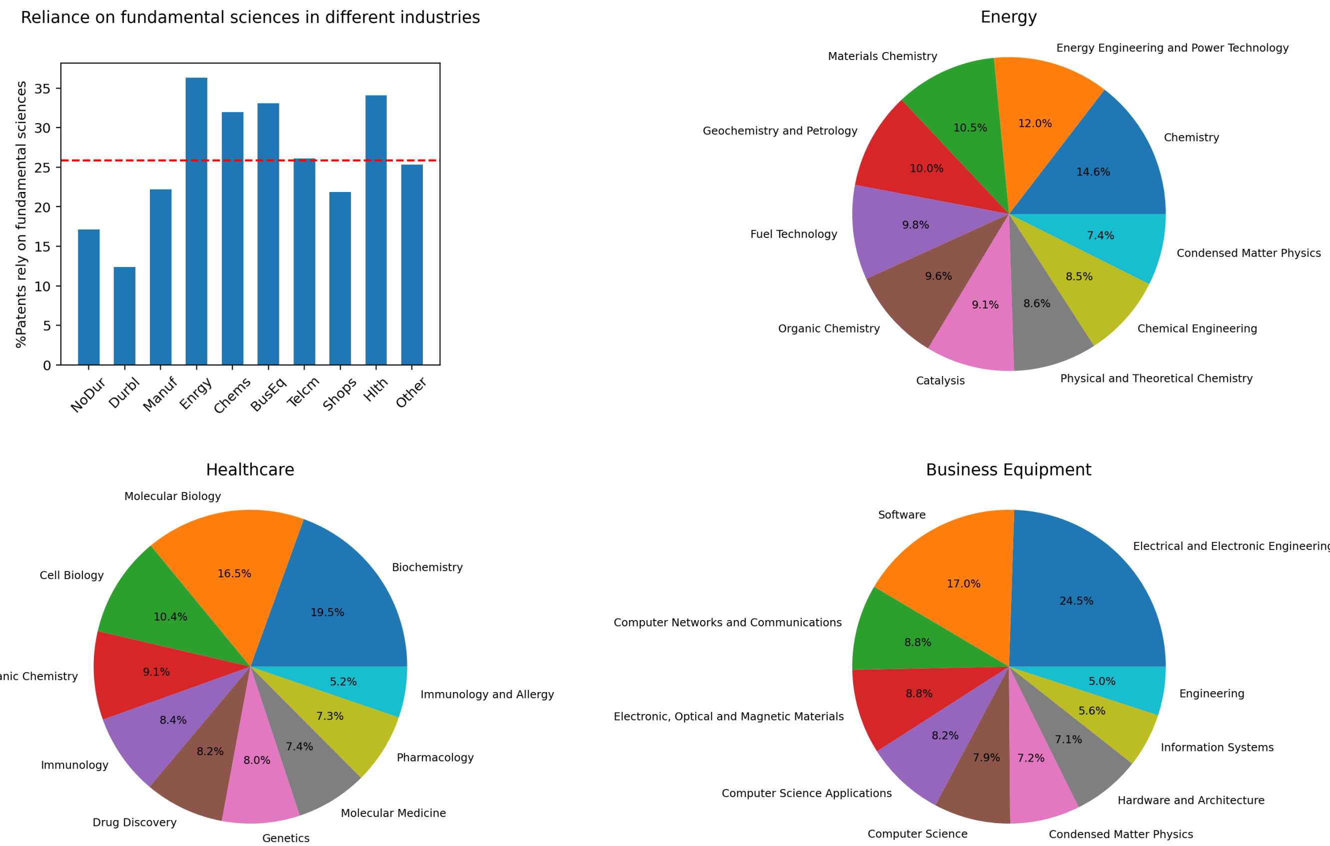

Figure 2

The bar chart illustrates the reliance on fundamental science across different industries, and the pie charts highlight the subject areas most relied upon by the patents in energy, healthcare, and business equipment industries. The bar chart illustrates the percentage of patents heavily relying on fundamental sciences across various Fama-French 12 industry classifications from 1996 to 2018. We define patents heavily relying on fundamental sciences as patents referencing more scientific publications than the 75th percentile of the patent distribution for the same technology class and grant year. Each bar represents a specific industry, showing the share of patents heavily relying on fundamental sciences over the total patents in that industry from 1996 to 2018. The red dashed line at 25.9% in the bar chart represents the average percentage of patents that rely on fundamental sciences per industry. Three pie charts present the top ten 4-digit Scopus subject areas most frequently referenced by patents in the industries of energy, healthcare, and business equipment. The top 10 subject areas highlighted represent at least 40% of publications referenced in each industry, and the fractions in each pie chart are reweighted to 100%, providing a focused perspective on the predominant scientific subject areas that each industry relies on.

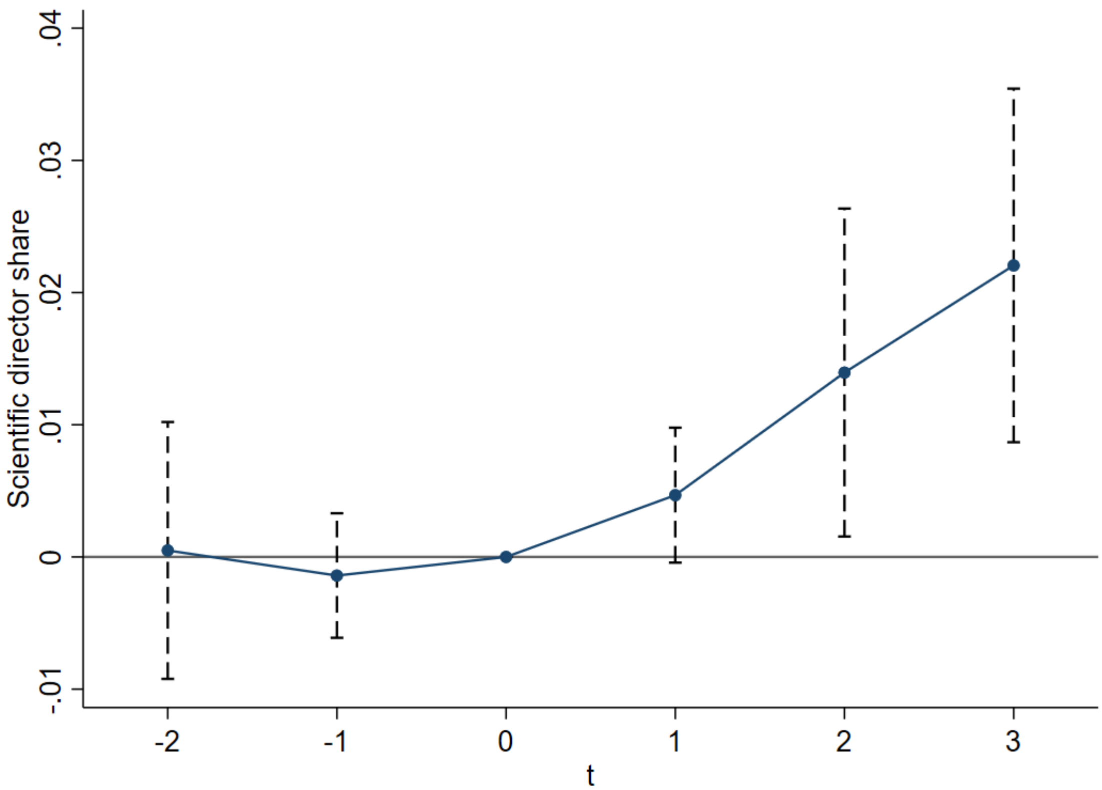

Figure 3

The figure plots differences (and 95% confidence intervals of the differences) between treatment and control firms regarding their changes in SciD share relative to the Human Genome Project event year. Treatment firms include those in the industry capable of converting human genome data into commercialized devices or products, which are drugs and pharmaceutical products (13) and lab equipment (37) in the Fama-French 48 industry classification. Control firms are firms in other industries. Our analysis is based on the event year 2001 when the full draft of the sequence and initial analysis of the HGP became publicly available.

Table 1
Firm characteristics

This table presents the firm characteristics between firms with and without a SciD. The sample is the CCM and BoardEx merged dataset from 1996 to 2018. Group A includes firm-year observations for firms with at least one SciD during the sample period, comprised of 48,064 firm-year observations. Group B includes observations during the sample period with zero SciDs, comprised of 20,460 firm-year observations. R&D, CAPEX, cash, free cash flow, and PPE are scaled by a firm's total assets at the beginning of the year. The data is winsorized at 1% and 99%. *, **. *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	With SciD (A)		Without SciD (B)				
	Mean	St. Dev.	Mean	St. Dev.	Diff. (A-B)	t-stat	P-val.
Firm Fundamental							
Log (Size)	6.11	2.11	5.53	1.79	0.58	36.85***	0.00
Leverage	0.20	0.21	0.24	0.23	-0.03	-18.09***	0.00
RD	0.09	0.21	0.03	0.09	0.06	49.41***	0.00
CAPEX	0.05	0.06	0.06	0.07	-0.01	-17.76***	0.00
Cash	0.25	0.26	0.17	0.20	0.08	44.22***	0.00
ROA	0.02	0.28	0.08	0.20	-0.05	-28.65***	0.00
Free Cash Flow	0.01	0.24	0.06	0.16	-0.05	-29.54***	0.00
PPE	0.23	0.22	0.28	0.25	-0.05	-24.69***	0.00
Log(Sale)	5.65	2.66	5.37	1.97	0.28	15.11***	0.00
Nasdaq	0.49	0.50	0.48	0.50	0.01	2.62***	0.01
Scientific CEO	0.13	0.33	0.03	0.18	0.09	37.57***	0.00
Age	18.33	14.96	14.14	12.26	4.19	35.32***	0.00
Valuation							
MV/BV	3.46	5.43	2.84	4.92	0.62	14.8***	0.00
Tobin's q	2.33	1.87	1.94	1.55	0.38	27.79***	0.00
Annual return	0.13	0.64	0.12	0.63	0.01	1.46	0.15
Firm Growth							
ΔAsset	0.12	0.39	0.11	0.36	0.01	2.06**	0.04
ΔSale	0.14	0.47	0.13	0.40	0.01	3.36***	0.00

Table 2
SciD characteristics

This table presents the SciD characteristics. Panel A shows the SciDs' characteristics regarding author profile and academic experience. The author profile contains *#Publications*, *h-index* and *citations* until 2021. The *#Publications* is the number of publications authored by a SciD. The *H-index* is a SciD's largest number h such that h publications have at least h citations. The *Citations* is the number of citations received by publications of a SciD. *Professor*, is an indicator variable that equals 1 if a SciD is a full-time professor in the university and 0. *Academic in Ivy League*, is an indicator variable that equals 1 if a SciD holds or has held an academic position in Ivy League universities and 0. Panel B compares SciD and non-SciDs regarding education credentials, patent activity, experience, age, tenure, executive activities in other firms, and an affiliated director indicator. *MBA(JD)*, is an indicator variable that equals 1 if a director holds an MBA(JD) degree and is 0 otherwise. *Inventor Dir.*, is an indicator variable that equals 1 if a director is a patent inventor and 0. *Finance(Executive) Exp.*, is an indicator variable that equals to 1 if a director has finance(executive) experience and is 0 otherwise. *Age(Tenure)* is a director's age(tenure) in year t. *Executive in other*, is an indicator variable that equals 1 if a director is executive in other firms and is 0 otherwise. *Affiliated director*, is an indicator variable that equals 1 if a director is an affiliated director and is 0 otherwise. Panel C contains 2,199 inventor directors. Inventor directors are outside directors who are patent inventors. 1,097 inventor directors are SciDs, and 1,102 are non-SciDs. We compare the patent portfolio of Scientific inventor directors to non-scientific inventor directors in terms of *#Patents*, *Adj. cites*, *Scope*, *Generality* and *Originality*. *#Patents* is the number of patents for inventor directors' patent portfolios. *Adj.cites* is the average adjusted citations per patent for inventor directors' patent portfolios. The citations are adjusted by the technology class and grant year-fixed effects to minimize the truncation issue of patent data, followed by Hall et al. (2001). *Scope* is the average scope per patent for inventor directors' patent portfolios. *Generality* is the average generality per patent for inventor directors' patent portfolios. *Originality* is the average originality per patent for inventor directors' patent portfolios. *, **. *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: SciD characteristics

	Author Profile			Academic Exp.	
	#Publications	H-index	Citations	Professor	Academic in Ivy League
Obs.	6236	6236	6236	6236	6236
Mean	45.96	12.18	3337.06	0.27	0.05
St.Dev.	125.99	25.63	13542.42	0.45	0.22
Min	0.00	0.00	0.00	0.00	0.00
25%	0.00	0.00	0.00	0.00	0.00
50%	2.00	1.00	4.00	0.00	0.00
75%	25.00	11.00	823.00	1.00	0.00
Max	2447.00	356.00	388360.00	1.00	1.00

Table 2
SciD characteristics

Panel B: SciD and Non-SciD

	Scientific Directors (SciDs)		Non-Scientific Directors (Non-SciDs)				
	Mean	St.Dev.	Mean	St.Dev.	Diff.(SciDs−Non-SciDs)	t-stat	P-val.
Firm-Director-Year level comparison							
Age	62.28	8.79	60.41	9.48	1.87	46.11***	0.00
Tenure	7.04	5.86	6.99	6.07	0.05	1.79*	0.07
Executive in other firms	0.05	0.22	0.06	0.23	-0.01	-5.48***	0.00
Affiliated director	0.01	0.12	0.02	0.14	-0.01	-11.53***	0.00
Director level comparison							
MBA	0.17	0.37	0.32	0.46	-0.15	-23.99***	0.00
JD	0.04	0.19	0.08	0.27	-0.04	-12.34***	0.00
Finance Exp.	0.27	0.44	0.42	0.49	-0.15	-21.84***	0.00
Executive Exp.	0.83	0.38	0.93	0.26	-0.10	-25.38***	0.00
Inventor Dir.	0.18	0.38	0.03	0.18	0.14	46.1***	0.00

Panel C: Inventor directors

	Scientific Directors (SciDs)		Non-Scientific Directors (Non-SciDs)				
	Mean	St.Dev.	Mean	St.Dev.	Diff.(SciDs−Non-SciD)s	t-stat	P-val.
#Patents	23.52	46.95	9.68	16.29	13.84	9.24***	0.00
Adj. Cites	1.85	3.81	1.75	3.97	0.10	2.12**	0.03
Scope	2.33	1.65	1.93	1.28	0.40	21.78***	0.00
Generality	0.60	0.25	0.57	0.26	0.03	8.87***	0.00
Originality	0.90	0.15	0.88	0.16	0.02	10.46***	0.00
N	1097		1102				

Table 3
SciD presence and the reliance on fundamental science

This table presents Probit and Poisson regression models examining the relation between SciD presence and the firm's reliance on fundamental science. The independent variable is the firm's reliance on fundamental science, calculated as the ratio of patents that heavily rely on fundamental science to the total number of patents over the past three years. Patents that heavily rely on fundamental science are those patents referencing more scientific publications than the 75th percentile value within the patent distribution for the same technology class and grant year. Columns 1 and 2 present the Probit regression of SciD appointment on the firm's patent reliance on fundamental science. The dependent variable in column 1 is an indicator variable that equals 1 if the firm appoints a SciD in the following year and 0 otherwise. Additionally, we categorize a SciD as relevant if their expertise aligns with at least one of the three subject areas most frequently referenced by the firm's patents in the past three years. The dependent variable in column 2 is the indicator variable that equals 1 if the firm appoints a relevant SciD in the following year and 0 otherwise. Columns 3 and 4 present Poisson regression models for the number of SciDs and the number of relevant SciDs, respectively, in relation to the firm's reliance on fundamental science. The dependent variable in column 3 is the number of SciDs on the board in year t+1. The dependent variable in column 4 is the number of relevant SciDs on the board in year t+1. Control variables are firm size, CAPEX, R&D, firm age, annual return, leverage, board independence, a scientific CEO indicator, the number of patents, PPE, and Cash. Variable definitions are in Table A.1. All regressions include firm and year-fixed effects. Standard errors are clustered at the SIC 4-digit industry level. Robust standard errors are reported in parentheses.*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Probit Regression		Poisson Regression	
	SciD Appt.	Rel. SciD Appt.	No. SciD	No. Rel. SciD
		t+1		
	(1)	(2)	(3)	(4)
Reliance on Fundamental Science	0.196***	0.865***	0.044	1.507***
	(0.070)	(0.140)	(0.046)	(0.192)
Size	0.093***	0.010	0.101***	0.056**
	(0.017)	(0.040)	(0.013)	(0.028)
CAPX	-0.128	-0.583	0.081	0.263
	(0.277)	(1.001)	(0.116)	(0.453)
RD	0.145***	0.199***	0.077***	0.113***
	(0.053)	(0.072)	(0.020)	(0.041)
Age	-0.049	-0.270***	0.157***	-0.002
	(0.039)	(0.086)	(0.030)	(0.072)
Annual Return	0.042***	0.014	-0.001	0.003
	(0.014)	(0.037)	(0.004)	(0.013)
Leverage	0.086	-0.158	-0.071	-0.190**
	(0.063)	(0.108)	(0.047)	(0.077)
Board Independence	-1.560***	-1.091***	0.900***	0.865***
	(0.129)	(0.256)	(0.061)	(0.230)
Scientific CEO	-0.028	0.149*	0.026	0.137***
	(0.042)	(0.088)	(0.025)	(0.045)
#Patents	0.034**	0.181***	0.005	0.183***
	(0.017)	(0.035)	(0.009)	(0.020)
PPE	0.117	1.252***	0.194**	0.322
	(0.154)	(0.309)	(0.086)	(0.230)
Cash	0.103	0.214	0.127***	0.204**
	(0.083)	(0.148)	(0.043)	(0.081)
Constant	-1.483***	-0.911	-1.268***	-2.099***
	(0.224)	(0.589)	(0.153)	(0.406)
Observations	34,613	6,352	41,740	11,119
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	Industry	Industry	Industry	Industry
Pseudo R-squared	0.099	0.101	0.249	0.255

Table 4
Scientific Directors and innovation output

This table reports regression models examining the relation between SciDs and firm innovation. $\#Patents_{t+1,t+3}$ (columns 1 and 2) are defined as firm i's the total number of patents filed (and eventually granted) for the next 3 years. $Avg.Adj.cites_{t+1,t+3}$ (columns 3 and 4) are defined as firm i's average adjusted citation per patent filed (and eventually granted) for the next 3 years. The citations are adjusted by the technology class and grant year fixed effects to minimize the truncation issue of patent data, followed by Hall et al. (2001). $Avg.Value_{t+1,t+3}$ (columns 5 and 6) are defined as firm i's average market value(Kogan et al., 2017) per patents of patents filed (and eventually granted) for the next n years. $\#B.through\ Patents_{t+1,t+3}$ (columns 7 and 8) are defined as firm i's total number of breakthrough patents filed (and eventually granted) for the next 3 years. The breakthrough patents are influential patents that received more citations than the 90th percentile values of the patents in the same technology class and grant year. $\#Funda.\ Patents_{t+1,t+3}$ (columns 9 and 10) are defined as firm i's total number of fundamental patents (and eventually granted) for the next 3 years. The fundamental patents are patents that cite at least one scientific publication and received more citations than the 75th percentile values of the patents in the same technology class and grant year. *SciD* is an indicator variable that equals one if firms have at least one SciD in the year t and zero otherwise. Control variables are firm size, CAPEX, R&D, firm age, annual return, leverage, board independence and a scientific CEO indicator. Panel A employs the OLS regressions, and we use the log transformation for dependent variables in Panel A, which is the logarithm of one plus innovation output. Panel B presents Poisson regression coefficients for raw innovation output and the OLS regression of Log ($Avg.Value_{t+1,t+3}$) since $Avg.Value_{t+1,t+3}$ is not a count variable, against the SciD indicator variable. Variable definitions are in Table A.1. All regressions include SIC 4-digit industry and year-fixed effects. Standard errors in columns 1, 3, 5, 7 and 9 clustered at the firm level are reported in parentheses. Standard errors in columns 2, 4, 6, 8 and 10 clustered at the SIC 4-digit industry level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: OLS Regression

	#Patents		Avg.Adj.cites		Avg.Values		#B.through Patents		#Funda. Patents	
	t+1,t+3		t+1,t+3		t+1,t+3		t+1,t+3		t+1,t+3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SciD	0.176***	0.176***	0.029***	0.029***	0.056***	0.056***	0.093***	0.093***	0.088***	0.088***
	(0.033)	(0.040)	(0.010)	(0.010)	(0.020)	(0.021)	(0.023)	(0.025)	(0.024)	(0.022)
Size	0.448***	0.448***	0.058***	0.058***	0.315***	0.315***	0.287***	0.287***	0.262***	0.262***
	(0.016)	(0.039)	(0.003)	(0.005)	(0.009)	(0.016)	(0.013)	(0.029)	(0.029)	(0.013)
CAPX	0.872***	0.872***	0.174***	0.174**	0.363**	0.363	0.750***	0.750***	0.610***	0.610***
	(0.227)	(0.336)	(0.061)	(0.079)	(0.155)	(0.267)	(0.161)	(0.260)	(0.230)	(0.155)
RD	1.216***	1.216***	0.315***	0.315***	0.533***	0.533***	0.623***	0.623***	0.667***	0.667***
	(0.151)	(0.257)	(0.045)	(0.070)	(0.067)	(0.117)	(0.090)	(0.132)	(0.140)	(0.094)
Age	0.070***	0.070***	-0.015***	-0.015**	0.056***	0.056***	0.034**	0.034*	0.033*	0.033**
	(0.022)	(0.025)	(0.006)	(0.008)	(0.013)	(0.018)	(0.016)	(0.018)	(0.018)	(0.015)
Annual Return	0.040***	0.040***	0.016***	0.016***	0.068***	0.068***	0.034***	0.034***	0.029***	0.029***
	(0.007)	(0.009)	(0.003)	(0.004)	(0.005)	(0.009)	(0.005)	(0.007)	(0.006)	(0.005)
Leverage	-0.545***	-0.545***	-0.139***	-0.139***	-0.310***	-0.310***	-0.309***	-0.309***	-0.303***	-0.303***
	(0.080)	(0.108)	(0.022)	(0.027)	(0.050)	(0.079)	(0.059)	(0.067)	(0.068)	(0.058)
Board Independence	0.283***	0.283***	0.101***	0.101***	0.154**	0.154***	0.095	0.095	0.061	0.061
	(0.098)	(0.105)	(0.030)	(0.031)	(0.060)	(0.056)	(0.069)	(0.072)	(0.073)	(0.068)
Scientific CEO	0.474***	0.474***	0.099***	0.099***	0.230***	0.230***	0.308***	0.308***	0.330***	0.330***
	(0.074)	(0.082)	(0.019)	(0.020)	(0.041)	(0.044)	(0.058)	(0.053)	(0.060)	(0.059)
Constant	-2.030***	-2.030***	-0.097***	-0.097***	-1.485***	-1.485***	-1.414***	-1.414***	-1.315***	-1.315***
	(0.120)	(0.245)	(0.027)	(0.031)	(0.069)	(0.114)	(0.093)	(0.193)	(0.188)	(0.093)
Observations	51,139	51,139	51,139	51,139	51,139	51,139	51,139	51,139	51,139	51,139
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Industry	Firm	Industry	Firm	Industry	Firm	Industry	Firm	Industry
Adj. R^2	0.543	0.543	0.311	0.311	0.455	0.455	0.430	0.430	0.392	0.392

Panel B Poisson Regression

	#Patents		Avg.Adj.cites		Avg.Values		#B.through Patents		#Funda. Patents	
	t+1,t+3		t+1,t+3		t+1,t+3		t+1,t+3		t+1,t+3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SciD	0.320*	0.320	0.149***	0.149***	0.011	0.011	0.328**	0.328*	0.378*	0.378**
	(0.172)	(0.240)	(0.056)	(0.051)	(0.034)	(0.027)	(0.155)	(0.193)	(0.222)	(0.171)
Size	0.947***	0.947***	0.142***	0.142***	0.637***	0.637***	0.848***	0.848***	0.896***	0.896***
	(0.032)	(0.039)	(0.015)	(0.020)	(0.013)	(0.019)	(0.035)	(0.042)	(0.055)	(0.043)
CAPX	3.087**	3.087***	0.741*	0.741*	1.165***	1.165***	3.745***	3.745***	2.492***	2.492*
	(1.198)	(1.129)	(0.384)	(0.435)	(0.301)	(0.300)	(1.119)	(0.921)	(0.805)	(1.389)
RD	1.331***	1.331***	0.488***	0.488***	0.757***	0.757***	1.178***	1.178***	1.235***	1.235***
	(0.120)	(0.144)	(0.074)	(0.065)	(0.087)	(0.107)	(0.124)	(0.128)	(0.136)	(0.121)
Age	0.187	0.187	-0.112***	-0.112***	-0.149***	-0.149***	0.084	0.084	0.126	0.126
	(0.137)	(0.175)	(0.029)	(0.037)	(0.022)	(0.029)	(0.117)	(0.132)	(0.200)	(0.156)
Annual Return	0.108***	0.108***	0.073***	0.073***	0.216***	0.216***	0.146***	0.146***	0.131***	0.131***
	(0.031)	(0.027)	(0.016)	(0.021)	(0.010)	(0.015)	(0.031)	(0.029)	(0.034)	(0.038)
Leverage	-0.105	-0.105	-0.594***	-0.594***	-0.134	-0.134	-0.592	-0.592	-0.617	-0.617
	(0.382)	(0.465)	(0.130)	(0.166)	(0.089)	(0.136)	(0.411)	(0.465)	(0.510)	(0.468)
Board Independence	1.747***	1.747***	0.360**	0.360***	0.075	0.075	1.429***	1.429***	1.639***	1.639***
	(0.479)	(0.410)	(0.147)	(0.133)	(0.112)	(0.101)	(0.432)	(0.354)	(0.413)	(0.536)
Scientific CEO	0.285***	0.285**	0.210***	0.210***	0.078*	0.078	0.311***	0.311**	0.421***	0.421***
	(0.103)	(0.122)	(0.072)	(0.080)	(0.047)	(0.055)	(0.118)	(0.133)	(0.139)	(0.117)
Constant	-4.965***	-4.965***	-1.132***	-1.132***	-2.652***	-2.652***	-5.405***	-5.405***	-6.190***	-6.190***
	(0.728)	(1.188)	(0.128)	(0.152)	(0.120)	(0.163)	(0.636)	(0.849)	(1.115)	(0.798)
Observations	48,978	48,978	48,700	48,700	22,149	22,149	44,956	44,956	42,393	42,393
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Industry	Firm	Industry	Firm	Industry	Firm	Industry	Firm	Industry
Adj. R^2					0.684	0.684				
Pseudo R^2	0.848	0.848	0.184	0.184			0.762	0.762	0.763	0.763

Table 5
IV: Local Scientific Director(Local SciD) supply

This table presents the 2SLS regressions model using the Local Scientific Director(Local SciD) supply as the Instrument Variable(IV). The IV is the *Local SciD supply*, the logarithm of one plus the number of SciDs in the firm within 100 miles of focal firms' headquarters, excluding firms in the same SIC4 industry code. The instrumented variable is the *Scientific Director share(SciD share)*, which is the share of SciDs over the total number of directors on the board. Following by Knyazeva et al. (2013), the sample excludes firms in Alaska and Hawaii, firm-year observations with total assets less than 20 million and large firms in the top 25th percentile of total asset distribution. Column 1 shows the first-stage regression of SciD share on the local SciD supply. Columns 2 - 6 present the second stage regression of innovation output on $\widehat{\text{SciD share}}$. $\#Patents_{t+1,t+3}$ (column 2) is defined as the natural logarithm of one plus the firm i's the total number of patents filed (and eventually granted) for the next 3 years. $Avg.Adj.cites_{t+1,t+3}$ (column 3) are defined as the natural logarithm of one plus firm i's average adjusted citation per patent received on the firm's patents filed (and eventually granted) for the next 3 years. The citations are adjusted by the technology class and grant year fixed effects, followed by Hall et al. (2001). $Avg.\ Value_{t+1,t+3}$ (column 4) are defined as the natural logarithm of one plus firm i's average market value (Kogan et al., 2017) per patent of patents filed (and eventually granted) for the next 3 years. $\#B.through\ Patents_{t+1,t+3}$ (column 5) are defined as the natural logarithm of the firm i's breakthrough patents at 90th percentiles filed (and eventually granted) for the next 3 years. $\#Funda.\ Patents_{t+1,t+3}$ (column 6) are defined as the logarithm of one plus firm i's total number of fundamental patents (and eventually granted) for the next 3 years. Control variables are firm size, CAPEX, R&D, firm age, annual return, leverage, board independence, board size, a scientific CEO indicator and local scientists supply. Variable definitions are in Table A.1. All regressions include year and SIC 3-digit industry fixed effects. Standard errors clustered at the industry level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Local Scientific Director(Local SciD) supply						
	1st	2nd				
	SciD Share	#Patents	Avg. Adj. cites	Avg. Values	#B.through Patents	#Funda. Patents
		t+1,t+3				
	(1)	(2)	(3)	(4)	(5)	(6)
Local SciD Supply	0.005**					
	(0.002)					
$\widehat{\text{SciD Share}}$		12.488**	3.011	7.730*	5.743*	7.681**
		(6.183)	(2.336)	(4.632)	(3.414)	(3.588)
Size	0.004***	0.265***	0.036**	0.198***	0.147***	0.139***
	(0.001)	(0.064)	(0.015)	(0.037)	(0.040)	(0.042)
CAPX	-0.032	0.830	0.267*	0.637**	0.604**	0.523
	(0.034)	(0.522)	(0.148)	(0.319)	(0.296)	(0.337)
RD	0.128***	0.726	0.201	0.041	0.349	0.462
	(0.014)	(0.887)	(0.293)	(0.536)	(0.515)	(0.554)
Age	-0.000	-0.063	-0.026	-0.028	-0.059	-0.058
	(0.006)	(0.077)	(0.022)	(0.056)	(0.041)	(0.048)
Annual Return	-0.002**	0.070***	0.021***	0.088***	0.051***	0.052***
	(0.001)	(0.014)	(0.005)	(0.010)	(0.007)	(0.006)
Leverage	-0.044***	0.231	0.039	0.266	0.121	0.198
	(0.008)	(0.329)	(0.118)	(0.215)	(0.207)	(0.219)
Board Independence	0.166***	-1.801*	-0.382	-1.146	-0.822	-1.167*
	(0.038)	(1.003)	(0.394)	(0.749)	(0.580)	(0.645)
Board Size	0.024***	-0.144	-0.037	-0.076	-0.024	-0.060
	(0.009)	(0.185)	(0.060)	(0.116)	(0.091)	(0.102)
Scientific CEO	0.049***	-0.180	-0.056	-0.207	-0.017	-0.056
	(0.006)	(0.278)	(0.119)	(0.224)	(0.172)	(0.172)
Local Scientists Supply	0.001	-0.030**	-0.008	-0.016*	-0.016**	-0.018**
	(0.001)	(0.012)	(0.005)	(0.009)	(0.007)	(0.008)
Observations	40,743	32,586	32,586	32,586	32,586	32,586
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Industry	Industry	Industry	Industry	Industry	Industry
F statistic	39.65					

Table 6
Human Genome Project

This table presents Difference-in-Difference (DiD) models using the Human Genome Project (HGP). HGP is an international research project that identifies, maps and sequences all the genes of the human genome from 1990 to 2003. HGP published a draft sequence and initial analysis of the human genome in the journal Nature in 2001. The publicly available human genome data increases the economic benefits that SciDs bring to a firm, as SciD can utilize their expertise to help advance the firm develop genetic products. *Treatment* is an indicator variable that equals one if the firm is in the genetics-related industry and zero otherwise. The genetics-related industry includes drugs and pharmaceutical products (13) and lab equipment (37) based on the Fama-French 48 industries classification. *Post* is an indicator variable that equals 1 if the year is greater than the event year and zero otherwise. The event year is 2001, when the draft sequence and initial analysis of HGP are publicly available. $\textit{SciD share}_t$ (column 1) is defined as the share of SciDs over the total number of directors in the firm. $\textit{GD share}_t$ (column 2) is defined as the share of SciD with genetics expertise over the total number of directors in the firm. $\textit{Avg.Values}_{t+1}$ (column 3) is defined as the natural logarithm of firm i's average market value (Kogan et al., 2017) of patents filed in year t+1. $\textit{Avg.Adj.cites}_{t+1}$ (column 4) is defined as the firm i's average adjusted citation per patent filed (and eventually granted) in year t+1. The citations are adjusted by the technology class and grant year-fixed effects, followed by Hall et al. (2001). $\#\textit{Patents}_{t+1}$ (column 5) is defined as the total number of patents in year t+1. $\#\textit{B.through Patents(90/99)}_{t+1}$ (columns 6 and 7) is defined as firm i's the total number of breakthrough patents at the 90th/99th percentiles of all patents in the same technology class and grant year filed (and eventually granted) in year t+1. Columns 1, 2 and 3 use the OLS regression model. Columns 4, 5, 6 and 7 use the Poisson regression model. Control variables are firm size, CAPEX, R&D, firm age, annual stock return, leverage, board independence and a scientific CEO indicator. Variable definitions are in Table A.1. Panel B repeats the analysis on the treatment and propensity score matched control group. The matching variables are size, ROA, annual return and #Patents up to the event year 2001. Table A7 shows that the differences in the covariates of treatment and control groups are statistically insignificant after matching. All regressions have firm and year-fixed effects. Standard errors are clustered at the SIC 4-digit industry level. Robust standard errors are reported in parentheses.*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A Full sample

	OLS Regressions Non-Count Variables			Poisson Regressions Count Variables			
	SciD Share	GD Share	Avg.Values	Avg.Adj.cites	#Patents	#B.through Patents (90)	#B.through Patents (99)
	t+0		t+1				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment * Post	0.024**	0.019***	0.204**	0.136*	-0.561***	-0.191	0.684**
	(0.011)	(0.005)	(0.094)	(0.072)	(0.093)	(0.125)	(0.280)
Size	0.006***	0.000	0.111***	0.042*	0.461***	0.348***	0.193
	(0.001)	(0.001)	(0.030)	(0.024)	(0.075)	(0.089)	(0.134)
CAPEX	0.000	0.001	0.940***	0.039	1.527	1.970*	2.921*
	(0.012)	(0.003)	(0.328)	(0.274)	(0.968)	(1.018)	(1.531)
RD	0.013***	0.011***	0.125	0.090*	0.892***	0.807***	0.834
	(0.003)	(0.004)	(0.088)	(0.053)	(0.276)	(0.250)	(0.519)
Age	0.008**	-0.001	-0.161***	-0.204***	-0.165	-0.187	-0.123
	(0.003)	(0.001)	(0.057)	(0.061)	(0.121)	(0.139)	(0.207)
Annual Return	-0.001	0.000	0.103***	0.041***	0.023	0.037*	0.068**
	(0.001)	(0.000)	(0.009)	(0.014)	(0.024)	(0.022)	(0.027)
Leverage	-0.008*	-0.001	-0.056	-0.299***	-0.740***	-0.728***	-1.109***
	(0.005)	(0.002)	(0.091)	(0.098)	(0.189)	(0.269)	(0.365)
Board Independence	0.156***	0.018***	-0.304**	-0.051	0.190	0.151	0.083
	(0.014)	(0.006)	(0.125)	(0.142)	(0.197)	(0.215)	(0.501)
Scientific CEO	0.002	-0.001	0.002	0.066	0.025	0.038	0.051
	(0.005)	(0.002)	(0.034)	(0.055)	(0.068)	(0.084)	(0.118)
Constant	-0.049***	0.001	1.131***	0.608***	1.873***	0.944	0.329
	(0.014)	(0.005)	(0.240)	(0.222)	(0.650)	(0.661)	(1.146)
Observations	62,718	62,718	19,247	32,722	33,377	24,008	11,192
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adj. R^2	0.780	0.803	0.867				
Pseudo R^2				0.294	0.932	0.847	0.669

Table 6
Human Genome Project

Panel B Matched sample

	OLS Regressions Non-Count Variables			Poisson Regressions Count Variables			
	SciD Share	GD Share	Avg.Values	Avg.Adj.cites	#Patents	#B.through Patents (90)	#B.through Patents (99)
	t+0				t+1		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment * Post	0.025**	0.019***	0.255**	0.150*	-0.487***	-0.163	0.598**
	(0.012)	(0.005)	(0.100)	(0.078)	(0.138)	(0.139)	(0.272)
Size	0.005**	0.001	0.141***	0.043	0.428***	0.297**	0.032
	(0.002)	(0.001)	(0.040)	(0.038)	(0.114)	(0.142)	(0.188)
CAPEX	0.004	0.000	0.752	-0.446	0.028	1.364	3.183
	(0.025)	(0.007)	(0.461)	(0.438)	(1.247)	(1.654)	(2.447)
RD	0.009**	0.014***	0.162	0.131*	0.837***	0.666**	0.560
	(0.004)	(0.005)	(0.101)	(0.068)	(0.272)	(0.272)	(0.550)
Age	0.011*	-0.004	-0.150*	-0.049	-0.293	-0.326	-0.480*
	(0.006)	(0.004)	(0.087)	(0.085)	(0.201)	(0.243)	(0.288)
Annual Return	-0.000	0.000	0.098***	0.041**	0.010	0.056	0.114***
	(0.001)	(0.000)	(0.011)	(0.018)	(0.035)	(0.037)	(0.040)
Leverage	-0.011	-0.001	0.007	-0.265	-0.741***	-0.213	-0.316
	(0.008)	(0.002)	(0.120)	(0.176)	(0.259)	(0.217)	(0.355)
Board Independence	0.179***	0.028**	-0.321	-0.170	0.191	-0.119	-0.299
	(0.021)	(0.011)	(0.196)	(0.215)	(0.246)	(0.231)	(0.766)
Scientific CEO	-0.002	-0.002	0.057	-0.035	-0.000	-0.100	-0.197*
	(0.006)	(0.003)	(0.041)	(0.071)	(0.064)	(0.131)	(0.111)
Constant	-0.044*	0.007	0.729**	0.379	3.104**	2.299**	3.533**
	(0.026)	(0.011)	(0.345)	(0.316)	(1.305)	(1.120)	(1.717)
Observations	22,943	22,943	8,415	14,333	14,531	10,425	4,656
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adj. R-squared	0.777	0.781	0.856				
Pseudo R-squared				0.290	0.941	0.862	0.719

Table 7
Scientific Director's influence on the firm's patents

This table reports regression models examining the relation between SciDs' influence and innovation output. *SciD influence*$_{\mathtt{i,d,t}}$ is SciD $\mathtt{d}$'s influence on firm $\mathtt{i}$'s patents, in year $\mathtt{t}$, which is $\frac{\text{Cum \#SciDIP}_{\mathtt{i,d,[t-n,t]}}}{\text{Cum \#Patents}_{\mathtt{i,[t-n,t]}}}$. The SciD-influenced patent (SciDIP) is the firm's patent that cites at least one SciD's publications while the SciD is on the board. The numerator of *SciD influence*$_{\mathtt{i,d,t}}$ is the cumulative number of the SciDIP from the year SciDs join the board of firm $\mathtt{i}$ until year $\mathtt{t}$. *#Patents*$_{\mathtt{t+1,t+n}}$ (columns 1 and 2) are defined as firm $\mathtt{i}$'s total number of patents filed (and eventually granted) from year t+1 to t+n. *Avg.Adj.Cites*$_{\mathtt{t+1,t+n}}$ (columns 3 and 4) are defined as the firm $\mathtt{i}$'s average adjusted citation per patent filed (and eventually granted) for the next n years. The citations are adjusted by the technology class and grant year fixed effects, followed by Hall et al. (2001). *Avg.Value*$_{\mathtt{t+1,t+n}}$ (columns 5 and 6) are defined as firm $\mathtt{i}$'s average market value (Kogan et al., 2017) of patents filed from year $\mathtt{t+1}$ to $\mathtt{t+n}$. *B.through patents* $_{\mathtt{t+1,t+n}}$ (columns 7 and 8) is defined as firm $\mathtt{i}$'s total number of breakthrough patents filed (and eventually granted) for the next n years. The breakthrough patents are influential patents that received more citations than the 90th percentile values of the patents in the same technology class and grant year. The regression sample is at the firm, SciD and year level. Control variables are firm size, CAPEX, R&D, firm age, annual return, leverage, board independence and a scientific CEO indicator. Panel A employs the OLS regressions, and we use the log transformation for dependent variables in Panel A, which is the logarithm of one plus innovation output. Panel B presents the results of Poisson regressions of raw innovation output and the OLS regression of Log (*Avg.Value*$_{\mathtt{t+1,t+n}}$) since *Avg.Value*$_{\mathtt{t+1,t+n}}$ is not a count variable, against the SciD influence. Variable definitions are in Table A.1. All regressions include firm×director and year-fixed effects. Standard errors clustered at the SIC 4-digit industry are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A OLS Regression

	#Patents		Avg.Adj.Cites		Avg.Values		#B.through Patents	
	t+1,t+3	t+1,t+5	t+1,t+3	t+1,t+5	t+1,t+3	t+1,t+5	t+1,t+3	t+1,t+5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SciD influence	0.178	-0.030	0.387***	0.215***	0.385***	0.384***	0.688***	0.946***
	(0.268)	(0.274)	(0.062)	(0.041)	(0.128)	(0.074)	(0.137)	(0.230)
Size	0.131***	0.115***	0.003	-0.004	0.015	0.002	0.060***	0.053***
	(0.016)	(0.016)	(0.005)	(0.006)	(0.013)	(0.014)	(0.012)	(0.012)
CAPEX	0.143	0.084	-0.018	0.004	0.061	0.169**	0.079	0.012
	(0.104)	(0.092)	(0.036)	(0.036)	(0.074)	(0.082)	(0.096)	(0.104)
RD	0.085***	0.069**	0.044	0.011	0.057***	0.004	0.038	0.048*
	(0.029)	(0.034)	(0.041)	(0.021)	(0.021)	(0.015)	(0.041)	(0.025)
Age	-0.012	0.010	-0.036**	-0.018	0.015	0.047	0.009	0.023
	(0.043)	(0.048)	(0.017)	(0.017)	(0.030)	(0.032)	(0.027)	(0.034)
Annual Return	0.011***	0.007*	0.003	-0.002	0.016***	0.009***	0.008***	0.006**
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Leverage	-0.212***	-0.142***	-0.047***	-0.035**	-0.022	0.040	-0.138***	-0.105**
	(0.042)	(0.040)	(0.014)	(0.017)	(0.073)	(0.067)	(0.039)	(0.043)
Board Independence	0.137**	0.100*	0.059**	0.063*	-0.072	-0.028	0.054	0.052
	(0.060)	(0.059)	(0.026)	(0.033)	(0.055)	(0.060)	(0.047)	(0.052)
Scientific CEO	0.148***	0.118**	0.022	0.004	0.036	0.021	0.069	0.021
	(0.055)	(0.054)	(0.022)	(0.027)	(0.036)	(0.033)	(0.043)	(0.054)
Constant	0.658***	1.079***	0.401***	0.433***	0.809***	0.852***	0.342***	0.572***
	(0.164)	(0.185)	(0.060)	(0.062)	(0.107)	(0.114)	(0.106)	(0.134)
Observations	70,828	57,101	70,828	57,101	70,828	57,101	70,828	57,101
Firm * Director FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adj. R^2	0.940	0.960	0.723	0.786	0.866	0.896	0.923	0.948

Panel B Poisson Regression

	#Patents		Avg.Adj.cites		Avg.Values		#B.through Patents	
	t+1,t+3	t+1,t+5	t+1,t+3	t+1,t+5	t+1,t+3	t+1,t+5	t+1,t+3	t+1,t+5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SciD influence	-0.368	-0.516	0.348***	0.080	0.439***	0.515***	1.278	0.965
	(0.797)	(0.822)	(0.096)	(0.180)	(0.140)	(0.127)	(1.047)	(1.029)
Size	0.264***	0.211***	-0.002	-0.032	0.028	0.007	0.173**	0.126**
	(0.073)	(0.064)	(0.019)	(0.024)	(0.034)	(0.030)	(0.071)	(0.061)
CAPEX	0.602	0.319	-0.350**	-0.124	0.460**	0.461**	0.747	0.098
	(0.744)	(0.629)	(0.169)	(0.193)	(0.222)	(0.193)	(0.920)	(0.785)
RD	0.580**	0.431**	0.107	0.016	0.071	0.009	0.348*	0.334**
	(0.235)	(0.168)	(0.090)	(0.058)	(0.048)	(0.023)	(0.204)	(0.161)
Age	-0.031	0.035	-0.122*	-0.039	-0.073	-0.026	-0.071	0.006
	(0.188)	(0.173)	(0.072)	(0.067)	(0.058)	(0.058)	(0.173)	(0.161)
Annual Return	-0.005	0.009	0.020**	-0.003	0.040***	0.024***	-0.000	0.017
	(0.026)	(0.020)	(0.009)	(0.008)	(0.009)	(0.006)	(0.024)	(0.016)
Leverage	-0.450**	-0.463***	-0.106*	-0.054	0.116	0.169	-0.249	-0.270*
	(0.177)	(0.163)	(0.059)	(0.064)	(0.127)	(0.107)	(0.177)	(0.138)
Board Independence	-0.052	-0.281*	0.101	0.200	-0.370***	-0.283**	0.019	-0.234
	(0.227)	(0.163)	(0.163)	(0.203)	(0.123)	(0.120)	(0.227)	(0.173)
Scientific CEO	0.116	0.080	-0.036	-0.067	0.005	0.004	0.122	0.071
	(0.084)	(0.084)	(0.058)	(0.072)	(0.041)	(0.042)	(0.096)	(0.092)
Constant	4.992***	6.035***	0.783***	0.705***	1.577***	1.505***	3.691***	4.644***
	(0.619)	(0.536)	(0.221)	(0.212)	(0.215)	(0.226)	(0.625)	(0.576)
Observations	44,019	36,584	43,068	35,965	35,821	31,880	32,540	27,560
Firm * Director FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adj. R^2					0.928	0.946		
Pseudo R^2	0.973	0.981	0.296	0.292			0.935	0.954

Table 8
Scientific Directors' expertise and firm relevant innovation

This table reports regression models examining the relation between SciDs' expertise and relevant innovation output by using firm $\mathtt{i}$, subject area $\mathtt{s}$ and year $\mathtt{t}$ level dataset. The key explanatory variables are $\mathit{Expertise(Pub)}_{\mathtt{i,s,[t-3,t]}}$ and $\mathit{Expertise(Cites)}_{\mathtt{i,s,[t-3,t]}}$. $\mathit{Expertise(Pub)}_{\mathtt{i,s,[t-3,t]}}$ is the logarithm of one plus the average number of publications per SciD of firm $\mathtt{i}$ in the subject area $\mathtt{s}$ over the past three years. $\mathit{Expertise(Cites)}_{\mathtt{i,s,[t-3,t]}}$ is the logarithm of one plus the average number of cites received by SciD's publications per SciD of firm $\mathtt{i}$ in the subject area $\mathtt{s}$ over the past three years. $\#\mathit{Patents}_{\mathtt{i,s,[t+1,t+3]}}$ (columns 1 and 2) are defined as firm $\mathtt{i}$'s the total number of patents filed (and eventually granted) for the next 3 years in the subject area $\mathtt{s}$. $\mathit{Avg.Adj.cites}_{\mathtt{i,s,[t+1,t+3]}}$ (columns 3 and 4) are defined as firm $\mathtt{i}$'s average adjusted citation per patent filed (and eventually granted) for the next 3 years in the subject area $\mathtt{s}$. The citations are adjusted by the technology class and grant year fixed effects to minimize the truncation issue of patent data, followed by Hall et al. (2001). $\mathit{Avg.Value}_{\mathtt{i,s,[t+1,t+3]}}$ (columns 5 and 6) are defined as firm $\mathtt{i}$'s average market value(Kogan et al., 2017) per patents of patents filed (and eventually granted) for the next 3 years in the subject area $\mathtt{s}$. $\#\mathit{B.through\ Patents}_{\mathtt{i,s,[t+1,t+3]}}$ (columns 7 and 8) are defined as firm $\mathtt{i}$'s total number of breakthrough patents filed (and eventually granted) for the next 3 years in the subject area $\mathtt{s}$. The breakthrough patents at the 90th percentile are influential patents that received more citations than the 90th percentile values of the patents in the same technology class and grant year. $\#\mathit{Funda.\ Patents}_{\mathtt{i,s,[t+1,t+3]}}$ (columns 9 and 10) are firm $\mathtt{i}$'s the number of fundamental patents filed (and eventually granted) for the next 3 years in the subject area $\mathtt{s}$. Fundamental patents that cite at least one scientific publication and received more citations than the 75th percentile values of the patents in the same technology class and grant year. Control variables are firm size, CAPEX, R&D, firm age, annual return, leverage, board independence and a scientific CEO indicator. Columns 1, 2, 3, 4, 7, 8, 9, and 10 exploit the Poisson regression because of count-dependent variables. Columns 5 and 6 exploit the OLS regression of Log($\mathit{Avg.Value}_{\mathtt{i,s,[t+1,t+3]}}$) on expertise of SciD. Variable definitions are in Table A.1. All regressions include firm, subject area and year-fixed effects. Standard errors are clustered at the SIC 4-digit industry level. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	#Patents		Avg. Adj. Cites		Avg. Values		#B.through Patents		#Funda. Patents	
					t+1,t+3					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Expertise(Pub)	0.472***		0.150***		0.032**		0.509***		0.572***	
	(0.118)		(0.037)		(0.015)		(0.112)		(0.080)	
Expertise(cites)		0.170***		0.054***		0.008		0.187***		0.193***
		(0.038)		(0.014)		(0.006)		(0.029)		(0.024)
Size	0.392***	0.392***	0.036	0.036	0.037	0.037	0.291***	0.294***	0.276***	0.279***
	(0.075)	(0.075)	(0.032)	(0.031)	(0.033)	(0.033)	(0.091)	(0.092)	(0.083)	(0.084)
CAPX	0.799	0.732	-0.060	-0.054	0.727**	0.727**	0.915	0.894	0.930	0.863
	(0.811)	(0.788)	(0.393)	(0.396)	(0.337)	(0.337)	(1.061)	(1.076)	(0.776)	(0.774)
RD	0.706***	0.692***	0.133*	0.134*	0.034	0.034	0.641***	0.641***	0.430***	0.430***
	(0.233)	(0.229)	(0.076)	(0.077)	(0.065)	(0.065)	(0.202)	(0.207)	(0.113)	(0.114)
Age	-0.097	-0.094	-0.128*	-0.127*	-0.019	-0.019	-0.075	-0.073	-0.195*	-0.194*
	(0.121)	(0.121)	(0.070)	(0.069)	(0.064)	(0.064)	(0.140)	(0.141)	(0.105)	(0.107)
Annual Return	0.017	0.013	0.021**	0.020*	0.067***	0.067***	0.020	0.015	0.016	0.013
	(0.028)	(0.027)	(0.010)	(0.011)	(0.008)	(0.008)	(0.027)	(0.026)	(0.029)	(0.029)
Leverage	-0.746***	-0.740***	-0.164**	-0.164**	0.070	0.070	-0.659**	-0.640**	-0.697***	-0.684***
	(0.202)	(0.198)	(0.078)	(0.078)	(0.081)	(0.081)	(0.309)	(0.295)	(0.210)	(0.204)
Board Independence	-0.079	-0.109	-0.039	-0.050	-0.223*	-0.223*	-0.219	-0.270	-0.378	-0.421
	(0.227)	(0.224)	(0.169)	(0.171)	(0.127)	(0.128)	(0.239)	(0.241)	(0.273)	(0.270)
Scientific CEO	0.013	0.009	-0.036	-0.036	0.021	0.021	-0.098	-0.104	-0.121	-0.129
	(0.078)	(0.078)	(0.038)	(0.038)	(0.040)	(0.040)	(0.127)	(0.124)	(0.118)	(0.116)
Constant	2.408***	2.414***	0.380	0.382	1.339***	1.340***	1.309*	1.302*	2.166**	2.161**
	(0.725)	(0.723)	(0.307)	(0.305)	(0.332)	(0.332)	(0.773)	(0.779)	(0.913)	(0.901)
Observations	118,487	118,487	117,584	117,584	72,887	72,887	100,083	100,083	93,889	93,889
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subject area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adjust R-squared					0.882	0.882				
Pseudo R-squared	0.805	0.805	0.234	0.234			0.724	0.725	0.725	0.723

Table 9
Inventor productivity within the SciD community

The table compares the innovation performance of the SciD-affiliated inventors to that of other inventors within the SciD community using the inventor, community and year-level dataset. We use Poisson regressions due to the count nature of the dependent variable. The key explanatory variable is the *SciD-affiliated inventor*, an indicator variable that equals 1 if an inventor is in a SciD community and also works for the firm where the SciD sits on the board and 0 otherwise. The dependent variables in columns 1 and 4 are the average and maximum of patent claims in the inventor's patent portfolio. The patent claim is the scope of patent protection, and patent with larger claims has a wide scope for patent protection. The dependent variables in columns 2 and 5 are the average and maximum of adjusted citations in the inventor's patent portfolio. In column 3, the dependent variable represents the share of breakthrough patents at the 90th percentile over the total number of patents in the inventor's patent portfolio. The dependent variable in column 6 is the total number of breakthrough patents at the 90th percentile in the inventor's patent portfolio. Control variables include the inventor's experience and a female indicator variable. Variable definitions are in Table A.1. All regression includes community-by-year fixed effects. Standard errors are clustered at the inventor level. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	The Quality of the Inventor's Patent Portfolio at Year t from 1996 to 2016					
	Avg Claim	Avg Adj. cites	B.through Patents Share	Max Claim	Max Adj. cites	#B.through Patents
SciD-affiliated inventor	0.028*	0.063***	0.024***	0.063***	0.098***	0.060***
	(0.015)	(0.015)	(0.006)	(0.016)	(0.019)	(0.012)
Female	-0.009***	-0.004*	-0.001	-0.014***	-0.011***	-0.007***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
Experience	0.005***	0.029***	0.008***	0.062***	0.106***	0.062***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Constant	2.883***	0.500***	0.092***	2.860***	0.464***	0.057***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
Observations	1,318,219	1,318,219	1,318,219	1,318,219	1,318,219	1,318,219
Community by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Inventor	Inventor	Inventor	Inventor	Inventor	Inventor
Pseudo R^2	0.361	0.283	0.274	0.322	0.227	0.175

Table 10
Inventor productivity within a firm

The table compares performance between SciD-affiliated inventors and other inventors who are not in the SciD community but in the firm where the SciD holds a board position. This table presents OLS regression models in columns 3 and 7, and other columns are Poisson regression models due to the count data dependent variable. The key explanatory variable is the *SciD-affiliated inventor*, an indicator variable that equals 1 if an inventor is in a SciD community and also works for the firm where the SciD serves on the board and 0 otherwise. The dependent variables in columns 1 and 5 are the average and maximum of patent claims in the inventor's patent portfolio. The patent claim is the scope of patent protection, and patent with larger claims has a wide scope for patent protection. The dependent variables in columns 2 and 6 are the average and maximum of adjusted citations in the inventor's patent portfolio. The dependent variables in columns 3 and 7 are the average and maximum of market values of patents in the inventor's portfolio. In column 4, the dependent variable represents the share of breakthrough patents at the 90th percentile over the total number of patents in the inventor's patent portfolio. The dependent variable in column 8 is the total number of breakthrough patents at the 90th percentile in the inventor's patent portfolio. Control variables for firm characteristics and inventor characteristics: firm size, CAPEX, R&D, firm age, annual return, ROA, sales, PPE, inventor's experience, female inventor indicator, and "inventor in other coms" indicator. "inventor in other coms" is an indicator variable that equals to 1 if the inventor is in another SciD's community and 0. Variable definitions are in Table A.1. All regressions include firm, year and cohort fixed effects. The inventor's cohort is defined as the group of inventors who join the firm in the same year. Standard errors are clustered at the inventor level. Robust Std. Err. are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	The Quality of the Inventor's Patent Portfolio at Year t from 1996 to 2016							
	Avg Claim	Avg Adj. cites	Avg Value	B.through Patents share	Max Claim	Max Adj. cites	Max Value	#B.through Patents
SciD-affiliated inventors	0.053***	0.173***	-2.151***	0.230***	0.141***	0.336***	0.160***	0.463***
	(0.011)	(0.028)	(0.434)	(0.032)	(0.012)	(0.029)	(0.014)	(0.037)
Size	-0.022***	-0.069***	-5.642***	-0.077***	-0.012***	-0.062***	0.065***	-0.084***
	(0.004)	(0.011)	(0.223)	(0.009)	(0.004)	(0.013)	(0.005)	(0.014)
CAPX	0.169***	0.642***	0.470	0.244**	0.162***	0.674***	2.375***	0.437**
	(0.032)	(0.121)	(1.830)	(0.118)	(0.037)	(0.131)	(0.051)	(0.170)
RD	0.064***	-0.231***	17.023***	-0.118***	0.088***	-0.241***	0.082***	-0.116
	(0.015)	(0.055)	(1.316)	(0.044)	(0.017)	(0.064)	(0.021)	(0.072)
Age	-0.033***	-0.184***	4.970***	-0.297***	-0.062***	-0.231***	0.163***	-0.407***
	(0.005)	(0.020)	(0.227)	(0.017)	(0.006)	(0.023)	(0.009)	(0.026)
Annual Return	0.004***	0.020***	1.465***	0.024***	0.003**	0.019***	0.153***	0.033***
	(0.001)	(0.005)	(0.081)	(0.004)	(0.001)	(0.005)	(0.002)	(0.006)
ROA	0.009	-0.083**	41.920***	0.082**	0.011	-0.100**	0.317***	0.066
	(0.011)	(0.038)	(1.188)	(0.033)	(0.013)	(0.046)	(0.016)	(0.059)
Sales	-0.003	-0.022**	-3.451***	-0.020**	0.006	-0.017	0.015***	0.031**
	(0.004)	(0.010)	(0.218)	(0.009)	(0.004)	(0.012)	(0.005)	(0.013)
PPE	-0.159***	0.084	-30.001***	0.048	-0.198***	-0.001	-1.020***	-0.129
	(0.015)	(0.060)	(1.060)	(0.057)	(0.018)	(0.073)	(0.025)	(0.083)
Female	0.003	-0.010	0.036	-0.015**	-0.010***	-0.058***	-0.019***	-0.107***
	(0.002)	(0.009)	(0.083)	(0.007)	(0.002)	(0.010)	(0.002)	(0.012)
Experience	-0.003	0.026*	0.116	0.067	0.008	0.050**	0.032***	0.145***
	(0.005)	(0.015)	(0.417)	(0.042)	(0.007)	(0.020)	(0.009)	(0.048)
Inventor in other coms	0.015***	0.087***	-0.960***	0.112***	0.072***	0.213***	0.033***	0.331***
	(0.001)	(0.006)	(0.059)	(0.005)	(0.001)	(0.006)	(0.001)	(0.007)
Constant	3.359***	1.669***	85.223***	-0.245	3.323***	1.881***	0.738***	-0.106
	(0.034)	(0.114)	(3.582)	(0.214)	(0.044)	(0.149)	(0.066)	(0.312)
Observations	1,470,203	1,467,893	1,470,207	1,429,008	1,470,203	1,467,893	1,470,207	1,429,008
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Inventor	Inventor	Inventor	Inventor	Inventor	Inventor	Inventor	Inventor
Pseudo R^2	0.099	0.117		0.064	0.116	0.118		0.086
Adj. R^2			0.466				0.745	

Table 11
Appointment and departure announcement returns

This table presents the average stock Cumulative Abnormal Return (CAR) on SciD appointments and departures. The sample consists of 7,804 independent director appointments, including 1,238 SciD appointments. We use the 8-k filing date as the appointment date. We calculate the CAR using market-adjusted return. Panel A presents the market reaction to SciD appointments. Panel B compares the appointment returns of SciDs to propensity score-matched non-SciDs. The matching variables in year t-1 are firm size, ROA, director age, director tenure, indicator variables for Ivy League graduates, executive experience, and finance experience. Variable definitions are in Table A.1. Panel C compares SciD appointment returns to those of non-SciDs within the same firm. Regressions in panel C contains SciDs and all non-SciDs in the SciD's firm. Columns 1 to 6 add firm and year-fixed effects. Columns 2 and 5 include the following firm financial characteristics: firm size, ROA, CAPEX, R&D, firm age, annual stock return, PPE, sale and Tobin's q. Columns 3 and 6 include both director and financial characteristics. Panel D presents announcement returns for SciDs' departures due to death. We collect the SciD death announcements from Audit Analytics and use the date of the first news of a director's death as our event date. There are 34 SciD deaths and 203 Non-SciD deaths. The matched sample in panel D is constructed using firm and director characteristics in year t-1, including firm size, ROA, and indicator variables for executive, finance experience, and independent director. Due to missing matching variables, there are 31 SciD death events available in the matched sample. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: SciD appointment returns

		SciD	t-stat
CAR(-2,2)	Mean	0.62%	3.32***
CAR(0,1)	Mean	0.31%	2.32**
CAR(0,2)	Mean	0.56%	3.15***

Panel B: Matched Comparison

		Treated	Control	Diff(T-C)	t-stat
CAR(-2,2)	Mean	0.74%	-0.14%	0.89%	1.68*
CAR(-2,2)	Median	0.23%	-0.29%	0.52%	2.71***
CAR(0,2)	Mean	0.62%	-0.05%	0.67%	2.23***
CAR(0,2)	Median	0.22%	-0.01%	0.23%	2.42**
CAR(0,1)	Mean	0.33%	0.10%	0.23%	0.95
CAR(0,1)	Median	0.08%	-0.02%	0.10%	1.08

Table 11
Appointment and departure announcement returns

Panel C: Regressions of SciD appointment CARs

	CAR(0,1)			CAR(0,2)		
	(1)	(2)	(3)	(4)	(5)	(6)
SciD	0.004***	0.004**	0.003*	0.005***	0.005***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Director Tenure			-0.000			0.000
			(0.000)			(0.000)
Director Age			0.000			0.000
			(0.000)			(0.000)
Ivy League			0.002			0.002
			(0.002)			(0.002)
Executive Exp			0.001			0.005
			(0.005)			(0.007)
Finance Exp			-0.002			-0.002
			(0.002)			(0.002)
Constant	0.001**	0.002	-0.005	0.002***	0.058**	0.040
	(0.001)	(0.017)	(0.018)	(0.001)	(0.025)	(0.024)
Observations	2,239	2,239	2,124	2,239	2,239	2,124
Control variables	No	Yes	Yes	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Industry	Industry	Industry	Industry	Industry	Industry
Adj. R^2	0.055	0.057	0.052	0.045	0.047	0.036

Panel D: SciD Departure announcements CARs due to deaths

		Full Sample			**Matched Sample**		
		SciD	Non-SciD	Diff(SciD-NsciD)	SciD	Non-SciD	Diff(SciD-NsciD)
CAR(0,1)	Mean	-0.87%	0.07%	-0.94%	-0.83%	0.20%	-1.03%
CAR(0,2)	Mean	-2.05%**	0.16%	-2.21%**	-2.20%**	0.77%	-2.97%*
N		34	203		31	31	

Table 12
Scientific Directors and firm valuation

This table reports regression models examining the relation between SciDs and firm valuation. We measure firm valuation using the average of Tobin's q for the next n years. More specifically, the dependent variable is *Avg. Tobin's* $q_{t+1,t+n}$, the natural logarithm of the average of Tobin's q from year t+1 up to year t+n. The key explanatory variable is *SciD*, which is an indicator variable that equals to one if the firm has at least one SciD in the year t and is otherwise 0. Control variables are: firm size, CAPEX, R&D, firm age, annual return, leverage, board independence and a scientific CEO indicator. Variable definitions are in Table A.1. All regressions include SIC 4-digit industry and year-fixed effects. Standard errors are clustered at the SIC 4-digit industry level. Robust standard errors are reported in parentheses.*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	t+1,t+2	t+1,t+3	t+1,t+4	t+1,t+5
	(1)	(2)	(3)	(4)
SciD	0.034**	0.031**	0.028**	0.026*
	(0.013)	(0.014)	(0.014)	(0.015)
Size	0.010*	0.009	0.008	0.007
	(0.006)	(0.006)	(0.006)	(0.006)
CAPEX	0.763***	0.702***	0.639***	0.580***
	(0.136)	(0.138)	(0.137)	(0.134)
RD	0.649***	0.688***	0.655***	0.632***
	(0.114)	(0.118)	(0.117)	(0.122)
Age	-0.049***	-0.048***	-0.049***	-0.049***
	(0.010)	(0.010)	(0.010)	(0.010)
Annual Return	0.135***	0.114***	0.099***	0.084***
	(0.006)	(0.006)	(0.005)	(0.005)
Leverage	-0.120***	-0.131***	-0.137***	-0.141***
	(0.043)	(0.044)	(0.043)	(0.043)
Board Independence	0.022	0.033	0.040	0.047
	(0.035)	(0.036)	(0.037)	(0.037)
Scientific CEO	0.123***	0.121***	0.121***	0.122***
	(0.019)	(0.019)	(0.020)	(0.021)
Constant	0.511***	0.522***	0.534***	0.547***
	(0.040)	(0.042)	(0.042)	(0.043)
Observations	56,456	51,139	46,192	41,586
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	Industry	Industry	Industry	Industry
Adj. R^2	0.309	0.323	0.334	0.342

A Louvain Algorithm

The Louvain algorithm detects communities according to the relative density of connections inside a community with respect to connections outside communities. The algorithm form a community by optimize the modularity function. The modularity measures the density of link inside communities compared to links between communities. The modularity of community C is calculated as the following:

$$Q = \frac{\sum_{in}}{2m} - (\frac{\sum_{tot}}{2m})^2 \tag{17}$$

- $\sum_{in}$ is the sum of edges between nodes within the community c;
- $\sum_{tot}$ is the sum of all edge for nodes in the community c(including edges which link to other communities);
- m is the sum of a ll of edge weights in the network;

Louvain algorithm assign each node to its own community. Then for each node i Louvain algorithm calculate the change in modularity in two steps, which are:

- Step 1: Remove the node i from its own community D, and calculate $\Delta Q(D- > i)$
- Step 2: Merge node i to neighbour community C, and calculate $\Delta Q(i- > C)$

According to the following formula, we need to calculate Q_{after} and Q_{before}.

$$\Delta Q(D- > i) = Q_{\text{Before removing i from D}} - Q_{\text{After merge i to C}} \tag{18}$$

$$Q_{\text{Before}} = \frac{\sum_{in} + k_{i,in}}{2m} - (\frac{\sum_{tot} + k_i}{2m})^2 \tag{19}$$

$$Q_{\text{After}} = \frac{\sum_{in}}{2m} - [0 + (\frac{k_i}{2m})^2] \tag{20}$$

- $k_{i,in}$: is the sum of edges between node i and C
- k_i: is the sum of all edges between node i

Given that $\Delta Q(i- > C)$ can be derived similarly, we can calculate:

$$\Delta Q(D- > i- > C) = \Delta Q(D- > i) - \Delta Q(i- > C) \tag{21}$$

Louvain algorithm iterates the above process and forms a community when $\Delta Q(D- > I- > C)$ does not increase. Generally speaking, this algorithm forms a community with a maximized number of edges within the community and minimizes the number of edges connected to other communities. The community contains nodes closely connected within communities but rarely connected to outside communities.

Table A1
Variables Definitions

Variable name	Definitions	Tables
Independent variables		
SciD	Indicator variable equals 1 if the firm has at least one SciD; zero otherwise.	Tables 11,12 and 4
Local SciD supply	Local SciD supply is the logarithm of one plus the number of SciD in firms headquartered within 100 miles of the focal firm's headquarters, excluding firms in the same four-digit SIC (SIC4) industry.	Table 5
SciD's influence	The cumulative number of SciDIP over the cumulative number of patents. SciDIP is the patent that cites the SciD's publications.	Table 7
SciD-affiliated inventors	Indicator variable that equals one if inventors are in a SciD's community and also work for the firm where the SciD sit on the board, and zero otherwise	Table 10, 9
Treatment	Indicator variable that equals one if firms are in the genetics-related industries. The genetics-related industries include the drugs and pharmaceutical products (13) and lab equipment (37) industries identified from the Fama-French 48 industry classification, and zero otherwise.	Table 6
Post	Indicator variable that equals one if the year is greater than 2001, and zero otherwise.	Table 6
Firm's reliance on fundamental science	the proportion of patents that heavily rely on fundamental science over the total number of patents with a three-year rolling window. Patents that heavily rely on fundamental science are those patents referencing more scientific publications than the 75th percentile value within the patent distribution for the same technology class and year.	Table 3
Expertise(Pub)	the logarithm of one plus the average number of SciD's publications in the subject area over the past three years.	Table 8
Expertise(Cites)	the logarithm of one plus the average number of cites received by SciD's publications in the subject area over the past three years.	Table 8
Local Scientists supply	the logarithm of one plus the number of tenured assistant/associate/full professors (including professors who are on the tenure track) around the firm's headquarters within 100 miles.	Table 5
Dependent variables		
Avg Tobin's $q_{t+1,t+n}$	The natural logarithm of average Tobin's q over the next n years	Table 12
$\#Patents_{t+1,t+n}$	The natural logarithm of one plus firm i's the total number of patents filed (and eventually granted) for the next n years.	Table 5 and Panels A of Tables 4 and 7
$\#Patents_{t+1,t+n}$	Firm i's the total number of patents filed (and eventually granted) for the next n years.	Table 6 and Panels B of Tables 4 and 7
Avg. Adj. $cite_{t+1,t+n}$	The natural logarithm of one plus firm i's the average adjusted cites of patents filed (and eventually granted) for the next n years. The adjusted cites are the number of cites over the average cites of patents in the same technology field and granted year.	Table 5 and Panels A of Tables 4 and 7
Avg. Adj. $cite_{t+1,t+n}$	Firm i's the average adjusted cites of patents filed (and eventually granted) for the next n years. The adjusted cites are the number of cites over the average cites of patents in the same technology field and granted year.	Table 6 and Panels B of Tables 4 and 7
Avg. $Value_{t+1,t+n}$	The natural logarithm of one plus firm i's the average market value of patents filed (and eventually granted) for the next n years.	Table 5 and Panels A of Tables 4 and 7
Avg. $Value_{t+1,t+n}$	Firm i's the natural logarithm of the average market value of patents filed (and eventually granted) for the next n years.	Table 6 and Panels B of Tables 4 and 7
#B.through $patents_{t+1,t+n}$	The natural logarithm of one plus firm i's the number of breakthrough patents filed (and eventually granted) for the next n years. The breakthrough patents at the 90 percentile are patents that received more citations than the citations at 90 percentile within the same technology class and year.	Table 5 and Panels A of Tables 4 and 7
#B.through $patents_{t+1,t+n}$	Firm i's the number of breakthrough patents filed (and eventually granted) for the next n years. The breakthrough patents at the 90 percentile are patents that received more citations than the citations at 90 percentile within the same technology class and year.	Table 6 and Panels B of Tables 4 and 7
#Funda $Patents_{t+1,t+n}$	The natural logarithm of one plus firm i's the number of fundamental patents filed (and eventually granted) for the next 3 years in the subject area s. Fundamental patents that cite at least one scientific publication and received more citations than the 75% percentile values of the patents in the same technology class and grant year.	Table 5 and Panels A of Tables 4
#Funda $Patents_{t+1,t+n}$	Firm i's the number of fundamental patents filed (and eventually granted) for the next 3 years in the subject area s. Fundamental patents that cite at least one scientific publication and received more citations than the 75% percentile values of the patents in the same technology class and grant year.	Table 8 and Panels B of Table 4
#B.through $patents(99)_{t+1,t+n}$	Firm i's the number of breakthrough patents(99) filed (and eventually granted) for the next n years. The breakthrough patents(99)are patents that received more citations than the citations at 99 percentile within the same technology class and year.	Table 6
Avg(Max) Claim	The average (maximum) number of claims for patents in inventors' portfolios.	Tables 10 and9
Avg(Max) Adj. cites	The average (maximum) number of adjusted cities per patent for patents in inventors' portfolios.	Tables 10 and9
Avg(Max) Adj. value	The average (maximum) market value per patent for patents in inventors' portfolios.	Tables 10
B.through patents share	The number of breakthrough patents(90) over total number of patents in inventors' portfolios.	Tables 10 and 9
#B.through patents	The number of breakthrough patents(90) in inventors' portfolios.	Tables 10 and 9
Scientific Director share (SciD share)	The ratio of the number of SciD to the total number of directors	Table 6
Genetic director share (GD share)	The ratio of the number of SciD with genetics expertise over the number of total directors on the board.	Table 6

Table A1
Variables Definitions

Firm characteristics		
Size	The natural logarithm of total asset(AT). Source: Compustata	Tables 11,12,4,5,7,6,10
CAPEX	Capital expenditure over total assets(CAPX/AT). Source: Compustata	Tables 11,12,4,5,7,6,10
RD	Research and Development expenditure over total assets(XRD/AT) Source: Compustata	Tables 11,12,4,5,7,6,10
Age	The natural logarithm of a firm's age measured as the difference between the current year and the first year the firm appears in CCM. Source: Compustata	Tables 11,12,4,5,7,6,10
Annual Return	The annual stock return of firm $((\mathrm{prcc\_f_t} + \mathrm{dvpsx\_f_t} \,/\, \mathrm{ajex_t}) \,/\, ((\mathrm{prcc\_f_{t-1}}/\mathrm{ajex\_f_{t-1}}))$. Source: Compustata	Tables 11,12,4,5,7,6,10
Leverage	Total leverage over total assets((Dltt+DLC)/AT). Source: Compustata	Tables 11,12,4,5,7,6,10
Board Independence	The total number of independent directors over the total number of directors on the board	Tables 11,12,4,5,7,6,10
Scientific CEO	Indicator variable that equals one if firms have scientific CEO, and zero otherwise.	Tables 11,12,4,5,7,6,10
Director characteristics		
Director tenure	Tenure of the outside director prior to the appointment year	Table 11
Director Age	The age of the outside director	Table 11
Ivy League	Indicator variable that equals one if the director graduated from an Ivy League university (Brown University, Columbia University, Cornell University, Dartmouth College, Harvard University, Princeton University, University of Pennsylvania, and Yale University) and zero otherwise	Table 11
Finance Exp	Indicator variable equals one if the director has financial experience (CFO or treasurer title or worked in banking, finance, and investment firms) prior to the appointment year and zero otherwise	Table 11
Executive Exp	Indicator variable equals one if the director has executive experience (CEO, CFO, CIO, COO, president, VP, executive VP, senior VP, partner, managing director, and treasurer) prior to the appointment year and zero otherwise	Table 11
Professor	Indicator variable equals one if the director is or was a professor at the university. The professor does not include the processor of education, teaching or practice.	Table 2
Academic in Ivy League	Indicator variable equals one if the director is or was an assistant/associate/full professor at the Ivy League university.	Table 2
Publication portfolio of SciD		
#Publications	The total number of publications in SciD' publication portfolio	Table 2
#Citations	The total number of publication citations received by SciDs' publication	Table 2
H-index	The H-index of the SciD. The h-index is the largest number of h such that h articles have at least h citations each.	Table 2

Table A2
Summary statistics of firm characteristics

This table shows the firm characteristics of firm-year observations for CCM and BoardEx merged data from 1996 to 2018. R&D, CAPEX, ROA, cash, dividend, free cash flow, and PPE are scaled by total assets. The total debt and book common equity value are adjusted according to Ivo Welch's leverage guide. The data is winsorized at 1% and 99%.

	N	Mean	St. Dev.	25%	50%	75%
Size	68524	5.94	2.04	4.44	5.88	7.36
Δ Asset	68524	0.11	0.38	-0.04	0.03	0.16
Leverage	68524	0.21	0.22	0.01	0.16	0.34
M/B	68524	2.21	1.79	1.18	1.61	2.50
Tobin's q	68524	2.21	1.79	1.18	1.61	2.50
R&D	43742	0.10	0.16	0.01	0.05	0.13
R&D missing	68524	0.36	0.48	0.00	0.00	1.00
Capex	68524	0.05	0.06	0.02	0.03	0.06
ROA	68524	0.04	0.26	0.02	0.10	0.16
Cash	68524	0.22	0.25	0.04	0.13	0.33
Dividend	68524	0.01	0.03	0.00	0.00	0.01
Log(Sales)	68524	5.56	2.48	4.10	5.78	7.26
Δ Sale	68524	0.14	0.45	-0.01	0.05	0.19
Free Cash Flow	68524	0.02	0.22	0.00	0.07	0.13
PPE	68524	0.25	0.23	0.07	0.16	0.36
Log(MV)	68524	6.05	2.07	4.55	6.03	7.43
Log(BV)	68524	4.99	2.15	3.64	5.09	6.42
Annual Return	68524	0.13	0.63	-0.22	0.00	0.32
HHI	68524	0.31	0.21	0.16	0.24	0.40

Table A3
Share of directors types by fiscal years

The table shows the number and proportion of outside directors and SciDs for the sample period 1996 to 2018. The last column shows the share of SciDs over outside directors. The last row shows the total number of unique directors in each category, respectively.

Year	Outside	Scientific	Scientific/Outside
1996	5,570	1,048	0.19
1997	6,782	1,278	0.19
1998	7,991	1,491	0.19
1999	9,539	1,737	0.18
2000	11,618	2,115	0.18
2001	13,578	2,468	0.18
2002	15,642	2,804	0.18
2003	18,345	3,219	0.18
2004	20,885	3,694	0.18
2005	21,900	3,884	0.18
2006	22,037	3,848	0.17
2007	21,752	3,744	0.17
2008	20,818	3,491	0.17
2009	19,672	3,231	0.16
2010	19,150	3,125	0.16
2011	18,930	3,026	0.16
2012	18,907	2,954	0.16
2013	19,321	3,041	0.16
2014	20,258	3,248	0.16
2015	20,291	3,269	0.16
2016	20,036	3,178	0.16
2017	20,054	3,211	0.16
2018	17,903	3,023	0.17
Total	39,283	6,236	

Table A4
Performance metrics for different subject areas

This table presents the performance metrics at aggregated levels and separated by different subject areas. The aggregated measure contains the macro average, weighted average, and sample average. Macro average calculates the metric independently for each class and then takes the average. Weighted average calculates the metric for each class and weights it by the number of observations in that class. sample average computes the metric over the individual binary decisions for each observation (each abstract in our case), rather than for each class.

	Precision	**Recall**	**F1-Score**	**Obs.**
Biochemistry	0.82	0.80	0.81	8726
Chemistry	0.73	0.63	0.68	3730
Computer Science	0.84	0.84	0.84	9527
Engineering	0.76	0.74	0.75	11158
Materials Science	0.63	0.59	0.61	4308
Medicine	0.89	0.84	0.87	10349
Pharmacology	0.69	0.57	0.62	2128
Physics	0.71	0.66	0.68	5049
macro avg	0.76	0.71	0.73	54975
weighted avg	0.79	0.75	0.77	54975
samples avg	0.82	0.81	0.79	54975

Table A5
The value of fundamental patents

The table compares the market value, generality and originality of fundamental patents to other patents in the same firm, technology class and year. The independent variable is an indicator variable that equals 1 if the patent is fundamental patents and 0 otherwise. The dependent variable in column 1 is the market value of the patent. The dependent variable in column 2 is the logarithm of generality. Column 3 has the logarithm of originality as the dependent variable. The regression includes firm, technology class by grant year, and year fixed effects. Standard errors are clustered at the SIC 4-digit industry level. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

	Value	Generality	Originality
	(1)	(2)	(3)
Fundamental Patents	0.030***	0.133***	0.015***
	(0.008)	(0.013)	(0.001)
Size	0.040	-0.009**	-0.001
	(0.069)	(0.003)	(0.002)
CAPX	0.652	0.151***	0.108***
	(0.438)	(0.045)	(0.017)
RD	-0.056	-0.029	-0.019*
	(0.263)	(0.022)	(0.011)
Age	0.103	-0.028***	-0.021***
	(0.094)	(0.007)	(0.003)
Annual Return	0.148***	0.004***	0.002***
	(0.018)	(0.001)	(0.000)
Leverage	0.111	0.000	-0.010
	(0.173)	(0.016)	(0.008)
Board Independence	-0.383*	-0.018	-0.028***
	(0.205)	(0.014)	(0.005)
Scientific CEO	0.106	-0.014**	-0.002
	(0.092)	(0.006)	(0.002)
Scientific Patents	-0.018***	-0.059***	0.021***
	(0.005)	(0.004)	(0.002)
Constant	1.432*	-0.394***	-0.037**
	(0.765)	(0.033)	(0.017)
Observations	1,045,603	637,973	974,991
Firm FE	Yes	Yes	Yes
Technology class by grant year	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Cluster	Industry	Industry	Industry
Adjust R-squared	0.760	0.807	0.257

Table A6
Distribution properties of the treatment and control directors after matching

The table compares the distributional properties of directors in the treatment and control groups after propensity matching in table 11. The treatment group includes the appointments of SciDs. The control group are a subset of the non-SciD appointment that matched on firm and director characteristics. Firm characteristics include firm size and ROA. Director characteristics include director age, tenure, executive experience, finance experience and ivy league university. This table shows the differences between the director and firm characteristics after matching. No statistically significant differences exist between the treatment and control groups after matching. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

	Treatment	Control	Diff (T-C)	t-Statistics	P-Value
Director Age	58.56	58.63	0.07	0.21	0.83
Director Tenure	6.11	5.79	0.32	0.67	0.50
Size	6.11	6.07	0.02	0.33	0.74
ROA	-0.07	-0.08	0.01	0.42	0.67
Executive experience	0.87	0.88	-0.01	-0.40	0.69
Finance experience	0.17	0.17	0.00	0.34	0.73
Ivy League university	0.32	0.31	0.01	0.47	0.64

Table A7

Distribution properties of the treatment and control firms after matching for HGP event

The table compares the distributional properties of firms in the treatment and control groups after propensity matching in panel B of table 6. The treatment group comprises firms in genetic-related industries, while the control group consists of firms in industries with limited ability to leverage research results from HGP. The matching characteristics include firm size, ROA, annual return and the number of patents up to the event year 2001. This table shows the differences between the firm characteristics up to the event year 2001 after matching. No statistically significant differences exist between the treatment and control groups after matching. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

	Treatment	Control	Diff (T-C)	t-Statistics	P-Value
Size	4.47	4.3	0.09	1.44	0.15
ROA	-0.13	-0.12	-0.01	-0.68	0.50
Annual Return	0.18	0.21	-0.03	-0.92	0.36
No.Patents	12.71	19.53	-6.82	-1.27	0.20