Finance Research Letters xxx (xxxx) 104147

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl



# The power of paper: Scientific disclosure and firm innovation

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ARTICLE INFO

*Keywords:*
Scientific disclosure
Corporate innovation
Market signal
Human capital
Standard

*JEL classification:*
O32
O36
G31

ABSTRACT

This research investigates the relationship between scientific disclosure and innovation in Chinese listed firms from 2006 to 2018. Our findings indicate a positive correlation between scientific disclosure and both the quantity and quality of a firm's patents. Scientific disclosure enhances innovation by enhancing market credibility, pursuing standards, and attracting high-quality talent. The positive impact of scientific disclosure is particularly notable in firms with high levels of knowledge and R&D density, as well as those with independent central research institutes and state-owned enterprises. Overall, our investigation emphasizes the crucial significance of scientific disclosure in promoting innovation in emerging markets.

## 1. Introduction

Innovation is an essential driver of economic development for countries and companies seeking to maintain competitiveness in technology and business (Acemoglu et al., 2018). Considering its importance, innovation has been extensively studied theoretically and empirically, as evidenced by numerous studies in various disciplines (Hall and Rosenberg, 2010). This study seeks to analyze the consequences of scientific disclosure on innovation performance.

Scientific disclosure refers to research activities funded by private firms and guided by developing new basic knowledge (Arora et al., 2018; Rotolo et al., 2022). Most of China's funding for fundamental research is allocated to the public sector, which includes government-owned laboratories and educational institutions. They generate numerous academic articles, but hardly applicable to private firms. Chinese firms are therefore more reliant on foreign technologies and their own weak ability in basic research. As a result, the connection between scientific disclosure and innovation has received limited attention in previous research, highlighting the need for further investigation in this domain (Hsu et al., 2021).

China's innovation system has undergone significant transformation during the past decades. The country's national innovation system was deeply influenced by the Soviet Union, resulting in a system in which the scientific research and production sectors operate independently. Over time, a framework for scientific and technological innovation has been established, dominated by the Chinese Academy of Sciences, universities, research institutions of central ministries and commissions, local scientific research institu-

We acknowledge the valuable and insightful suggestions from Dongmin Kong, and seminar participants at Zhongnan University of Economics and Law for their helpful suggestions. We also acknowledge the financial support from the Major Project of National Social Science Foundation of China (21ZDA010), the National Natural Science Foundation of China (71991473; 71772178), and the Innovation and Talent Base for Digital Technology and Finance (B21038). All errors are our own.

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https://doi.org/10.1016/j.frl.2023.104147
Received 17 April 2023; Received in revised form 14 June 2023; Accepted 22 June 2023
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tions, as well as national defense science, technology, and industry departments. Since the onset of reforms and opening-up in 1978, China's innovation system has been evolving. Many research institutions have established subsidiaries to pursue business ventures, while the government has promoted firms as the primary force driving technological innovation. Large and medium-sized enterprises have established technology centers and strengthened cooperation with universities. However, the bulk of firms' R&D expenditure goes into experimental development, and investment in basic scientific research remains relatively low.

We constructed a novel firm-level data by manually collecting data from 2296 firms over the period 2006–2018, resulting in a total of 19,477 firm-year observations. We matched the publication records of publicly-listed Chinese firms on the core journals from the China National Knowledge Infrastructure (CNKI), which covers approximately 8500 Chinese journals, and Scopus, which covers over 20,000 English journals, with the firm's patent data from the China National Intellectual Property Administration.

The literature similar to our study comes from Arora et al. (2021). They used 800,000 published papers from US public companies between 1980 and 2015, along with citation data for patents related to those papers, to study how corporate scientific research affects a company's inventions and spillover effects on competitors. They found that when scientific research is used internally, it produces more papers, but when it is used by competitors, it produces fewer papers. In addition, they examined the impact of corporate publications on downstream patents and found that a company's own publication stock, citations of its own scientific discoveries, and citations of competitors' scientific discoveries all significantly stimulated the company's patent output. However, they did not further explore the mechanisms behind this impact and did not address potential endogeneity issues well.

This study utilized manually collected data on publications and patents of listed companies in China to investigate how scientific disclosures affect corporate innovation, and obtained results consistent with those of Arora et al. (2021). Our findings suggest that scientific disclosure promotes innovation in Chinese listed firms, especially in those with more influential publications, higher science and R&D intensity, independent central research institutes, and state ownership. This positive effect is confirmed through various robustness checks, including policy shock analysis, instrumental variable approach, and propensity score matching method. Scientific disclosure sends strong market signals, supports preemptive technical standards, and attracts innovative talent, thus boosting firm innovation.

Research gaps are to be filled by addressing the following three less- or un-explored issues. Firstly, we explore the determinant of innovation from a fresh perspective, scientific disclosure, which refers to research activities funded by private firms and guided by the development of new basic knowledge (Arora et al., 2018), affects innovation performance. Secondly, although China has demonstrated strong ambitions to catch up and lead in the global innovation competition, it is still regarded as technologically weak, particularly in the field of basic scientific research (Fang et al., 2020). Thirdly, China's investment in basic research primarily flows into the public sector, such as government labs and universities. Although these public sectors generate a significant number of scholarly articles, private firms find it challenging to apply them to their work. Consequently, existing literature on basic scientific research primarily focuses on the government, universities, and public-funded research institutions, with limited studies exploring scientific disclosure and its consequences in firms (Huang et al., 2017; Hsu et al., 2021). Therefore, it is vital to further study the nexus between scientific disclosure and innovation.

## 2. Related literature and hypotheses development

### 2.1. Scientific disclosure and innovation

According to Rotolo et al. (2022), the academic publishing activity of private firms can enhance their internal innovation capacity. Innovation can be significantly influenced by scientific advancements. Research shows that scientific disclosure drives creativity in firms (Simeth and Cincera, 2016). Firstly, firms can conduct fundamental scientific research and publish their findings to supplement their R&D and innovation activities. Secondly, engaging in research activities can help corporate researchers develop crucial skills and identify new commercial applications or technologies (Friesike et al., 2015). Thirdly, academic exchanges and interactions can enhance companies' capacity to recognize, assimilate, and apply novel external knowledge, improving efficiency and productivity (Marx and Hsu, 2022). Finally, adopting publicly-funded basic scientific research can help lower a firm's R&D expenses (Akcigit et al., 2021).

Additionally, investments in basic scientific research can help corporations absorb external technology (Audretsch and Belitski, 2020). Corporate scientists play a crucial role in identifying promising new inventions, collaborating with external researchers, and adapting external technologies. Scientific disclosure and participation in academic conferences are effective ways for firms to remain embedded in external scientific networks and leverage scientific progress for innovation (Rosenberg, 2010). Moreover, Marx and Hsu (2022) found that a firm's scientific research capabilities can improve the adoption and business development of cutting-edge technologies, leading to enhanced productivity. Based on this premise, we put forward the following hypothesis:

**Hypothesis 1a**. Scientific disclosure has a positive impact on innovation.

A firm's scientific disclosure may not always lead to increased innovation output due to two potential reasons. Firstly, the costs associated with salaries and equipment necessary for basic scientific research can result in insufficient investment in patenting activities. High salaries are often necessary to attract and retain scientists with PhDs, who require significant remuneration (Stephan, 2012). Additionally, corporate lab equipment carries a high cost that can increase rapidly. This means that if a firm invests heavily in basic scientific activities, it may risk under-investing in patenting. Secondly, a firm's incentives and rewards system may guide researchers towards publishing over innovation patent-related activities. Researcher's time and effort will be dictated by incentives within a firm, which are closely tied to publishing output. However, if incentives shift towards patenting, researchers may invest more time and effort in patent-related activities, as seen in IBM's change in reward system resulting in a decline in publishing and an increase in patenting (Bhaskarabhatla and Hegde, 2014). Overall, it is important for firms to find a balance between publishing and patenting activities to maximize innovation output.

**Hypothesis 1b**. Scientific disclosure has a negative impact on innovation.

### 2.2. Mechanisms: signaling, standards, and human capital

Scientific disclosure can enhance a firm's academic reputation. Scientific papers conducted by a firm can function as a credible signal regarding its capacity for innovation, which can be recognized by various stakeholders (Arora et al., 2018). By publishing scientific papers, a firm can directly communicate to the capital market, demonstrating its strong technical capabilities, important scientific discoveries, or new products developed (Almeida et al., 2011; Arora et al., 2021). Furthermore, scientific disclosure can heighten the likelihood of obtaining external contracts, grants, or subsidies (Simeth and Cincera, 2016). In conclusion, the above discussion highlights the importance of scientific disclosure through market signal effects. Therefore, we propose the second hypothesis:

**Hypothesis 2**. Scientific disclosure can promote innovation through market signal effects.

Corporate publication is a potential tool for technology diffusion and for gaining an advantage as a first-mover (Lück et al., 2020). The capacity of a company to carry out fundamental scientific research, as indicated by its publication records, has been a significant catalyst in the creation of national and industrial standards (Smith et al., 2010). Engaging in standard-setting activities can help to build a company's reputation and increase its chances of being selected (Zhao et al., 2023). Additionally, competitive companies are more likely to establish standards to leverage their advantage, whereas less competitive companies may employ standards that are incompatible with their competitors (Blind et al., 2022). Firms are likely to initiate innovation initiatives in collaboration with firms engaged in standardization endeavors, as cooperation fosters knowledge transfer, which boosts innovation (Zhang et al., 2020). In light of these considerations, we propose the following hypothesis:

**Hypothesis 3**. Scientific disclosure promote innovation through standard strategies.

Scientific disclosure is an important factor in attracting high-quality scientists and engineers to a firm, particularly "star scientists," who prioritize academic reputation and research opportunities over monetary rewards (Arora et al., 2018). Encouraging scientific disclosure can also contribute to a positive employer reputation in the talent market. Job seekers may view firms that value and respect scientific research talent (Hsu and Kuhn, 2022; Martínez and Parlane, 2023). Furthermore, Scientists are typically self-motivated and knowledge producers tend to select firms with strong academic publishing records to advance their career development. Therefore, firms with strong publishing abilities can gain talent dividends to some ext*ent*. We propose the following hypothesis:

**Hypothesis 4**. Scientific publishing promote innovation by increasing human capital.

## 3. Research design

### 3.1. Model

The model used to analyze the impact of scientific disclosure on a firm's innovation activities is presented in the following specification:

$$Ln\left(1 + Inno_{i,t}\right) = \alpha + \beta Ln\left(1 + Publish_{i,t-1}\right) + \gamma X_{i,t-1} + YearFE + FirmFE + \varepsilon_{i,t} \quad (1)$$

This study measures innovation performance (*Inno*) by quantity (*Patent_total*) and quality (*Patent_citation*). The scientific publication capacity of the firm is the key independent variable (*Publish*), along with other controls (*X*), including R&D input, firm size, firm age, capital intensity, labor productivity, return on assets, market-to-book ratio, sales growth, capital structure, cash holding, stock volatility, stock return, managerial ownership, institutional ownership, local economic development, and product market competition.

### 3.2. Data sources

In this study, we select Chinese A-share listed firms as our research unit for the period spanning from 2006 to 2018. This specific period has been chosen for a few compelling reasons. Firstly, Chinese listed firms have traditionally been disclosing their R&D expenditure data in their annual reports since 2006. Secondly, we decided to end our study in 2018 since this was the last year that granted patent data were almost complete when we commenced with the research. Thirdly, our study employs the number of firms' patents granted to serve as a proxy for a firm's innovation. The time frame from when a company files for a patent application to when it gets granted by the China National Intellectual Property Administration is generally two years or more. Hence, concluding our sample period in 2018 seems appropriate. Moreover, we excluded financial firms from our study, given their unique and incomparable annual reports (Chang et al., 2015). This resulted in a sample comprising 2296 listed firms, with 19,477 firm-year observations, after removing samples with incomplete data or zero patent grants.

### 3.3. Variables

#### 3.3.1. Corporate innovation

The aim of this study is to investigate corporate innovation by analyzing the number of patents filed and granted (*Patent_total*). Data for this study were sourced from the China National Intellectual Property Administration (CNIPA), which grants three types of patents: invention, utility model, and design patents. To focus solely on the most novel and inventive categories, we excluded design patents. We also utilized an alternative measurement (*Patent_citation*) that reflects a firm's innovation quality. To do this, following the approach of Hall et al. (2005) and developing an adjust factor index for patent citations. This involved calculating the mean forward citation value for patents filed in the same year and technology class, which we named the type-year average. Next, we calculated the mean forward citation value for patents filed within the same technology type but disregarding the applying year, which we termed the class average. To capture the variation across years but not across technology types, we constructed a citation adjustment factor based on the corresponding type and year averages. Finally, we scaled each technology type's patent citation adjustment factor in each applying year by the corresponding type average. Then, adjusted each granted patent's forward citation count by this citation adjustment factor and summed all the forward citations adjusted by the listed firms in each applying year.

#### 3.3.2. Scientific disclosure

In order to assess a firm's scientific disclosure, we utilize two different measurements: (i) A binary proxy *Publish_dummy* is defined as equal to 1 if a firm has published at least one article in a given year, and 0 otherwise; and (ii) Ln(1 + *Publish*), which is defined as the log of one plus the count of academic articles published by the firm in core journals within a year. In order to investigate the innovation effect of scientific disclosure, our focus is on natural science papers, which include published papers and excluded dissertations, reviews, newspapers, and conference papers.

Based on the definition of Simeth and Cincera (2016), a firm's scientific disclosure is considered a scientific article that has been published by employees affiliated with that firm or its subsidiaries in a core journal. To determine the yearly publications of each listed firm, we followed a detailed process. Initially, we collected basic information from 84,856 listed firms and their respective subsidiaries. We then utilized two comprehensive databases, namely China National Knowledge Infrastructure (CNKI) and Elsevier's Scopus, to search for academic articles published under each firm's affiliation. The former is the largest and most comprehensive source of China-based information resources and publications, while the latter covers more than 20,000 journals. Subsequently, we summed up the yearly number of publications for each individual firm and performed an additional verification of all the data with another database. For detailed information on our searching and matching procedures, please refer to Online Appendix B.

#### 3.3.3. Control variables

Following prior studies (Chang et al., 2015; Gao et al., 2020; Islam and Zein, 2020), we control an array of corporate characteristics that may have important effects on innovation output, which including the natural log of R&D expenses, serving as an important input to innovation (Ln(1 + *R&D_exp*)), the natural log of total assets, used to control a firm's size (Ln(*Assets*)), the natural log of the difference between year *t* minus the year when a firm enters the database, which captures the effects of a firm's life cycle (Ln(*Firm_age*)), the natural log of the net property, plant, and equipment (PPE) scaled by the number of a firm's employees, proxying capital intensity (Ln(*PPE/employees*)), the natural log of a firm's total sales scaled by the number of employees, measuing labor productivity (Ln(*Sales/employees*)), net income divided by total assets, capturing operating profitability (*ROA)*, market-to-book ratio, a proxy for growth opportunities (M/B), the growth rate of sales revenue (*Sales_growth)*, the book value of total debts divided by the book value of total assets, accounting for capital structure (*Leverage)*, the book value of cash assets divided by total assets, representing the effect of cash holdings (*Cash/Assets)*, the standard deviation of daily stock returns in a fiscal year (*Stock_volatility*), buy-and-hold stock return calculated in a given year (*Stock_return*), the ratio of the number of shares held by executives to the total number of shares, representing the controlling power of managers (*Managerial_ownership*), the ratio of the shares held by institutional investors scaled by the total shares, reflecting corporate governance (*Institutional_ownership*), the natural log of GDP per capita in a firm's location, a proxy for local economic development (Ln(*Local_gdp*)), the Herfindahl index (*Herfindahl*) and its squared term ($Herfindahl^2$), measuring the degree of market competition.

### 3.4. Descriptive statistics

Table 1 displays the sample distribution of listed firms, comprising 19,477 observations over the sample period. Nearly half of the firms (49.25%, 9592) have at least one publication record (*Publish_dummy* = 1). The ratio of listed firms with at least one publication to those without declines slightly from 51% in 2006 to approximately 44% during the sample period. When examining the firm distribution by industry, the medical products industry has the highest number of companies with publishing records (972 firms, constituting 68% of the industry), followed by the computers, communication, and other electronic equipment industry (787, 38%); chemical raw materials and chemical products (741, 45%); electric equipment and machinery (677, 48%); special-purpose machinery (650, 51%); and general-purpose machinery (501, 57%). In summary, companies that are capital- and technology-intensive tend to publish more in academic journals.

Table 2 depicts the descriptive statistics. On average, listed firms obtain around 17 invention and utility model patents and receive 31 citations during the sample period. Additionally, a listed firm has approximately 5 academic journal publications; nevertheless, the count of publications reaches 858.5 at most. Given the substantial standard deviation of most control variables, utiliz-

**Table 1**
Sample distribution.

| | *Publish_ dummy* = 0 | *Publish_ dummy* = 1 | Total | Percent (%) |
|---|---|---|---|---|
| Panel A: sample distribution by year | | | | |
| 2006 | 364 | 376 | 740 | 50.81 |
| 2007 | 362 | 435 | 797 | 54.58 |
| 2008 | 407 | 496 | 903 | 54.93 |
| 2009 | 431 | 539 | 970 | 55.57 |
| 2010 | 437 | 605 | 1042 | 58.06 |
| 2011 | 660 | 705 | 1365 | 51.65 |
| 2012 | 805 | 831 | 1636 | 50.79 |
| 2013 | 888 | 901 | 1789 | 50.36 |
| 2014 | 884 | 904 | 1788 | 50.56 |
| 2015 | 992 | 907 | 1899 | 47.76 |
| 2016 | 1132 | 938 | 2070 | 45.31 |
| 2017 | 1271 | 976 | 2247 | 43.44 |
| 2018 | 1252 | 979 | 2231 | 43.88 |
| Total | 9885 | 9592 | 19,477 | 49.25 |
| Panel B: sample distribution by industry | | | | |
| Manufacture of medical products | 448 | 972 | 1420 | 68.45 |
| Manufacture of computers, communication and other electronic equipment | 1281 | 787 | 2068 | 38.06 |
| Manufacture of chemical raw materials and chemical products | 889 | 741 | 1630 | 45.46 |
| Electric equipment and machinery | 734 | 677 | 1411 | 47.98 |
| Manufacture of special purpose machinery | 629 | 650 | 1279 | 50.82 |
| Manufacture of general purpose machinery | 382 | 501 | 883 | 56.74 |
| Manufacture of automobiles | 308 | 411 | 719 | 57.16 |
| Smelting and pressing of nonferrous metals | 191 | 333 | 524 | 63.55 |
| Building projects | 76 | 297 | 373 | 79.62 |
| Smelting and pressing of ferrous metals | 55 | 280 | 335 | 83.58 |
| Software and information technology services | 603 | 279 | 882 | 31.63 |
| Nonmetal mineral products | 318 | 247 | 565 | 43.72 |
| Production and distribution of electric power and heat power | 115 | 219 | 334 | 65.57 |
| Processing of food from agriculture products | 95 | 204 | 299 | 68.23 |
| Mining and washing of coal | 26 | 195 | 221 | 88.24 |
| Manufacture of railway, ships, aerospace and other transportation equipment | 113 | 192 | 305 | 62.95 |
| Manufacture of alcohol, beverages, and refined tea | 159 | 182 | 341 | 53.37 |
| Textile industry | 195 | 173 | 368 | 47.01 |
| Manufacture of rubber and plastics | 296 | 166 | 462 | 35.93 |
| Food manufacturing | 98 | 155 | 253 | 61.26 |
| Other | 2874 | 1931 | 4805 | 40.19 |
| Total | 9885 | 9592 | 19,477 | 49.25 |

This table presents sample distribution of the number of firms have publications, the number of firms have no publications, and the percentage of firms with publications in the sample by year (Panel A) and by industry (Panel B).

ing the winsorization method to handle potential outliers and conducting heterogeneity analysis on multiple dimensions seems necessary.

## 4. Empirical analyses

### *4.1. Baseline results*

Table 3 presents the findings of baseline model. The results in columns (1) and (3) demonstrate that the coefficients on *Publish_dummy* are statistically significant at the 1% level and positive, demonstrating a considerable positive association between a firm's publication record and its innovation performance. Columns (2) and (4) present the estimates using measurement of publication (*Publish*). Similarly, we find that each additional article published by the firm increases the amount of granted patents by two and patent citations by six. Therefore, our results across all specifications suggest that academic publications contribute to firm innovation. These findings support Hypothesis 1a while rejecting Hypotheses 1b and 1c.

To ensure the robustness and validity of our primary conclusions, we conducted a battery of robustness checks, which encompassed: controlling for contemporaneous granted patents; using the number of patents filed as the dependent variable; using the

**Table 2**
Descriptive statistics.

| Variables | N | Mean | Std | Median | Min | Max |
|---|---|---|---|---|---|---|
| Panel A: Variables of innovation | | | | | | |
| *Patent_total* | 19,477 | 16.829 | 107.891 | 2.000 | 0.000 | 3868.000 |
| *Patent_citation* | 19,477 | 31.258 | 313.279 | 0.000 | 0.000 | 15,002.417 |
| Panel B: Variables of scientific disclosure | | | | | | |
| *Publish* | 19,477 | 4.644 | 29.928 | 0.000 | 0.000 | 858.514 |
| *Publish_dummy* | 19,477 | 0.492 | 0.500 | 0.000 | 0.000 | 1.000 |
| Panel C: Control variables | | | | | | |
| *R&D_exp* | 19,477 | 147.1 | 758.1 | 31.4 | 0.0 | 49,190.4 |
| *Assets* | 19,477 | 14,720 | 78,474 | 3101 | 46 | 2432,558 |
| *Firm_age* | 19,477 | 9.803 | 6.014 | 8.000 | 2.000 | 29.000 |
| *PPE/employees* | 19,477 | 603.5 | 2878.4 | 266.2 | 0.1 | 14,5097.6 |
| *Sales/employees* | 19,477 | 1390.5 | 3514.4 | 782.4 | 10.7 | 138,088.5 |
| *ROA* | 19,477 | 0.055 | 0.059 | 0.051 | −0.180 | 0.235 |
| *M/B* | 19,477 | 0.944 | 0.950 | 0.627 | 0.102 | 5.439 |
| *Sales_growth* | 19,477 | 0.165 | 0.305 | 0.124 | −0.468 | 1.526 |
| *Leverage* | 19,477 | 0.430 | 0.202 | 0.427 | 0.053 | 0.887 |
| *Cash/Assets* | 19,477 | 0.161 | 0.124 | 0.125 | 0.011 | 0.611 |
| *Stock_volatility* | 19,477 | 0.031 | 0.009 | 0.029 | 0.013 | 0.057 |
| *Stock_return* | 19,477 | 0.227 | 0.752 | −0.001 | −0.707 | 3.266 |
| *Managerial_ownership* | 19,477 | 0.061 | 0.128 | 0.000 | 0.000 | 0.585 |
| *Institutional_ownership* | 19,477 | 0.369 | 0.239 | 0.367 | 0.000 | 0.883 |
| *Local_gdp* | 19,477 | 61,811 | 30,505 | 58,833 | 5750 | 153,095 |
| *Herfindahl* | 19,477 | 0.124 | 0.140 | 0.079 | 0.015 | 1.000 |

This table presents the descriptive statistics for the primary variables specified in Online Appendix A over the period of analysis from 2006 to 2018. All continuous variables are truncated at the 1st percentile and 99th percentile to mitigate the impact of outliers.

patent density of the firm, defined as the number of filed patents or patent citations per 1000 employees, as the dependent variable; utilizing negative binomial regressions to account for the fact that patent and citation counts are non-negative count data; excluding firms with no filed patents; excluding firms that lack published papers; excluding firms that engaged in mergers and acquisitions in the previous years; excluding firms located in the four national science center cities-Beijing, Shanghai, Shenzhen, and Hefei; and excluding firms that are university-owned. The results are presented in Online Appendix D, which indicates that all estimates, although varying somewhat in magnitude, remain positive and significant. Our findings demonstrate that firm publication has a favorable influence on innovation and persists despite using alternative methodologies and imposing various sample restrictions.

### 4.2. Endogeneity issue

#### 4.2.1. Policy shock analysis

In 2012, the Chinese government aimed to make China a global leader in technology by deepening "technological system reform and accelerate national innovation system construction" and fostering talent exchange. This policy encourages collaborations between researchers in companies and scientific organizations, which is expected to increase innovation output. To measure its effectiveness, we added a binary attribute *Year2012* and its interaction with $\text{Ln}(1+\textit{Publish})$ to the baseline model. The findings in Table 4 verify a positive impact of the 2012 innovation policy on innovation performance.

#### 4.2.2. Instrumental variable approach

The key variable of interest, corporate scientific disclosure, may be endogenous as firms with high innovation ability can attract more scientists, hence acquire more academic publications. To address this form of endogeneity, we adopt the instrumental variable (IV) approach to tackle endogeneity in the relationship between scientific disclosure and innovation. Motivated by Fisman and Svensson (2007), we construct the instrument as $\text{Ln}(1+\textit{Publish\_peer})$, whereas the variable *Publish_peer* is the average number of firm articles published in core academic journals among other firms in the same industry and the same year. It is expected to be an ideal instrument as a company's publication behavior can be highly correlated to its peer companies due to firm competition or mimicking behavior, and its innovation performance is less likely to be affected by the publication of its peers, therefore the assumptions of instrument relevance and exclusion criteria can be well satisfied.

Table 5 presents the results obtained using the IV method. The IV estimates of the publication coefficient remain reasonably robust across different specifications, which is reassuring. Specifically, the coefficients on $\text{Ln}(1+\textit{Publish})$ are 0.553 and 0.972, respectively. The following three facts lend some credence to the belief that the instruments chosen are proper: (i) the Anderson-Rubin likelihood ratio (LR) test implies that the null hypothesis can be rejected and the publication impact is significant. (ii) The Cragg-Donald F value lies well above the commonly used critical value 10, suggesting that the instrument chosen is not weak. (iii) Given that the corresponding impacts from OLS are about 1/4–1/5 of those from IV model, we expect that weak instrument only underestimates rather than overestimates the relationship between firm publication and innovation.

**Table 3**
Baseline results: scientific disclosure and innovation.

| Variables | *Ln*(1 + *Patent_total*) | | *Ln*(1 + *Patent_citation*) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Publish_dummy* | 0.141*** | | 0.221*** | |
| | (0.020) | | (0.024) | |
| *Ln*(1 + *Publish*) | | 0.133*** | | 0.199*** |
| | | (0.014) | | (0.017) |
| *Ln*(1 + *R&D_exp*) | 0.029*** | 0.027*** | 0.032*** | 0.029*** |
| | (0.003) | (0.003) | (0.004) | (0.004) |
| *Ln*(*Assets*) | 0.288*** | 0.255*** | 0.322*** | 0.274*** |
| | (0.016) | (0.016) | (0.018) | (0.018) |
| *Ln*(*Firm_age*) | −0.378*** | −0.377*** | −0.414*** | −0.412*** |
| | (0.020) | (0.021) | (0.024) | (0.024) |
| *Ln*(*PPE/employees*) | −0.075*** | −0.069*** | −0.113*** | −0.104*** |
| | (0.013) | (0.013) | (0.015) | (0.015) |
| *Ln*(*Sales/employees*) | −0.057*** | −0.059*** | −0.028 | −0.031* |
| | (0.015) | (0.015) | (0.017) | (0.017) |
| *ROA* | 1.365*** | 1.432*** | 1.239*** | 1.341*** |
| | (0.205) | (0.204) | (0.239) | (0.238) |
| *M/B* | −0.076*** | −0.076*** | −0.082*** | −0.082*** |
| | (0.021) | (0.021) | (0.023) | (0.023) |
| *Sales_growth* | 0.001 | 0.014 | 0.025 | 0.045 |
| | (0.033) | (0.033) | (0.038) | (0.038) |
| *Leverage* | 0.085 | 0.110 | 0.019 | 0.058 |
| | (0.072) | (0.071) | (0.083) | (0.082) |
| *Cash/Assets* | 0.159* | 0.160* | 0.192* | 0.195* |
| | (0.092) | (0.092) | (0.108) | (0.108) |
| *Stock_volatility* | −14.390*** | −14.292*** | −15.034*** | −14.897*** |
| | (2.017) | (2.010) | (2.346) | (2.336) |
| *Stock_return* | 0.011 | 0.013 | 0.021 | 0.024 |
| | (0.022) | (0.022) | (0.026) | (0.026) |
| *Managerial_ownership* | 0.184** | 0.182** | 0.269*** | 0.265** |
| | (0.085) | (0.085) | (0.104) | (0.104) |
| *Institutional_ownership* | 0.261*** | 0.232*** | 0.296*** | 0.254*** |
| | (0.050) | (0.050) | (0.058) | (0.058) |
| *Ln*(*Local_gdp*) | −0.241*** | −0.252*** | −0.182*** | −0.199*** |
| | (0.024) | (0.024) | (0.028) | (0.028) |
| *Herfindahl* | 0.033 | 0.026 | 0.127 | 0.114 |
| | (0.298) | (0.298) | (0.345) | (0.344) |
| *Herfindahl2* | −0.154 | −0.147 | −0.144 | −0.130 |
| | (0.290) | (0.289) | (0.340) | (0.339) |
| Constant | −0.120 | 0.372 | −0.976** | −0.252 |
| | (0.323) | (0.319) | (0.380) | (0.375) |
| Year FE | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES |
| Observations | 16,976 | 16,976 | 16,976 | 16,976 |
| Adjusted R2 | 0.290 | 0.293 | 0.266 | 0.270 |

This table displays the outcomes of the impact of scientific disclosure on corporate innovation. Standard errors are clustered at the firm level and presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels (two-tailed), respectively. The definitions of all variables are provided in Appendix A.



*4.2.3. PSM procedure*

Sample bias may arise partly because firms' decisions to publish or not their articles are non-random, in other words, some firms, regardless of whether or not they are innovative, may not engage in publications (exclusion bias). A PSM technique (Rosenbaum and Rubin, 1983) is used in this study to mitigate possible selection bias. Firstly, we identify the firms with at least one academic article as the treated category, and those with no publication as the untreated category. We then utilize a probit regression approach to estimate the propensity score for each firm, indicative of the predicted likelihood that a firm can successfully publish a research paper based on the observed covariates. Thirdly, we employ various matching algorithms, such as one-to-one nearest-neighbor matching, radius matching, and Mahalanobis matching, to create two groups comprised of firms with comparable propensity scores, but assigned either to the "treatment" or "control" group. Finally, we compute three treatment effects to evaluate the impact of scientific disclosure on innovation performance.

Table 6 displays the outcomes of the three treatment effect estimators (ATT, ATE, and ATU) for each of the seven matching routines used in this study. In summary, the results indicate that academic publication has a positive effect on corporate innovation across all waves, regardless of the matching algorithm used. The comparison of the ATE with the OLS estimate suggests that using parametric techniques such as OLS is appropriate for controlling for observable differences.

**Table 4**
The effects of the 2012 policy shock.

| Variables | $Ln(1+Patent\_total)$ | | $Ln(1+Patent\_citation)$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Ln(1+Publish)$ | 0.139*** | 0.119*** | 0.234*** | 0.210*** |
| | (0.016) | (0.019) | (0.018) | (0.022) |
| $Year2012$ | 0.232*** | 0.216*** | 0.172*** | 0.152*** |
| | (0.038) | (0.038) | (0.044) | (0.044) |
| $Ln(1+Publish) \times Year2012$ | | 0.037* | | 0.045* |
| | | (0.022) | | (0.025) |
| Controls | YES | YES | YES | YES |
| Year FE | NO | NO | NO | NO |
| Firm FE | YES | YES | YES | YES |
| Observations | 16,793 | 16,793 | 16,793 | 16,793 |
| Adjusted R2 | 0.290 | 0.290 | 0.256 | 0.256 |

This table presents the outcomes of the impact of the policy shock in 2012 on innovation. Standard errors are clustered at the firm level and presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels (two-tailed), respectively. The definitions of all variables are provided in Appendix A.

**Table 5**
Instrumental variable approach.

| Variables | 1st Stage | 2nd Stage | |
|---|---|---|---|
| | $Ln(1+Publish)$ | $Ln(1+Patent\_total)$ | $Ln(1+Patent\_citation)$ |
| | (1) | (2) | (3) |
| $Ln(1+Publish)$ | | 0.553*** | 0.972*** |
| | | (0.132) | (0.174) |
| $Ln(1+Publish\_peer)$ | 0.181*** | | |
| | (0.013) | | |
| Controls | YES | YES | YES |
| Year fixed effect | YES | YES | YES |
| Firm fixed effect | YES | YES | YES |
| Joint test of excluded IV | $F = 16.36$ | | |
| Cragg-Donald Wald F statistic | 193.69 | | |
| Stock-Yogo weak ID test (10% maximal IV size) | 16.38 | | |
| Observations/Adjusted R2 | 16,793/0.147 | 16,793 | 16,793 |

This table presents the outcomes of the impact of scientific disclosure on innovation using the instrumental variable approach. Standard errors are clustered at the firm level and presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels (two-tailed), respectively. The definitions of all variables are provided in Appendix A.

## 5. Mechanism analysis

### 5.1. Market signal

Scientific disclosure can become a credible signal about its innovation capacity, product quality, scientific discovery, and tacit knowledge and will send a direct signal to the capital market, indicating that a firm has strong enough technical capabilities, has made important scientific discoveries, or underdeveloped new products (Almeida et al., 2011; Arora et al., 2018). For small and micro firms or start-ups, publishing scientific papers can attract more attention from potential investors (Belenzon and Patacconi, 2014). Scientific disclosure also matters in obtaining external grants, subsidies, or contracts (Simeth and Cincera, 2016). We measure market signal effects using two variables: Ln(1 + *News_focus*) and Ln(1 + *Gov_subsidy*), representing the number of news reports and government R&D subsidies received by the firm. After controlling for scientific disclosure, both variables exhibit a significant positive relationship with innovation outcomes (5.1% and 3.1%, respectively) according to Panel A of Table 7, confirming hypothesis H2.

### 5.2. Standards strategy

We postulate that firms with a robust publishing record are more likely to be chosen by the government as one of the drafting units for standards. We employ two variables: Ln(1 + *Stand_gov*) and Ln(1 + *Stand_ind*), which represent the natural logarithm of one plus the number of national and industry standards, respectively. The collection process of national and industrial standards drafted by a firm and its' subsidiaries is shown in Online Appendix C. The outcomes demonstrated in Panel B of Table 7 indicate that a firm's scientific disclosure has a significant impact on standards, which, in turn, influences innovation. These results provide robust evidence that scientific disclosure contributes to a firm's innovation output through its participation in national and industry standards, supporting our hypothesis H3.

**Table 6**
The regression results using PSM procedure.

| Panel A: the dependent variable is Ln(1 + *Patent_total*). | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | One-to-one matching | Neighbors matching | Radius (1:4) matching | Radius matching | Kernel matching | Local linear regression | Spline matching | Mahalanobis matching |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ATT | 0.230*** | 0.277*** | 0.276*** | 0.274*** | 0.275*** | 0.284*** | 0.276*** | 0.286*** |
| | (0.047) | (0.039) | (0.045) | (0.035) | (0.033) | (0.035) | (0.036) | (0.027) |
| ATU | 0.124*** | 0.128*** | 0.128*** | 0.108*** | 0.116*** | 0.102*** | 0.111*** | 0.246*** |
| | (0.031) | (0.027) | (0.028) | (0.023) | (0.020) | (0.022) | (0.024) | (0.024) |
| ATE | 0.176*** | 0.202*** | 0.201*** | 0.190*** | 0.195*** | 0.192*** | 0.193*** | 0.266*** |
| | (0.029) | (0.023) | (0.029) | (0.026) | (0.023) | (0.022) | (0.025) | (0.022) |
| Panel B: the dependent variable is Ln(1 + *Patent_citation*) | | | | | | | | |
| | One-to-one matching | Neighbors matching | Radius (1:4) matching | Radius matching | Kernel matching | Local linear regression | Spline matching | Mahalanobis matching |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ATT | 0.286*** | 0.356*** | 0.356*** | 0.346*** | 0.347*** | 0.355*** | 0.345*** | 0.400*** |
| | (0.056) | (0.045) | (0.047) | (0.039) | (0.036) | (0.038) | (0.042) | (0.029) |
| ATU | 0.225*** | 0.221*** | 0.221*** | 0.193*** | 0.203*** | 0.186*** | 0.196*** | 0.336*** |
| | (0.037) | (0.031) | (0.038) | (0.024) | (0.025) | (0.024) | (0.031) | (0.029) |
| ATE | 0.255*** | 0.288*** | 0.287*** | 0.268*** | 0.274*** | 0.269*** | 0.270*** | 0.368*** |
| | (0.036) | (0.029) | (0.036) | (0.026) | (0.027) | (0.024) | (0.031) | (0.025) |

### 5.3. Human capital

By matching a firm's inventors and scientists with its managers, we can identify executives with inventor or scientist backgrounds. Subsequently, we compute the number of managers possessing inventor experience (*Inventor_executive*) and academic experience (*Academic_executive*) to represent the impact of human capital. Our results demonstrate that academic publication records can enhance human capital, providing support for the last hypothesis, H4, in our study (Panel C of Table 7).

## 6. Further analysis

### 6.1. Adjusting corporate publications based on journal impact factor

We substitute the key testing variable, Ln(1 + *Publish*), with five distinct variables. Specifically, Ln(1 + *Publish*50*p*) refers to the quantity of scholarly articles published by a company in journals with an impact factor exceeding the median value within the same discipline. Similarly, Ln(1 + *Publish*60*p*), Ln(1 + *Publish*70*p*), Ln(1 + *Publish*80*p*), and Ln(1 + *Publish*90*p*) represent the number of academic publications by a firm in journals with impact factors surpassing the 60th, 70th, 80th, and 90th percentiles, respectively. Regression results reveal that the coefficients of all the newly defined covariates are statistically positive (Table 8). Demonstrating that firms with publications in top-tier journals experience a statistically significant enhancement in their innovation capabilities.

### 6.2. Heterogeneity analysis

Sectors such as ICT, pharmaceutical manufacturing, and chemical industries place a greater emphasis on delving into new scientific knowledge, closely monitoring the progress of science's boundaries, actively participating in academic conferences, and publishing articles in top-tier academic journals. Following Hsu et al. (2021), we categorized the sample firms into two sub-groups, based on their industry's knowledge density. Knowledge density refers to the number of academic publications per 1000 R&D employees. Firms with a knowledge density above (below) the industry average are categorized as high (low) knowledge density firms. We found that the beneficial impact of corporate publications on innovation is stronger among firms with high knowledge density.

Additionally, firms with independent central research institutes tend to exhibit better innovation performance compared to those without. State-owned enterprises tend to benefit more from the impact of corporate publications on innovation compared to Non SOEs. More details on the results of the heterogeneity test are provided in Online Appendix E due to article length limitations.

## 7. Conclusions

This study explores the influence of scientific disclosure on innovation using a data of corporate scientific publications. The results show that scientific disclosure has a positive effect on innovation, especially for firms with more influential publications, higher density of science and R&D, or SOEs/independent central research institutes. The study suggests that scientific disclosure sends credible market signals, supports preemptive technical standards, and attracts innovative talent. The shortcomings of this study lie in the in-

**Table 7**
Mechanism analysis.

Panel A: Market signal effect

| Variables | $Ln(1+News\_focus)$ | $Ln(1+Pat\_total)$ | $Ln(1+Gov\_subsidy)$ | $Ln(1+Pat\_total)$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Ln(1+Publish)$ | 0.118*** | 0.123*** | 0.174*** | 0.130*** |
| | (0.010) | (0.014) | (0.022) | (0.014) |
| $Ln(1+News\_focus)$ | | 0.099*** | | |
| | | (0.011) | | |
| $Ln(1+Gov\_subsidy)$ | | | | 0.020*** |
| | | | | (0.005) |
| Observations | 16,976 | 16,976 | 16,976 | 16,976 |
| Adjusted R2 | 0.424 | 0.297 | 0.279 | 0.294 |
| Proportion of mediate | 0.051 | | 0.031 | |
| Sobel-Goodman tests | 0.000 | | 0.000 | |

Panel B: Standards strategy

| Variables | $Ln(1+Stand\_gov)$ | $Ln(1+Pat\_total)$ | $Ln(1+Stand\_ind)$ | $Ln(1+Pat\_total)$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Ln(1+Publish)$ | 0.080*** | 0.099*** | 0.078*** | 0.102*** |
| | (0.006) | (0.014) | (0.006) | (0.014) |
| $Ln(1+Stand\_gov)$ | | 0.463*** | | |
| | | (0.027) | | |
| $Ln(1+Stand\_ind)$ | | | | 0.455*** |
| | | | | (0.025) |
| Observations | 16,976 | 16,976 | 16,976 | 16,976 |
| Adjusted R2 | 0.182 | 0.310 | 0.156 | 0.313 |
| Proportion of mediate | 0.328 | | 0.321 | |
| Sobel-Goodman tests | 0.000 | | 0.000 | |

Panel C: Human capital

| | $Inventor\_executive$ | $Ln(1+Pat\_total)$ | $Academic\_executive$ | $Ln(1+Pat\_total)$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Ln(1+Publish)$ | 0.111*** | 0.103*** | 0.189*** | 0.125*** |
| | (0.016) | (0.013) | (0.014) | (0.015) |
| $Inventor\_executive$ | | 0.282*** | | |
| | | (0.007) | | |
| $Academic\_executive$ | | | | 0.044*** |
| | | | | (0.011) |
| Observations | 16,976 | 16,976 | 16,976 | 16,976 |
| Adjusted R2 | 0.165 | 0.373 | 0.118 | 0.294 |
| Proportion of mediate | 0.257 | | 0.038 | |
| Sobel-Goodman tests | 0.000 | | 0.000 | |

This table reports the mechanism analysis results of the effects of scientific disclosure on innovation through market signal, and standards strategy. Standard errors in the brackets are adjusted for clustering at the firm level. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Appendix A provides definitions for all variables.

ability to obtain direct citation relationships between corporate patents and papers. Future research directions include further exploring the interactive relationship between corporate scientific disclosure and innovative behavior; analyzing the relation at the level of patents and papers and examining the motivations for corporate scientific disclosure.

The conclusions drawn from this study are beneficial to firms and governments to promote innovation capacity and scientific development. Private firms could focus on their long-term goals and balance the relationship between basic scientific research, applied technology research and product innovation. The government could provide a high-quality intellectual property protection environment, encourage enterprises to recruit doctors and post-doctoral researchers to carry out cutting-edge scientific research, as well as support the establishment of key laboratories and R&D centers by enterprises.

## Ethical approval

The manuscript was not submitted to multiple journals for consideration at the same time.
The submitted work is original and has not been published elsewhere in any form or language (in part or in whole).

**Table 8**
Scientific disclosure in journals of different levels and innovation.

| Variables | $Ln(1+Pat\_total)$ | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $Ln(1+Publish50p)$ | 0.135***<br>(0.016) | | | | |
| $Ln(1+Publish60p)$ | | 0.149***<br>(0.018) | | | |
| $Ln(1+Publish70p)$ | | | 0.153***<br>(0.019) | | |
| $Ln(1+Publish80p)$ | | | | 0.152***<br>(0.023) | |
| $Ln(1+Publish90p)$ | | | | | 0.159***<br>(0.028) |
| Controls | YES | YES | YES | YES | YES |
| Year fixed effect | YES | YES | YES | YES | YES |
| Firm fixed effect | YES | YES | YES | YES | YES |
| Observations | 16,976 | 16,976 | 16,976 | 16,976 | 16,976 |
| Adjusted R2 | 0.292 | 0.293 | 0.292 | 0.291 | 0.291 |

This table reports the results of the effects of scientific disclosure in journals of different levels on innovation. Bracketed standard errors are adjusted for clustering at the firm level. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% level (two-tailed), respectively. The definitions of all variables can be found in Appendix A.



### Consent to participate

Not applicable.

### Consent to publish

Not applicable.

### Uncited references

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### 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.

### Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2023.104147.

### References

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N., Kerr, W., 2018. Innovation, reallocation, and growth. Am. Econ. Rev. 108 (11), 3450–3491.
Akcigit, U., Hanley, D., Serrano-Velarde, N., 2021. Back to basics: basic research spillovers, innovation policy, and growth. Rev. Econ. Stud. 88 (1), 1–43.
Almeida, P., Hohberger, J., Parada, P., 2011. Individual scientific collaborations and firm-level innovation. Ind. Corp. Change 20 (6), 1571–1599.
Arora, A., Belenzon, S., Patacconi, A., 2018. The decline of science in corporate R&D. Strat. Manag. J. 39 (1), 3–32.
Arora, A., Belenzon, S., Sheer, L., 2021. Knowledge spillovers and corporate investment in scientific research. Am. Econ. Rev. 111 (3), 871–898.
Audretsch, D.B., Belitski, M., 2020. The role of R&D and knowledge spillovers in innovation and productivity. Eur. Econ. Rev. 123 (C), 103391.
Belenzon, S., Patacconi, A., 2014. How does firm size moderate firms' ability to benefit from invention? Evidence from patents and scientific publications. Eur. Manag. Rev. 11 (1), 21–45.
Bhaskarabhatla, A., Hegde, D., 2014. An organizational perspective on patenting and open innovation. Org. Sci. 25 (6), 1744–1763.
Blind, K., Krieger, B., Pellens, M., 2022. The interplay between product innovation, publishing, patenting and developing standards. Res. Policy 51 (7), 104556.
Fang, J., He, H., Li, N., 2020. China's rising IQ (Innovation Quotient) and growth: firm-level evidence. J. Dev. Econ. 147 (C), 102561.
Friesike, S., Widenmayer, B., Gassmann, O., Schildhauer, T., 2015. Opening science: towards an agenda of open science in academia and industry. J. Technol. Transf. 40 (4), 581–601.
Gao, H., Hsu, P., Li, K., Zhang, J., 2020. The real effect of smoking bans: evidence from corporate innovation. J. Financ. Quant. Anal. 55 (2), 387–427.
Hall, B.H., Rosenberg, N., 2010. Handbook of the Economics of Innovation. Elsevier Press.
Hall, B.H., Jaffe, A., Trajtenberg, M., 2005. Market value and patent citations. Rand J. Econ. 36 (1), 16–38.
Hsu, D.H., Kuhn, J.M., 2022. Academic stars and licensing experience in university technology commercialization. Strat. Manag. J. 44 (3), 887–905.
Hsu, D.H., Hsu, P.H., Zhao, Q., 2021. Rich on paper? Chinese firms' academic publications, patents, and market value. Res. Policy 50 (9), 104319.
Huang, K.G.L., Geng, X., Wang, H., 2017. Institutional regime shift in intellectual property rights and innovation strategies of firms in China. Org. Sci. 28 (2), 355–377.
Islam, E., Zein, J., 2020. Inventor CEOs. J. Financ. Econ. 135 (2), 505–527.
Lück, S., Balsmeier, B., Seliger, F., Fleming, L., 2020. Early disclosure of invention and reduced duplication: an empirical test. Manag. Sci. 66 (6), 2677–2685.

Martínez, C., Parlane, S., 2023. Academic scientists in corporate R&D: a theoretical model. Res. Policy 52 (5), 104744.
Marx, M., Hsu, D.H., 2022. Revisiting the entrepreneurial commercialization of academic science: evidence from "Twin" discoveries. Manag. Sci. 68 (2), 1330–1352.
Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70 (1), 41–55.
Rotolo, D., Camerani, R., Grassano, N., Martin, B.R., 2022. Why do firms publish? A systematic literature review and a conceptual framework. Res. Policy 51 (10), 104606.
Simeth, M., Cincera, M., 2016. Corporate science, innovation, and firm value. Manag. Sci. 62 (7), 1970–1981.
Smith, K.T., Smith, M., Wang, K., 2010. Does brand management of corporate reputation translate into higher market value? J. Strat. Mark. 18 (3), 201–221.
Stephan, P., 2012. How Economics Shapes Science. Harvard University Press, MA.
Zhang, M., Wang, Y., Zhao, Q., 2020. Does participating in the standards-setting process promote innovation? Evidence from China. China Econ. Rev. 63 (C), 101532.
Zhao, Q., Luo, Q., Zhao, X., Yu, Y., 2023. Corporate key labs: breakthrough or white elephant? China Econ. Rev. 79, 101954.