How Scientists on Corporate Boards Drive Innovation by Bridging Research and Development*

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Abstract

Scientific research is a fundamental driver of innovation. Yet, corporate investment in scientific research is declining relative to patent development, potentially delaying the economic benefits of valuable scientific research. This study investigates how Scientists on Corporate Boards (BdScis), drawn from industry and academia, support corporate innovation by bridging the scientific research to patent gap. We measure scientific expertise using BdScis' publications. Network analysis shows that firms are more successful in recruiting and retaining talented inventors from their BdScis' professional networks. To address endogeneity concerns, we examine local supplies of BdSci candidates and the Human Genome Project's technological shock to establish causality.

Keywords: corporate innovation, scientific research, scientists, inventors, patents, machine learning

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1 Introduction

Scientific research has long been considered an essential input in the innovation process,[1] as it provides the technology foundation for innovation activity,[2] it improves R&D efficiency,[3] and enhances the usefulness and economic value of patents.[4] However, concerns persist about the capacity of firms to fully appropriate the economic benefits of scientific research due to its vast volume and inherent complexity. Critically, scientific knowledge is not freely accessible to all; only organizations with substantial scientific capabilities can successfully realize its value (Cohen and Levinthal, 1989; Rosenberg, 1990).

A common narrative in the innovation literature is that firms maintain their scientific capabilities through their costly scientific research.[5] However, this view appears less relevant in the 21st century. More recently, US firms have significantly reduced their investments in scientific research, with the share of research expenses in total corporate R&D dropping from 38.26% in 1955 to below 20% in recent years, as illustrated in Figure 1. Mezzanotti and Simcoe (2023) document that firms typically cut investment in scientific research first when facing high funding costs, and such reductions lead to lower innovation output. Also, Arora et al. (2018) shows a decreased willingness of firms to invest in science, possibly due to managerial short-termism. The rising cost of scientific research, particularly the high cost of scientists, further discourages firms from conducting scientific research. All this evidence suggests that the trend toward reduced investment in corporate research is unlikely to be reversed in the near future. Thus, firms need a new channel to strengthen their ability to utilize advances in scientific knowledge to spawn innovation. Given the increasing reliance of corporate innovation on public domain scientific research, as highlighted by the rise in the percentage of firms' patents based on scientific research from 7.37% in 1980 to 35.18% in 2016,[6] identifying new channels to bridge the expanding gap between scientific research and patent development is more urgent than ever.

In this study, we explore a potential channel for bridging the gap between scientific research and patent development by appointing academic or industry scientists to corporate boards, namely Board Scientists (BdScis). We define BdScis as outside directors: (1) who have scientific publications; (2) who are inventors with doctoral degrees. Contrary to common assumptions, we find that 70% of BdScis are industry scientists, working in government, research institutes, or other firms. In recent years, BdScis have become increasingly prevalent among publicly listed firms, being represented in 50% of firms and accounting for 40% of firm-year observations over our 1996–2018 sample period.

Typical BdScis are prestigious scientists at the cutting edge of their scientific fields, enabling

[1] see Lerner et al. (2024); Nelson (1986); Mansfield (1991)

[2] see Marx and Fuegi (2020); Ahmadpoor and Jones (2017); Arora et al. (2023)

[3] see Sorenson and Fleming (2004); Griliches (1986)

[4] see Krieger et al. (2024); Arora et al. (2024a)

[5] see Berchicci (2013); Fabrizio (2009)

[6] see Figure 2

them to identify promising scientific ideas with commercial promise and to tap into their professional networks of talented inventors and scientists. This first function of BdScis is consistent with the suggestion of Satell (2016) that firms can effectively access scientific research simply by appointing scientists who can consistently monitor related scientific research in the public domain. As important boardroom advisors, BdScis can also shape a firm's long-term innovation strategy and help mitigate managerial short-termism, which Arora et al. (2018) identify as a major reason why many firms withdrew from internal scientific research projects. More specifically, we investigate how BdScis contributes to a firm's innovation success through their scientific knowledge and assistance in recruiting skilled inventors and scientists from their professional networks.

Recent anecdotal evidence suggests that corporate directors are becoming more deeply involved in their firms' innovation activities. For example, the percentage of firms with science and technology board committees has more than doubled in the past five years (Spencer, 2023). Unlike regular board meetings, which typically occur four times a year, science and technology board committees have more flexible schedules and may meet as frequently as circumstances require (Regeneron, 2021). Corporate CEOs also hold a positive view of the value added by their BdScis scientific knowledge and advice. For example, Bionovo's CEO highlighted the role of BdSci John Baxter in advancing the firm's clinical trial programs (PRNewswire, 2008). Sundar Pichai, Alphabet's CEO, expressed enthusiasm on the appointment of Nobel laureate Frances Arnold to their corporate board, emphasizing the potential benefits of her extensive scientific knowledge.

Empirically, we compile a novel dataset that includes detailed publication profiles of BdScis and comprehensive information on firms' patents. Using the firms' patent citations to scientific articles and BdScis' publications profiles, we construct two dynamic measures of BdScis' scientific knowledge that track both their evolving expertise and its changing relevance to the technologies referenced in a firm's current patent filings. Additionally, we introduce a new innovation measure, called 'fundamental patents', which are patents strongly rooted in basic scientific research and that serve as a foundational basis for many subsequent patents. Fundamental patents aim to capture a firm's activities in transforming scientific ideas into valuable innovations, which can be built upon. These fundamental patents are more valuable and innovative than comparable patents of the same firm, technology class, and grant year. Lastly, using BdScis' professional network, comprising 1 million individuals and 20 million connections among scientific authors and inventors, we examine the role of BdScis in recruiting skilled inventors to their firms.

Our first measure of the scientific knowledge of BdScis captures the direct influence of their publications on a firm's patents, which is based on the fraction of a firm's patents that directly cite a BdSci's publications after she joins the board, scaled by the total number of firm patents awarded over this same period. Direct patent citations to a BdSci's publications indicate that a patent builds directly on a BdSci's scientific knowledge, clearly indicating the influence of a BdSci's expertise on a firm's innovation activities. Empirically, we analyze how time-series variations in a BdSci's influence is associated with the quality of the firm's patents, utilizing director $\times$ firm fixed effects for this purpose. We find new evidence that firms produce higher-quality innovations as a BdSci's influence on a firm's patents rises through her currently established scientific expertise and with the increasing focus of a firm's innovative activities in fields that overlap with a BdSci's expertise. This provided direct evidence that a BdSci contributes to a firm's innovation by drawing on the knowledge of their recent scientific work.

Patent citations to BdSci's publications are direct evidence of a BdSci influence, but relying solely on them can be overly conservative, as patents typically cite only prior art that is immediately related to the current invention (e.g., Giczy et al., 2022; Lerner and Seru, 2021). Thus, we also employ a second measure to account for the fact that BdSci can influence a firm's innovation in areas that, while not directly cited by a patent, nevertheless remain highly relevant to the firm's patent technologies. We use a Large Language Model (LLM) to categorize patents into subject areas relevant to the development of the focal patent. Specifically, we use the SciBERT model, a BERT-based framework fine-tuned on millions of scientific articles, designed to understand and classify scientific concepts. We train the SciBERT model on multi-label classification assignments using over 340,000 abstracts of BdScis' publications and patents that cite at least one scientific publication.[7] Next, we use the trained model to categorize patents into relevant, non-mutually exclusive scientific subject areas, including Biochemistry, Chemistry, Computer Science, Engineering, Materials Science, Medicine, Pharmacology, and Physics. Intuitively, we ask the LLM to learn to associate specific words, phrases, and sentence structures with scientific subject areas during the training process and then classify the remaining patents by recognizing patterns based on these learned associations.

Our second measure is based on the recent publications of a BdSci, linking her publication activities to a firm's patents based on LLM-assigned scientific subject areas for these patents. Recent BdSci publications are likely to be exogenous to a firm's innovation activities, thereby mitigating concerns about the endogeneity of direct citations to a BdSci's publications, which firms might strategically use to signal the value of their innovations. More specifically, we measure the scientific expertise of a BdSci by examining their recent publications over the prior three years. Recent publications provide a more current and relevant assessment of a BdSci's state-of-the-art expertise. Moreover, the outcome variables we measure include both the quality and quantity of a firm's subsequent patents, each associated with a BdSci's dynamically changing areas of expertise. Our empirical evidence suggests that in areas where a BdSci has recently published more papers or received more citations, a firm produces more patents, and these patents are of better quality. Moreover, we show that firms produce 1.77 times more high-quality patents built on the scientific research in areas where their BdScis have recently been actively conducting research.

[7] More specifically, a large portion of the abstracts in our training dataset consists of BdScis' scientific publications. We collect the subject areas for this portion using Scopus 2-digit subject area codes. The remaining part of the training dataset includes patents that cite scientific publications, and we determine the scientific subject areas of these patents based on the Scopus 2-digit subject area codes of the cited publications.

We argue that our two measures of a BdSci's technical expertise are superior to the existing measures of specialists' expertise in the literature. The existing literature relies on static measures of expertise such as a BdSci's past life 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 expertise. However, these commonly used measures are very noisy and, more importantly, assume a specialist's expertise remains static over time and that a homogeneous level of specialist expertise exists for all individuals in the same expertise category. In contrast, our measures account for changes in a specialist's expertise over time, and they recognize that specialists possess varying levels of relevant expertise depending on their recent publication activity and the technology classes that support a firm's recent patents.

Regarding the BdSci network channel, we investigate whether tapping into the BdSci's professional network can reduce a firm's asymmetric information problem when hiring an inventor of unknown ability. We refer to this hiring practice as BdSci-affiliated network hiring. From a BdSci's professional network of all past scientific co-authors and co-inventors, we construct the inner community of professional connections. These inner communities consist of co-authors and co-inventors who connect more closely with a BdSci than with other individuals within their professional networks.

We investigate a BdSci's role in enhancing the human capital of a firm through the firm's hiring of inventors who are in a BdSci's inner community. On average, BdSci-affiliated inventors hired by a firm are more productive and have better innovation outcomes than other inventors in a BdSci's community, i.e., suggesting that BdSci recommends high-quality candidates in their inner community to join their firms. Furthermore, BdSci-affiliated inventors continue to outperform the cohort of non-affiliated inventors joining the firm in the same year measured over the subsequent years of their employment at the firm. This suggests that BdScis also help retain affiliated inventors. Our findings are new to the literature and reflect how a BdSci's professional network can provide valuable soft information about potential inventor appointments and help select and recruit these inventors to the firm, and increase their retention after they are hired.

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

In our study, we focus on a major scientific breakthrough achieved in the early 21st century 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, that greatly relaxes the technology constraints on successful drug development and opens up broad new possibilities in gene therapy. Despite these scientific advances, it is important to recognize that firms still face challenges in effectively translating basic scientific knowledge into commercialized therapies.

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

We find that following the HGP shock, firms operating in industries able to commercialize genetics knowledge show a higher propensity to appoint new BdScis to their boards. This includes both BdScis in general and BdScis with genetics expertise (Genetic BdScis). Our empirical finding is consistent with a theoretical prediction of Garlappi et al. (2017) by showing that firms appoint more BdScis who share similar expertise and can accurately evaluate the risk of a new drug project when facing these risky new investment opportunities. To assess the impact of BdScis on firms' innovation quality, we compare the innovation outcomes of firms that appointed a Genetic BdSci within two years of the HGP shock to the outcomes in other firms in the same genetic-related industry. We find that firms with newly appointed Genetic BdScis exhibit significant improvements in both the quantity and quality of their patents, relative to comparable firms within the same industry. The strength of our empirical design lies in the premise that the technological progress resulting from the HGP shock exogenously raises the demand for BdScis, which we attribute to their increased value to pharmaceutical firms' applied research activities. By utilizing this exogenous shock, we can infer that the observed changes in board composition and subsequent R&D improvements are from the specific influence of BdScis with relevant expertise. Moreover, the results are robust to a matched sample based on firm size, ROA, annual stock return, and pre-shock patent innovation activities.

To further strengthen our identification strategy, we employ the local supply of BdSci candidates as an instrumental variable (IV) to predict a BdSci's presence on a firm's board. The local supply of BdSci candidates is measured by the number of BdScis at other firms headquartered within 60 miles of the focal firm's headquarters, excluding potentially competing firms within the same industry (the same SIC4 code). In the first stage, we find a strong and statistically significant relationship between the supply of local BdSci candidates and the presence of BdScis on the focal firm's board. We argue that a firm's headquarters location is typically determined early in its life based on economic considerations separate from local BdSci supply, and thus, it can be treated as exogenously determined for our purposes. In addition, we control for the geographical effects on corporate innovation by incorporating the local supply of university scientists, measured by the number of tenured assistant, associate, and full professors at nearby universities. By employing an IV approach, we estimate the Local Average Treatment Effect (LATE), which suggests that the appointment of a new BdSci to a firm's board leads to a positive impact on patent innovation.

Scientific research often requires long gestation periods and lacks frequent, easily interpreted milestones, making it challenging for non-expert investors to evaluate a firm's research progress. This uncertainty surrounding scientific research investments can cause generalist boards who lack scientific expertise to put pressure on managers to prioritize short-term profits. In contrast, BdScis are well-positioned to evaluate ongoing scientific research and potentially alleviate investor concerns. In this study, we explore the relationship between stock performance and the presence of BdScis, examining how their expertise may influence investor decisions and firm valuation.

Our analysis finds that BdScis contribute positively to firm value. First, we show that within an industry, the presence of BdScis is positively associated with Tobin's Q, highlighting the long-term valuation benefits of having BdScis on the board. Second, we find an average –2.42% drop in CAR[0, +2] following BdSci death announcements, which is significantly more negative than the market reactions to the deaths of other outside directors. Director death announcements are particularly useful to study because they are generally unexpected and exogenous, providing a unique lens through which to understand investor expectations about the value that BdScis add to a firm.

Lastly, BdScis are uniquely positioned to search for promising scientific ideas due both to their intensive and extensive scientific knowledge, while as board members, this gives them strategic influence over a firm's long-term innovation direction. However, there is another possible channel to drive innovation output, which could have a similar influence on firm innovation as BdScis, namely hiring an inventor CEO or a PhD CEO who can also have an important influence on firm innovation (Islam and Zein, 2020; He and Hirshleifer, 2022). Both Islam and Zein (2020) and He and Hirshleifer (2022) focus primarily on the role of the CEO in the patent development stage. In contrast, we highlight the role of BdSci in enhancing firms' capabilities to utilize scientific research. Specifically, we address the rising concern regarding the widening gap between scientific research and patent innovation. Also, our results are robust when we alternatively include an indicator for an inventor CEO.

Regarding the role in bridging research and development, CEO scientists and other corporate scientists can have similar expertise to BdScis. Thus, it is important to distinguish the influence of BdScis from those of CEO scientists and corporate scientists. On average, we find that scientist CEOs publish fewer papers and these papers attract fewer citations than is typically the case for BdScis, and CEO scientists' research activities decline dramatically after they assume the CEO role[8]. Scientist CEOs appear less frequently in the sample, and our results remain robust when controlling for scientist CEOs in our analysis.

Our paper makes several contributions to the existing literature. Firstly, the literature on scientific research and innovation previously established a link between scientific research and successful innovation, highlighting the role of scientific knowledge in driving innovation activities and

[8]Research activities are measured by both publications numbers and citations counts.

enhancing innovation efficiency (e.g. Nelson, 1959a; 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 laboratories, and publishing fewer scientific papers (Mezzanotti and Simcoe, 2023; Arora et al., 2018). This raises a critical question: If firms are cutting back on internal research activities, how do they effectively utilize scientific research to support their corporate innovations? This question is important not only because it negatively impacts corporate innovation, but also because it leads to social opportunity losses (Arora et al., 2020, 2018). Social opportunity losses occur when a large gap exists between scientific research and resulting corporate innovations that remain unrealized for longer than necessary. For example, Penicillin was discovered in 1928, but it did not become commercially available until 1945 (Satell, 2016).

Our study contributes to the above mentioned literature by introducing a new channel through which basic scientific research is connected to firm innovation. Specifically, by having a BdSci with cutting-edge scientific knowledge on the board, firms can benefit from a BdSci's 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, BdScis can assist in selecting and hiring particularly talented inventors from their professional networks and then assisting the firm in retaining these valuable employees. Importantly, we highlight the increased economic benefits of having BdScis following major scientific breakthroughs, such as the release of the Human Genome Project findings. Although our paper draws inspiration from Yao et al. (2024), it differs by focusing exclusively on directors with scientific publications, addressing concerns that having doctoral degrees alone may not indicate scientific expertise or inventor capability. This narrower definition enables a more precise analysis of the role of scientific expertise in firm innovation.

Second, we develop a novel method for mapping patents based on BdScis underlying scientific knowledge, which offers new insights into how scientific research influences patented innovations. A primary challenge in understanding the impact of scientific research on innovations is in 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 innovations by 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 by patents to link scientific knowledge to specific technologies (e.g., Ahmadpoor and Jones, 2017; Arora et al., 2021; Marx and Fuegi, 2020). However, 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. Basic science can 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, AI technology 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. In this regard, it is important to recognize that patent applications include a technology classification that the USPTO uses. However, this does not indicate the primary science on which the patent is based. We classify patents on this latter basis so that we can link them to the scientific publications of BdScis.

Third, we document new evidence on the advisory role of outside directors by specifically examining the impact of a BdSci 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 and dynamic nature of director expertise. Importantly, we demonstrate that this heterogeneity in BdSci expertise matters for corporate innovation. For instance, a BdSci's contributions to corporate innovation activities vary, depending on their recent publication activities and the relevance of their expertise 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), BdScis include not only academic directors (making up 30% of BdScis), but also industry experts/practitioners. Including these industry practitioners in our study is particularly salient because they bring together scientific knowledge combined with practical experience needed to commercialize scientific research.

Last, our paper contributes to the existing literature on boards of directors by examining the impact of the Human Genome Project as a novel exogenous shock to board structure and the demand for particular types of director expertise. 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 with China (Linck et al., 2008; Guo and Masulis, 2015; Balsmeier et al., 2017; Chen et al., 2020), or cross sectional variation 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 an existing BDSci, but also from appointing new directors with related scientific expertise. In addition, scientific breakthroughs, which result in the emergence of new product opportunities, serve as particularly useful exogenous shocks for examining the sensitivity of 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 BdSci's advisory services over her management monitoring ability around such events. Also, we document the strategic practice of appointing new directors with specific expertise as part of a firm's strategic response to major technological changes in related fields.

2 Data and Method

Our core dataset consists of information on firms' innovation, board membership, directors' publication profiles and patent portfolios. For each firm-year observation in the sample, we collect the financial characteristics, innovation output, and board structures. Board structures include directors' names, classifications (inside or outside), employment, educational credentials, scientific publications, and patents to enable us to examine the relation between firm innovations 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 1 provides the sample characteristics.

2.1 Innovation data

We begin by linking three patent-related 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.[9] 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). An important subset of NPL is scientific publications cited by patents, which are labelled Scientific Non-Patent Literature (SNPL). SNPL is very informative about the scientific foundation on which a patent is based. Marx and Fuegi (2020) map a patent's NPL citations to scientific publications and provides information related to the SNPL, such as authors' 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.

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

2.2 Scientific knowledge data

We collect the scientific profiles of outside directors 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 of high-quality articles allows us to identify successful scientists, their range of expertise, and their networks of co-authors. Secondly, Scopus provides an author-level data structure, enabling us to construct an individual scientific profile for each director.

We convert director names into a Scopus-compatible query format and search the Scopus database. For each director, we gather all associated Scopus identifiers, names, and historical as well as current affiliations returned by the query. A major challenge is that many outside directors share the same or similar names as authors in Scopus. To address this data challenge, we establish links between outside directors and scientific authors by cross-referencing their names with their employment histories. We consider an outside director to be a scientific author if there is an overlap in their affiliations history. More details on the matching process can be found in Appendix A.

The scientific knowledge data consists of the authors' personal biographic information, scientific impact, active research subject areas, and publication identifiers. For each linked profile, we retrieve all Scopus publication identifiers and gather detailed publication information, such as title, year, citation count (as of 2021), co-authors, journal name, and DOI. The final dataset comprises 274,790 publications authored by 3,586 BdSci. Journal articles constitute the largest proportion of Scopus publications (74.19%), followed by conference papers (9.02%) and reviews (6.64%). The top three research fields represented in our sample are biochemistry (9.65%), molecular biology (8.58%), and oncology (7.02%).

2.3 Network analysis and professional community construction

We construct a BdSci's professional network to investigate the relation between firm value and a BdSci's network. Our measure of a BdSci's professional network combines the BdScis at the firm, with her co-inventors and co-authors, and other inventors at the same firm. There are around one million nodes (people) in this combined professional network. Nodes (people) are connected through inventions and publications, while the strength of the connections is determined by the number of patents, publications, or both that exist between each pair of nodes. The network is measured as of December 2021.

To construct the inventor-scientist network, we map the patent profiles of BdScis 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. To prevent double-counting, we implement a two-step procedure to identify the patent profiles associated with each scientific author who is also an inventor. Details of this procedure are further described in Appendix B

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 research field frequently collaborate with others in the same research area, 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 BdSci and assume that the BdSci knows these authors well. For example, the researchers in a BdSci'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 analysis.

2.4 Variables construction

For our sample, we extract the following firm characteristics: 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 the CCM database. CAPEX and R&D are scaled by total assets. All variable definitions are provided in Table A1.

2.4.1 BdSci and BdSci's influence

BdScis are defined as (1) outside directors with scientific publications, or (2) outside directors who are inventors holding doctoral degrees. Including the second group is important because they may represent scientists who focus on applied research and have many patents, but often no publications. 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 4,047 BdScis, where 5% of these BdScis have no publications.

We present BdSci characteristics in Panel A of Table 2. On average, BdScis have authored 71 scientific publications, received an average of 5142 citations, and had an average H-index of 19 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 BdSci 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 BdSci with the most citations, and he was a leader of the human genome project and a former Science Advisor to the President of the United States. American geneticist Michael S Brown is the BdSci with the highest H-index who won the Nobel Prize in Physiology/Medicine in 1985.

Examining our BdSci 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 BdScis won at least one prestigious research award in science or technology. For example, BdSci Robert Langer won the Wolf Prize. Robert Kahn and Vint Cerf won the Turing Award. 85 BdScis are also US National Academy of Science members. Of our BdSci sample, 27% are full professors (excluding non-academic professors like professors of practice) at a university. 5% of the BdScis hold or have held an academic position (assistant professor to full professor) at Ivy League Universities.

We classify the primary subject area of BdScis based on the 2-digit Scopus subject area where a BdSci publishes her most papers (based on rank ordering). Figure A.1 illustrates the primary subject areas of 3,502 BdScis 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. A majority of BdScis specialize in life and health science, comprising 52% of our 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 BdScis, 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 BdSci sample, respectively. For the general social science category, the leading micro subject areas of the BdSci sample are business (10%), social science (4%), and economics (2%), respectively. We use the terms $BdSci_{\mathrm{i,t}}$ and $BdSci\ share_{\mathrm{i,t}}$ to refer to BdScis at firm i for a given year t. $BdSci_{\mathrm{i,t}}$ is an indicator variable equal to 1 if firm $\mathtt{i}$ has at least one BdSci on the board at year $\mathtt{t}$, and 0 otherwise. $BdSci\ share_{\mathrm{i,t}}$ is the ratio of the number of BdScis scaled by the total number of directors in firm $\mathtt{i}$ in year $\mathtt{t}$.

Furthermore, we gauge a BdSci’s influence on a firm’s patents by assessing the Scientific Non-Patent Literature (SNPL) citations of the firm’s 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 BdScis' publications using the DOI of each publication. We identify firm patents that reference BdSci's publications while the BdSci is on a firm's board, labeling these patents as BdSci-influenced patents (BdSciIP). BdSciIP presents a group of firm patents that are directly influenced by the scientific work of the BdSci. We then employ BdSciIP to quantify the BdSci's innovation influence at the firm over their appointment period, which is the cumulative number of BdSciIPs divided by the cumulative number of patents awarded to the firm over the same time period. The cumulative number of BdSciIPs allows us the measure how a BdSci's influence on the firm's patents varies as of the year that the BdSci joined the board. The influence of a BdSci d at firm i in year t, and the year of the director's initial appointment in year t-n, is calculated by the following summation formula:

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

We use the cumulative number of BdSciIP and patents up to the focal year as a BdSci'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 BdSci's scientific works influence more of a firm's innovation activity when the firm has proportionally more patents that cite BdSci's publications. For example, Michael Brown, is a BdSci who joined Regeneron Pharmaceuticals in 1991. Regeneron Pharmaceuticals' patents gradually cite more of Michael Brown's scientific publications over subsequent years. Michael Brown's influence rises with the growth in the share of Regeneron Pharmaceuticals' patents that cite Michael Brown's scientific works scaled by the firm's total number of patents over the same period.

2.5 Deep learning method using SciBERT

Apart from the influence of BdScis, their level of expertise also plays a critical role in a firm's innovation activity. We measure the expertise of BdScis 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 BdScis 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 BdSci's work serve as two measures of a director's knowledge and expertise. BdScis 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 BdSci 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 BdSci 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 BdSci's subject areas, we use the Large Language Model (LLM) of deep learning.

2.5.1 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 randomly selects a pair of sentences and then it must 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 information content of the paragraph.

2.5.2 Training the model and performance

Our labeled dataset includes 340,000 abstracts of BdSci'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 A3.

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 patents belong to the same scientific subject areas.

To measure the expertise of BdScis, 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 BdScis' 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 BdScis' publications over the past three years, which provides a more current and relevant assessment of their expertise. We construct our BdSci expertise measure for director $\mathtt{d}$ 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 for BdSci $\mathtt{d}$ of firm $\mathtt{i}$ in subject area $\mathtt{s}$. We employ a log transformation due to the variable's skewed distribution. The formulas for the expertise variables are defined as follows:

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

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

2.6 Bridging Between R&D and Innovation Quality

This section describes two groups of outcome variables: one outcome category captures bridging activities between research and development, and the other outcome category captures the quality of a firm's innovations. The outcome variables that capture bridging activities between research and development include *Science-based Patents (Sci. Pat.)*, *Fundamental Patents (Funda. Pat.)*, and *Government Patents (Gov. Pat.)*.

Inspired by Arora et al. (2024b), *Sci. Pat.* refers to patents that cite at least one SNPL, and the number of citing SNPL is above the 75th percentile of patents in the same technology class and year. In contrast, Arora et al. (2024b) defines *Sci. Pat.* as patents in the top three quartiles. Our stringent definition ensures that these patents provide stronger evidence of a narrower gap between scientific research and patent innovation. In robustness analysis, we find that our results hold when using *Sci. Pat. (90)*, defined as patents that cite more SNPL than the 90th percentile of patents in the same technology class and year.

A limitation of *Sci. Pat.* is that some of these patents may not be fundamentally important, as they may cite a large number of SNPL that generate little value for the firm. To address this limitation, we introduce *Funda. Pat.*, defined as patents based on scientific research that serve as foundational innovations for subsequent patents. For a patent to be classified as a *Funda. Pat.*, it must cite at least one scientific publication and receive more citations than the 75th percentile of patents in the same technology class and year. These two conditions not only insure that *Funda. Pat.* are developed from scientific research, but also that they are important patents that generate a large number of citations. In Table A4, we evaluate the quality of *Funda. Pat.* in terms of market value, generality, and originality. We compare *Funda. Pat.* to other patents within the same firm, technology class, and grant year. We find that they have a 3% higher market value, 13.3% greater generality, and 1.5% higher originality than other similar patents in the same firms, technology class, and year.

The government often plays an important role in funding scientific research and promoting the commercialization of research, as documented in (e.g., Arrow, 1962; Nelson, 1959b; Howell, 2024; Fleming et al., 2019), making *Gov. Pat.* a good measure of the bridging of research and development activities. We obtain data on *Gov. Pat.* from Gross and Sampat (2025). *Gov. Pat.* are patents whose titles are held by individual firms, but they were funded at least partially by the U.S. Federal government. Firms can retain titles to patents developed with government support, provided that the government retains a royalty-free license to use these innovations, as stipulated by the Bayh-Dole Act.

To construct innovation output measures at the firm and year levels, we map patents to a firm based on the patent's application year and link. To capture bridging activities between R&D of firm i in year t+1, we calculate the share of firm i's total number of patents in year t+1 that are represented by *Gov. Pat.*, *Funda. Pat.*, and *Sci. Pat.*. We use a share of these three types of patents rather than raw numbers because the share better reflects the shifts in a firm's innovation strategy. In robustness analysis, we find that the results from using raw numbers are similar.

To capture the quality of a firm's innovation output, we use *Number of Patents (#Pat.)*, *Adjusted Cites(Adj.cites)*, *Patent's Market Value(Values)* in Kogan et al. (2017), and *Number of Breakthrough Patents(#B.through Pat.)*. More specifically, $\#Pat._{i,t+1}$ is the total number of patents filed and eventually granted in firm i at year $t+1$. We use *Adj.cites* to address the truncation issue in the citations dataset, we use the number of raw cites over the average cites of patents in the same technology class and grant year Hall et al. (2001). $Adj.cites_{i,t+1}$ is firm i's average *Adj.cites* per patent in year $t+1$.[10] $Value_{t+1}$ is the logarithm of the average market value of firm i's patents in year $t+1$. $\#B.through\ Pats_{i,t+1}$ represent the number of patents ranked in the 90th percentile of patent citations at firm i in year $t+1$.

2.7 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 1 presents a comparison between firms with and without BdScis on their boards based on firm fundamentals, valuation, and growth characteristics. The sample is divided based on whether firms have at least one BdSci during the sample period. Throughout the sample period, there are 34,128 firm-year observations without BdScis and 34,396 firm-year observations with at least one BdSci. The average number of BdScis per firm-year observation is 0.63. Firms with BdScis, on

[10] All patent citations are counted as of December 2021.

average, are larger in total assets and their average Tobin's q is higher. They also exhibit lower leverage, less cash holdings, invest more in R&D, and have higher valuations, highlighting their economic significance.

Contrary to common perceptions, we find that 69% of BdScis are industry scientists. Panel B of Table 2 highlights the differences between industry and academic BdScis in terms of their publication profiles and inventor status. Industry BdScis are more likely to be inventors, but tend to publish fewer papers and receive fewer citations. Panel C of Table 2 compares the characteristics of BdScis with those of non-BdScis. We find that BdScis are more likely to be inventors, but less likely to hold professional degrees such as JDs or MBAs, or to have experience in finance and executive roles. This suggests that BdScis possess different skill sets and offer distinct types of expertise compared to non-BdScis. Specifically, most BdScis specialize in basic sciences such as medicine, biochemistry and engineering. These basic science areas exhibit more innovation in terms of patents granted. Conversely, non-BdScis typically have generalized management skills for corporate operations such as finance, management and law.

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 BdScis and non-BdScis. On average, firms with scientific inventor directors outperform firms without scientific inventor directors in both the quality and quantity of their patent portfolios. More specifically, firms with scientific inventor directors have more patents with more adjusted citations, larger scope, and larger generality and originality than firms without scientific inventor directors, and these differences are statistically significant.

3 Empirical results

3.1 BdScis and Bridging Activities Between R&D

We begin our analysis by examining the role of BdSci in bridging R&D and enhancing innovation quality. BdScis represent a distinct subset of outside directors. Unlike traditional outside directors, who often bring operational experience, political connections, or strategic business expertise, BdScis are characterized primarily by their scientific expertise. This unique background is particularly valuable because basic scientific research is a key source of innovative ideas and plays a crucial role in driving innovation (Arora et al., 2021). The majority of BdScis are prestigious scientists who work at the forefront of scientific research, which allows them to identify promising state-of-the-art scientific discoveries that are ripe for future innovation. The scientific expertise of BdScis positions them to act as a bridge between science research and patent innovation. Moreover, the integrity of BdScis, which stems in part from the value scientists place on their professional reputations, is a key factor that insures that they provide honest and insightful advice on a firm's research progress.

We expect BdScis to play an important role in bridging R&D activities and enhancing innovation performance as a result of their scientific expertise and superior advisory capabilities.

Many examples come to mind. First, John Baxter, serving as a BdSci 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). A second example is Robert Langer, who is a BdSci 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 highlights 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).

First, we examine whether BdScis play an important role in bridging R&D by using the following regression:

$$Y_{i,t+1} = \alpha_0 + \alpha_j + \alpha_t + \beta_1 \mathrm{BdSci}_{i,t} + \lambda X'_{i,t} + e_{i,t} \tag{4}$$

where for firm i in year t, $Y_{i,t+1}$ includes the share of *Gov. Pat.*, *Sci. Pat.*, and *Funda. Pat.*, relative to the firm's total number of patents, as detailed in Section 2.6. $\mathrm{BdSci}_{i,t}$ is an indicator variable that equals one if firms have at least one BdSci in the year t and zero otherwise. The main coefficient of interest (β_1). X represents the vector of firm control variables: total assets, R&D, CAPEX, firm age, annual returns, financial leverage, share of independent directors and an indicator for a scientific CEO;[11] α_j and α_t are SIC 4-digit industry fixed effects and year fixed effects, respectively.

Coefficients shown in Columns (1-3) of Table 10 are positive and statistically significant at 1%, showing that firms with *BdSci* have a larger share of *Gov.Pat.*, *Sci.Pat.*, and *Funda.Pat.* than other firms in the same industry. More specifically, firms with a *BdSci* produce 0.3% more *Gov. Pat.*, 3.2% more *Sci. Pat.*, and 1.3% more *Funda. Pat.* than other similar firms within the same industry, suggesting that these firms place greater emphasis on scientific research in their innovation activities.

Second, we investigate the role of BdSci in enhancing innovation output using Equation 4, where innovation qualities are measured using firm i's *#Pat.*, *Adj.cites*, *Value* and *B.through Pat.* in the next year.

Columns (4-7) of Table 3 report Poisson regressions for count dependent variables and OLS regressions for non-count dependent variables. The results indicate that firms with BdScis demonstrate superior innovation performance in terms of the quantity and quality of their patents compared to other firms within the same industry without BdScis. Column 4 focuses on the relationship between BdScis and *#Pat.*, and we observe a positive coefficient of 0.292, which is statistically significant at the 10% level. This suggests that firms with BdScis have 1.34 ($e^{0.292}$) times more patents

[11] The results are robust to controlling for the scientific expertise of other executives, such as the Chief Technology Officer(CTO), Chief Scientific Officer(CSO) and Chief Medical Officer(CMO).

than other firms in the same industry without BdScis. Moving to *Adj.cites* in column 5, we find the coefficients are statistically significant at the 5% level. The coefficient of BdSci is 0.051 in column 5. This estimate indicates that firms with BdScis on the board produce 0.051 higher average adjusted cites per patent compared to similar firms in the same industry without BdScis. Column 7 shows that firms with BdScis produce more breakthrough patents, with β_1 equal to 0.313, which is statistically significant at the 5% level. This coefficient estimate suggests that firms with BdSci produce 1.37 ($e^{0.313}$) times more breakthrough patents. In untabulated tests, we find that our results are robust to using alternative industry fixed effects, such as FIC industry codesHoberg and Phillips (2016) and 3-digit SIC codes, as well as when we measure the outcome variables over different time horizons, such as the next 3 or 5 years.

4 Endogenous director appointments

The appointment of BdScis by innovative companies reflects an endogenous board selection process. This endogeneity implies that BdScis may not causally enhance firm innovation; rather, they may be appointed because innovative firms already have prior ties with these scientists. For example, innovative firms are more likely than others to collaborate with university researchers through R&D contracts and may consequently have stronger connections to BdScis in universities or research institutions. Moreover, BdSci candidates may themselves prefer to join more innovative firms, reinforcing the non-random matching between BdScis and firm innovation.

In this section, we address the above endogeneity concern using two complementary strategies. First, we exploit exogenous shocks from technological breakthroughs, such as the Human Genome Project. Second, we use the local supply of BdScis as an instrumental variable to capture director preferences for serving on local boards.

4.1 Human genome project

We examine whether a positive technological shock results in an increase in a firm's demand for BdScis. In this experiment, we begin by assuming that a positive technology shock will increase the value to a firm of having BdScis 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 BdSci and a firm's demand for these BdScis. This can be because these BdScis can help guide the firm's new investments in the shock-affected technology or help recruit relevant experts due to their professional connections with these scientists. It can also be because these BdScis can provide valuable guidance to a 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 focus on an industry-specific 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 to the shocked industry, some firms were known to pay significant amounts of money to obtain privately patented human genome data prior to the HGP data's public release date so as 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 BdScis due to their increased expected value to firms in the genetics-related industries. We investigate whether firms in industries that benefit from HGP appoint more BdScis and subsequently produce more patents following 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, we classify genetics-related industries to 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 gene sequence map and the initial analysis of the HGP became publicly available. We hypothesize that the economic benefits of having a BdSci increase after the public release of the HGP findings, leading to a rising demand for BdScis by firms in genetics-related industries. It is important to note that, in our analysis of HGP, we do not claim a causal effect of BdScis on firms' innovation output. Instead, our focus is on the causal effect of a major exogenous technology breakthrough on the economic benefit of having a BdSci on the board and the subsequent firm demand for BdSci.

We first investigate whether firms in genetics-related industries are more likely to hire BdScis in general or BdScis with genetics expertise, which we hereafter denoted as genetics BdScis, following the public release of the HGP results, which we attribute to the rise in the expected economic benefits associated with having a BdSci. The first stage regression equation is specified as follows:

$$\text{BdSci/genetics BdSci share}_{i,t} = \alpha_i + \alpha_t + \beta \text{genetics industry}_i * \text{Post2001}_t + \lambda X'_{i,t} + +e_{i,t} \tag{5}$$

where *BdSci/genetics BdSci share*$_{i,t}$ is the ratio of the number of BdScis or genetics BdScis scaled by the total number of directors at firm i in year t; X is a vector of the firm control variables defined in Equation 4; 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 4 shows that firms in the genetics-related industries hired more BdScis and genetics BdScis to their boards after 2001. Column 1 presents OLS regression of BdSci share against the interaction between *genetics industries* and *post 2001*. The coefficient in column 1 is 0.027 and statistically significant at the 1% level, suggesting that firms in the genetics-related industry have 2.7% more BdScis than firms in other non-genetics industries after the HGP shock. Additionally, figure 3 presents the time trend in the board's share of BdScis before and after 2001 and indicates no pre-trend in the two years prior to the HGP treatment year. Column 3 evaluates the effect of HGP on the share of genetics BdScis 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 BdScis than other firms after the HGP shock, as predicted.

Covariate imbalances between firms in genetics-related and non-genetics industries may bias comparisons and inferences. To mitigate this concern, we implement a propensity score matching approach to construct a control group of firms with comparable characteristics. The matching covariates include firm size, ROA, annual return, and number of patents, measured up to the event year 2001. Notably, including patent activity helps address the concern that firms with stronger innovation capacity may be more likely to appoint BdScis. Table A5 confirms that, after matching, the differences in covariates between the treatment and control groups are statistically insignificant. Columns 3 and 4 in Panel A of Table 4 present the analysis based on the matched sample. We find that our results remain robust. Specifically, the dependent variables in columns 1 and 2 are the shares of BdScis and genetics BdScis on the board. The estimated coefficients are 0.031 and 0.019, respectively, both statistically significant at the 1% level, indicating that firms in genetics-related industries appoint more BdScis and genetics BdScis than comparable firms in other industries following the 2001 technology HGP shock.

There are two limitations of the analysis of the HGP's effect on the BdSci share of directors. First, we assume that the economic benefits of BdSci appointments increase following the HGP. However, this assumption may be fragile if firms appoint BdScis primarily to signal the promise of their genetics-related products, rather than to leverage their expertise. Second, although we implement propensity score matching, cross-industry comparisons may still be biased due to unobserved industry heterogeneity. To overcome these limitations, we refine our analysis by focusing exclusively on genetics-related industries and then comparing changes in innovation output between genetics firms that appointed new Genetics BdScis within two years after the 2001 shock and firms that did not in Panel B of Table 4. Our regressions take the following form:

$$\text{Innovation output}_{i,t+1} = \alpha_i + \alpha_t + \beta_1 \text{Gen. BdSci}_i * \text{Post2001}_t + \lambda X'_{i,t} + +e_{i,t} \tag{6}$$

where *Gen. BdSci*i,t is an indicator variable equal to 1 if firm i appoints a Genetics BdSci within two years after the event, and 0 otherwise; the dependent variable, *Innovation output*$i,t+1$, represents the innovation output of firm i in year $t+1$; X is a vector of firm-level control variables as defined in Equation 4; α_i and α_t denote firm and year fixed effects, respectively. All standard errors are clustered at the 4-digit industry level.

Panel B of table 4 shows that firms that appointed genetic BdScis produce more patents and breakthrough patents than other firms in the same genetics industries after 2001. The dependent variable in column 1 is the number of patents in the next year. Column 1 reports Poisson regression estimates of the number of patents on the interaction between *Gen. BdSci* and *post*. The coefficient in column 1 is 0.419 and statistically significant at 5%, suggesting that firms appointing genetic

BdScis produce 1.52 ($e^{0.419}$) times more patents than similar firms in the genetic industries after 2001. The dependent variable of column 2 is the number of breakthrough patents at the 90% level for the next year. The coefficient in column 2 is 0.570, which is statistically significant at the 1% level, indicating that firms with new genetic BdScis have 1.77($e^{0.570}$) times more breakthrough patents than other firms in the genetic industries after 2001. Column 3 investigates the effect of the HGP shock on the number of breakthrough patents at 99% in the next year. These breakthrough patents at the 99% level are economically more significant, as they receive more citations than the 99th percentile of the citation distribution within the same technology class and grant year. Interestingly, column 3 shows that firms in the genetics industry have 2.9($e^{1.068}$) times more breakthrough patents at 99% level than similar firms in the genetic industries after 2001. Columns 4 and 5 show no statistically significant relationship when the dependent variables are patent market value and adjusted citations.

Overall, we find that firms in industries that benefit most from genetics knowledge are more likely to appoint BdScis in the post-2001 period than comparable firms in other industries. By comparing firms that appoint new Genetics BdScis to similar firms within the genetics industry that did not, we find that the former group experienced greater increases in both patent quantity and quality after 2001. This suggests that BdScis with relevant genetics expertise contribute positively to firm innovation. Thus, our evidence is consistent with a positive technology shock increasing the value of BdScis, which in turn leads to more frequent appointments in the affected industries. This evidence of the increased presence of BdSci post-HGP is inconsistent with a reverse causality explanation, as the HGP exogenously increased the economic value of BdSci. This result confirms that firms are benefiting from the scientific expertise of BdSci that is enhanced by the HGP breakthrough.

4.2 Local BdSci supply

The analysis of the HGP shock provides only suggestive evidence on the effect of BdScis on firms' innovation output and is limited to a single industry, raising concerns about external validity. This section addresses these limitations by examining the relationship between the presence of BdScis on corporate boards and innovation outcomes, using the local supply of BdSci candidates as an instrumental variable (IV). The IV approach helps address these limitations by estimating the Local Average Treatment Effect (LATE), which captures the causal effect of BdSci presence—induced by variation in the local supply instrument—on innovation output across innovative industries.

Following Knyazeva et al. (2013), the Local BdSci supply is the logarithm of one plus the number of BdScis in firms headquartered within 60 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 be appointed to the focal firm's board due to competition concerns and anti-trust legal liability. In addition, we exclude firms located in Alaska and Hawaii, comprising only a handful of observations. The

Compustat dataset continuously updates firms' headquarters information, but fails to account for historical changes in headquarters locations. To overcome this limitation, we use the dataset from Jennings et al. (2017), which provides historical headquarters data and captures changes in firms' headquarters locations.

To calculate the local BdSci supply, We first measure the distance between the focal firm and other firms by using the Great Circle Distance. The inputs of Earth's Great Circle Distance (EGCD) are the longitudes and latitudes of the two headquarters locations. The output of EGCD is the distance between the 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, BdSci 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 60 miles of the focal 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 BdSci 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 BdScis are generally in short supply and thus represent a scarce human resource for a firm. Firms often rely on BdScis to advise them on their major innovative projects. In such cases, the firm could demand substantial time and energy from a BdSci 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 BdSci candidates since they minimize the time needed to attend board meetings.

Empirically, column 1 of Table 5 presents the first stage regression as the following statistical model:

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

where $BdSci_{i,t}$ is an indicator variable equal to 1 if the firm i has at least one BdSci in year t and 0 otherwise.

The coefficient of the local BdSci candidate supply in Column 1 of Table 5 is statistically significant at the 1% level, suggesting that likelihood of having a BdSci on the board increases by 0.016 for each 1% increase in the local BdSci supply. The F statistic is 140.36, 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 BdSci supply only affects innovation output through the share of BdScis on a board. We conclude that the IV meets the relevance and exclusion conditions.

In the second stage, we regress future innovation metrics on the predicted share of BdScis based on the fitted value of the local BdSci candidate supply regressions, denoted with a hat, which is specified as:

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

where *Innovation output*$_{i,t+1}$ is the logarithm of the innovation output of firm i over years 1 through 3; X is a vector of the firm control variables defined below Equation 4; while α_j and α_t are three-digit SIC industry and year fixed effects.

Table 5 shows that the fitted values of the BdSci share are positively related to the number of new patents and the average market value of the new patents. The IV estimates should be interpreted as Local Average Treatment Effects (LATE). Firms with a greater local BdSci supply tend to appoint more BdScis, and these treated firms with more BdScis produce more patents and a larger average market value per patent within the same industry. More specifically, the dependent variable in column 3 is the logarithm of average market values of patents in the next year. The coefficient in column 3 is 0.866 and statistically significant at 10% level. Column 3 shows that for a 1% increase in the number of local BdSci candidates nearby the focal firm, the treated focal firm experiences a 1.4% (0.016×0.866) increase in the average market values of patents in the next year within the same industry. Examining the number of patents, the coefficient of column 4 is positive and statistically significant at 5%, suggesting that for a 1% increase in the local BdSci supply, the treated firms produce 3.131% (0.016×1.957) more patents than other similar firms in the same industry. Given that the endogenous variable *BdSci* is a binary variable, which may lead to biased estimates in a 2SLS model, we also use *BdSci share* as an alternative measure for the presence of BdScis. We present the results using *BdSci share* as the instrumented variable in Columns 5 to 8 of Table 5, and find similar results.

Overall, we find that the focal firms hire more BdScis to their boards of directors when there is a greater supply of local BdSci candidates. Importantly, these BdSci-appointing firms experience better innovation performance based on multiple innovation metrics than other firms in the same industry.

5 Channels: BdSci knowledge and professional networks

In this section, we explore the channels through which BdScis enhance firm value, focusing on two key characteristics: their scientific knowledge and professional networks. Firstly, we gauge the influence of BdScis on firm patents and examine the relation between their influence on firm patents and the efficiency of firm innovation in Section 5.1. In Section 5.2, we more rigorously assess the relation between firm innovation and BdSci expertise, measured by their recent publications. Finally, we investigate BdScis' role in its firm's recruitment and retention of inventors by leveraging their professional networks in Section 5.3.

5.1 BdSci influence on a firm's patents

This section investigates the relation between a BdSci's influence on firm patents and the quality and quantity of the firm's innovation output. As presented in Section 2.4.1, a BdSci's influence is measured by the firm's cumulative number of patents that cite the BdSci's work over the cumulative number of patents awarded to the firm. The increasing influence of BdScis on a firm's patent applications emphasizes the important advisory role of BdScis in the firm's innovation process, given that the scientific work of the BdSci is directly influencing a firm's patent inventors. Also, the greater influence of a BdSci suggests that a BdSci's expertise is more relevant to the technology underlying the firm's patents.

Our data is at the firm, BdSci and year level, and it allows us to include firm×director fixed effects. The firm×director fixed effect exploits the fact that a BdSci's influence can vary over time, so that within firm-director pairs can arguably change their effects on a firm's innovation outcomes such as after an exogenous shock. 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 BdSci. The inclusion of firm×director fixed effects allows us to capture the time series variation in a BdSci's influence within a specific firm-BdSci pair. The firm×director fixed effects facilitate an examination of the correlation between shifts in a BdSci'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:

$$\text{Innovation output}_{i,d,t+1} = \alpha_0 + \beta \text{BdSci's influence}_{i,d,t} + \alpha_{i,d} + \alpha_t + X'_{i,t}\lambda + e_{i,t}, \tag{9}$$

where *Innovation output*$_{i,d,t+1}$ is the innovation output of firm i given BdSci d is on the board in the next year; X is a vector of firm control variables defined below Equation 4; 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. Table 6 reports Poisson regression estimates for count-based dependent variables (Cohn et al., 2022) and OLS regression estimates for the non-count dependent variables.

Panel A of table 6 shows firms produce higher-quality innovation output when the BdScis have a greater influence on a firm's patent innovation activity. The dependent variables in column 2 are the average adjusted cites in the next year. The coefficient in column 2 is 0.869, and is statistically significant at the 5% level, suggesting that firms receive 0.869 more average adjusted citations when BdSci influence increases by one unit. For the average value of patents, the coefficients in column 3 is 0.77, which are significantly different from zero at the 1% level, indicating that firms have 77% larger average market value for their patents when BdSci influence increases by one unit.

5.2 BdSci expertise and a firm's innovation activity

In Section 5.1, we assess a BdSci's influence on a firm's patents by examining a firm's patents that directly reference the scientific works of a BdSci. However, there are two limitations to this measure of a BdSci's influence. First, relying only on direct citations to a BdSci's publications is an overly conservative approach to determining the connection between a firm's patents with a BdSci's expertise and influence. A firm's innovation activities can also be influenced by a BdSci's expertise when a firm's patent is based on the body of knowledge in the same areas where BdScis actively do research. Secondly, this BdSci influence measure provides limited insights into the influence of their recent scientific research. For instance, BdScis might begin working on new areas of research that are beneficial to a firm's innovation activity, but these publications in these novel research domains, which are not directly cited by a firm's recent patents due to the lag between scientific research publications and patent applications (Ahmadpoor and Jones, 2017).

We use the deep learning method described in Section 2.5, to address the limitations of the prior measure of a BdSci's influence. We construct a patent dataset that is denoted by firm, scientific subject area, and year, where we identify a patent's main scientific subject areas based on the deep learning method. We also match the subject areas of a firm's patents with the subject areas of a BdSci's publications over the prior 3 years. The analysis allows us to evaluate the impact of a BdSci's expertise on a firm's patents that benefit from this knowledge base, even if these patents do not directly cite a BdSci's publications. Also, we investigate the effect of a firm's innovation activities on a BdSci's recent research activities. Our regressions have the following form:

$$\text{Innovation output}_{i,s,t+1} = \alpha_0 + \alpha_i + \alpha_t + \alpha_s + \beta_1 \text{Expertise}_{i,s,[t-3,t]} + \lambda X'_{i,s,t} + e_{i,s,t} \qquad (10)$$

We use two BdSci expertise measures as described in Section 2.5. 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 BdScis 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 BdScis authored in the past three years. We further match the BdSci's expertise to the firm's innovation output by subject areas. $\text{Innovation output}_{i,s,t+1}$ is the innovation output in subject area s for firm i in the next year; X represents the vector of firm control variables used earlier below Equation 4; 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. Table 7 reports Poisson regression estimates for count-based dependent variables (Cohn et al., 2022) and OLS regression estimates for the non-count dependent variables.

Columns 1 and 2 of table 7 show that a firm produces more patents in subject areas where a BdSci has more publications or receives more citations. More specifically, the coefficient of column 1 is 0.449 and statistically significant, suggesting that a firm is associated with 1.567($e^{0.449}$) times more patents in the subject areas where a firm's BdScis publish more. The coefficient of column 2 is 0.164 and statistically significant at the 1% level, suggesting that a firm is associated with

1.178($e^{0.0.164}$) times more patents in subject areas where BdScis receive more 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 1.165($e^{0.153}$) and 1.058($e^{0.056}$) times more average adjusted cites per patent in the subject areas where a BdSci publishes more papers and receives more citations. Columns 5 and 6 suggest that a BdSci's expertise is positively correlated with the average market value of a patent. The β_1 estimates of $\text{Expertise(pub)}_{i,s,[t-3,t]}$ and $\text{Expertise(cites)}_{i,s,[t-3,t]}$ are 0.047 and 0.014 and are statistically significant at the 1% level. Columns 7 and 8 suggest that firms are associated with 1.63 ($e^{0.488}$) and 1.198 ($e^{0.181}$) times more breakthrough patents in the subject areas when the BdScis publish 1% more publications and receive 1% more citations respectively. Lastly, we observe that firms produce more fundamental patents in subject areas where BdScis have a greater level of expertise. The β_1 estimates in columns 9 and 10 are 0.566 and 0.195, and they are statistically significant, suggesting that the firm produces 1.761 ($e^{0.566}$) and 1.215 ($e^{0.195}$) more fundamental patents in the subject areas where BdScis publish more papers and receive more citations respectively. In summary, BdSci expertise is significantly positively related to the frequency of patents, the quality of the average patent and the average valuation of these patents.

5.3 BdSci professional networks

While we find that BdScis serve as a bridge between scientific research and patent innovation and enhance the quality of firm innovation, another valuable resource they offer is their extensive scientific networks. Given that many BdScis are affiliated with universities and laboratories, which are places with large supplies of scientists and inventors, this means that BdScis are generally well-connected and knowledgeable about many highly qualified and productive inventors in the field. Furthermore, BdScis, particularly those who also serve as professors, are not only close to the supply of scientists and inventors, but they also play a key role in the training and guidance of junior scientists and inventors as part of their university duties. Consequently, it is reasonable to expect that BdScis can leverage their professional networks to help the firms where they are board members recruit promising inventors who could potentially lead some of the firm's research projects.

To test the proposition that BdScis help firms recruit talented inventors, we first form inner communities of BdScis' extensive professional networks. These inner communities encompass firms' BdScis, inventors affiliated with their firms, and BdScis' co-authors and co-inventors. The intuition behind constructing inner communities is that they comprise scientists and inventors who collaborate closely with individual BdScis through publication and patent collaborations. A scientist (inventor) becomes a member of a BdSci's community only when this scientist (inventor) has a closer working relationship with the BdSci, which is demonstrated by having a significant number of co-authorships and successful patent collaborations compared to other scientists (inventors) in a

BdSci's network. A BdSci's inner communities represent this BdSci's more important professional relationships.

Calculating inner communities annually allow us to classify groups of scientists (inventors) who closely collaborate with BdScis on a dynamic basis. We assume BdScis are familiar with scientists (inventors) in their corresponding communities. Within the communities associated with each BdSci, we additionally categorize inventors into two groups: those affiliated with the BdSci's firm (BdSci-affiliated inventors) and those with other affiliations (Non BdSci-affiliated inventors). The BdSci-affiliated inventors are defined as those inventors who are in a BdSci's community and who also work for the firm where the BdSci sits on the board. Non BdSci-affiliated inventors are inventors who are in the communities of a BdSci, but do not work at the BdSci's firm.

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

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

$$y_{f,q,t} = \alpha_0 + \alpha_{q,t} + \beta \text{BdSci-affiliated inventors}_{f,t} + \lambda X'_{i,t} + +e_{i,t} \tag{11}$$

where $y_{f,q,t}$ is the performance metric of inventor f in community q and year t. The quality of an inventor's patent portfolio is measured using four metrics: the average and maximum number of adjusted citations, the share of breakthrough patents, and the total number of breakthrough patents. To represent an inventor's relative performance, we construct percentile ranks for each performance metric within their respective communities, as reported in Columns (1–4) of Table 8. The outcome variables in Columns (5–8) of Table 8 are indicator variables equal to 1 if an inventor's performance metrics are in the top 10th percentile, and 0 otherwise. The "BdSci-affiliated inventors" is an indicator variable equal to one if the inventor is a BdSci-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.

Table 8 indicates that BdSci-affiliated inventors hired by the firm rank higher and are more likely to be among the top 10% of inventors within the BdSci's community across various metrics, including adjusted citations and the number of breakthrough patents. All coefficients in Columns (1–4) are positive and statistically significant at the 1% level, indicating that BdSci-affiliated inventors rank 0.044, 0.045, 0.029, and 0.033 percentiles higher than other inventors in the BdSci's communities in terms of average adjusted citations, maximum adjusted citations, share of breakthrough patents, and total number of breakthrough patents in their portfolios, respectively. Moreover, the coefficients in Columns 7 and 8 are positive and statistically significant, indicating that BdSci-affiliated inventors are more likely to be ranked in the top 10% of the BdSci's communities regarding the share and total number of breakthrough patents. In sum, Table 8 shows that BdSci-affiliated inventors are more productive than other inventors in the BdScis' communities. This suggests that BdScis can effectively identify more productive inventors within their communities and help recruit them to the firms where they are board members. Our results are also robust when we use raw innovation quality measures instead of relative ranks.

We next assess whether BdSci-affiliated inventors can continuously be productive after joining a BdSci's firm. The analysis involves a comparison of the performances between BdSci-affiliated inventors and other inventors in the firm where the BdSci holds a board position, but who are not in the BdSci's community. We run an inventor, firm, and year-level regression of patent quality against a BdSci-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.

$$y_{i,f,c,t} = \alpha_0 + \alpha_i + \alpha_t + \alpha_c + \beta_1 \text{BdSci-affiliated inventors}_{i,f,c,t} + \lambda X'_{i,f,c,t} + e_{i,f,c,t} \qquad (12)$$

where $y_{i,f,c,t}$ is the performance metric of inventor f in firm i, cohort c and year t. The inventor performance metrics are the same as those defined in Equation 11. Columns (1–4) of Table 9 report the relative percentile ranks of an inventor among all inventors within the same firm and year. Columns (5–8) of Table 9 present indicator variables equal to 1 if an inventor's performance metrics fall within the top 10% of all inventors in the same firm and year, and 0 otherwise. The key explanatory variable "BdSci-affiliated inventors" is, an indicator variable that equals 1 if the inventor is a BdSci-affiliated in firm i. X is a vector of firm characteristics defined in Equation 4 and the following inventor characteristics: a female indicator and experience. It is important to note inventors in a BdSci firm may not necessarily work closely with BdSci or be part of the BdSci's community. However, these inventors could still benefit from being in the community of BdScis 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 BdScis at other firms and is zero otherwise. All regression includes firm, year, and cohort fixed effects.

Table 9 shows that BdSci-affiliated inventors, defined as inventors who actively collaborate with their BdScis or are closely connected to individuals in the BdSci's network, exhibit significantly stronger performance than other inventors within the same firm. More specifically, all coefficients in Table 9 are positive and statistically significant at the 1% level, indicating that BdSci-affiliated inventors not only rank higher than other inventors, but are also more likely to be among the top 10% performers within their firms, compared to inventors who are not part of the BdSci's communities. For example, BdSci-affiliated inventors are 2.3%, 5.2%, 1.6%, and 3.3% more likely to be top 10% performers than other inventors within the firm when patent quality is measured by the average and maximum number of adjusted citations, the share of breakthrough patents, and the total number of breakthrough patents in their patent portfolios, respectively.

In summary, both tables 8 and 9 indicate that BdSci-affiliated inventors exhibit higher productivity compared to other inventors within the BdSci community, and these BdSci-affiliated inventors maintain their high productivity levels after joining the firm. This suggests that BdScis 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 BdScis in terms of the firms' talent-hiring process since we cannot observe a firm's choice set of talented inventor candidates or an inventor's choice set of potential employers.

6 Long-Term Firm Valuation and Shareholder Assessments of the Benefits of BdScis

Investment in scientific research often involves long time horizons and a lack of periodic milestones to assess research progress, making it difficult for non-expert investors to evaluate a firm's innovation success. The inherent uncertainty of scientific research may tempt managers to prioritize short-term gains and o underinvest in long-term scientific projects (Garlappi et al., 2017). We view BdScis to be well-positioned to effectively assess a firm's ongoing scientific research and thus, help address these investor concerns. Our study investigates how the presence of BdScis on the board affects stock performance, exploring their potential to influence manager decisions and the overall valuation of the firm. We hypothesize that BdScis can positively contribute to a firm's valuation, given the long-term nature and valuation benefits of their support to a firm's innovation activity measure by patents.

We follow the convention of using Tobin's q as a forward looking measure of firm value (e.g., Arora et al., 2021; Gompers et al., 2003; Morck et al., 1988, among many others). Long-term firm value is calculated from its Tobin's q averaged over the next n years. We investigate the relation between BdScis and firm value using the following panel regression:

$$\text{Avg Tobin's } q_{i,[t+1,t+n]} = \alpha_0 + \alpha_j + \alpha_t + \beta_1 \text{BdSci}_{i,t} + X'_{i,t}\lambda + e_{i,t}, \tag{13}$$

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. $BdSci_{i,t}$ is an indicator variable equal to one if the firm has at least one BdSci on the board for the full year t and is otherwise 0. X is a vector of firm control variables used in Equation 4 and an 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.

Panel A of table 10 shows that firms with BdScis have superior long-term firm valuations compared to firms without BdScis within the same 4-digit industry. More specifically, the β_1 in column 1 is 0.030 and is significantly greater than zero, suggesting that over the next 2 years, BdSci firms have a 3.0% larger firm valuation relative to non-BdSci firms in the same industry. Column 2 presents the relation between a BdSci and the firm valuation over the next three years and shows that firms with BdScis are on average associated with a 2.8% larger firm valuation compared to non-BdSci firms within the same industry. In column 3, the results reveal a 2.6% larger firm valuation associated with firms having BdScis over the subsequent four years relative to non-BdSci firms within the same industry. Moving to column 4, which uses Tobin's q averaged over the next 5 years, the coefficient is positive, but not statistically significant.

Panel B of Table 10 presents 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 over time. 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, market reactions to director deaths should be more informative about a director's value to a firm.

We collect 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 our event date. We find 23 BdSci death events and 170 non-BdSci death events. The average three-day CAR[0,2] after a BdSci death is -2.42%. The average 3-day CAR[0,2] after a non-BdSci director death is 0.38%. The difference in these departure announcement returns between scientific and non-BdScis is -2.80% and statistically significant at the 5% level. We also employ propensity score matching to create a non-BdSci firm control group with similar firm and director characteristics to the BdSci sample. The matching firm and director characteristics we use in year $t-1$ include size, ROA, and indicator variables for executive and finance experience, and an independent director. The differences in CAR[0,2]s between BdSci and Non-BdSci firms is -3.74% and statistically significant at the 10% level.

7 Conclusion

This paper provides novel evidence on the advisory role of directors, exploring how outside directors can enhance a firm's value through their specialized expertise. Scientists on corporate boards (BdSci), 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 negative market reactions to BdSci deaths underscore the valuation benefits of BdScis from a shareholder's viewpoint. We further evaluate the long-term firm valuation impact of BdScis using Tobin's Q as a forward looking measure of shareholder value. It reveals a positive association between firms with BdScis and long-term valuations compared to similar firms without BdScis within the same industry.

Moreover, we find that firms with BdScis are more productive in terms of innovation than non-BdSci firms in the same industry. We address the concern about the endogenous nature of director appointments using several approaches. First, we use the local supply of BdSci candidates as an IV to predict BdScis and separately use the Human Genome Project as an exogenous shock that raises the economic benefits of BdScis. Using 2SLS regressions, we find that firms have more BdScis on the board when there is a larger local supply of BdSci candidates, and these firms have better innovation outcomes than other firms in the same industry. In addition, firms in the genetics-related industry hire more BdScis to their boards after the 2001 HGP shock compared to similar firms in other industries. Moreover, firms in the genetics-related industries appoint more BdScis with genetic expertise.

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

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

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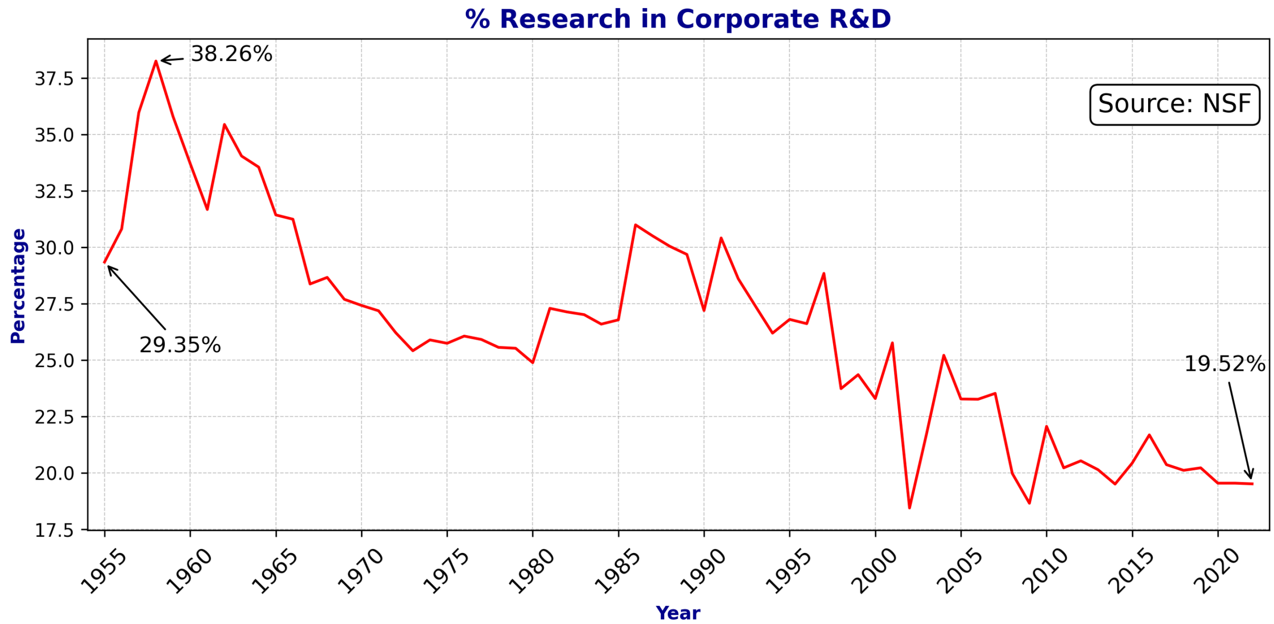

Figure 1

This figure presents the percentage of research expenditure in total corporate R&D from 1955 to 2021, based on data from the NSF website.

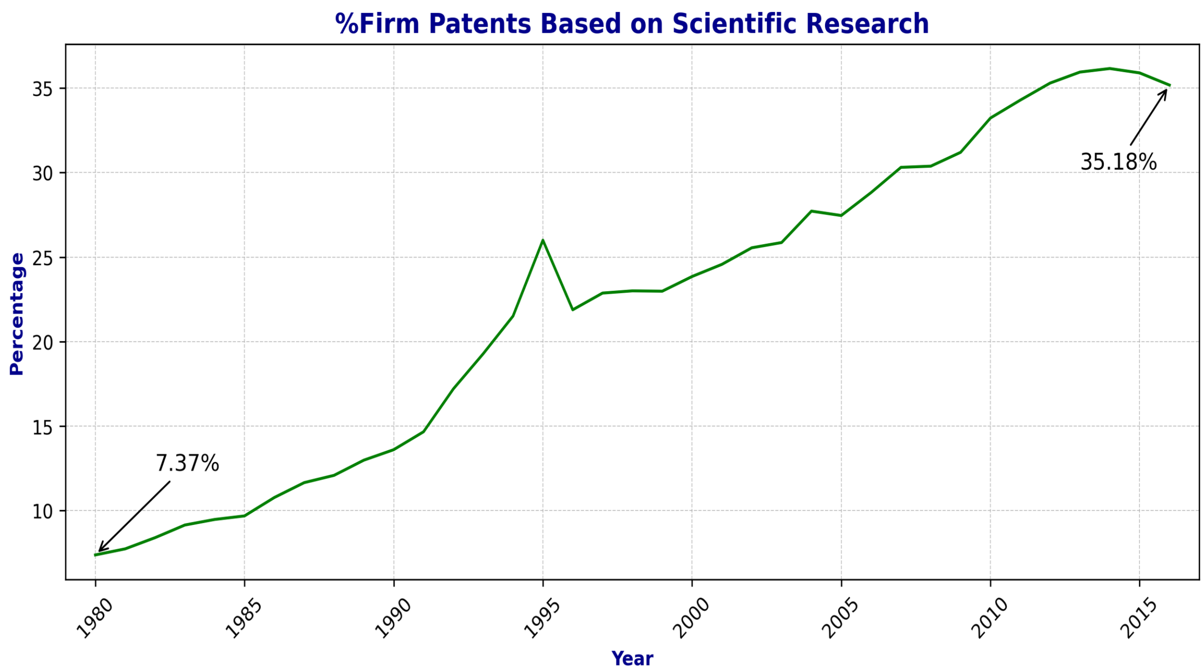

Figure 2

This figure presents the percentage of firms' patents based on scientific research as a share of their total patents from 1980 to 2016. Patents based on scientific research are defined as those that cite scientific publications.

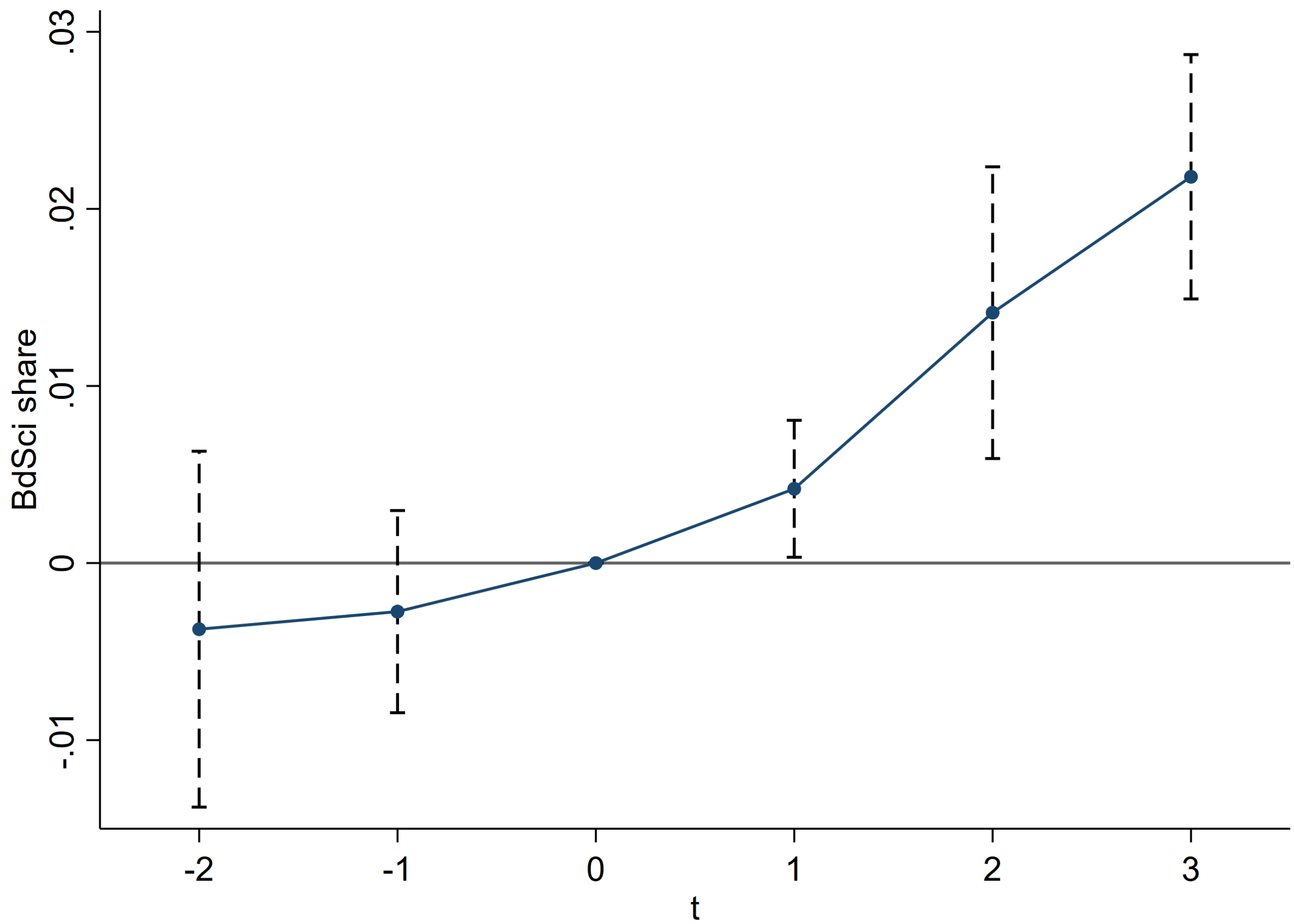

Figure 3

The figure plots differences (and 95% confidence intervals of the differences) between treatment and control firms regarding their changes in BdSci 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 BdSci. 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 BdSci during the sample period, comprised of 34,396 firm-year observations. Group B includes observations during the sample period with zero BdScis, comprised of 34,128 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 BdSci (A)		Without BdSci (B)				
	Mean	St. Dev.	Mean	St. Dev.	Diff. (A-B)	T-stat.	P-val.
Firm Fundamental							
Log (Size)	6.19	2.15	5.69	1.88	0.50	31.92***	0.00
Leverage	0.20	0.21	0.23	0.23	-0.03	-15.68***	0.00
RD	0.11	0.17	0.09	0.15	0.02	13.8***	0.00
CAPEX	0.05	0.06	0.06	0.07	-0.01	-14.57***	0.00
Cash	0.24	0.25	0.2	0.24	0.04	20.95***	0.00
ROA	0.03	0.27	0.05	0.24	-0.02	-8.6***	0.00
Free Cash Flow	0.01	0.23	0.03	0.2	-0.02	-9.76***	0.00
PPE	0.23	0.21	0.27	0.25	-0.04	-22.04***	0.00
Log(Sale)	5.83	2.52	5.4	2.17	0.43	23.41***	0.00
Nasdaq	0.49	0.50	0.48	0.50	0.01	1.69*	0.09
Sci. CEO	0.13	0.33	0.07	0.26	0.06	25.21***	0.00
Age	19.09	15.12	15.05	13.19	4.04	37.26***	0.00
Valuation							
MV/BV	3.49	5.39	3.06	5.18	0.43	10.66***	0.00
Tobin's q	2.34	1.89	2.08	1.68	0.26	18.99***	0.00
Annual Return	0.14	0.63	0.12	0.63	0.02	2.67***	0.01
Firm Growth							
ΔAsset	0.14	0.46	0.14	0.45	0.00	0.19	0.85
ΔSale	0.12	0.38	0.11	0.38	0.01	1.12	0.26

Table 2
BdSci characteristics

This table presents the BdSci characteristics. Panel A shows the BdScis' characteristics regarding author profile. The author profile contains *#Publications*, *h-index* and *citations* until 2021. The *#Publications* is the number of publications authored by a BdSci. The *H-index* is a BdSci'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 BdSci. Panel B compares industrial BdScis with academic BdScis in terms of their publication profiles and inventor statuses. *Inventor*, is an indicator variable that equals 1 if a BdSci is a patent inventor and 0. Panel C compares the education and previous experience of BdScis and non-BdScis.*Finance(Executive) Exp.*, is an indicator variable that equals to 1 if a director has finance(executive) experience and is 0 otherwise. *MBA(JD)* is an indicator variable that equals to 1 if a director holds a MBA(JD) degree. Panel C contains 2,199 inventor directors. Inventor directors are outside directors who are patent inventors. 1,097 inventor directors are BdScis, and 1,102 are non-BdScis. 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: BdSci Author Profile

	Author Profile		
	#Publications	H-index	Citations
Obs	4047.00	4047.00	4047.00
Mean	70.82	18.77	5142.05
St. Dev.	150.67	29.81	16532.89
Min	0.00	0.00	0.00
25%	2.00	1.00	6.00
50%	12.00	6.00	214.00
75%	64.00	25.00	2933.00
Max	2447.00	356.00	388360.00

Panel B: Industry VS Academic Scientists

	Industry Scientists		Academic Scientists			
	Mean	St. Dev.	Mean	St. Dev.	T-stat.	P-val.
#Publications	30.93	70.53	161.12	226.06	-27.62***	0.00
H-index	10.62	17.83	37.23	41.11	-28.73***	0.00
Citations	1904.44	6461.82	12471.05	26842.51	-19.61***	0.00
Inventor	0.30	0.46	0.20	0.40	6.33***	0.00
N	2807		1240			

Table 2
BdSci characteristics

Panel C: BdSci VS Non-BdSci

	BdScis		Non-BdScis			
	Mean	St.Dev.	Mean	St.Dev.	t-stat	P-val.
Director level comparison						
MBA	0.16	0.36	0.31	0.46	-20.05***	0.00
JD	0.03	0.18	0.08	0.27	-10.77***	0.00
Finance Exp.	0.27	0.44	0.41	0.49	-17.35***	0.00
Executive Exp.	0.85	0.36	0.92	0.28	-14.66***	0.00
Inventor	0.27	0.44	0.03	0.17	66.24***	0.00

Panel D: Inventor directors

	BdScis		Non-BdScis			
	Mean	St.Dev.	Mean	St.Dev.	t-stat	P-val.
Director level comparison						
#Patents	23.52	46.95	9.68	16.29	9.24***	0.00
Adj. Cites	1.85	3.81	1.75	3.97	2.12**	0.03
Scope	2.33	1.65	1.93	1.28	21.78***	0.00
Generality	0.60	0.25	0.57	0.26	8.87***	0.00
Originality	0.90	0.15	0.88	0.16	10.46***	0.00
N	1097		1102			

Table 3
BdScis and Activities of Bridge Between R&D

This table reports regression models examining the role of BdSci in bridging R&D and enhancing firm innovation. *BdSci* is an indicator variable that equals one if firms have at least one BdSci in the year t and zero otherwise. The dependent variables in Columns(1-3) measure the activities in bridging R&D, which are the share of *Gov.Pat.*, *Sci.Pat.*, and *Funda.Pat.* over the total number of patents at firm i at year t+1. *Gov.Pat.(Column 1)* are patents whose titles are held by individual firms, but they were funded at least partially by the U.S. Federal government. *Sci.Pat.(Column 2)* are patents that cite at least one SNPL, and the number of citing SNPLs is above the 75th percentile of patents in the same technology class and year. *Funda.Pat.(Column 3)* are patents that cite at least one scientific publication and receive more citations than the 75th percentile of patents in the same technology class and year. The dependent variables in Columns (4-7) are patent qualities, which are $\#Pat._{i,t+1}$, $Adj.cites_{i,t+1}$, $Value_{i,t+1}$, and $\#B.through\ Patents_{i,t+1}$. $\#Pat._{i,t+1}$ (Column 4) are defined as firm i's total number of patents filed (and eventually granted) for the next year. $Adj.cites_{i,t+1}$ (Column 5) are defined as firm i's average adjusted citation per patent filed (and eventually granted) for the next year. 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). $Value_{i,t+1}$ (Column 6) is defined as the logarithm of firm i's average market value(Kogan et al., 2017) per patent filed (and eventually granted) for the next year. $\#B.through\ Patents_{i,t+1}$ (Column 7) are defined as firm i's total number of breakthrough patents filed (and eventually granted) for the next year. 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. Control variables are firm size, CAPEX, R&D, firm age, annual return, leverage, board independence and a scientific CEO indicator. This table presents Poisson regression coefficients for count innovation output and the OLS regression of $Avg.Value_{t+1}$ and $Adj.cites_{t+1}$. Variable definitions are in Table A.1. All regressions include SIC 4-digit industry and year-fixed effects. Standard errors are clustered at the industry level and are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Bridging R and D			**Patent Output**			
	Gov. Pat.	Sci. Pat.	Funda. Pat.	#Pat.	Adj.cites	Value	#B.through Pat.
			t+1				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BdSci	0.003***	0.032***	0.013***	0.292*	0.051**	-0.012	0.313**
	(0.001)	(0.006)	(0.003)	(0.176)	(0.023)	(0.033)	(0.160)
Size	0.000	0.028***	0.013***	0.958***	0.100***	0.633***	0.861***
	(0.000)	(0.003)	(0.002)	(0.041)	(0.011)	(0.019)	(0.043)
CAPEX	0.011	0.068	0.045*	3.393***	0.378**	1.332***	4.404***
	(0.010)	(0.047)	(0.023)	(1.270)	(0.187)	(0.301)	(1.027)
RD	0.007***	0.162***	0.080***	1.296***	0.428***	0.698***	1.175***
	(0.002)	(0.047)	(0.017)	(0.138)	(0.106)	(0.134)	(0.129)
Age	-0.000	-0.008**	-0.006***	0.232	-0.044**	-0.148***	0.113
	(0.000)	(0.003)	(0.002)	(0.176)	(0.019)	(0.030)	(0.133)
Annual Return	0.000	-0.001	0.006***	0.100***	0.047***	0.240***	0.152***
	(0.000)	(0.003)	(0.002)	(0.024)	(0.014)	(0.015)	(0.028)
Leverage	-0.004*	-0.052***	-0.035***	-0.153	-0.302***	-0.165	-0.649
	(0.002)	(0.017)	(0.008)	(0.449)	(0.055)	(0.151)	(0.439)
Board Independence	0.003	0.040**	0.025**	1.829***	0.144**	0.041	1.460***
	(0.002)	(0.016)	(0.012)	(0.401)	(0.060)	(0.098)	(0.358)
Scientific CEO	0.004	0.081***	0.035***	0.283**	0.188***	0.056	0.317**
	(0.003)	(0.015)	(0.010)	(0.126)	(0.064)	(0.055)	(0.133)
Constant	-0.000	-0.091***	-0.028*	-6.404***	-0.165**	-2.583***	-6.789***
	(0.002)	(0.026)	(0.016)	(1.196)	(0.071)	(0.169)	(0.873)
Observations	59,782	59,782	59,782	57,223	59,782	19,602	52,613
Industry 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	0.0323	0.0943	0.156		0.109	0.6741	
Pseudo R-squared				0.829			0.721

Table 4
Human Genome Project

This table presents Difference-in-Difference (DiD) models using the Human Genome Project (HGP). The HGP is an international research project that identified, mapped, and sequenced all the genes of the human genome from 1990 to 2003. In 2001, the HGP published a draft sequence and an initial analysis of the human genome in the journal Nature. The availability of human genome data enhanced the economic benefits that BdScis bring to firms, as BdScis could leverage their expertise to help firms advance the development of genetic products. Panel A tests how the economic benefits of BdScis changed relative to the control groups. The economic benefits of BdScis are measured by $BdSci\ share_t$ (columns 1 and 3) and $Gen.\ BdSci\ share_t$ (columns 2 and 4), defined as the share of BdScis or BdScis with genetic expertise over the total number of directors in the firm. *Treatment* is an indicator variable that equals one if the firm is in a genetics-related industry, defined as including drugs and pharmaceutical products (13) and lab equipment (37) based on the Fama-French 48 industry classification, and zero otherwise. *Post* is an indicator variable that equals one 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 the HGP became publicly available. Columns 3 and 4 repeat the analysis using the treatment and propensity score matched control group. The matching variables are size, ROA, annual return, and #Patents up to the event year 2001. Panel B compares the changes in innovation quality for firms that appointed a new Genetic BdSci within two years following the event relative to other firms in the genetics-related industries. *Gen. BdSci* in Panel B is an indicator variable equals to 1 if a firm appoint a new Gen.BdSci within 2 years after the event and 0 otherwise. The innovation qualities in Panel B are $\#Pats_{t+1}$, $\#B.through\ Patents(90/99)_{t+1}$, $Values_{t+1}$, $Adj.Cites_{t+1}$. This table presents Poisson regression coefficients for count innovation output and the OLS regression of $Avg.Value_{t+1}$ and $Adj.cites_{t+1}$. 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. Table A5 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 BdSci Share

	BdSci Share	Gen.BdSci Share	BdSci Share	Gen.BdSci Share
	Full sample		Matched sample	
	(1)	(2)	(3)	(4)
Treatment × Post	0.027***	0.019***	0.031***	0.019***
	(0.010)	(0.005)	(0.010)	(0.005)
Size	0.005***	0.000	0.005***	0.001
	(0.001)	(0.001)	(0.002)	(0.001)
CAPEX	0.002	0.001	0.002	0.000
	(0.009)	(0.003)	(0.020)	(0.007)
RD	0.012***	0.011***	0.008**	0.014***
	(0.003)	(0.004)	(0.004)	(0.005)
Age	0.003	-0.001	0.001	-0.004
	(0.003)	(0.001)	(0.005)	(0.004)
Annual Return	-0.001	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)
Leverage	-0.007**	-0.001	-0.005	-0.001
	(0.003)	(0.002)	(0.005)	(0.002)
Board Independence	0.098***	0.018***	0.118***	0.028**
	(0.011)	(0.006)	(0.015)	(0.011)
Scientific CEO	0.003	0.001	-0.001	-0.002
	(0.004)	(0.002)	(0.006)	(0.003)
Constant	-0.030***	0.000	-0.025	0.007
	(0.011)	(0.005)	(0.019)	(0.011)
Observations	62,718	62,718	22,943	22,943
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	Industry	Industry	Industry	Industry
Adj. R-squared	0.771	0.803	0.745	0.781

Table 4
Human Genome Project

Panel B Firms hired new Gen.BdSci VS other treatment firms					
	#Pat.	#B.through Pa.(90)	#B.through Pa.(99)	Values	Adj.Cites
			t+1		
	(1)	(2)	(3)	(4)	(5)
Gen. BdSci × Post	0.419**	0.570***	1.068***	-0.361	0.354
	(0.184)	(0.077)	(0.210)	(0.330)	(0.257)
Size	0.323***	0.303***	-0.011	0.155**	-0.045
	(0.079)	(0.101)	(0.140)	(0.059)	(0.041)
CAPEX	2.740***	1.619	0.238	0.037	-0.519
	(0.600)	(1.026)	(2.180)	(0.488)	(0.384)
RD	0.383**	0.432**	0.960***	0.204*	0.068*
	(0.178)	(0.182)	(0.291)	(0.096)	(0.033)
Age	-0.349***	-0.382	-0.762*	-0.137**	-0.027
	(0.122)	(0.250)	(0.392)	(0.058)	(0.082)
Annual Return	0.061***	0.108***	0.159***	0.073***	0.060**
	(0.014)	(0.028)	(0.042)	(0.020)	(0.025)
Leverage	-0.183	-0.052	0.509***	0.160	-0.337*
	(0.264)	(0.178)	(0.170)	(0.113)	(0.161)
Board Independence	0.728**	0.791**	1.707***	-0.240	-0.176
	(0.321)	(0.349)	(0.446)	(0.395)	(0.301)
Scientific CEO	-0.079	-0.021	-0.322	-0.061	0.025
	(0.070)	(0.091)	(0.394)	(0.040)	(0.072)
Constant	1.607***	0.271	3.278**	0.738**	1.255**
	(0.617)	(0.607)	(1.631)	(0.245)	(0.451)
Observations	5,823	4,128	1,569	3,906	6,977
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cluster	Industry	Industry	Industry	Industry	Industry
Adj. R-squared				0.847	0.410
Pseudo R-squared	0.843	0.722	0.794		

Table 5
IV: Local BdSci supply

This table presents the 2SLS regression models using the Local BdSci supply as the instrumental variable (IV). The IV is the *Local BdSci supply*, measured as the logarithm of one plus the number of BdScis in firms located within 60 miles of the focal firm's headquarters, excluding firms in the same SIC4 industry code. The instrumented variables are *BdSci* (Columns 1–4), a binary indicator equal to 1 if the firm has a BdSci and 0 otherwise, and *BdSci share* (Columns 6–9), the proportion of BdScis relative to the total number of board directors. Columns 1 and 5 shows the first-stage regression of *BdSci* and *BdSci share* on the local BdSci supply. Other columns present the second stage regression of innovation output on $\widehat{\text{BdSci}}$ and $\widehat{\text{BdSci share}}$. $Adj.cites_{t+1}$ (columns 2 and 6) are defined as the firm i's average adjusted citation per patent received on the firm's patents filed (and eventually granted) for the next year. The citations are adjusted by the technology class and grant year fixed effects, followed by Hall et al. (2001). $Value_{t+1}$ (columns 3 and 7) are defined as the natural logarithm of firm i's average market value (Kogan et al., 2017) per patent of patents filed (and eventually granted) for the next year. $\#Patents_{t+1}$ (columns 4 and 8) is defined as the natural logarithm of the firm i's the total number of patents filed (and eventually granted) for the next year. 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 4-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.

	1st	2nd			1st	2nd		
	BdSci	Adj.cites	Values	#Pat.	BdSci Share	Adj.cites	Values	#Pat
			t+1				t+1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local BdSci Supply	0.016***				0.004**			
	(0.006)				(0.002)			
$\widehat{\text{BdSci}}$		1.445	0.866*	1.957**				
		(1.158)	(0.471)	(0.882)				
$\widehat{\text{BdSciShare}}$						5.141	2.804*	6.332**
						(4.394)	(1.475)	(3.156)
Size	0.044***	0.035	0.630***	0.477***	0.006***	0.069***	0.643***	0.507***
	(0.005)	(0.046)	(0.027)	(0.060)	(0.001)	(0.021)	(0.022)	(0.055)
CAPEX	0.046	0.437*	1.486***	1.169**	-0.012	0.545**	1.551***	1.316**
	(0.074)	(0.259)	(0.380)	(0.581)	(0.024)	(0.269)	(0.379)	(0.564)
RD	0.171***	0.186	0.644***	0.895**	0.053***	0.162	0.610***	0.818*
	(0.046)	(0.177)	(0.124)	(0.400)	(0.011)	(0.200)	(0.134)	(0.431)
Age	0.033***	-0.089	-0.155***	-0.041	0.000	-0.043	-0.129**	0.017
	(0.011)	(0.060)	(0.047)	(0.036)	(0.004)	(0.032)	(0.051)	(0.059)
Annual Return	-0.009***	0.061***	0.243***	0.087***	-0.002***	0.058***	0.240***	0.080***
	(0.002)	(0.019)	(0.016)	(0.018)	(0.001)	(0.018)	(0.015)	(0.020)
Leverage	-0.119***	-0.143	-0.034	-0.290	-0.030***	-0.158	-0.016	-0.249
	(0.025)	(0.131)	(0.184)	(0.205)	(0.005)	(0.116)	(0.201)	(0.261)
Board Independence	0.017***	-0.020	0.030	-0.122***	0.002	-0.006	0.030	-0.122***
	(0.007)	(0.022)	(0.023)	(0.039)	(0.003)	(0.017)	(0.024)	(0.039)
Board Size	0.440***	-0.447	-0.328	-0.592	0.124***	-0.454	-0.318	-0.570
	(0.050)	(0.510)	(0.257)	(0.398)	(0.027)	(0.525)	(0.272)	(0.473)
Scientific CEO	0.123***	0.045	-0.003	0.158*	0.039***	0.022	-0.016	0.128
	(0.020)	(0.185)	(0.074)	(0.081)	(0.005)	(0.207)	(0.083)	(0.101)
Local Scientists supply	-0.005***	0.009	-0.001	-0.005	-0.001	0.005	-0.002	-0.008
	(0.002)	(0.006)	(0.006)	(0.008)	(0.000)	(0.004)	(0.006)	(0.007)
Observations	57,803	54,758	17,800	17,809	57,803	54,758	17,800	17,809
Industry 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
Cragg-Donald Wald F	140.36				171.11			

Table 6
BdSci's influence on the firm's patents

This table reports regression models examining the relation between BdScis' influence and innovation output. *BdSci influence*$_{\mathtt{i,d,t}}$ is BdSci $\mathtt{d}$'s influence on firm $\mathtt{i}$'s patents, in year $\mathtt{t}$, which is $\frac{\text{Cum \#BdSciIP}_{\mathtt{i,d,[t-n,t]}}}{\text{Cum \#Patents}_{\mathtt{i,[t-n,t]}}}$. The BdSci-influenced patent (BdSciIP) is the firm's patent that cites at least one BdSci's publications while the BdSci is on the board. The numerator of *BdSci influence*$_{\mathtt{i,d,t}}$ is the cumulative number of the BdSciIP from the year BdScis join the board of firm $\mathtt{i}$ until year $\mathtt{t}$. *#Pat.*$_{\mathtt{t+1}}$ (column 1) are defined as firm $\mathtt{i}$'s total number of patents filed (and eventually granted) in year t+1. *Adj.Cites*$_{\mathtt{t+1}}$ (column 3) is defined as the firm $\mathtt{i}$'s average adjusted citation per patent filed (and eventually granted) for the next year. The citations are adjusted by the technology class and grant year fixed effects, followed by Hall et al. (2001). *Avg.Value*$_{\mathtt{t+1}}$ (column 5) are defined as firm $\mathtt{i}$'s average market value (Kogan et al., 2017) of patents filed for the next year. *B.through patents* $_{\mathtt{t+1}}$ (column 7) is defined as firm $\mathtt{i}$'s total number of breakthrough patents filed (and eventually granted) for the next year. 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, BdSci and year level. Control variables are firm size, CAPEX, R&D, firm age, annual return, leverage, board independence and a scientific CEO indicator. This table presents Poisson regression coefficients for count innovation output and the OLS regression of *Avg.Value*$_{\mathtt{t+1}}$ and *Adj.cites*$_{\mathtt{t+1}}$. 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.

	#Pat.	Adj.cites	Values	#B.through Pat.	#Funda. Pat.
			t+1		
	(1)	(2)	(3)	(4)	(5)
BdSci influence	0.028	0.869*	0.770***	1.736	0.946
	(0.876)	(0.497)	(0.175)	(1.278)	(1.602)
Size	0.335***	-0.019	0.064	0.243***	0.305***
	(0.080)	(0.018)	(0.040)	(0.082)	(0.065)
CAPEX	1.039	0.066	0.783***	1.719*	1.290*
	(0.888)	(0.145)	(0.234)	(1.032)	(0.753)
RD	0.710**	0.031	0.131	0.483**	0.499***
	(0.321)	(0.027)	(0.084)	(0.218)	(0.144)
Age	-0.067	-0.112***	-0.091	-0.148	-0.240
	(0.205)	(0.040)	(0.069)	(0.183)	(0.151)
Annual Return	0.018	0.023**	0.070***	0.021	0.024
	(0.020)	(0.009)	(0.012)	(0.023)	(0.022)
Leverage	-0.327*	-0.166***	0.071	-0.185	-0.438**
	(0.176)	(0.058)	(0.145)	(0.180)	(0.188)
Board Independence	0.063	0.051	-0.437***	0.122	-0.052
	(0.301)	(0.063)	(0.143)	(0.292)	(0.345)
Scientific CEO	-0.041	0.010	0.056	-0.108	-0.173*
	(0.055)	(0.048)	(0.043)	(0.117)	(0.091)
Constant	3.167***	0.944***	1.559***	2.066***	2.406***
	(0.702)	(0.175)	(0.247)	(0.671)	(0.483)
Observations	49,502	83,417	32,611	35,750	35,055
Firm*Director FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cluster	Industry	Industry	Industry	Industry	Industry
Adj. R-squared		0.4865	0.897		
Pseudo R-squared	0.957			0.885	0.908

Table 7
BdScis' expertise and firm relevant innovation

This table reports regression models examining the relation between BdScis' 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 $\textit{Expertise(Pub)}_{\mathtt{i,s,[t-3,t]}}$ and $\textit{Expertise(Cites)}_{\mathtt{i,s,[t-3,t]}}$. $\textit{Expertise(Pub)}_{\mathtt{i,s,[t-3,t]}}$ is the logarithm of one plus the average number of publications per BdSci of firm $\mathtt{i}$ in the subject area $\mathtt{s}$ over the past three years. $\textit{Expertise(Cites)}_{\mathtt{i,s,[t-3,t]}}$ is the logarithm of one plus the average number of cites received by BdSci's publications per BdSci of firm $\mathtt{i}$ in the subject area $\mathtt{s}$ over the past three years. $\#\textit{Patents}_{\mathtt{i,s,[t+1,t+3]}}$ (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 $\mathtt{s}$. $\textit{Adj.cites}_{\mathtt{i,s,t+1}}$ (columns 3 and 4) are defined as firm $\mathtt{i}$'s average adjusted citation per patent filed (and eventually granted) for the next year 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). $\textit{Value}_{\mathtt{i,s,t+1}}$ (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 year in the subject area $\mathtt{s}$. $\#\textit{B.through Patents}_{\mathtt{i,s,t+1}}$ (columns 7 and 8) are defined as firm $\mathtt{i}$'s total number of breakthrough patents filed (and eventually granted) for the next year 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. $\#\textit{Funda. Patents}_{\mathtt{i,s,t+1}}$ (columns 9 and 10) are firm $\mathtt{i}$'s the number of fundamental patents filed (and eventually granted) for the next year 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. This table presents Poisson regression coefficients for count innovation output and the OLS regression of $\textit{Avg.Value}_{\mathtt{t+1}}$ and $\textit{Adj.cites}_{\mathtt{t+1}}$. 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.

	#Pat.		Adj.cites		Values		#B.through Pat.		#Funda. Pat.	
	t+1									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Expertise(Pub)	0.449***		0.153***		0.047***		0.488***		0.566***	
	(0.106)		(0.025)		(0.017)		(0.111)		(0.084)	
Expertise(Cites)		0.164***		0.056***		0.014***		0.181***		0.195***
		(0.032)		(0.009)		(0.005)		(0.028)		(0.026)
Size	0.463***	0.462***	0.026	0.025	0.085***	0.085***	0.370***	0.371***	0.352***	0.354***
	(0.083)	(0.084)	(0.018)	(0.018)	(0.028)	(0.028)	(0.091)	(0.093)	(0.078)	(0.079)
CAPEX	1.071	1.006	0.192	0.193	1.059***	1.060***	1.756*	1.726*	1.495**	1.427*
	(0.805)	(0.796)	(0.186)	(0.186)	(0.289)	(0.289)	(1.003)	(1.016)	(0.751)	(0.757)
RD	0.843***	0.829***	0.030	0.031	0.091	0.091	0.794***	0.790***	0.508***	0.503***
	(0.250)	(0.254)	(0.047)	(0.047)	(0.081)	(0.081)	(0.233)	(0.241)	(0.137)	(0.139)
Age	-0.178	-0.171	-0.106***	-0.106***	-0.037	-0.037	-0.189	-0.182	-0.295*	-0.290
	(0.173)	(0.174)	(0.037)	(0.037)	(0.051)	(0.051)	(0.165)	(0.167)	(0.177)	(0.180)
Annual Return	0.026	0.023	0.029***	0.029***	0.107***	0.107***	0.051***	0.047**	0.038	0.037
	(0.022)	(0.022)	(0.009)	(0.009)	(0.009)	(0.009)	(0.018)	(0.019)	(0.023)	(0.023)
Leverage	-0.751***	-0.745***	-0.157***	-0.157***	0.030	0.029	-0.667***	-0.652***	-0.710***	-0.700***
	(0.189)	(0.189)	(0.059)	(0.059)	(0.083)	(0.083)	(0.247)	(0.241)	(0.187)	(0.187)
Board Independence	0.020	-0.015	-0.030	-0.034	-0.300**	-0.302**	-0.153	-0.206	-0.348	-0.396
	(0.267)	(0.264)	(0.078)	(0.078)	(0.129)	(0.129)	(0.264)	(0.258)	(0.310)	(0.311)
Scientific CEO	-0.004	-0.008	0.015	0.014	0.030	0.030	-0.079	-0.084	-0.115	-0.123
	(0.066)	(0.067)	(0.037)	(0.037)	(0.050)	(0.050)	(0.093)	(0.092)	(0.093)	(0.090)
Constant	0.766	0.773	0.659***	0.660***	1.202***	1.203***	-0.297	-0.304	0.584	0.582
	(0.947)	(0.958)	(0.142)	(0.142)	(0.253)	(0.253)	(0.873)	(0.891)	(1.081)	(1.086)
Observations	132,019	132,019	158,607	158,607	57,023	57,023	110,494	110,494	104,024	104,024
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
Cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adj. R-squared			0.213	0.213	0.848	0.848				
Pseudo R-squared	0.778	0.779					0.668	0.669	0.673	0.673

Table 8
Inventor productivity within the BdSci community

The table uses an inventor, community, and year-level dataset to compare the performance of the BdSci-affiliated inventors to other inventors within the BdSci community. The main explanatory variable is the *BdSci-affiliated inventor*, a binary indicator equal to 1 if the inventor belongs to the BdSci community and is employed by the firm where the BdSci serves on the board, and 0 otherwise. Inventor performance is measured using four metrics: the average and maximum number of adjusted cites, the share of breakthrough patents, and the total number of breakthrough patents in their patent portfolios. Columns (1–4) present the relative percentile ranks of the performance metrics for each inventor within the communities and year. Columns (5–7) are indicator variables equal to 1 if the performance metrics are in the top 10th percentile, and 0 otherwise. 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)	(7)	(8)
	The Quality of the Inventor's Patent Portfolio at Year t from 1996 to 2016							
	Relative Rank				Indicator: Top 10% Performer			
	Avg.adj.cites	Max.adj.cites	B.through Pat. Share	#B.through Pat.	Avg.adj.cites	Max.adj.cites	B.through Pat. Share	#B.through Pat.
BdSci-affiliated inventors	0.044***	0.045***	0.029***	0.033***	0.009	0.006	0.016*	0.027***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
Female	-0.004***	-0.006***	-0.002**	-0.003***	-0.001	-0.005***	0.001	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience	0.002***	0.004***	0.001***	0.002***	0.001***	0.003***	0.000**	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.530***	0.498***	0.532***	0.518***	0.102***	0.050***	0.083***	0.026***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1,318,219	1,318,219	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	Yes	Yes
Cluster	Inventor	Inventor	Inventor	Inventor	Inventor	Inventor	Inventor	Inventor
Adj. R^2	0.024	0.006	0.041	0.052	0.011	0.006	0.028	0.011

Table 9
Inventor productivity within a firm

The table examines the performance of BdSci-affiliated inventors relative to other inventors who are not in the BdSci's community but in the same firms. The main explanatory variable is the *BdSci-affiliated inventor*, a binary indicator equal to 1 if the inventor belongs to the BdSci community and is employed by the firm where the BdSci serves on the board, and 0 otherwise. Inventor performance is measured using four metrics: the average and maximum number of adjusted cites, the share of breakthrough patents, and the total number of breakthrough patents in their patent portfolios. Columns (1–4) present the relative percentile ranks of the performance metrics for each inventor within the firms and year. Columns (5–7) are indicator variables equal to 1 if the performance metrics are in the top 10th percentile, and 0 otherwise. The control variables include firm size, CAPEX, R&D, firm age, annual return, ROA, sales, PPE, inventor experience, a female inventor indicator, and an "inventor in other coms" indicator. The "inventor in other communities" variable equals 1 if the inventor belongs to the community of a BdSci at a different firm, and 0 otherwise. Variable definitions are provided in Table A.1. All regressions control for firm, year, and cohort fixed effects, where a cohort is defined as the group of inventors who joined 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							
	Relative Rank				Indicator: Top 10% Performer			
	Avg.adj.cites	Max.adj.cites	B.through Pat. Share	#B.through Pat.	Avg.adj.cites	Max.adj.cites	B.through Pat. Share	#B.through Pat.
BdSci-affiliated inventors	0.040***	0.059***	0.030***	0.040***	0.023***	0.052***	0.016***	0.033***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
Size	-0.010***	-0.009***	-0.008***	-0.004***	-0.003*	-0.001	-0.002	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
CAPX	-0.012	-0.024	-0.002	-0.011	-0.003	-0.009	-0.055***	-0.017
	(0.016)	(0.016)	(0.011)	(0.012)	(0.018)	(0.018)	(0.016)	(0.017)
RD	-0.021***	-0.010*	-0.015***	-0.005	-0.020***	-0.010	-0.008	0.022***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.007)	(0.007)	(0.005)	(0.006)
Age	-0.013***	-0.008***	-0.007***	-0.005***	-0.012***	-0.003	-0.005**	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Annual Return	0.000	0.000	-0.000	-0.000	0.000	0.000	0.000	-0.004***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
ROA	0.004	0.009*	0.003	0.006*	0.006	0.012**	0.014***	0.050***
	(0.005)	(0.005)	(0.003)	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)
Sales	-0.003*	-0.002*	-0.001	-0.001	-0.005***	-0.004**	-0.003**	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
PPE	-0.009	-0.004	-0.012**	0.003	0.004	0.006	0.008	-0.029***
	(0.008)	(0.008)	(0.005)	(0.006)	(0.008)	(0.009)	(0.007)	(0.008)
Female	-0.007***	-0.011***	-0.004***	-0.006***	-0.001	-0.006***	-0.000	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure	0.005*	0.007**	0.006***	0.007***	0.004*	0.006**	0.004*	0.009***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)
Inventor in other coms	0.037***	0.054***	0.023***	0.028***	0.013***	0.033***	0.007***	0.034***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.632***	0.585***	0.583***	0.531***	0.194***	0.116***	0.135***	0.064***
	(0.018)	(0.020)	(0.011)	(0.011)	(0.017)	(0.019)	(0.016)	(0.017)
Observations	1,470,157	1,470,157	1,470,207	1,470,207	1,470,207	1,470,207	1,470,207	1,470,207
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
Adj. R-squared	0.016	0.023	0.019	0.024	0.012	0.017	0.014	0.025

Table 10
BdScis and firm valuation

This table reports regression models examining the relation between BdScis 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* $q_{\mathrm{t+1,t+n}}$, the natural logarithm of the average of Tobin's q from year t+1 up to year t+n. The key explanatory variable is *BdSci*, which is an indicator variable that equals to one if the firm has at least one BdSci 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. Panel B presents announcement returns for BdScis' departures due to death. We collect the BdSci death announcements from Audit Analytics and use the date of the first news of a director's death as our event date. There are 23 BdSci deaths and 170 Non-BdSci deaths. The matched sample in panel B 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 20 BdSci death events available in the matched sample. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Long-Term Valuation

	Avg. Tobin's q			
	t+1,t+2	t+1,t+3	t+1,t+4	t+1,t+5
	(1)	(2)	(3)	(4)
BdSci	0.030**	0.028*	0.026*	0.024
	(0.015)	(0.015)	(0.016)	(0.016)
Size	0.009	0.008	0.007	0.006
	(0.006)	(0.006)	(0.006)	(0.006)
CAPEX	0.774***	0.711***	0.648***	0.590***
	(0.139)	(0.141)	(0.139)	(0.137)
RD	0.651***	0.691***	0.658***	0.633***
	(0.117)	(0.120)	(0.120)	(0.126)
Age	-0.048***	-0.048***	-0.048***	-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	-0.127***	-0.137***	-0.143***	-0.147***
	(0.044)	(0.045)	(0.045)	(0.044)
Board Independence	0.016	0.026	0.034	0.041
	(0.035)	(0.035)	(0.036)	(0.037)
Sci. CEO	0.083***	0.085***	0.090***	0.094***
	(0.020)	(0.020)	(0.021)	(0.021)
Constant	0.532***	0.543***	0.556***	0.569***
	(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-squared	0.307	0.320	0.331	0.339

Panel B: BdSci Departure announcements CARs due to deaths

		Full Sample			Matched Sample		
		BdSci	Non-BdSci	Diff(BdSci-NBdSci)	BdSci	Non-BdSci	Diff(BdSci-NBdSci)
CAR(0,1)	Mean	-1.07%	0.29%	-1.36%	-1.04%	1.39%	-2.43%*
CAR(0,2)	Mean	-2.42%	0.38%	-2.80%**	-2.70%	1.04%	-3.74%*
N		23	170		20	20	

Table A1
Variables Definitions

Variable name	Definitions	Tables
Independent variables		
BdSci	Indicator variable equals 1 if the firm has at least one BdSci; zero otherwise.	Tables 3 and 10
Local BdSci supply	Local BdSci supply is the logarithm of one plus the number of BdSci in firms headquartered within 60 miles of the focal firm's headquarters, excluding firms in the same four-digit SIC (SIC4) industry.	Table 5
BdSci's influence	The cumulative number of BdSciIP over the cumulative number of patents. BdSciIP is the patent that cites the BdSci's publications.	Table 6
BdSci-affiliated inventors	Indicator variable that equals one if inventors are in a BdSci's community and also work for the firm where the BdSci sit on the board, and zero otherwise	Table 8, 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 4
Post	Indicator variable that equals one if the year is greater than 2001, and zero otherwise.	Table 4
Expertise(Pub)	the logarithm of one plus the average number of BdSci's publications in the subject area over the past three years.	Table 7
Expertise(Cites)	the logarithm of one plus the average number of cites received by BdSci's publications in the subject area over the past three years.	Table 7
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 60 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 10
#Patents$_{t+1}$	Firm i's the total number of patents filed (and eventually granted) for the next year.	Table 3, 4, 7, and 6
Adj. cite$_{t+1}$	Firm i's the average adjusted cites of patents filed (and eventually granted) for the next year. The adjusted cites are the number of cites over the average cites of patents in the same technology field and granted year.	Table 3, 4, 7, and 6
Value$_{t+1}$	Firm i's the natural logarithm of the average market value of patents filed (and eventually granted) for the next years.	Table 3, 4, 7, and 6
#B.through patents$_{t+1}$	Firm i's the number of breakthrough patents filed (and eventually granted) for the next year. 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 3, 4, 7, and 6
#Funda Patents$_{t+1}$	Firm i's the number of fundamental patents filed (and eventually granted) for the next year 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 3, 4, 7, and 6
#B.through patents(99)$_{t+1}$	Firm i's the number of breakthrough patents(99) filed (and eventually granted) for the next year. The breakthrough patents(99) are patents that received more citations than the citations at 99 percentile within the same technology class and year.	Table 3, 4, 7, and 6
Avg(Max) Adj. cites	The average (maximum) number of adjusted cities per patent for patents in inventors' portfolios.	Tables 8 and9
B.through patents share	The number of breakthrough patents(90) over total number of patents in inventors' portfolios.	Tables 8 and 9
#B.through patents	The number of breakthrough patents(90) in inventors' portfolios.	Tables 8 and 9
BdSci share	The ratio of the number of BdSci to the total number of directors	Table 4
Gen. BdSci share	The ratio of the number of BdSci with genetics expertise over the number of total directors on the board.	Table 4

Table A1
Variables Definitions

Firm characteristics		
Size	The natural logarithm of total asset(AT). Source: Compustata	Table 1, 3, 4, 5, 7, 6, 8, 10
CAPEX	Capital expenditure over total assets(CAPX/AT). Source: Compustata	Table 1, 3, 4, 5, 7, 6, 8, 10
RD	Research and Development expenditure over total assets(XRD/AT) Source: Compustata	Table 1, 3, 4, 5, 7, 6, 8, 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	Table 1, 3, 4, 5, 7, 6, 8, 10
Annual Return	The annual stock return of firm ((prcc_f$_{\mathrm{t}}$ + dvpsx_f$_{\mathrm{t}}$ / ajex$_{\mathrm{t}}$) / ((prcc_f$_{\mathrm{t-1}}$/ajex_f$_{\mathrm{t-1}}$)). Source: Compustata	Table 1, 3, 4, 5, 7, 6, 8, 10
Leverage	Total leverage over total assets((Dltt+DLC)/AT). Source: Compustata	Table 1, 3, 4, 5, 7, 6, 8, 10
Board Independence	The total number of independent directors over the total number of directors on the board	Table 1, 3, 4, 5, 7, 6, 8, 10
Scientific CEO	Indicator variable that equals one if firms have scientific CEO, and zero otherwise.	Table 1, 3, 4, 5, 7, 6, 8, 10
Director characteristics		
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 2 and 10
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 2 and 10
Publication portfolio of BdSci		
#Publications	The total number of publications in BdSci' publication portfolio	Table 2
#Citations	The total number of publication citations received by BdScis' publication	Table 2
H-index	The H-index of the BdSci. The h-index is the largest number of h such that h articles have at least h citations each.	Table 2

A Matching between BdSci and their Scientific Profile

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 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 BdSci 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 BdScis are linked to more than one author profile. First, suppose the BdSci'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 BdScis who do not have CVs, we compare the subject areas in their minor profile to the BdSci's subject areas in their primary profile or information online.

B Matching between authors and inventors

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.

C 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:

$$Q = \frac{\sum_{in}}{2m} - (\frac{\sum_{tot}}{2m})^2 \tag{14}$$

- $\sum_{in}$ 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}.

$$\Delta Q(D->i) = Q_{\text{Before removing i from D}} - Q_{\text{After merge i to C}} \tag{15}$$

$$Q_{\text{Before}} = \frac{\sum_{in} + k_{i,in}}{2m} - (\frac{\sum_{tot} + k_i}{2m})^2 \tag{16}$$

$$Q_{\text{After}} = \frac{\sum_{in}}{2m} - [0 + (\frac{k_i}{2m})^2] \tag{17}$$

- $k_{i,in}$: 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:

$$\Delta Q(D->i->C) = \Delta Q(D->i) - \Delta Q(i->C) \tag{18}$$

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.

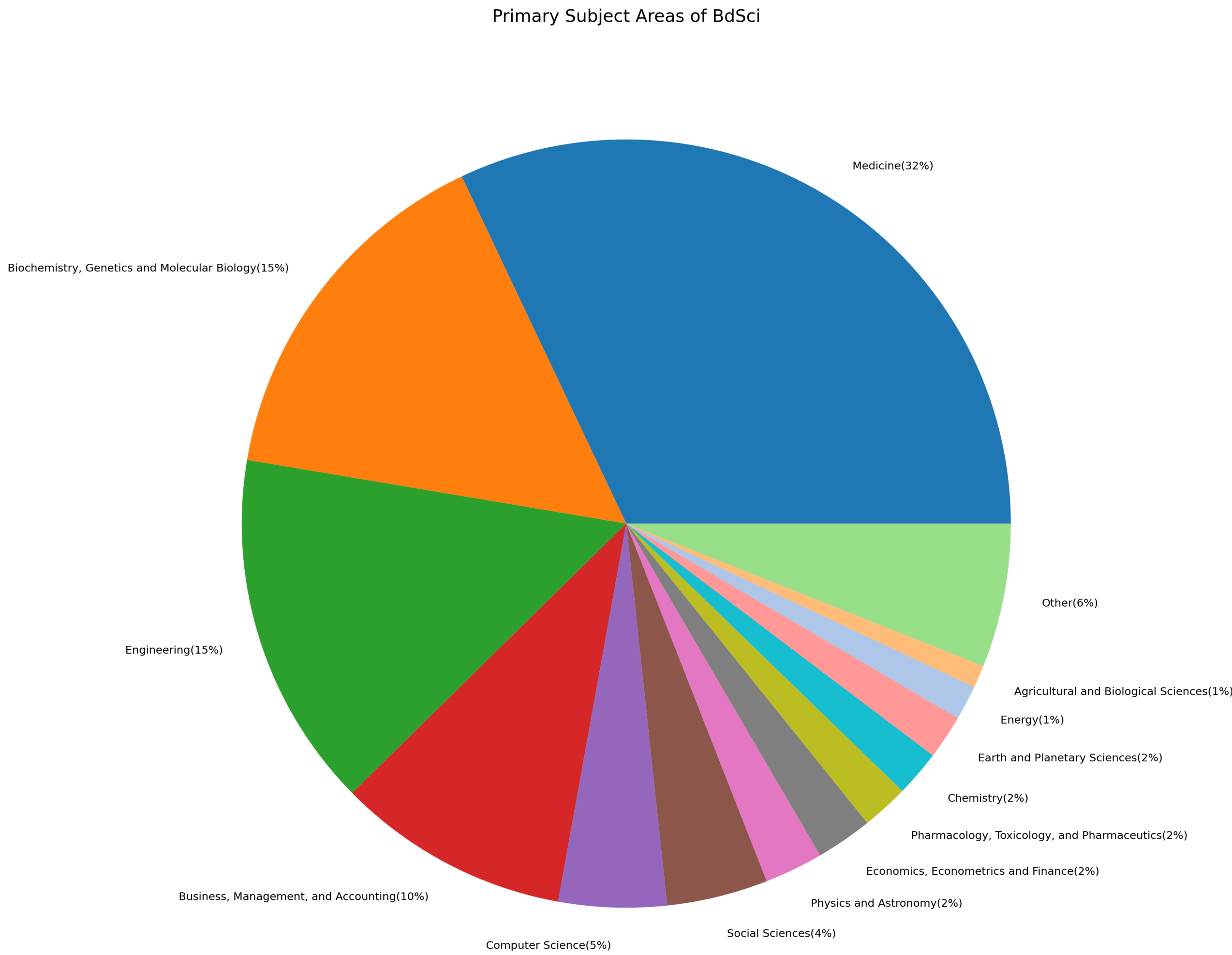

Figure A.1

The pie chart illustrates the primary subject areas of BdSci, defined as the 2-digit Scopus subject area where BdScis publish most frequently. The chart is based on a sample of 3,502 BdScis with publication records and subject area information available. The percentages of BdScis 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%)

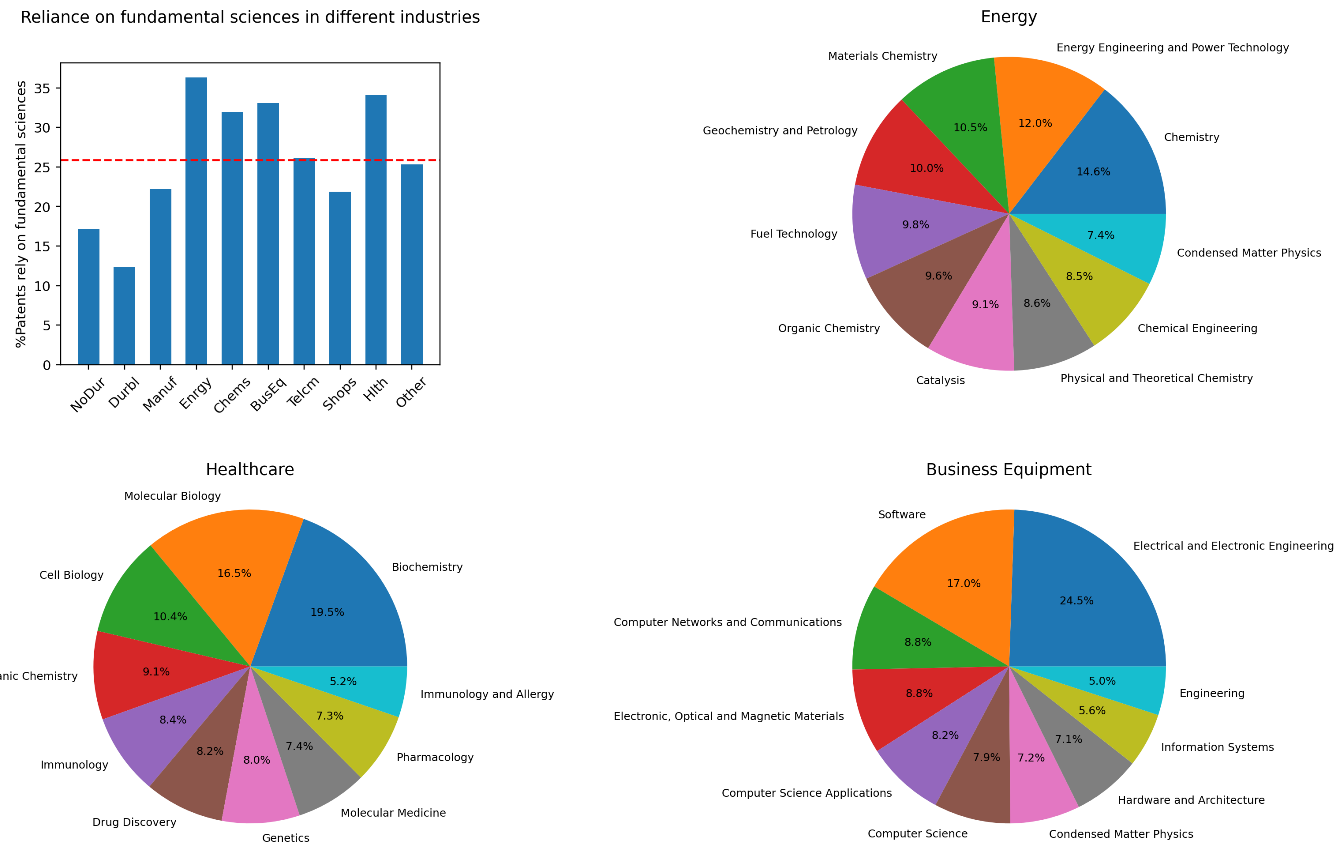

Figure A.2

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.

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
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.**
Engineering	0.76	0.74	0.75	11158
Medicine	0.89	0.84	0.87	10349
Computer Science	0.84	0.84	0.84	9527
Biochemistry	0.82	0.80	0.81	8726
Physics	0.71	0.66	0.68	5049
Materials Science	0.63	0.59	0.61	4308
Chemistry	0.73	0.63	0.68	3730
Pharmacology	0.69	0.57	0.62	2128
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 A4
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 A5

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 4. 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