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The knowledge linkage between science and technology influences corporate technological innovation: Evidence from scientific publications and patents

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ABSTRACT

Scientific knowledge has been shown to be a key contributor to corporate technological innovation; hence, modern inventive firms place a strong emphasis on scientific research. However, little is known about how the knowledge linkage between science and technology (ST linkage) of corporations fosters their technological innovation. In an effort to fill this vacuum in the literature, we investigate how multiple properties of ST linkage influence corporate technological innovation. We conducted a Zero-inflated Negative Binomial regression using scientific publications, patents, and firm-level data from 671 pharmaceutical and 686 semiconductor corporations to test our hypotheses. We find that the higher the proportion of corporations citing their published scientific publications in patents, the more likely they are to produce more patents, and corporate technological innovation benefits from the utilization of scientific knowledge produced in the early stages. Furthermore, the positive effects of the aforementioned factors on the technological innovation performance of corporations are present in both scientific research strategies (e.g., independent vs. joint research). These findings contribute to the understanding of the underlying mechanism of corporate basic research facilitating technological innovation. This study also provides meaningful advice regarding how corporations can enhance their technological innovation through scientific research.

1. Introduction

Schumpeter's innovation theory (1934) emphasizes that innovation is the engine of value creation, capable of introducing new technologies and expanding market opportunities, which contributes significantly to economic growth. Especially for corporations in fast-paced or highly competitive markets, innovation is critical for their success, survival, and renewal (Hervas-Oliver et al., 2021). By establishing the sustainable innovation, corporations can leverage their existing resources and capabilities to transform these elements into innovations and gain profits, thereby achieving sustainable competitive advantages and promoting long-term development and economic growth (Hunt and Morgan, 1995). Hence, how to enhance technological innovation has become an urgent problem for corporations.

Knowledge is the most essential competitive resource for corporate innovation (Fallatah, 2018). Knowledge-based theory of the firm (Grant, 1996) provides a useful account of innovation; namely, innovation is the renewal and reform of knowledge. Therefore, to keep up with future technological advancements, corporations need to continually acquire new and diversified knowledge (Gonzalez and de Melo, 2018). As a crucial source of knowledge, scientific research has become the main means by which corporations acquire knowledge. Previous studies have revealed that the knowledge obtained by corporations originates mostly from research carried out by universities and research institution (Bikard and Marx, 2020), which enables corporations to increase their attempts at innovation (Karhade and Dong, 2021). However, other researchers have long underlined the importance of in-house scientific research. (Suzuki et al., 2017) pointed out that universities and research institutions were not the only places where corporations can gain knowledge. Corporations are evolving from consumers utilizing external knowledge to develop technology to vital creators of knowledge (Jong and Slavova, 2014). Caiazza et al. (2015) illustrated that knowledge

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might be generated endogenously by the corporation; that is to say, scientific research by the corporation could also output knowledge. A higher capacity to generate knowledge is arguably one of the most important factors for a company to become highly innovative (Camisón-Haba et al., 2019). Thus, as their innovation strategies grow more refined, corporations are becoming more actively involved in the creation of knowledge (Leung and Sharma, 2021).

A consensus has been reached among researchers that scientific advancement contributes to corporate technological innovation. Researchers have investigated corporate scientific research in terms of financial investment, researchers, quantity, quality, and research strategies (Barge-Gil et al., 2020; Bikard and Marx, 2020; Añón Higón, 2016; Choi and Lee, 2022). Meanwhile, another issue of concern is how and through what channels scientific research contributes to technological advancement. When answering these questions, the literature has predominantly relied on patent-to-paper citations. The assumption made in this approach is that when a scientific publication is cited by a patent, it indicates that the patent generally exploits the knowledge offered in the paper. In other words, knowledge flows from the realm of science to that of technology (Narin and Olivastro, 1992; Ba and Liang, 2021; Hötte et al., 2021). Such knowledge linkage between science and technology can reflect the technological impact of scientific research (Ke, 2023). However, there exists a limited body of research regarding the effect of ST linkage of corporations on their innovation performance, with uncertainties surrounding the specific mechanisms and outcomes involved.

Touching upon how corporations can improve their innovation performance, this problem holds the promise of great value for not only corporations, but also nations seeking technological advancement that contributes to maintaining competitiveness (Leung and Sharma, 2021). An influential view, based on Arrow's work (1962), asserts that scientific research impact innovation through the effect of knowledge spillover (Ardito et al., 2019). In this sense, it is the flow of knowledge between the two socially structured realms of science and technology that causes scientific research to prompt innovation. As the key role in connecting academia and industry, corporations can greatly facilitate the knowledge flow from science to technology. Our analysis, therefore, particularly takes into account the knowledge linkage between science and technology in corporations, which offers a complementary perspective to previous studies. Specifically, we attempt to investigate how the ST linkage in corporations affects corporate innovation, revealing possible pathways by which scientific research can act on technological innovation.

To this end, this study will examine the following research question: (i) How does the knowledge linkage between science and technology in corporations influence their technological innovation performance? Moreover, we seek to determine if the aforementioned effects manifest differently in different basic research strategies of corporations, namely in-house (independent research) and external (in collaboration with other institutions) research. Thus, the second question is: (ii) How does the in-house knowledge linkage versus the external knowledge linkage between science and technology influence corporate technological innovation performance?

As is usual in this type of research (Ba and Liang, 2021; Ke, 2020b; Ke, 2020a), this paper makes use of citation-based linkages, specifically, scientific publications cited in patents, to illustrate the knowledge linkage between science and technology. Our study attempts to examine the influence of the intensity and time lag of such knowledge linkage on corporate technological innovation performance. We conduct an empirical study utilizing the wealth of corporate data available. Given the varying proclivity for innovation observed across industries, we empirically test our model on pharmaceutical and semiconductor corporations because the knowledge linkage between science and technology occurs most heavily in these two sectors and they are both regarded as science-based fields (Krieger et al., 2021). To begin with, the panel data of 671 pharmaceutical corporations and 686 semiconductor corporations from 2010 to 2020 is collected from COMPUSTAT.[1] Then, information about their patents and papers is integrated from the USPTO and Scopus, respectively. The database, Reliance on Science, provides patent-paper linkages for the research. A Zero-inflated Negative Binomial regression model is adopted to validate our predictions, and several robustness tests are used to ensure the model's results are robust.

Our findings extend previous evidence on the mechanism by which scientific research of corporations impacts their innovation to emphasize the importance of the knowledge linkage between science and technology for corporate technological innovation performance, integrating existing research on this relationship. Furthermore, our analysis provides insight into how corporations boost their technological innovation through scientific research.

The remainder of the paper is organized as follows: In Section 2, the theories underlying the empirical approaches are elaborated and hypotheses are presented. In Section 3, our research methods and sample data are introduced. In Section 4, we demonstrate the empirical results. Finally, in Section 5, we summarize the main results and discuss their theoretical contribution and managerial implications, as well as some limitations of our research and directions for future research.

2. Conceptual background and hypotheses development

The research model containing all the established relationships is shown in Fig. 1.

2.1. The intensity of the knowledge linkage between science and technology and corporate technological innovation

It is widely acknowledged that science and technology follow different logics. Scientific research is "[…] experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundation of phenomena and observable facts, without any particular application or use in view (OECD, 2015)." Rather than implementing any specific applications, it aims to advance scientific knowledge by decreasing complexity and illuminating the causal linkages that behind phenomena (Partha and David, 1994). It is precisely abstract knowledge that scientific research pursues (Rosenberg and Nelson, 1994). On the contrary, technological innovation is the method, instrument, and process by which the world is transformed, as a kind of technological invention and improvement based on scientific knowledge (Sauermann and Stephan, 2013). It is purpose-oriented and concerned with resolving specific issues and difficulties (Arthur, 2007), aiming to commercialize a particular usage.

Growing evidence suggests that corporate innovation is driven by scientific research. Numerous innovations originate in scientific research, because the theoretical foundations for innovating and overcoming bottlenecks can be found in scientific findings (Mowery et al., 2020). This view is supported by Ke (2020a), which analyzed the evolution of the citation linkage between life science related patents and biomedical research over a 37-year period and claimed that compared with applied research, innovation relied more on basic research. Following a similar conceptualization, a systematic review covering 20 years of research on academic engagement with industry argues that knowledge flow enables basic research to be connected to innovative performance of corporations (Perkmann et al., 2013). In spite of that, the incongruity in orientation, specifically the divergence between the quest for abstract knowledge in scientific research and the focus on precise issue resolution in technological innovation, has the potential to

[1] https://www.marketplace.spglobal.com/en/datasets/compustat-fundamentals-(8).

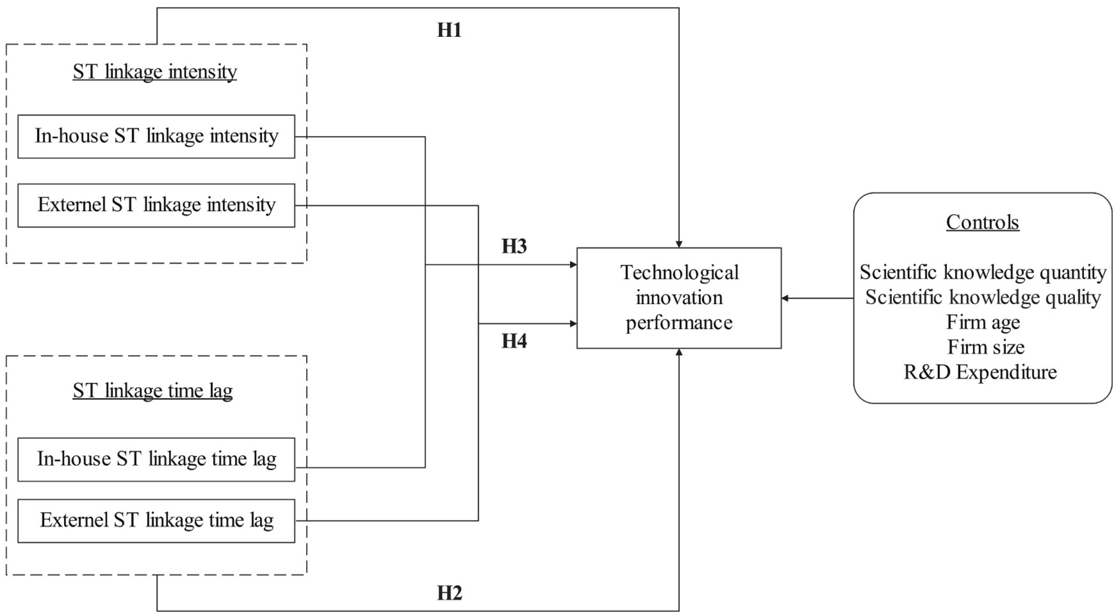

Fig. 1. Research model.

engender a schism between the realms of science and technology, thereby obstructing the flow of knowledge (Stokes, 2011). The silence and abstract nature of scientific knowledge makes it more difficult to share and transfer, especially when there is no strong link between science and technology. Because as scientific knowledge becomes more fragmented, corporations are likely to find it significantly more difficult to assimilate and comprehend it and apply it to innovation (Granovetter, 1992).

In this context, intensifying the knowledge linkage between science and technology has the potential to be extremely beneficial for corporate innovation. On the one hand, an intensive ST linkage can help to reduce the knowledge distance. The knowledge distance reflects the differences and similarities in knowledge sources and knowledge receiver (Colombelli et al., 2013), which is crucial for knowledge diffusion, transfer, and flow within networks (Liyanage and Barnard, 2003). The closer the knowledge distance, the more similar the knowledge they possess and the more conducive to the flow of knowledge (Sudhindra et al., 2020). An intensive ST linkage between science and technology means they share more associated knowledge, and thus contributes to better application the knowledge derived from scientific research in corporations. In other words, the knowledge distance between science and technology is shorter and the knowledge flow is easier, so corporate innovation performance is improved.

On the other hand, as the ST linkage intensifies, innovation's impact becomes incremental. For example, the influence of corporate innovations that make reference to scientific knowledge is enhanced (Wang and Li, 2018). Fleming and Sorenson (2004) define innovation as a process of recombination. And they highlight that science acts as a map in the search process of invention. In other words, scientific knowledge enables inventors to avoid swaths of less productive solution space and to make more direct discoveries of advantageous combinations, enhancing the efficiency of their search.

Given the foregoing, we propose the following hypothesis:

H1. : As the knowledge linkage between science and technology becomes more intensive, the corporate technological innovation performance is improved.

2.2. The time lag of the knowledge linkage between science and technology and corporate technological innovation

Corporations conduct scientific research on the grounds that achieve first-mover advantage (Rosenberg, 1990), as it allows them to alter the learning curve, lowering costs, improving performance, and also posing a barrier to new entrants. For example, first movers are able to consolidate their market positions through patent protection if their scientific findings can be transformed into patents. Scientific research enables corporations to gain new knowledge first and thus develop new products or technologies ahead of competitors (Añón Higón, 2016).

In light of their scientific impact, despite the high risk and delayed impact (Stephan et al., 2017), novel science has been supposed to contribute to innovation in different settings and from different perspectives in particular (Ke, 2018). Narin and Olivastro's (1992) empirical analysis of U.S. patents from 1975 to 1989 demonstrates that, on average, electronic and pharmaceutical patents might reference more recent scientific publications, with a median lag of three to four years. The result is further explained by Veugelers and Wang (2019), who draw on all the Web of Science SCIE journal articles published in 2001 and all the patents in PATSTAT (October 2013 edition) and found that a tiny percentage of scientific articles, namely the 1 % of extremely novel scientific papers in their area, were considerably and significantly more likely to have a direct innovative influence than equivalent non-novel publications. This indicates that, to some extent, scientific knowledge that is novel can have a direct effect on innovation as it tends to be cited by innovation. On the other hand, novel scientific knowledge could have an indirect effect on innovation because it has a good chance of being used in new scientific publications (Foster et al., 2015), which in turn could lead to more innovation.

In the same line, the novelty of science benefits innovation due to not only its more patent citations but also its significant impact in broader field (Ke, 2020b). In other words, the more novel the scientific knowledge, the greater the likelihood that it will have a wider impact and be applicable to a more diverse range of innovation. Furthermore, the impact of novel scientific knowledge on innovation is unprecedented, which means that innovative areas unaffected before can be reached by the scientific domains of novel publications (Veugelers and Wang, 2019). This contributes to the establishment of links between more areas of science and technology, which enables corporations to combine and reorganize knowledge from disparate fields in order to develop new knowledge for innovation. At the same time, an empirical study based on a sample of the Derwent World Patents Index identifies that, when compared to older scientific research, recent scientific research makes the greatest contribution to patent quality (Wang and Li, 2021). To sum up, the evidence presented in this section suggests that the knowledge linkage of a short time lag between science and technology may develop more technological innovation.

Based on the above reasoning, the third hypothesis can be expressed as:

H2. : The timely knowledge linkage between science and technology can improve corporate technological innovation performance.

2.3. The in-house knowledge linkage between science and technology and corporate technological innovation

Scientific research in corporations can be performed either in-house or externally. In-house scientific research refers to research activities carried out entirely by corporations themselves. It is the process by which corporations repurpose existing knowledge to create new knowledge, which means they generate, develop, and commercialize their own ideas (Andries and Thorwarth, 2014), reflecting the linkage between scientific and technical knowledge within corporations. Conversely, scientific research outsourced or conducted in collaboration with other institutions is defined as "external scientific research" (Chesbrough et al., 2006), a way for corporations to absorb knowledge from outside and incorporate it into their current knowledge.

It is now well established from a variety of studies that firms are able to benefit from scientific research, since by developing a stream of knowledge for innovation, they are able to boost their innovative performance and bring higher profits (Leung and Sharma, 2021). This is better explained by organizational learning theory (Levitt and March, 1988), which states that organizations are more competitive when they dedicate time and resources to knowledge creation. The process enables them to respond rapidly to fast-changing market conditions, embrace the lessons learned from failure, and thus develop more knowledge about best practices. Furthermore, it is particularly challenging to identify and acquire knowledge via market mechanisms (Von Hippel, 1994). Corporations need to conduct in-house scientific research in order to be the first to gain novel knowledge in a specific domain. More specifically, if a corporation comes up with a new product or technology ahead of its competitors; that is, to be a market first-mover (Polidoro and Theeke, 2012), it may be able to hold on to the market for a short time, namely, a temporary monopoly. This is because the more unique a corporation's product and market are, the more valuable it could be to its customers (Sjödin et al., 2020). Therefore, in-house scientific research enables corporations to perform well in technological innovation.

Notwithstanding the advantage, corporations also face numerous adverse results to conducting scientific research in-house. First of all, the great investment and high uncertainty in the results make it a high-risk activity for corporations. Profits are often generated in a few years after they start investing in scientific research (Castellacci et al., 2022). Especially, scientific research even has a detrimental effect on short-term (profitability) (Leung and Sharma, 2021). This runs counter to corporations' goal of maximizing their interests. Another challenge lies in the balance between the benefits from the use of science in corporations' own downstream inventions and the costs of spillovers to their rivals (Arora et al., 2021). As argued by Simeth and Cincera (2016), knowledge spillovers may minimize the cost of imitating and provide rivals with insights into future trends. This may let rivals steal a march on future technological innovations.

In this context, we hypothesize:

H3a. : The in-house knowledge linkage between science and technology are expected to have a positive effect on corporate technological innovation performance.

H3b. : The in-house knowledge linkage between science and technology are expected to have a negative effect on corporate technological innovation performance.

2.4. The external knowledge linkage between science and technology and corporate technological innovation

Corporations may turn to collaborate with other research institutions to mitigate the risk and cost of knowledge acquisition (Krieger et al., 2021). According to the social development theory (Au, 2007), the alliance with the more knowledgeable other that has a better understanding or a higher research ability level, universities, for example, will greatly support corporations' scientific research. This helps to shorten the innovation process by bridging the knowledge gap between science and technology, especially for corporations that lack capacity to research and resources. Moreover, since knowledge creation and exchange are the foundation for corporate innovation (Walsh et al., 2016), as a source of creativity, collaboration between a corporation's knowledge base and external research is closely related to its innovation performance (Zhou et al., 2021). Because heterogeneous scientific knowledge acquired through such collaboration is likely to shock a corporation's original knowledge system and increase the possibility of knowledge reorganization.

External joint scientific research, on the other hand, can be a disruption for a firm's innovation process. A significant reason for corporation to disclose their scientific findings in academic journal is to strengthen connections with the scientific community. Specifically, academic scientists prefer to interact with scientists from firms who contribute to open science (Simeth and Lhuillery, 2015). And thus, corporations are able to gain knowledge benefiting their own innovation from academic scientists. However, collaboration with public research institutions helps corporations skip the exploration of knowledge by getting explicit knowledge about how to be more innovative (Simeth and Raffo, 2013). But the core of corporate innovation is the tacit knowledge gained through "learning by doing" and "learning by using", which is difficult to obtain from external research (Bryson et al., 2015). Corporations tends to exhibit path-dependent behavior in their innovation process, directing their innovation in specific directions based on their prior experience and expertise, as well as their accumulated skills and capabilities (Nelson, 1985). These conditions, however, are not facilitated by the organizational inertia that occurs when corporations engage in long-term external knowledge acquisition activities. And this detriment of the long-term development of their innovation capacity (Liu et al., 2015).

Therefore, we can formulate the hypotheses as follows:

H4a. : The external knowledge linkage between science and technology are expected to have a positive effect on corporate technological innovation performance.

H4b. : The external knowledge linkage between science and technology are expected to have a negative effect on corporate technological innovation performance.

3. Data and methods

3.1. Data and sampling frame

To test our hypotheses, we make use of data from four databases. The first source, COMPUSTAT (Market, 2022), is a database of financial, statistical, and market information on active and inactive global companies throughout the world, which provides detailed historical data on quarterly and annual financial statements and indicators for over 24, 000 listed companies in the US, Canada, and a few other places since the mid-1950s. Focusing on the pharmaceutical and semiconductor sectors, we collect panel data about the established year, size (measured by total assets), and R&D expenses for all corporations. In light of the fact that there are too many observations with missing values before 2010, we ultimately compile data over the 2010–2020 period, including 671 pharmaceutical corporations and 686 semiconductor corporations.

The second source is the United States Patent and Trademark Office (USPTO), the federal agency responsible for granting U.S. patents and registering trademarks. At the forefront of the nation's technological advancement and achievement, the USPTO promotes stronger and more effective IP protection around the world (USPTO, 2022a). The United States is widely acknowledged as the world's largest commercial and technological market as well as the world's largest manufacturing economy. So a plurality of corporations tends to file patents in the USPTO, especially if they entail significant changes to existing products or procedures. This makes its patent information phenomenal in terms of both quality and quantity of data, and increase rapidly (Kim and Lee, 2015). Consequently, the USPTO is considered a representative data source for patent research.

Prior to obtaining patents held by above corporations, each corporation's assignee identification number is required to be identified in the USPTO. Since patent assignees in the USPTO may sign their names differently, we remove suffixes such as Ltd., Co., S.A., and so on. Then we match assignee names that include corporate names and manually delete incorrect ones. After getting the corresponding identification numbers, there are 752 assignee identification numbers for 305 pharmaceutical corporations and 789 assignee identification numbers for 435 semiconductor corporations. According to these assignee identification numbers, 54,706 utility patents of 293 pharmaceutical corporations and 324,384 utility patents of 423 semiconductor corporations granted to them before November 10, 2021 are selected, because they are "any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof" (USPTO, 2022b).

The third source is Scopus. Developed by Elsevier, it covers hundreds of thousands of journals, with a broader range of journals than Web of Science. As a repository of thesis data, Scopus is often used to collect the scientific information. Specifically, for our analysis, we conduct a search using the corporate name as the keyword for all papers published by the corporation up to November 24, 2021. To avoid bias caused by different signatures for the same corporation, suffixes such as Ltd., Co., S.A., and so on are removed to ensure that all papers published by the corporation are included in our dataset as far as possible. A manual review of the search results for corporations with varying publication sizes reveals an accuracy of >99 %, which proves the retrieval is credible. The results show 483 pharmaceutical corporations have published 262, 533 papers and 469 semiconductor corporations have published 101, 998 papers.

Furthermore, we complement our dataset with patent-paper linkages via *Reliance on Science* (Marx and Fuegi, 2020b; Marx and Fuegi, 2020a). It is a publicly-available set of citations from U.S. patents (1947–2018) and non-U.S. patents (1782–2018) to scientific articles (1800–2018). Based on scientific references appearing either in the body of the patent or on its "front page", they linked patents from the USPTO to a comprehensive collection of scientific publications from Microsoft Academic Graph (MAG), which claimed to capture >160 million theses. The dataset provides 22,660,003 connections between 3,017,441 patents and 4,017,152 MAG articles. A confidence score is also assigned for each patent-paper linkage. This score is defined by the ratio of false negatives to false positives in a random sample. We use patent-paper linkages whose confidence scores are above 8 after checking accuracy randomly by hand.

Eventually, we integrate data from the four previously mentioned sources to build the sample for the empirical analysis. For corporations with multiple organizational structures, all branch names are replaced by the name of the headquarters. Since it is usual to concentrate only on patent-holding corporations in past studies (Aghion et al., 2013), we choose corporations with at least one utility patent. The sampling criteria enables us to obtain 293 pharmaceutical corporations, which have 54, 706 utility patents and 112, 402 papers in total, and 423 semiconductor corporations, which have 324, 384 utility patents and 48, 828 papers. Details are shown in Table 1. On average, every pharmaceutical corporation owns 186.71 utility patents and publishes 383.62 papers, while the figures for every semiconductor corporation are 766.87 and 115.43. The data is then divided by the year. In this manner, we build a time-series sample. Ultimately, we obtain 3194 observations of pharmaceutical corporations and 4630 observations of semiconductor corporations.

3.1.1. Variables

3.1.1.1. Dependent variable. We follow the literature (Aldieri et al., 2022; Tan et al., 2022) in measuring a corporation's technological innovation through its patenting outcomes. Patents are typical proxies of innovation activities (Kim and Lee, 2015). First of all, the patent documents are informative and thoroughly describe the technology on a well-founded basis. Also, they are structured and standardized, making them easy for analysis. Thirdly, patent data is also easily accessible due to the need for real-time updates. As such, they are widely utilized in innovation activities research.

There are three types of patents in the USPTO: utility, design, and plant. In general, the level of innovativeness required for a utility patent is higher than the others. So, we only focus on a corporation's utility patents. *Num_patents*, defined as the number of utility patents granted in a given year of a corporation, is the proxy for its technological innovation performance.

3.1.1.2. Independent variable. Tracing and understanding how knowledge flows from science to technology has been a central theme in the innovation literature. Since Narin and Olivastro's (1992) seminal work, increasing lines of evidence have suggested that citation-based linkages, such as scientific publications cited in patents, signal the knowledge linkage between science and technology (Ba and Liang, 2021; Hötte et al., 2021). Therefore, to capture the ST linkage in every corporation, we construct the following indicators.

The intensity of the ST linkage (*Intensity*) is defined as the proportion of scientific knowledge to the total scientific and technological knowledge utilized in the innovation as specified in the patent. Inspired by the measurement which was suggested by Trajtenberg et al. (1997), it is calculated by the percentage of the total number of scientific references cited by its patents to the total number of patent references in a corporation. The formula is:

$$Intensity = \frac{\sum_{i}^{n} NPR_i}{\sum_{i}^{n} Reference_i} \tag{1}$$

where *Intensity* is the intensity of the ST linkage of the focal corporation in a given year, n represents the number of granted patents that applied in the given year, $Reference_i$ represents the number of references in the i^{th} patent, and NPR_i represents the number of papers published by the focal corporation cited in the i^{th} patent. The knowledge linkage tends to be closer when a corporation's patents cite a greater proportion of its

Table 1
The sample details.

	Pharmaceutical corporations	Semiconductor corporations
The number of corporations	293	423
The number of utility patents	54, 706	324, 384
Average number of utility patents	186.71	766.87
The number of papers	112, 402	48, 828
Average number of papers	383.62	115.43

papers.

The time lag of the ST linkage (*Timeliness*) is defined as the average number of years passed from the year when cited papers are published to the year when patents are granted to a corporation (Ke, 2020b). The formula is:

$$Timeliness = \frac{\sum_{i}^{n}\sum_{j}^{NPR_i}\left(Year_i - Year_j\right)}{\sum_{i}^{n} NPR_i} \tag{2}$$

where *Timeliness* is the timeliness of the ST linkage of the focal corporation in a given year, $Year_i$ represents the application year of the i^{th} patent, and $Year_j$ represents the publication year of the j^{th} paper cited in the i^{th} patent. When there is a shorter time lag between papers and patents, science and technology can be linked timelier.

Furthermore, drawing on concepts from (Andries and Thorwarth, 2014) and (Chesbrough et al., 2006) to distinguish between in-house and external scientific research, we construct scientific research modes according to scientific publications authors. If a paper is completed entirely by a corporation on its own, it is referred to as "in-house scientific research". On the contrary, a paper co-authored by a corporation and other institutions represents "external scientific research". The knowledge linkage between in-house or external science and technology is defined the same as aforementioned. Therefore, we define indicators as follows:

$$Intensity\_in-house = \frac{\sum_{i}^{n} NPR\_in_i}{\sum_{i}^{n} Reference_i} \tag{3}$$

where *Intensity_in-house* is the intensity of the knowledge linkage between in-house science and technology of the focal corporation in a given year, and NPR_in_i represents the number of papers solely attributed to the focal corporation cited in the i^{th} patent.

$$Intensity\_external = \frac{\sum_{i}^{n} NPR\_ex_i}{\sum_{i}^{n} Reference_i} \tag{4}$$

where *Intensity_external* is the intensity of the knowledge linkage between external science and technology of the focal corporation in a given year, and NPR_ex_i represents the number of co-published papers of the focal corporation cited in the i^{th} patent.

$$Timeliness\_in-house = \frac{\sum_{i}^{n}\sum_{j}^{NPR_i}\left(Year_i - Year\_in_j\right)}{\sum_{i}^{n} NPR_i} \tag{5}$$

where *Timeliness_in-house* is the timeliness of the knowledge linkage between in-house science and technology of the focal corporation in a given year, and $Year\_in_j$ represents the publication year of the j^{th} paper solely attributed to the focal corporation cited in the i^{th} patent.

$$Timeliness\_external = \frac{\sum_{i}^{n}\sum_{j}^{NPR_i}\left(Year_i - Year\_ex_j\right)}{\sum_{i}^{n} NPR_i} \tag{6}$$

where *Timeliness_external* is the timeliness of the knowledge linkage between in-house science and technology of the focal corporation in a given year, and $Year\_in_j$ represents the publication year of the j^{th} co-published papers of the focal corporation cited in the i^{th} patent.

3.1.1.3. Controls. To alleviate concerns about confusing impacts from contextual factors, we incorporate a set of firm-level controls into our models (Martinez-Senra et al., 2015).

The scientific knowledge stock of a corporation is also considered a significant factor influencing its innovation activities, it reflects its ability to engage in scientific research in the past (Añón Higón, 2016; Colombo et al., 2021). We define the quantity of scientific knowledge in a corporation (*Knowledge_ quantity*) as the accumulated number of published papers in a given year (Choi and Lee, 2022). It is calculated by using a perpetual inventory method with a 15 % depreciation rate and thus the scientific knowledge stock of corporation *i* in year *t* is $Knowledge\_quantity_{i,t} = Num\_paper_{i,t} + (1 - \delta)\ Knowledge\_quantity_{i,t-1}$, where $Num\_paper_{i,t}$ is the number of scientific publications by corporation *i* in year *t* and δ is a depreciation rate of 0.15 (Arora et al., 2021). The number of citations to a corporation's scientific publications is another measure of firm-level scientific research capabilities. It presents the relative quality of the corporation's stock of scientific knowledge (*Knowledge_quality*) (Gittelman and Kogut, 2003; Zahringer et al., 2017). The number of citations to each article is normalized using the mean and standard deviation of citations received by all sampled publications in its publication year, which is accumulated from the beginning of the publication period to the time of the observed innovation (Gittelman and Kogut, 2003). Specifically, the quality of scientific knowledge of corporation *i* in year *t* is $Knowledge\_quality_{i,t} = \frac{\sum_{established\_year}^{t} Norimalized\_citations_{i,t}}{\sum_{established\_year}^{t} Num\_paper_{i,t}}$, yielding an average citation measure for the corporation as a whole. Due to the association with innovation activities, *Firm age* may have an effect on corporate innovation performance, as older corporations are able to accumulate considerable innovation experience during its development to sustain innovative advantages (Coad et al., 2016). We measure it by the number of years between the corporation's inception and the focusing year. Besides, *Firm size* has a significant impact on its behavior and decision-making (Schumpeter, 1934), hence influence corporate innovation performance (Andries and Thorwarth, 2014). In this study, total assets are taken into account to measure the size of the corporation. Moreover, we control for the effect of *RD_expenditure*, which has been proven to be crucial for reinforcing the corporate capacity for continuous innovation[2] (Barge-Gil et al., 2020).

3.2. Descriptive statistics

We first take a preliminary look at variables in Tables 2(a) and 2(b), which show the summary statistics and the correlation matrix. The values of *Firm size* and *RD_expenditure* are processed as the natural logarithm. The correlation matrix does not indicate that collinearity is an actionable concern. Despite this, the variance inflation factors (VIFs) for all major variables are calculated, and the results are below customary thresholds.

An inspection of Tables 2(a) and 2(b) reveals that, on average, semiconductor corporations have approximately four times as many utility patents per year as pharmaceutical corporations. However, the substantial variation ($\sigma_p = 27.812$, $\sigma_s = 209.404$) indicates that corporations in our sample, especially semiconductor corporations, have varying capacities for producing utility patents. Interestingly, *Knowledge_ quantity* of semiconductor corporations is 5493.135, less than a half of that of pharmaceutical corporations (13,387.350). This may imply that semiconductor corporations have pursued somewhat more

[2] Definitions are from COMPUSTAT: *Year Established* is the year in which the corporation was established or first opened its ledgers for business. *Total Assets* is the universal assets owned by the company as of the date indicated, as carried on the balance sheet and defined under the indicated accounting principles. *R&D Expenditure* is the gross amount spent on research and development during the year before deducting any reimbursements and inclusive of stock-based compensation apportioned to research and development.

Table 2(a)
Descriptive statistics of pharmaceutical corporations.

	Mean	Std. dev.	1	2	3	4	5	6	7	8	9	10	11
Dependent variable													
1. Num_patents	7.660	27.812											
Controls													
2. Firm age	40.616	50.793	0.226***										
3. Firm size	5.310	2.589	0.429***	0.502***									
4. RD_expenditure	2.613	2.460	0.452***	0.403***	0.778***								
5. Knowledge_stock	13,387.350	2245.986	−0.377***	−0.327***	−0.447***	−0.528***							
6. Knowledge_quality	−0.068	0.193	0.068***	−0.084***	−0.131***	−0.046***	−0.032*						
Independent variable													
7. Intensity	0.003	0.025	0.436***	0.194***	0.311***	0.416***	−0.401***	0.067***					
8. Timeliness	0.887	2.624	0.452***	0.257***	0.359***	0.435***	−0.406***	0.060***	0.650***				
9. Intensity_in-house	0.001	0.005	0.500***	0.201***	0.340***	0.408***	−0.449***	0.067***	0.828***	0.585***			
10. Timeliness_in-house	0.717	2.624	0.536***	0.232***	0.368***	0.416***	−0.419***	0.064***	0.548***	0.809***	0.670***		
11. Intensity_external	0.002	0.021	0.459***	0.182***	0.315***	0.413***	−0.341***	0.071***	0.834***	0.628***	0.575***	0.495***	
12. Timeliness_external	0.717	2.318	0.432***	0.243***	0.332***	0.403***	−0.347***	0.057***	0.573***	0.877***	0.461***	0.595***	0.684***

Notes: Observations = 3194.
[*] Significant at the 10 % level.
[***] Significant at the 1 % level.

Table 2(b)
Descriptive statistics of semiconductor corporations.

	Mean	Std. dev.	1	2	3	4	5	6	7	8	9	10	11
Dependent variable													
1. Num_patents	40.602	209.404											
Controls													
2. Firm age	25.003	16.321	0.154***										
3. Firm size	12.259	1.880	0.368***	0.395***									
4. RD_expenditure	9.164	2.110	0.381***	0.258***	0.775***								
5. Knowledge_stock	5493.135	1037.308	−0.306***	−0.564***	−0.536***	−0.501***							
6. Knowledge_quality	−0.034	0.181	0.009***	−0.049***	−0.079***	−0.077***	0.066***						
Independent variable													
7. Intensity	0.0004	0.006	0.199***	0.091***	0.180***	0.206***	−0.167***	−0.002					
8. Timeliness	0.347	1.565	0.365***	0.168***	0.303***	0.331***	−0.310***	−0.012	0.585***				
9. Intensity_in-house	0.0001	0.002	0.178***	0.082***	0.157***	0.179***	−0.146***	0.010	0.968***	0.534***			
10. Timeliness_in-house	0.292	1.532	0.350***	0.163***	0.280***	0.303***	−0.284***	−0.006	0.553***	0.883***	0.547***		
11. Intensity_external	0.0003	0.005	0.226***	0.090***	0.184***	0.206***	−0.179***	0.004	0.805***	0.588***	0.764***	0.540***	
12. Timeliness_external	0.279	1.442	0.387***	0.147***	0.275***	0.295***	−0.281***	−0.007	0.521***	0.860***	0.469***	0.654***	0.645***

Notes: Observations = 4630.
[***] Significant at the 1 % level.

intense involvement in innovating, while pharmaceutical corporations have taken a more active role in scientific research. In addition, in comparison with pharmaceutical corporations, semiconductor corporations tend to have more assets and invest more in R & D, although their mean age of only about 25 years old is much younger than pharmaceutical corporations, which average over 40 years old.

From the descriptive statistics in the Tables 2(a) and 2(b), we can also find that corporate papers account for only 0.04 % of all references in semiconductor corporations' patents on average, while the figure for pharmaceutical corporations' patents is 0.3 %. It seems that pharmaceutical corporations have a more intensive knowledge linkage between science and technology, but corporate papers cited in pharmaceutical corporations' patents are not as novel as those cited in semiconductor corporations' patents. Furthermore, innovation in both types of corporations is likely to rely more heavily on external scientific research in terms of intensity and timeliness.

4. Results

4.1. Main results

Negative Binomial regression was applied to test the hypotheses due to the over-dispersion feature of variables (i.e., the variance of each sub-group is higher than the mean within each sub-group). More specifically, to account for the effect of an excess of zero data, we used a Zero-inflated Negative Binomial regression model with robust standard errors (Greene, 1994). Moreover, given the time lag of being granted after filing the application for a patent (Office and Mitra-Kahn, 2013) and the lag of the influence of the variables, independent variables and control variables were lagged by one year in the regression model (Zahringer et al., 2017). The results are presented in Tables 3(a)(a) and 3(b), which show how the independent variables affect corporate innovation performance in pharmaceutical and semiconductor corporations.

Model 1 contains all the control variables. In the pharmaceutical industry, as expected, it is evident that corporations with a longer historical presence, more assets, a higher level of investment in R&D activities, and a larger number of published papers perform better at innovating ($p < 0.01$). In the semiconductor industry, however, it is observed that there is no significant correlation between the age of a corporation and its technological innovation when considering the intensity and timeliness of the ST linkage. Furthermore, the estimated coefficient on *Knowledge_quality* of semiconductor corporations is significantly negative at the 1 % level, suggesting that increasing number of citations to a corporation's papers adversely affects its ability to produce more patents.

In Model 2, the intensity of the ST linkage is included in addition to the control variables. The estimated coefficient on *Intensity* is significantly positive at the 1 % level. Supporting hypothesis H1, this finding confirms that the intensity of the ST linkage is positively linked to corporate technological innovation performance. In other words, increasing proportion of patent citations to a corporation's papers may boost its invention productivity.

Model 3 examines the impact of the timeliness of the ST linkage on corporate technological innovation performance. It is important to note that hypothesis H2 lacks empirical validation. The observed positive coefficient on *Timeliness* ($p < 0.01$) suggests that an increased time interval between patents and publications has the potential to generate a bigger number of patents.

However, when *Intensity* and *Timeliness* are added simultaneously in Model 4, the estimated coefficients both become smaller ($p < 0.01$). This indicates the possibility of an interaction effect between these two variables. We therefore included the interaction term between *Intensity* and *Timeliness* in Model 5 and found a negative and significant coefficient. The negative coefficient on the interaction term suggests the presence of an attenuation effect. This effect means that the interaction between *Intensity* and *Timeliness* reduces their overall effect on the dependent variable, making their influence weaker. In other words, an increase in the proportion of earlier scientific references in patents tends to diminish the positive effects of an increase in the proportion of corporate papers and the time gap between patents and publications on the number of corporate patents.

Models 6 and 7 enable us to test hypotheses H3 a/b and H4 a/b. The

Table 3(a)
Panel data regression results of the knowledge linkage between science and technology on pharmaceutical corporations' innovation performance.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Firm age	0.009720***	0.004416***	0.002676***	0.002673***	0.002026***	0.003915***	0.004268***	0.002940***
	(0.001090)	(0.000865)	(0.000738)	(0.000755)	(0.000759)	(0.000751)	(0.000820)	(0.000706)
Firm size	0.195769***	0.094290***	0.065461***	0.060662***	0.060134***	0.028191	0.065616***	0.022165
	(0.025452)	(0.023667)	(0.023085)	(0.022954)	(0.022910)	(0.022415)	(0.024186)	(0.022164)
RD_expenditure	0.296218***	0.318026***	0.403544***	0.374473***	0.366980***	0.395888***	0.331100***	0.396386***
	(0.027422)	(0.024740)	(0.024917)	(0.024789)	(0.024593)	(0.023796)	(0.024927)	(0.023952)
Knowledge_quantity	0.000040**	0.000083***	0.000074***	0.000079***	0.000070***	0.000077***	0.000017	0.000074***
	(0.000017)	(0.000017)	(0.000017)	(0.000017)	(0.000017)	(0.000017)	(0.000015)	(0.000016)
Knowledge_quality	1.637356***	−0.026722	−0.057904	−0.207861	−0.241508	−0.179238	−0.036043	−0.402280**
	(0.260236)	(0.184176)	(0.180914)	(0.178527)	(0.176295)	(0.171844)	(0.184127)	(0.172179)
Intensity		1.210059***		0.501210***	0.749768***			
		(0.060245)		(0.066696)	(0.081294)			
Timeliness			0.287774***	0.202500***	0.295619***			
			(0.012545)	(0.016361)	(0.019636)			
Intensity * Timeliness					−0.086864***			
					(0.012702)			
Intensity_in-house						0.598325***		0.273964***
						(0.080380)		(0.067468)
Timeliness_in-house						0.146031***		0.127259***
						(0.014359)		(0.013251)
Intensity_external							0.815120***	0.397357***
							(0.084650)	(0.072668)
Timeliness_external							0.146171***	0.075115***
							(0.021899)	(0.018376)
Constant	−1.729877***	−2.313583***	−2.146819***	−2.215805***	−2.084416***	−2.001042***	−1.236014***	−2.027331***
	(0.266790)	(0.282805)	(0.266306)	(0.272139)	(0.266248)	(0.271346)	(0.242778)	(0.260806)
Observations	2901	2901	2901	2901	2901	2901	2901	2901
Pseudo R-squared	0.103	0.141	0.146	0.151	0.154	0.152	0.139	0.160

Notes: *Significant at the 10 % level. **Significant at the 5 % level. ***Significant at the 1 % level. Standard errors are reported in parentheses.

Table 3(b)
Panel data regression results of the knowledge linkage between science and technology on semiconductor corporations' innovation performance

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Firm age	0.022063***	0.000751	−0.001740	−0.001638	−0.002544	−0.002170	−0.002597	−0.003604*
	(0.002742)	(0.002242)	(0.002205)	(0.002199)	(0.002124)	(0.002216)	(0.002139)	(0.002120)
Firm size	0.335313***	0.137466***	0.120841***	0.118450***	0.103606***	0.121111***	0.117382***	0.102936***
	(0.032841)	(0.029849)	(0.029329)	(0.029354)	(0.028697)	(0.029158)	(0.028917)	(0.028651)
RD_expenditure	0.647334***	0.654074***	0.666835***	0.662738***	0.664497***	0.673268***	0.690053***	0.683688***
	(0.029929)	(0.025599)	(0.025106)	(0.025125)	(0.024590)	(0.024948)	(0.024858)	(0.024549)
Knowledge_quantity	0.000488***	0.000230***	0.000181***	0.000186***	0.000172***	0.000169***	0.000157***	0.000144***
	(0.000039)	(0.000039)	(0.000039)	(0.000039)	(0.000039)	(0.000039)	(0.000038)	(0.000038)
Knowledge_quality	−0.437540***	−0.390904***	−0.445119***	−0.431650***	−0.381432***	−0.450569***	−0.421621***	−0.434936***
	(0.142151)	(0.133055)	(0.125529)	(0.126651)	(0.129977)	(0.125650)	(0.126617)	(0.124413)
Intensity		1.605486***		0.378307***	1.614830***			
		(0.074067)		(0.127122)	(0.170427)			
Timeliness			0.635977***	0.496613***	0.292075***			
			(0.028321)	(0.052919)	(0.044658)			
Intensity * Timeliness					−0.129544***			
					(0.010484)			
Intensity_in-house						0.455434***		−0.025415
						(0.125055)		(0.075698)
Timeliness_in-house						0.508444***		0.268813***
						(0.054971)		(0.046088)
Intensity_external							0.384246***	0.194288*
							(0.107527)	(0.101043)
Timeliness_external							0.494047***	0.353276***
							(0.045014)	(0.043624)
Constant	−11.266254***	−7.458264***	−7.042980***	−7.022327***	−6.794474***	−7.023383***	−7.062141***	−6.755114***
	(0.439171)	(0.417925)	(0.408753)	(0.410544)	(0.403739)	(0.410448)	(0.398782)	(0.398092)
Observations	4207	4207	4207	4207	4207	4207	4207	4207
Pseudo R-squared	0.0912	0.115	0.118	0.119	0.124	0.118	0.121	0.123

Notes: *Significant at the 10 % level. **Significant at the 5 % level. ***Significant at the 1 % level. Standard errors are reported in parentheses.

effects of the knowledge linkage between in-house and external science and technology on corporate technological innovation were examined, respectively. The coefficients are consistent with those in Models 2, 3, and 4. The results indicate that there is a positive relationship between the intensity and timeliness of knowledge linkage between in-house and external science and technology, as evidenced by the significant positive coefficients ($p < 0.01$). Specifically, a higher proportion and an earlier published year of both in-house and external scientific references in patents are associated with increased number of corporate patents.

However, it is important to note that when *Intensity_in-house*, *Intensity_external*, *Timeliness_in-house, and Timeliness_external* are added simultaneously in Model 8, the coefficient on *Intensity_in-house* is no longer significant in semiconductor corporations. This suggests that within the semiconductor sector, patent production in corporations that

Table 4(a)
Panel data regression results of the knowledge linkage between science and technology on pharmaceutical corporations' innovation performance. The dependent variable is measured by the total number of forward citations of patents.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Firm age	0.009029***	0.003823**	0.001249	0.001356	0.000516	0.003126**	0.004354***	0.002254*
	(0.001796)	(0.001500)	(0.001255)	(0.001336)	(0.001383)	(0.001325)	(0.001465)	(0.001296)
Firm size	−0.079619*	−0.327926***	−0.345528***	−0.374121***	−0.375628***	−0.364582***	−0.341409***	−0.399572***
	(0.041822)	(0.041646)	(0.041145)	(0.040910)	(0.040828)	(0.040570)	(0.042831)	(0.040066)
RD_expenditure	0.608112***	0.704021***	0.789880***	0.765910***	0.769948***	0.772817***	0.715694***	0.779179***
	(0.046707)	(0.042736)	(0.043419)	(0.042719)	(0.042686)	(0.042021)	(0.043432)	(0.041556)
Knowledge_quantity	0.000056**	0.000089***	0.000055*	0.000064**	0.000067**	0.000051	0.000023	0.000054*
	(0.000027)	(0.000031)	(0.000030)	(0.000031)	(0.000031)	(0.000033)	(0.000026)	(0.000031)
Knowledge_quality	2.344898***	0.279206	0.222275	0.053036	0.036072	0.237593	0.278758	−0.092179
	(0.405109)	(0.314555)	(0.314227)	(0.290769)	(0.287273)	(0.281129)	(0.321030)	(0.268914)
Intensity		1.545864***		0.702474***	0.968866***			
		(0.117524)		(0.126532)	(0.162618)			
Timeliness			0.361295***	0.242219***	0.360627***			
			(0.023375)	(0.032149)	(0.043881)			
Intensity * Timeliness					−0.105439***			
					(0.029270)			
Intensity_in-house						0.804369***		0.347332**
						(0.152103)		(0.147685)
Timeliness_in-house						0.148364***		0.144488***
						(0.028087)		(0.027149)
Intensity_external							1.066190***	0.649946***
							(0.163926)	(0.142122)
Timeliness_external							0.169769***	0.052283
							(0.046203)	(0.039381)
Constant	−0.085059	−0.209997	0.300087	0.236431	0.190425	0.467976	0.779702*	0.422157
	(0.422721)	(0.496356)	(0.470504)	(0.492431)	(0.483145)	(0.509924)	(0.416841)	(0.487900)
Observations	2901	2901	2901	2901	2901	2901	2901	2901
Pseudo R-squared	0.0458	0.0649	0.0655	0.0690	0.0697	0.0678	0.0637	0.0723

Notes: *Significant at the 10 % level. **Significant at the 5 % level. ***Significant at the 1 % level. Standard errors are reported in parentheses.

participate in both independent and collaborative scientific research are more inclined to be stimulated by citing collaborative research outcomes.

4.2. Robustness checks

How the knowledge linkage between science and technology affects corporate technological innovation and the moderating effect of knowledge stocks were empirically analyzed. To ensure the robustness of the research results, we further conducted robustness testing on two dimensions.

We first changed the measurement of the dependent variable. Given that citation is a commonly used proxy to measure patent quality (Wang and Li, 2021), we recalculated the total number of forward citations of patents as a proxy for the innovation performance of a corporation.

Table 4(a) demonstrates the estimation results of corporations in the pharmaceutical industry. In contrast to the findings shown in Table 3(a), the observed relationship between *Firm size* and the dependent variable changes from positive to negative. This suggests that the increase in size of a pharmaceutical company rather discourages its patents from receiving more citations.

The coefficients shown in Table 4(b) show more differences with those displayed in Table 3(b), suggesting a disparity in the effect of variables on the number of patents and the forward citations of patents in the semiconductor industry. According to the findings presented in Table 4(b), the inclusion of independent variables in the model reveals a statistically significant negative impact of *Firm age* on the quality of patents ($p < 0.01$). This observation underscores the higher likelihood of more citations for patents generated by emerging semiconductor companies. Meanwhile, the coefficient on *Firm size* is not statistically significant, indicating that increasing firm size has no effect on patent quality.

We also verified the robustness of our results using a truncation of the sample from 2015 to 2020, and the results were consistent with the main analysis.

5. Discussion and conclusions

The relationships between science and technology outcomes in corporations have long been recognized (Slavova and Jong, 2021; Castellacci et al., 2022; Zhou et al., 2021). This prolific line of research underlines the promotion role of science in corporate innovation. Along this line, we contribute to the stream by focusing on the knowledge linkage between science and technology. The purpose of this paper is to examine the impact of the knowledge linkage between science and technology in corporations on their technological innovation performance. Drawing on patents, scientific publications, and firm-level data from 671 pharmaceutical and 686 semiconductor corporations, we conducted an empirical study to test our hypotheses. By doing so, this study paves the way for several theoretical and managerial implications.

5.1. Theoretical implications

First, this study enriches the literature on corporate innovation by investigating factors influencing technological innovation performance from the perspective of the technological impact of corporate scientific research. A considerable volume of research on corporate innovation sheds light on the prominent place of scientific research in driving technological advancements. These studies have investigated corporate scientific research in terms of financial investment, researchers, quantity, quality, and research strategies (Barge-Gil et al., 2020; Bikard and Marx, 2020; Añón Higón, 2016; Choi and Lee, 2022). In parallel, much research effort has been devoted to exploring how and through what channels scientific research contributes to technological development. When answering these questions, it is proposed that the inclusion of scientific publications referenced in patents serves as a signal of the reliance of these patents on the knowledge contained in those publications, or the flow of knowledge from the realm of science to that of technology (Narin and Olivastro, 1992; Ba and Liang, 2021; Hötte et al., 2021). In other words, the knowledge linkage between science and technology can reflect the technological impact of scientific research (Ke, 2023). Far less is known, however, about whether and how it will

Table 4(b)
Panel data regression results of the knowledge linkage between science and technology on semiconductor corporations' innovation performance. The dependent variable is measured by the total number of forward citations of patents.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Firm age	0.025789***	−0.020306***	−0.020276***	−0.021679***	−0.023840***	−0.022563***	−0.021389***	−0.003497*
	(0.004698)	(0.003421)	(0.003412)	(0.003391)	(0.003261)	(0.003429)	(0.003275)	−0.002124
Firm size	0.393432***	0.050606	0.051212	0.041241	0.022456	0.042592	0.051725	0.682382***
	(0.050931)	(0.043989)	(0.043712)	(0.043650)	(0.042545)	(0.043374)	(0.042656)	−0.024595
RD_expenditure	0.545916***	0.638298***	0.653269***	0.644687***	0.653200***	0.657328***	0.675635***	0.106634***
	(0.047089)	(0.032802)	(0.032584)	(0.032458)	(0.031547)	(0.032265)	(0.031861)	−0.028649
Knowledge_quantity	0.000297***	−0.000257***	−0.000262***	−0.000284***	−0.000331***	−0.000320***	−0.000307***	0.000141***
	(0.000058)	(0.000062)	(0.000061)	(0.000062)	(0.000062)	(0.000063)	(0.000060)	−0.000038
Knowledge_quality	−0.394191***	−0.284410**	−0.314635***	−0.294837**	−0.265617**	−0.308240***	−0.290302**	−0.023877
	(0.125411)	(0.123871)	(0.117103)	(0.120347)	(0.124315)	(0.117508)	(0.121558)	−0.076313
Intensity		2.480187***		1.097751***	2.912409***			
		(0.111651)		(0.237205)	(0.300848)			
Timeliness			1.012151***	0.569178***	0.265167***			
			(0.046393)	(0.099813)	(0.078434)			
Intensity * Timeliness					−0.224258***			
					(0.018136)			
Intensity_in-house						1.503599***		−0.023877
						(0.223897)		(0.076313)
Timeliness_in-house						0.457755***		0.266649***
						(0.098960)		(0.046161)
Intensity_external							0.730626***	0.199243**
							(0.189955)	(0.101464)
Timeliness_external							0.704556***	0.354191***
							(0.079111)	(0.043832)
Constant	−8.712739***	−2.131746***	−2.221983***	−1.902183***	−1.479070**	−1.793438***	−2.156132***	−6.758762***
	(0.660352)	(0.612037)	(0.592006)	(0.607429)	(0.598818)	(0.609552)	(0.580519)	(0.398760)
Observations	4207	4207	4207	4207	4207	4207	4207	−0.003497*
Pseudo R-squared	0.0433	0.0676	0.0678	0.0688	0.0735	0.0690	0.0707	−0.002124

Notes: *Significant at the 10 % level. **Significant at the 5 % level. ***Significant at the 1 % level. Standard errors are reported in parentheses.

affect corporate innovation. Therefore, we put special emphasis on the knowledge linkage between science and technology within corporations, highlighting the effect of the technological impact of corporate scientific research on technological innovation performance in this study.

Second, the evidence from this study theoretically suggests a possible explanation of the way in which scientific research advances corporate technological innovation. On the one hand, our findings suggest that the higher the proportion of corporations citing their published scientific publications in patents, the more likely they are to produce more patents. A plausible justification is that knowledge gained through scientific research can serve as a high-level, theoretical guide for corporate technology innovation. There is a consensus among scholars that science and technology follow different logics (Rosenberg and Nelson, 1994; Arthur, 2007). But when corporations challenge this paradigm, utilizing scientific research to support innovative activities for example, knowledge may flow from science to technology. Not only can such knowledge guide corporations in the direction of innovation, assist them in their innovation search, and direct them to invest their innovation resources in promising and lucrative areas (Fleming and Sorenson, 2004), but it can also provide methodological instructions to assist corporations in innovating using more advanced theories, methods, and instruments to help them understand how to innovate and improve their innovation process (McKelvey and Ljungberg, 2017). Moreover, corporations can accelerate the innovation process by making full use of scientific knowledge. Intensifying the ST linkage contributes to closing the knowledge distance between them, increasing knowledge similarity and facilitating the flow of knowledge (Sudhindra et al., 2020). Consequently, corporations tend to generate more innovations.

On the other hand, the regression results suggest that corporate technological innovation benefits from the utilization of scientific knowledge produced in the early stages. There may be an inconsistency with previous research while a large volume of studies has outlined the fact that patents cite more novel scientific publications than comparable non-novel ones (Ke, 2020b; Wang and Li, 2021). Unlike these studies, however, we are interested in how the gap between the publication year of the cited papers and the filing year of the citing patents influences its innovation performance. Notwithstanding innovation's preference for citing novel scientific findings, our study implies that it is the classic findings from scientific research that appear to generate more technological innovations. Such findings can be corroborated in subsequent studies, demonstrating their validity and reliability (Bikard and Marx, 2020). Given that corporate innovation's ultimate goal is profitability, what corporations seek is commercially viable innovation, which typically relies on low-uncertainty and reliable scientific findings. Thus, corporations are able to generate a greater number of patents by employing a greater proportion of mature scientific output in innovation activities.

Moreover, the positive effects of the aforementioned factors on the technological innovation performance of corporations are present in both scientific research strategies (e.g., independent vs. joint research). The findings of the regression analysis suggest that there is a positive relationship between the proportion of references in patent applications attributed to a corporation, whether they are sole-authored by the corporation or co-authored, can contribute to an increase in the number of subsequent patents. Nevertheless, it is observed that corporations operating in the semiconductor industry tend to generate a greater quantity of patents with improved quality when they enhance the utilization of joint scientific research outputs as references in their patent citations. This observation implies that the generation of patents within semiconductor businesses is more likely to be stimulated by joint scientific research. In this regard, our result echoes the empirical evidence provided by Lim (2004). He notes that the relationship between research and innovation is affected by the industries involved because the nature of innovation is different in the pharmaceutical industry and the semiconductor industry. In the pharmaceutical industry, while drug development is complex, innovation primarily revolves around a single active ingredient or compound, leading to a well-defined and distinct product (Stokes, 2011). In contrast, semiconductor products are "systemic" in nature (Hall and Ziedonis, 2001), involving hundreds of interconnected design and manufacturing stages. Therefore, the results obtained are highly influenced by even slight variations in the design and process parameters. The commercialization of any innovation in research necessitates a substantial amount of effort, as it must be meticulously integrated into the broader process. Within this particular context, allocating resources towards advancements in process technologies and the acquisition of tacit, embedded knowledge offer more effective means of gaining a competitive edge (Lim, 2004). Semiconductor corporations are thus investing resources in joint research with universities and other institutions to acquire more practical knowledge, thereby reducing the need to perform independent scientific research.

5.2. Policy and managerial implications

These results give managers ideas about how corporations can improve their technological innovation by making appropriate innovation strategies. Science-intensive industries, such as pharmaceuticals and semiconductors, are built on the advancement of science and technology. In these industries, scientific and technological knowledge co-evolve together. Collaboration between them is viewed as the engine that drives the industry forward, thereby contributing to the sector's growth (Oliver, 2004). Our study sheds light on the fact that corporations in these industries should not only focus on conducting and supporting scientific research but also seek out for scientific research that is more valuable. The findings suggest that the knowledge linkage with science is crucial, and that science-intensive corporations should utilize their own scientific research findings in technology development to the fullest extent. For example, managers should encourage scientific research in line with the direction of technological innovation and encourage innovation activities that building on corporate scientific outcomes, especially the earlier, more mature research results. Second, industry-specific characters must also be taken into account. Specifically, joint research can provide semiconductor companies with better opportunities to collaborate and cross-license technologies, thus leading to a web of interdependent patents covering different aspects of a product. Therefore, managers of semiconductor companies may contemplate engaging in joint research endeavors with external institutions and pursuing technological advancements based on the findings derived from the research.

5.3. Limitations and future research directions

This study has several limitations calling for future research. First, although patents are often used as proxies for innovation and can reflect a corporation's innovation efforts, they are not always a thorough assessment of corporate innovation. Previous research shows that corporate innovation contains rich and various ways, such as new products that are introduced and developed in the market, improved goods or services, and new or significantly improved processes (Caloghirou et al., 2021; Martinez-Senra et al., 2015). Therefore, the number of patents may overlook other significant performance indicators for firms' innovation, and may provide only a partial picture of the overall innovation performance of corporations. Future research should consider a variety of proxy measures of corporate innovation. Second, we empirically test hypotheses in two specific science-intensive industrial sectors, which may lead to limitations in generalizing results from pharmaceutical and semiconductor corporations to other settings. Much further study spanning more fields will be required in the future to demonstrate the generalizability of our results, given the diverse inclination for innovation reported across industries. Third, this research understates the significant differences in patent practices between the pharmaceutical and semiconductor industries. Pharmaceutical patents are product-centric, whereas semiconductor patents exhibit a complex landscape of multiple patents associated with a single product, which may cause the motivations of companies engaging in scientific research. Therefore, a more extensive and industry-specific analysis is required to delve deeper into the nuances between the two industries.

CRediT authorship contribution statement

Xi Chen: Investigation, Data curation, Writing – original draft. **Jin Mao:** Conceptualization, Methodology, Writing – review & editing. **Yaxue Ma:** Methodology, Investigation. **Gang Li:** Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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