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Corporate key labs: Breakthrough or white elephant?

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ABSTRACT

Based on manually collected data from Chinese listed firms' key laboratories at the state and provincial levels, this study shows that key laboratories improve firms' innovation output. Corporations with key laboratories at the state or provincial level produce more patents and citations than their counterparts. A series of endogenous treatment effects, including the Heckman two-step sample selection model, instrumental variable estimation, policy shock analysis, and propensity score matching, indicate that this study's main conclusion is robust and consistent. We also observe that key laboratories' beneficial impact on innovation output becomes more prominent for firms belonging to high-tech industries, those led by an inventor or scientist CEO, and those located in cities that enforce the protection of intellectual property. Further, key laboratories foster innovation mainly by developing scientific research capacity, increasing human capital, and improving R&D subsidies. Our findings demonstrate that key laboratories can benefit firms, their stakeholders, and the public in an emerging market such as China.

1. Introduction

Science and technology have long been recognized as crucial drivers of firms' growth and their ability to compete in the technology sector (Solow, 1957). Due to the importance and popularity of the topic of innovation in the scientific community, numerous theoretical and empirical studies have been conducted on the subject (Hall & Rosenberg, 2010; He & Tian, 2018, 2020). These studies have conducted heterogeneous examinations; some examined the influence of micro-level variables on innovation, such as managerial R&D experience (Li, Mbanyele, & Sun, 2022), CEOs' general managerial skills (Custódio, Ferreira, & Matos, 2019), top management team ability (Chemmanur, Kong, Krishnan, & Yu, 2019), managerial overconfidence (Heavey, Simsek, Fox, & Hersel, 2022), corporate governance (Keum, 2021), and corporate culture (Li, Mai, Shen, & Yan, 2021). Other studies have examined the drivers of innovation at the market level, such as competition in the product market (Gu, 2016), banking competition (Berger, Molyneux, & Wilson, 2020), intellectual property (IP) protection (Fang, Lerner, & Wu, 2017), analyst coverage (Guo, Pérez-Castrillo, & Toldrà-Simats, 2019), corporate taxes (Mukherjee, Singh, & Žaldokas, 2017), institutional investors (Brav, Jiang, Ma, & Tian, 2018), and credit supply (Cerqueiro, Hegde, Penas, & Seamans, 2017). Some have examined countries' institutional features that can spur innovation, including laws and regulations (Lin, Liu, & Manso, 2021), local culture (Boubakri, Chkir, Saadi, & Zhu, 2021), financial development at the national level (Moshirian, Tian, Zhang, & Zhang, 2021), national policy uncertainty (Bhattacharya, Hsu, Tian, & Xu, 2017), and religion (Bénabou, Ticchi, & Vindigni, 2015). However, few scholars have systematically explored whether and how corporate key

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laboratories, defined as private-sector- and government-funded research facilities with the goal of developing new fundamental knowledge (Arora, Belenzon, & Patacconi, 2018), spur innovation output.

Although basic scientific research has been the cornerstone of technological advancement in contemporary society (Rotolo, Camerani, Grassano, & Martin, 2022), it often comes with high costs and low returns. Additionally, asset specificity remains a prominent concern in private-sector investment decision-making (Bryan & Williams, 2021). Key laboratories' main outputs are characterized as public goods, which means that competitors can obtain the newly developed knowledge free of charge. Consequently, firms cannot obtain all the benefits of their scientific research. Furthermore, a firm conducting scientific research contradicts corporations' general goal, that is, to maximize profits. There is also the problem of agency. Private firms encourage their researchers to engage in basic scientific research, reduce their technological innovation and commercialization efforts, and participate more in academic activities outside the firm (Simeth & Cincera, 2016).

To encourage firms to participate in basic scientific research activities, become the main driving force of innovation, increase investment in R&D, and establish laboratories, the Chinese government issued the "National Medium- and Long-Term Science and Technology Development Plan Outline" in 2005. The Plan put forward specific requirements for companies to construct scientific research laboratories. Corporate key laboratories at the state and provincial levels are crucial for China's innovation system. These laboratories are essential for basic scientific research on industrial applications, the gathering of talents, and the conduction of scientific and technological exchanges. Furthermore, their main task is to carry out innovative technology research for the national industry, as well as joint basic technology research, promote the transformation and industrialization of primary scientific research outcomes, and participate in research while clarifying the definition of international, national, and industrial standards. Accordingly, the national government has issued a set of policies in taxation, subsidies, finance, government procurement, and IP transactions to promote the development of these key laboratories.

Our findings can be summarized as follows. By analyzing manually collected datasets of Chinese listed firms with corporate key laboratories at the state or provincial levels from 2013 to 2018, we found that firms with key laboratories generate more patents and forward citations. Moreover, corporate key laboratories tend to adopt explanatory and original innovation strategies. These key laboratories' effects are more significant among high-tech firms, those with an inventor or scientist CEO, and those located in cities with better IP protection environments. Additionally, these laboratories facilitate innovation mainly through three channels: promoting scientific research, increasing human capital, and R&D subsidies.

This study fills the following three gaps in the literature. First, this is the first study, to our knowledge, to examine whether, how, and to what extent corporate key laboratories affect innovation performance (measured as firms' number of patents and citations). Our empirical analysis is based on data from Chinese publicly traded companies. China has been criticized in the international community for its technological shortcomings, specifically in basic scientific research. Further, national funding for fundamental research is primarily directed toward the public sector, including government-owned laboratories and universities. These public companies, in turn, produce a number of academic articles with which private firms can hardly compete. Consequently, the existing basic scientific research conducted in China stems mainly from governmental, university, and publicly-funded research institutions. Despite this concentration in specific institutions, few studies have examined corporate key laboratories' effects on innovation output at the state and provincial levels, and even fewer have explored the nexus between corporate key laboratories and innovation performance.

Second, endogeneity issues may emerge when investigating corporate key laboratories' role in boosting innovation due to the presence of omitted variables, reverse causality, or sample selection bias. Accordingly, this is one of the few studies studying corporate key laboratories' impact on creativity, using various identification methodologies. Specifically, this study controls for industry and year fixed effects, as well as the interactive fixed effects between industry and year; applies first difference analysis by converting all attributes in our baseline model to their first differences based on which enterprises' cross-sectional variance are eliminated; uses two instrumental variables (IVs) based on the number of academicians whose hometown is the location of corporate headquarters and laboratory establishments operated by other firms from the same industry and city during a given year; utilizes a central government policy aimed to promote the development of corporate key laboratories as an exogenous policy shock; and adopts a propensity score matching (PSM) procedure.

Third, we have constructed proxy variables using manually collected data that have been overlooked in previous studies. These variables include lists of state and provincial key laboratories at the company level over the years; data on the company's scientific paper publications over time, and indicators of the company's innovation strategy. Currently, there is no literature that explores the economic effects of state and provincial key laboratories at the company level in China. Compared with existing studies on Chinese firms' innovation, the database we apply covers both forward-citation and backward-citation information of granted patents of Chinese listed firms, which helps us to better construct corporate innovation quality and innovation strategy metrics. Additionally, the publication of scientific papers by Chinese companies, which is an important reflection of their scientific research achievements has not received adequate attention. This study not only investigates the impact of key laboratories on the quantity and quality of patents but also delves further into their influence on corporate innovation strategies, which is a significant advancement in existing research.

This study is structured as follows: Section 2 examines the related literature and formulates the hypotheses. Section 3 discusses the sampling design, data, and methodology. Section 4 reports the empirical results. Section 5 addresses endogeneity concerns. Section 6 shows the outcome of cross-sectional heterogeneity analysis, robustness checks, mechanism analysis, and tests of potential competitive explanations. Finally, Section 7 concludes this paper.

2. Literature review and hypothesis formulation

2.1. Institutional background of corporate scientific research in China

The institutional background of the research activities of Chinese firms' key laboratories is unique. China's scientific and technological innovation system stems from a planned economic system; specifically, the former Soviet Union (characterized by the relative autonomy of its scientific research and production sectors) had a profound influence on China's innovation system. China has gradually formed an innovation framework dominated by the Chinese Academy of Sciences, universities, research institutions of the central ministries and commissions, local scientific research institutions, and national defense science, technology, and industry departments (Fu, 2015). Before the science and technology system reform in 1985, the following research institutes existed in China: 122 research institutes affiliated with the Chinese Academy of Sciences—mostly conducting scientific and applied studies; 622 national research institutes affiliated with different ministries and commissions—mostly engaged in industrial R&D activities; and 3946 provincial research institutes, which delivered local R&D, engineering design, and technology transfer services (Li, Wu, Chen, & Tao, 2015).

The "National Medium- and Long-Term Science and Technology Development Plan Outline" issued in 2005 describes the requirements for firms to construct their scientific research bases. Through the Plan, the government aimed to encourage private firms to become the main force of the country's innovation and establish R&D institutions. Meanwhile, the "Notice on Implementing Several Supporting Policies for the Outline of the National Medium- and Long-Term Program for Scientific and Technological Development" points out that the construction of firms' independent research bases should be strengthened. Subsequently, the document titled "Guiding Opinions on Relying on Transformed Institutions and Enterprises to Build State Key Laboratories" clarified the tasks, goals, principles, responsibilities, procedures, and application conditions, among other topics. Therefore, the Chinese government has formulated various supporting policies in the fields of taxation, finance, government procurement, and major technology planning to promote independent innovation in the private sector. Furthermore, the Ministry of Science and Technology prioritizes corporate key laboratories when addressing various national science and technology projects, aiming to support these laboratories' construction, operation, and scientific research.

In order to promote the construction of a national innovation system and support companies to carry out basic research, the Ministry of Science and Technology of the People's Republic of China issued the "Interim Measures for the Management of State Key Laboratories Relying on Firms" in 2012.[1] According to the policy of the Ministry of Science and Technology, various provinces have also introduced corresponding policies to support companies to build provincial key laboratories. Consequently, corporate key laboratories play an important part in the national innovation system and complement university laboratories. Corporate key laboratories' main tasks are to conduct basic and frontier technology research; participate in the development of international, national, and industry standards; cultivate talents; and promote industries' technological progress.

The science and technology administrative departments comprise corporate key laboratories' administrative departments. Their main responsibilities include formulating management regulations; formulating guidelines and policies; implementing the overall development plan; approving projects' establishment, development, adjustment, and cancellation; organizing evaluation and inspection; and supporting construction, operation funds, and policies. Companies are responsible for corporate key laboratories' construction and operation; specifically, their main responsibilities include planning the construction of key laboratories and providing personnel, funding, and facilities; recruiting laboratory directors, academic committee directors, and members; and conducting annual assessments of corporate key laboratories.[2]

2.2. Corporate key laboratories and innovation

Private firms' potential motivations to engage in basic scientific research have been divided into four main types. First, basic scientific research in a private firm's laboratory can improve internal R&D and innovation ability (Arora et al., 2018). Further, corporate key laboratories help private firms attract and retain high-quality scientists and engineers, especially "star scientists," because some scientists prefer having a good academic reputation and chances to conduct research rather than greater monetary compensation (Blind, Filipović, & Lazina, 2022). Such laboratories also encourage corporate researchers to participate actively in academic conferences and maintain close contacts with external academic circles (Rotolo et al., 2022). Thus, firms' development of corporate key laboratories can help them learn and absorb new knowledge, as well as to keep up with innovation in research (Martínez & Parlane, 2023; Simeth & Cincera, 2016). Second, corporate key laboratories can improve firms' academic and public reputation and networks, as well as their cooperation with external research institutions (e.g., universities; Hvide & Jones, 2018). Third, firms' scientific research capacity can help enhance the application and commercialization of new technologies and improve productivity (Arora et al., 2018). Finally, corporate key laboratories can serve as a strategic form of disclosure, promoting the diffusion of new technologies and allowing firms to capture a "first-mover" advantage (Chesbrough, 2006).

As described, corporate key laboratories can improve companies' internal R&D and innovation ability. Specifically, corporate innovation may be directly reliant on the scientific progress and discoveries promoted by its key laboratory. Scientific research improves technological productivity by guiding technology toward a more valuable "blue ocean" strategy (Arora et al., 2018). Further,

[1] https://www.most.gov.cn/xxgk/xinxifenlei/fdzdgknr/fgzc/gfxwj/gfxwj2012/201211/t20121119_97996.html.

[2] We provide details of a corporate laboratory in Online Appendix 2. The State Key Laboratory of Heavy Duty AC Drive Electric Locomotive Systems Integration, CRRC Zhuzhou Locomotive Co., Ltd.

firm scientists can collaborate with external scholars interested in new inventions and enable the company to adapt to external technologies. Additionally, the publishing of journal articles and academic conferences may be the most effective way for a company to remain engaged in external scientific networks (Rosenberg, 2009). Ahmadpoor and Jones (2017) also find that corporate publishing can promote basic cognition and application. These laboratories can further enhance the application and commercialization of new technologies and improve productivity. Therefore, we hypothesize that:

Hypothesis 1a. Corporate key laboratories positively affect innovation output.

However, there are two possible reasons for corporate key laboratories to not be conducive to innovation output. The first reason is the crowding effect of increasing salaries and equipment costs. Unlike applied research, scientific research in corporate key laboratories is more reliant on its scientists, with corporate scientists' salaries often contributing to a large portion of firms' scientific research budget. Further, most of these scientists are Ph.D. holders, requiring a relatively higher salary (Stephan, 2015).

Corporate key laboratories' equipment costs are high and increase quickly. Consequently, if a firm invests more resources in laboratory research activities, it may invest less in applied research activities (e.g., patenting). Further, individual scientists' time and attention to conducting experiments, writing articles, and applying for patents are limited. This implies that firms' incentives guide these employees' efforts. Then, considering that firm incentives are aimed at laboratory scientific research, the related researchers tend to invest more time and effort toward doing experiments and publishing papers rather than on innovation and patent-related activities. Examining IBM, Bhaskarabhatla and Hegde (2014) found that scientists care about changes in the reward system regarding their innovation outputs. Specifically, IBM implemented a policy allowing scientists to obtain 25%–50% of the benefits from patenting, leading to a significant increase in inventing and a considerable decrease in publishing.

The second reason is that corporate key laboratory research may not be conducive to innovation because inventive projects are less valued in corporate science. Discussions about the association between innovation and science have demonstrated that this association is becoming weaker. For example, Arora et al. (2018) described that many types of innovation promoted by corporate science relate to novel business methods or designs, not to scientific progress. Some examples include code scanning payment, bike-sharing, and online shopping, which do not build on scientific advances directly; instead, these comprise business model innovations aimed at increasing payment, transportation, and trading efficiency, respectively. This leads to the following hypothesis:

Hypothesis 1b. Corporate key laboratories negatively affect innovation output.

2.3. Mechanisms: Corporate science, human capital, and R&D subsidies

As described, corporate key laboratories have become an essential part of China's innovation system. Specifically, these laboratories have become indispensable for conducting basic scientific research on industrial applications, gathering and cultivating outstanding talents, and conducting scientific and technological exchanges. The main objectives of Chinese corporate key laboratories are conducting frontier and joint basic technology research applicable to industry; promoting the transformation and industrialization of primary research outcomes; and participating in the research and formulation of international, national, and industrial technical standards.

Further, corporate science has been an essential driving force of innovation in China. Most innovative basic theoretical knowledge is concentrated in public, academic departments (e.g., universities and research institutes) that distribute this knowledge widely. By conducting basic scientific research and publishing new findings in academic journals, a firm can obtain knowledge on the latest technological advancements, which in turn serves as a supplement to its R&D activities (Simeth & Cincera, 2016; Tijssen, 2009). In addition, corporate researchers can obtain key learning opportunities (Blind, Krieger, & Pellens, 2022), which help them sustain their mastery over cutting-edge knowledge and technology, identify emerging technologies, and find opportunities for commercializing research findings (Friesike, Widenmayer, Gassmann, & Schildhauer, 2015). Scientific research in corporate key laboratories also encourages researchers to participate actively in academic conferences and maintain close contacts with external academic circles. Indeed, research shows that these academic exchanges and interactions enable companies to discover, absorb, and utilize novel external information, thereby increasing efficiency and productivity (Arora et al., 2018; Simeth & Cincera, 2016).

In China, a firm's basic scientific research capacity is measured by its publishing records; this measure has been an essential driving force of standard-setting activities at the national and industrial level. Further, since only the government and a limited number of firms dominate the national standardization system, participating in the standard-setting process assists firms in developing a strong reputation nationally and attracting innovation partners. Research shows that "standard-setter" companies frequently incorporate technical requirements or patents that serve their own interests. On the one hand, more competitive organizations will strive to produce standards in order to capitalize on their advantage (Zhang, Wang, & Zhao, 2020). On the other hand, less competitive firms will frequently strive to utilize standards incompatible with those of their competitors. Furthermore, firms facing increased competition frequently collaborate on innovation projects with firms involved in standard-setting processes. Thus, participation in standard-setting activities can assist partakers in attracting high-quality innovative partners. This collaborative effort between organizations promotes the exchange of information, encourages organizational learning, and facilitates the sharing of ideas, all of which are essential for fostering innovation (Blind, Filipović, & Lazina, 2022). This leads to the following hypothesis:

Hypothesis 2. Corporate key laboratories promote innovation by stimulating corporate science.

As mentioned earlier, corporate key laboratories improve companies' human capital by attracting "star scientists" (Arora et al., 2018). Indeed, high-quality scientists bring new knowledge and capabilities, providing new incentives for corporate innovation and opportunities to embed professional and scientific networks. Firms can then use these scientific networks to contact other research groups. Moreover, encouraging article publishing can bolster a firm's reputation in the talent market, as job seekers are likely to perceive such companies as valuing scientific research talent, particularly if they employ "star scientists" who attract high-quality scientists seeking to collaborate with them (Hsu & Kuhn, 2022).

Scientists tend to choose firms with key laboratories based on considerations regarding career development. Further, conducting laboratory scientific research often brings satisfaction to scientists, meets their academic career expectations, and helps them find more career opportunities. It can also help them maintain close contact with academic circles and obtain academic reputation. On this topic, research shows that scientists who do not publish scientific papers soon "disappear" from academic circles (Fini, Lacetera, & Shane, 2010). Since scientists often have high self-motivation and do not need high material incentives, firms with key laboratories can obtain talents more easily, at least to a certain extent. Thus, we hypothesize:

Hypothesis 3. Corporate key laboratories can promote innovation by increasing human capital.

As innovation projects are often accompanied by relatively high uncertainty and failure risk, many innovative firms have insufficient funding for R&D projects, which is not conducive to corporate innovation (Manso, 2011; Nanda & Rhodes-Kropf, 2017). R&D subsidies from the government play an important role in corporate innovation projects (Howell, 2017). On one hand, key laboratories offer firms the opportunity to receive financial subsidies and funding directly from the government for their scientific research projects (Song, Sahut, Zhang, Tian, & Hikkerova, 2022). For example, the document "Guangdong Provincial Department of Science and Technology on the Management of the Construction and Operation of Provincial Enterprise Key Laboratories" stipulates that the ratio of new supporting funds to provincial financial funds for corporate key laboratories at the provincial level should be no lower than 2:1. Moreover, the competent municipal department should provide additional funds to these laboratories at a ratio not lower than 1:1.[3] In addition, according to the Annual Report of Hebei Key Laboratory 2020, the company's own investment accounts for 66.27% of the funding source of the key laboratory, whereas government investment accounts for 23.47%, of which the central government's input accounts for 11.8%, and that of the provincial government accounts for 10.49%.[4]

On the other hand, corporate key laboratories can improve academic reputation and provide credibility to companies' innovation capacity, product quality, scientific discovery, and tacit knowledge (Arora et al., 2018). For small and micro firms or startups, the establishment of corporate key laboratories attracts potential investors (Belenzon & Patacconi, 2014). Corporate scientific publishing is also important for obtaining external grants, subsidies, or contracts (Simeth & Cincera, 2016). Moreover, a favorable image in the academic field benefits firms' profitability and valuation, helps sustain an ideal investment climate, and lowers the cost of capital (Smith, Smith, & Wang, 2010). Subsequently, a lower cost of capital enables companies to boost their R&D investment. Thus, we hypothesize the following:

Hypothesis 4. Corporate key laboratories can promote innovation by attracting R&D subsidies for innovation projects.

3. Research design

3.1. Data sources

This study focuses on Chinese companies listed on the Shanghai and Shenzhen stock exchanges from 2013 to 2018. On average, there exists a two-year delay between the application date and the grant date of patents filed by inventors (Chang, Fu, Low, & Zhang, 2015). As the most recent year represented in the patent database is 2021, patents applied for in 2019 and 2020 may not be comprehensively reflected in the database, as it only encompasses granted patents. To mitigate this limitation, we follow the suggestion of Chang et al. (2015) and conclude our sample period in 2018. Financial listed firms are not included in our sample, as their financial statements and structures differ from those of other firms. In addition, we exclude specific handling firms (i.e., ST, *ST, and PT) and samples with null data for the major variables used in the regression analyses. After excluding companies based on these exclusion criteria, the final sample consists of 12,024 firm-year observations.

The primary test variable is corporate key laboratory, which is defined as a firm with at least one key laboratory at the state or provincial level in a fiscal year. We manually collect data on corporate key laboratories at both levels from different sources, including the annual reports of listed firms from the official websites of the Shanghai Stock Exchange,[5] the Shenzhen Stock Exchange,[6] the Ministry of Science and Technology of the People's Republic of China,[7] provincial departments of science and technology (e.g., Jiangsu Provincial Department of Science and Technology),[8] and listed firms' official websites (e.g., Shanghai Pharmaceuticals Holding Co., Ltd.; State Key Laboratory of Innovative Drugs and Pharmaceutical Technology).[9]

Listed firms' innovation output is our dependent variable. We obtain the applied patent data from the China National Intellectual

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3 http://www.gd.gov.cn/zwgk/lsgb/content/post_152983.html.
4 https://cxpt.hebkjt.cn:4430/archive/ndbg/2020-laboratory.pdf.
5 http://www.sse.com.cn/
6 http://www.szse.cn/
7 http://www.most.gov.cn/index.html
8 http://std.jiangsu.gov.cn/
9 http://www.sasac.gov.cn/n2588025/n2588124/c4115822/content.html

Property Administration.[10] To evaluate the quality of a firm's innovation performance, we match each patent with the data in the Innojoy Global Patent Database,[11] Google Patents,[12] and WinGo Database,[13] which include complete information on patents and citations.

We obtain data of other corporate finance and governance indicators mainly from the China Stock Market & Accounting Research,[14] the Chinese Research Data Services Platform,[15] SINOFIN CCER Database,[16] RESSET Database,[17] CnOpenData Database,[18] WIND Database,[19] and Baidu search.[20] The variables' detailed definitions are shown in Appendix A. All records are cross-checked for accuracy.

3.2. Models

Using the empirical model established in past research (Chang et al., 2015; Gao, Hsu, Li, & Zhang, 2020; Moshirian et al., 2021), in order to ascertain the effect of a corporate key laboratory on innovation output, the baseline regression model applied is as follows:

$$\begin{aligned} \mathrm{Ln}\left(1+Innovation_{i,t}\right) = {} & \alpha_0+\alpha_1 Laboratory\_dummy_{i,t}+\alpha_2 RD_{i,t}+\alpha_3 Size_{i,t}+\alpha_4 Firmage_{i,t}+\alpha_5 PPE_{i,t} \\ & +\alpha_6 Sales_{i,t}+\alpha_7 ROA_{i,t}+\alpha_8 MB_{i,t}+\alpha_9 Salesgrowth_{i,t}+\alpha_{10} Lev_{i,t}+\alpha_{11} Cashratio_{i,t} \\ & +\alpha_{12} Stockvolatility_{i,t}+\alpha_{13} Stockreturn_{i,t}+\alpha_{14} SOE_{i,t}+\alpha_{15} Institute_{i,t}+Industry \\ & +Year+Industry\times Year+\varepsilon_{i,t} \end{aligned} \tag{1}$$

where the dependent variable $Innovation_{i,t}$ is a proxy for the quantity and quality of the innovation output produced by company i during year t. The core test variable is $Laboratory\_dummy_{i,t}$, which refers to the dummy variable of the corporate key laboratory at the state or provincial level. We also introduce various control variables in the model, including *R&D*, *Size*, *Firmage*, *PPE*, *Sales*, *ROA*, *MB*, *Salesgrowth*, *Lev*, *Cashratio*, *Stockvolatility*, *Stockreturn*, *SOE*, *Institute*, *Industry*, *Year*, and *Industry*×*Year*. Appendix A presents the definition of all control variables.

3.3. Variables

In this section, we introduce the data sources and construction methods of the main variables applied in our analysis. Additionally, we offer detailed definitions of all the variables in the Online Appendix Table 1.

3.3.1. Dependent variable: Innovation output

Consistent with past research (Gao et al., 2020), we introduce four proxies to quantify innovation. The first is Ln(*Patent*), which is the natural log of 1 plus the number of patents filed by and ultimately awarded to a firm in a given year. The second is Ln(*Citation*), which equals the natural log of 1 plus the total number of citations received by a firm's patent applications.

However, since recently granted patents tend to have fewer citations, our raw number of citations may have truncation bias issues. To address this bias, we take the following steps to adjust patent citations' factor index (Hall, Jaffe, & Trajtenberg, 2001). First, the mean value of the number of forward citations of a patent in the same technology category and filed within the same year of the application, which we name "type-year average." Second, we disregard the patent's applying year and calculate the mean value of the number of forward citations of the patent in the same technology category, which we name "type average." Then, we develop a citation correction factor that accounts for changes across years, but not across technology categories. We define the patent citation adjustment factor in each applying year for each technology type as the type-year average scaled by the corresponding type average. Finally, the patent's number of forward citations is scaled by the complementary citation adjustment factor. Then, we sum up all the patents' forward citations that adjusted granted by the listed firms in an applying year.

Furthermore, this study attempts to assess corporate key laboratories' innovation effects, which are reliant on the work of creative employees, such as engineers and scientists. Hence, the third metric, Ln(*PatentPt*), is the natural log of 1 plus the number of patents per 1000 employees. Fourth, Ln(*CitationPt*) is the natural log of 1 plus the number of citations per 1000 employees.

3.3.2. Test variable: Corporate key laboratory

The test variable, *Laboratory_dummy*, is a dummy variable that equals 1 if the firm has at least one key laboratory at the state or provincial level in a given year, and 0 if not. In China, the status of a corporate key laboratory is not permanent. For example, according

[10] https://www.cnipa.gov.cn/
[11] http://www.daweisoft.com/innojoy.html
[12] https://patents.google.com/advanced
[13] http://www.wingodata.cn/#/dash/index
[14] https://cn.gtadata.com/
[15] https://www.cnrds.com/Home/Login
[16] http://www.ccerdata.cn/
[17] http://www.resset.cn/
[18] https://www.cnopendata.com/
[19] https://www.wind.com.cn/
[20] https://www.baidu.com/

to the document "Administrative Measures of Guangdong Provincial Department of Science and Technology on Construction and Operation of Provincial Enterprise Key Laboratory," there is a four-year assessment cycle for corporate key laboratories. We also develop two other factors, namely *Laboratory_state_dummy* and *Laboratory_provincial_dummy*, which are dummy variables that equal 1 if a firm has at least one corporate key laboratory at either the state or provincial level, respectively; if not, these dummy variables equal 0.

3.3.3. Control variables

The literature shows that several firm characteristics and other factors affect corporate innovation (Chang et al., 2015; Gao et al., 2020). Accordingly, we introduce various controls, including *R&D*, *Size*, *Firmage*, *PPE*, *Sales*, *ROA*, *MB*, *Salesgrowth*, *Lev*, *Cashratio*, *Stockvolatility*, *Stockreturn*, *SOE*, *Institute*, *Industry*, *Year*, and *Industry*×*Year*. We also winsorize continuous variables at the 1% level.

4. Empirical analyses

4.1. Descriptive statistics

Table 1 shows the distribution of corporate key laboratories by year and industry. In total, the sample contains 12,024 observations from 2013 to 2018. Further, 1275 firm-year observations (10.6% of total observations) have at least one key laboratory. In 2013, only 5.81% of the firms had at least one laboratory. Then, following several governmental measures to encourage the establishment of laboratories and the conduction of cutting-edge scientific research in the private sector, this ratio increased to 13.98% in 2018.

Table 1
Distribution of the sample by year and industry.

Panel A: Sample distribution by year

Year	No. of corporations	No. of corporate key laboratories	Corporate key laboratories (%)
2013	1789	104	5.81
2014	1788	80	4.47
2015	1899	271	14.27
2016	2070	217	10.48
2017	2247	291	12.95
2018	2231	312	13.98
Total	12,024	1275	10.60

Panel B: Sample distribution by industry

Industry	No. of corporations	No. of corporate key laboratories	Corporate key laboratories (%)
Manufacture of special purpose machinery	849	82	9.66
Manufacture of chemical raw materials and chemical products	964	111	11.51
Manufacture of medical products	829	124	14.96
Manufacture of automobiles	466	66	14.16
Electric equipment and machinery	985	152	15.43
Manufacture of computers, communication, and other electronic equipment	1301	113	8.69
Manufacture of general purpose machinery	566	82	14.49
Smelting and pressing of nonferrous metals	304	47	15.46
Manufacture of rubber and plastics	287	41	14.29
Software and information technology services	659	47	7.13
Metal products	260	34	13.08
Nonmetal mineral products	335	32	9.55
Manufacture of measuring instruments	178	29	16.29
Processing of food from agricultural products	173	27	15.61
Building projects	261	25	9.58
Textile industry	190	21	11.05
Food manufacturing	169	25	14.79
Smelting and pressing of ferrous metals	161	21	13.04
Polytechnic services	103	16	15.53
Farming	45	11	24.44
Chemical fiber	110	10	9.09
Paper-making and paper products	131	14	10.69
Manufacture of alcohol, beverages, and refined tea	191	18	9.42
Manufacture of railway, ships, aerospace, and other transportation equipment	158	16	10.13
Other	2349	111	4.73
Total	12,024	1275	10.60

Notes. The sample period is 2013–2018.

Panel B details the dispersion of corporate key laboratories across industries. The top 5 industries with the most laboratories are electric equipment and machinery (152 firms; 15.43% of the total in this industry); manufacture of medical products (124 firms; 14.96% of the total in this industry); manufacture of computers; communication and other electronic equipment (113 firms; 8.69% of the total in this industry); manufacture of chemical raw materials and chemical products (111 firms; 11.51% of the total in this industry); and manufacture of special purpose machinery (82 firms; 9.66% of the total in this industry).

The descriptive statistics for the primary dependent, independent, and control variables are shown in Table 2 panels A, B, and C, respectively. The mean and standard deviation of Ln(*Patent*) and Ln(*Citation*) are 1.206 (1.889) and 1.293 (1.835), respectively. Further, Ln(*PatentPt*) and Ln(*CitationPt*) are 0.748 (1.320) and 0.881 (1.398), respectively. These results show a large difference in the quantity and quality of corporate innovation output. Regarding independent variables, the average value of *Laboratory_dummy* is 0.106, demonstrating that at least one key laboratory is present in 10.6% of the firm-year data. The average values for *Laboratory_state_dummy* and *Laboratory_provincial_dummy* are 0.064 and 0.05, respectively; this indicates that 6.4% and 5% of observations have at least one key laboratory at the state level and one at the provincial level.

Panel C of Table 2 presents key summary statistics for the control variables. The mean values of *R&D*, *Size*, and *Firmage* are 10.282, 15.309, and 2.269, respectively. Further, the average value of *PPE* is 5.674, that of *Sales* is 6.815, that of *ROA* is 0.05, that of *MB* is 0.926, that of *Salesgrowth* is 0.162, that of *Lev* is 0.416, that of *Cashratio* is 0.151, that of *Stockvolatility* is 0.03, that of *Stockreturn* is 0.138, that of *SOE* is 0.333, and that of *Institute* is 0.387.

4.2. Correlation analysis

The correlation coefficients are shown in Online Appendix Table 3. All correlation coefficients between our key test variable (*Laboratory_dummy*) and innovation output proxies—Ln(*Patent*), Ln(*Citation*), Ln(*PatentPt*), Ln(*CitationPt*)—are significantly positive. The findings indicate that corporate key laboratories may promote innovation output. Moreover, most control variables are significantly associated with the dependent variables, indicating that the control variables used are reasonable. Most correlation coefficients among the explanatory variables are relatively low, suggesting that the risk for multicollinearity is relatively low in this study.

4.3. Univariate analysis

Then, we conduct a univariate analysis. Table 3 provides the detailed results of univariate tests between firms with and those without key laboratories. Regarding firms without key laboratories, the means for Ln(*Patent*), Ln(*Citation*), Ln(*PatentPt*), and Ln (*CitationPt*) are 1.161, 1.825, 0.733, and 1.29, respectively. These means for firms with key laboratories are 1.584, 2.427, 0.872, and 1.568, respectively. The differences are statistically significant, demonstrating that having a key laboratory can benefit the firm by creating more high-quality innovation.

Table 2
Main variables' descriptive statistics.

	Mean	Std. Dev.	P25	Median	P75
Panel A: Dependent variables					
Ln(*Patent*)	1.206	1.293	0.000	1.099	1.946
Ln(*Citation*)	1.889	1.835	0.000	1.718	3.186
Ln(*PatentPt*)	0.748	0.881	0.000	0.444	1.233
Ln(*CitationPt*)	1.320	1.398	0.000	0.966	2.296
Panel B: Independent variables					
Laboratory_dummy	0.106	0.308	0.000	0.000	0.000
Laboratory_state_dummy	0.064	0.245	0.000	0.000	0.000
Laboratory_provincial_dummy	0.050	0.217	0.000	0.000	0.000
Panel C: Control variables					
R&D	10.282	3.049	9.939	10.869	11.751
Size	15.309	1.308	14.408	15.117	16.010
Firmage	2.269	0.604	1.792	2.197	2.833
PPE	5.674	1.057	5.063	5.661	6.274
Sales	6.815	0.803	6.276	6.724	7.267
ROA	0.050	0.062	0.026	0.048	0.078
MB	0.926	1.010	0.338	0.581	1.069
Salesgrowth	0.162	0.348	−0.011	0.113	0.265
Lev	0.416	0.202	0.254	0.403	0.564
Cashratio	0.151	0.116	0.069	0.118	0.198
Stockvolatility	0.030	0.010	0.023	0.028	0.035
Stockreturn	0.138	0.579	−0.270	−0.018	0.388
SOE	0.333	0.471	0.000	0.000	1.000
Institute	0.387	0.234	0.189	0.395	0.568

Notes. The sample period is 2013–2018.

Table 3
Univariate analysis of the mean difference between the main dependent and independent variables among firms with and without a key laboratory.

	Without key laboratory		With key laboratory		Differences
	Obs	Mean	Obs	Mean	*T* value
Ln(*Patent*)	10,749	1.161	1275	1.584	−0.423***
Ln(*Citation*)	10,749	1.825	1275	2.427	−0.602***
Ln(*PatentPt*)	10,749	0.733	1275	0.872	−0.139***
Ln(*CitationPt*)	10,749	1.290	1275	1.568	−0.278***
R&D	10,749	10.167	1275	11.258	−1.091***
Size	10,749	15.289	1275	15.482	−0.193***
Firmage	10,749	2.265	1275	2.302	−0.037**
PPE	10,749	5.662	1275	5.773	−0.111***
Sales	10,749	6.815	1275	6.815	0.000
ROA	10,749	0.049	1275	0.054	−0.005**
MB	10,749	0.929	1275	0.901	0.028
Salesgrowth	10,749	0.163	1275	0.157	0.006
Lev	10,749	0.416	1275	0.413	0.003
Cashratio	10,749	0.151	1275	0.143	0.008**
Stockvolatility	10,749	0.030	1275	0.030	−0.000
Stockreturn	10,749	0.144	1275	0.086	0.058***
SOE	10,749	0.333	1275	0.332	0.001
Institute	10,749	0.387	1275	0.392	−0.005

Notes. t-tests are used to calculate the t-values for mean differences. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.4. Multivariate results

Table 4 shows the outcomes of our benchmark multiple regression analysis in Eq. (1). The regression model includes all control variables. The *Laboratory_dummy* shows a significant coefficient of 0.278; this means that increasing *Laboratory_dummy* by one unit results in a 27.8% increase in patents. Additionally, we find a statistically substantial positive correlation between corporate key laboratories and Ln(*Citation*). Hence, a one-unit increase in *Laboratory_dummy* results in a 40.8% increase in citations. Furthermore, the coefficients for Ln(*PatentPt*) and Ln(*CitationPt*) are 0.149 and 0.268, respectively, and both are statically significant. Economically, increasing *Laboratory_dummy* from 0 to 1 leads to a 14.9% and 26.8% increase in patents and citations per 1000 employees, respectively. Consequently, the findings suggest that corporate key laboratories can facilitate innovation output.

Regarding control factors, most coefficients are significant, which is consistent with earlier research. As the essential input of innovation activities, the control variable *R&D* shows a significantly positive correlation with all four variables of innovation output. The coefficients for *Size*, *ROA*, and *SOE* are all significantly positive, indicating that enterprises with a larger scale, higher *ROA*, and state affiliation have more patents and citations than their counterparts, leading to a higher innovation output level. Meanwhile, *Firmage* and *MB* are negatively correlated with the four dependent variables of innovation output; that is, older and higher market-to-book ratio firms present less innovation output, indicating that they lack the incentives to innovate.

5. Endogeneity issues

The findings demonstrate a stimulation of corporate key laboratories' impact on innovation output. However, this conclusion can be subject to endogeneity issues, including omitted variables and reverse causality biases. Specifically, even after including several controls in our baseline model, based on prior studies, some omitted variables may interfere in corporate key laboratories' impact on innovation output. For example, there may be omitted variables that influence whether a key laboratory implements its innovation activities. Furthermore, the reverse causality problem may entail that a positive impact of corporate key laboratories on innovation output may stem from firms with higher innovation tendency and capacity being the ones which actually attract the government for the establishment of these key laboratories.

This section identifies the causality between corporate key laboratories and innovation output by using various strategies. First, we introduce some potential omitted variables into our regression model to reduce the interference and test for reverse causality. Then, we address the endogeneity issue using the first-differencing, IV estimation, laboratory incentive policy shock analysis, and PSM approaches.

5.1. Potentially omitted variables and reverse causality tests

Although the government can provide financial subsidies, it takes financial support to establish a corporate key laboratory and keep it running. Thus, financial constraints are important within the context of key laboratories (Li, 2011) and also entail restrictions for investment in innovation projects. Accordingly, we introduce the Kaplan and Zingales (1997) financial constraint index (*KZ index*) and the Whited and Wu (2006) index (*WW index*) into our benchmark estimation. After re-running the baseline model with these two indexes, the coefficients for *Laboratory_dummy* remain considerably positive. Namely, the main conclusions are consistent and robust after controlling for financial constraints; the coefficients for the *KZ index* and *WW index* are negative, indicating that financial

Table 4
Corporate key laboratories' impact on innovation output.

	Ln(*Patent*)	Ln(*Citation*)	Ln(*PatentPt*)	Ln(*CitationPt*)
	(1)	(2)	(3)	(4)
Laboratory_dummy	0.278***	0.408***	0.149***	0.268***
	(0.040)	(0.055)	(0.028)	(0.045)
R&D	0.076***	0.117***	0.045***	0.079***
	(0.007)	(0.010)	(0.004)	(0.007)
Size	0.527***	0.679***	0.018	0.083***
	(0.031)	(0.038)	(0.018)	(0.027)
Firmage	−0.071**	−0.091*	−0.099***	−0.126***
	(0.035)	(0.047)	(0.024)	(0.038)
PPE	−0.094***	−0.125***	0.033*	0.033
	(0.022)	(0.030)	(0.018)	(0.026)
Sales	−0.022	−0.028	0.178***	0.226***
	(0.028)	(0.038)	(0.025)	(0.035)
ROA	0.945***	1.595***	0.391**	0.870***
	(0.243)	(0.351)	(0.183)	(0.293)
MB	−0.131***	−0.175***	−0.071***	−0.118***
	(0.030)	(0.039)	(0.017)	(0.026)
Salesgrowth	−0.011	0.031	0.016	0.055
	(0.030)	(0.044)	(0.026)	(0.041)
Lev	−0.143	−0.194	−0.236***	−0.346***
	(0.110)	(0.153)	(0.081)	(0.125)
Cashratio	0.173	0.183	0.335***	0.374**
	(0.146)	(0.199)	(0.118)	(0.176)
Stockvolatility	0.635	2.166	4.640***	6.852***
	(2.045)	(2.968)	(1.558)	(2.502)
Stockreturn	−0.002	0.010	0.015	0.020
	(0.023)	(0.033)	(0.020)	(0.030)
SOE	0.312***	0.361***	0.160***	0.206***
	(0.049)	(0.067)	(0.035)	(0.053)
Institute	−0.019	−0.053	−0.083	−0.129
	(0.078)	(0.109)	(0.058)	(0.090)
Constant	−6.838***	−8.687***	−1.248***	−2.307***
	(0.421)	(0.520)	(0.271)	(0.396)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry×Year FE	YES	YES	YES	YES
Observations	11,991	11,991	11,991	11,991
Adjusted R^2	0.438	0.403	0.272	0.269

Notes. Standard errors in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

constraints impede innovation output (Panel A in Table 5).

Prior studies show that corporate governance can be an essential driver of corporate innovation (Balsmeier, Fleming, & Manso, 2017; Gompers, Ishii, & Metrick, 2003). Considering that corporate key laboratories are related to relatively high-value equipment, have outstanding scientists in different fields, and need to maintain a relationship with the government and universities, the appropriate maintenance of such laboratories requires a high level of governance and internal control. Thus, we add a set of governance proxies to our baseline model, including the governance index (*G-index*) constructed by Gompers et al. (2003), board size (*Board_size*), CEO duality (*Duality*), and the shareholder ratio of qualified foreign institutional investors (*QFII*). Then, we re-run the model. Panel B in Table 5 reports the re-run results. These governance variables do not impact the main conclusions of the study.

The local development and cultural characteristics of the province in which a firm is located may influence the association of corporate key laboratories and innovation output. Companies prefer to move to regions with higher economic growth and innovation level, from where they can take better advantage of local markets and innovation resources (Chen, Yan, & Yang, 2020; Xiao, Wu, & Kim, 2021). Then, the natural log of the province's gross regional product (Ln(*local_gdp*)), the year-on-year growth rate of provincial gross regional product (*GDP_growth*), the total number of patents granted in provinces (Ln(*local_patents*)), the total number of scientific articles published in provinces (Ln(*local_papers*)), and the total technology transactions in provinces (Ln(*tech_trans*)) are introduced into our baseline regression model and controlled. Ln(*local_gdp*) and *GDP_growth* are adopted to measure local province economic growth level, while Ln(*local_patents*), Ln(*local_papers*), and Ln(*tech_trans*) are used to proxy local innovation level. The re-run results are shown in Panel C in Table 5, which shows that our main conclusions remain unchanged after further controlling for local economic growth and innovation level.

Government support for corporate key laboratories and technological innovation may also be an important omitted factor (He & Tian, 2020; Kondo, 2013). We further control for government support indicators, including the natural log of total provincial R&D investment expenditures (Ln(*local_R&D_fee*)), the ratio of provincial R&D investment to regional GDP (*Local_R&D_ratio*), the natural log of provincial government investment in R&D activities (Ln(*gov_R&D*)), the ratio of provincial government R&D investment to total R&D investment (*Gov_R&D_ratio*), and the provincial intellectual property protection index (*IPP_index*). According to the results of

Table 5
Tests for omitted variables and reverse causality.

	Ln(*Patent*)	Ln(*Citation*)	Ln(*PatentPt*)	Ln(*CitationPt*)
	(1)	(2)	(3)	(4)
Panel A: Controlling for financial constraints				
Laboratory_dummy	0.332***	0.493***	0.222***	0.360***
	(0.061)	(0.073)	(0.044)	(0.057)
KZ_index	−0.056***	−0.025	−0.031***	−0.009
	(0.015)	(0.019)	(0.011)	(0.014)
WW_index	−0.842*	−1.041*	−0.331	−0.584
	(0.509)	(0.620)	(0.399)	(0.496)
Observations	11,991	11,991	11,991	11,991
Adjusted R^2	0.269	0.239	0.225	0.191
Panel B: Controlling for corporate governance				
Laboratory_dummy	0.277***	0.407***	0.148***	0.267***
	(0.039)	(0.054)	(0.028)	(0.045)
G_index	0.039***	0.049**	0.021*	0.031*
	(0.014)	(0.020)	(0.011)	(0.018)
Board_size	0.019*	0.035**	0.013*	0.025**
	(0.011)	(0.015)	(0.008)	(0.012)
Duality	0.037	0.043	0.033	0.045
	(0.034)	(0.047)	(0.025)	(0.039)
QFII	0.068***	0.082**	0.027*	0.043*
	(0.026)	(0.032)	(0.014)	(0.022)
Observations	11,991	11,991	11,991	11,991
Adjusted R^2	0.440	0.405	0.274	0.271
Panel C: Controlling for local economic growth and innovation level				
Laboratory_dummy	0.276***	0.404***	0.150***	0.267***
	(0.039)	(0.054)	(0.028)	(0.045)
Ln(*local_gdp*)	−0.075	−0.086	−0.047	−0.062
	(0.059)	(0.080)	(0.044)	(0.067)
GDP_growth	0.032**	0.045**	0.021**	0.030**
	(0.013)	(0.018)	(0.009)	(0.014)
Ln(*local_patents*)	0.081**	0.129**	0.027	0.066
	(0.038)	(0.053)	(0.029)	(0.045)
Ln(*local_papers*)	0.026	0.025	0.026	0.024
	(0.032)	(0.045)	(0.024)	(0.037)
Ln(*tech_trans*)	0.047	0.052	0.032	0.044
	(0.033)	(0.046)	(0.025)	(0.038)
Observations	11,991	11,991	11,991	11,991
Adjusted R^2	0.443	0.408	0.275	0.273
Panel D: Controlling for government innovation support				
Laboratory_dummy	0.275***	0.401***	0.149***	0.265***
	(0.040)	(0.054)	(0.028)	(0.045)
IPP_index	0.001	0.002	0.001	0.002
	(0.002)	(0.003)	(0.002)	(0.003)
Ln(*local_R&D_fee*)	0.156	0.312**	0.089	0.217
	(0.113)	(0.156)	(0.087)	(0.133)
Local_R&D_ratio	0.004	−0.023	0.003	−0.014
	(0.033)	(0.046)	(0.025)	(0.039)
Ln(*gov_R&D*)	−0.073	−0.172	−0.054	−0.139
	(0.116)	(0.161)	(0.089)	(0.137)
Gov_R&D_ratio	0.005	0.010	0.004	0.009
	(0.005)	(0.007)	(0.004)	(0.006)
Observations	11,991	11,991	11,991	11,991
Adjusted R^2	0.442	0.408	0.275	0.272
Panel E: Controlling for local college innovation level				
Laboratory_dummy	0.278***	0.408***	0.150***	0.269***
	(0.040)	(0.054)	(0.028)	(0.045)
Ln(*coll_R&D_fee*)	0.065	0.088	0.011	0.036
	(0.051)	(0.070)	(0.038)	(0.058)
Ln(*coll_papers*)	−0.022	−0.031	0.021	0.018
	(0.071)	(0.101)	(0.053)	(0.084)
Ln(*coll_patents*)				

(*continued on next page*)

Table 5 (*continued*)

	Ln(*Patent*)	Ln(*Citation*)	Ln(*PatentPt*)	Ln(*CitationPt*)
	(1)	(2)	(3)	(4)
	0.018	0.043	0.003	0.018
	(0.033)	(0.047)	(0.026)	(0.040)
Ln(*coll_patents_trans*)	0.019	0.018	0.012	0.012
	(0.013)	(0.018)	(0.009)	(0.015)
Observations	11,991	11,991	11,991	11,991
Adjusted R^2	0.441	0.406	0.274	0.272
Panel F: Controlling for local culture				
Laboratory_dummy	0.279***	0.409***	0.149***	0.269***
	(0.040)	(0.055)	(0.028)	(0.045)
Lottery_culture	0.070	0.098	0.023	0.050
	(0.053)	(0.073)	(0.041)	(0.063)
Religion_culture	−0.014	−0.009	−0.022	−0.022
	(0.019)	(0.026)	(0.014)	(0.022)
Confucian_culture	0.053	0.112	0.059	0.107
	(0.099)	(0.136)	(0.070)	(0.109)
Observations	11,991	11,991	11,991	11,991
Adjusted R^2	0.438	0.403	0.272	0.269
Panel G: Controlling for city and city-year fixed effects				
Laboratory_dummy	0.254***	0.377***	0.129***	0.240***
	(0.042)	(0.058)	(0.031)	(0.048)
Observations	11,554	11,554	11,554	11,554
Adjusted R^2	0.453	0.419	0.275	0.275
Panel H: Controlling for past innovation success				
Laboratory_dummy	0.054**	0.109***	0.046**	0.072**
	(0.027)	(0.041)	(0.022)	(0.033)
Past innovation success	0.797***	0.602***	0.718***	0.536***
	(0.008)	(0.012)	(0.011)	(0.014)
Observations	9603	9603	9603	9603
Adjusted R^2	0.738	0.623	0.645	0.503

Notes. The model used here is the same as the one used in Table 4. The full set of control variables are included in all regressions as well as the Industry, Year, and Industry×Year fixed effects. Only the coefficient estimates of variables of interest are presented, for the sake of brevity. Standard errors shown in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are shown in Appendix A.

Panel D in Table 5, corporate key laboratories' positive impacts on innovation output are preserved after controlling for these city characteristics.

Corporate key laboratories are engaged in market-oriented basic research and application technology development, and there is a close connection with the basic research in college laboratories (Rotolo et al., 2022). Furthermore, a few local college innovation proxies are introduced into the benchmark model. After re-regressing the augmented model, the results indicate that corporate key laboratories' significantly positive effects on innovation output remain and our main conclusions remain unchanged (Panel E in Table 5).

Prior studies have demonstrated that local culture comprises an important influence factor in corporate innovation (Adhikari & Agrawal, 2016; He & Tian, 2018). Therefore, we included in the model the natural log of the provincial lottery sales per capita (*Lottery_culture*); the natural log of the number of provincial Buddhist, Taoist, Christian, Catholic, and Islamic temples (*Religion_culture*); and the natural log of the number of provincial Confucian temples (*Confucian_culture*). According to the results of Panel F in Table 5, corporate key laboratories' positive effects on innovation output are preserved after controlling for these city characteristics.

In addition, we further control for the city fixed effects, as well as the city and year interactive fixed effects (as shown in Panel G). The augmented regression model does not influence our primary conclusions.

Finally, we analyze reverse causality, namely, whether the association between corporate key laboratories and innovation output is bidirectional—that is, we assess whether innovative firms focus more on scientific research and, thus, have a greater tendency to establish corporate key laboratories (Hsu, Hsu, & Zhao, 2021). Hence, we control for the variable of *Past innovation success* and re-run the baseline model. Referring to Chang et al. (2015), *Past innovation success* is defined as the average number of granted patents during 2008–2012. Panel H reveals that the results for *Laboratory_dummy* remain steady and robust, suggesting that our primary findings are unaffected by reverse causality issues.

5.2. Heckman two-step sample selection model

The decision of a company to establish a key laboratory is not always random, which may lead to self-selection bias. To address this endogeneity issue due to sample self-selection, we used the Heckman two-step sample selection model to estimate the impact of key laboratories on firm innovation. In the first step, we estimated a Probit model with the dependent variable being whether the firm has set up a state or provincial key laboratory or not. In addition to the variables in the original benchmark model, including *R&D*, *Size*, *Firmage*, *PPE*, *ROA*, *MB*, *Salesgrowth*, *Lev*, *Cashratio*, *SOE*, and *Institute*, we also introduced Ln(*gov_R&D*) (provincial government investment in R&D activities), Ln(*tech_trans*) (total technology transactions in provinces), Ln(*coll_papers*) (the number of papers published by college laboratories in provinces), Ln(*coll_patents*) (the number of patents granted by college laboratories in provinces), and *Peer_R&D_ratio* (the average R&D density of all firms in the same industry in the same year, excluding the firm itself) as explanatory variables for the establishment of a key laboratory by a firm. A firm's decision to establish a key lab may be influenced by the R&D density of its competitors (*Peer_R&D_ratio*), and such a decision is unlikely to be closely correlated with corporate innovation.

Table 6 presents the specific results of the Heckman two-step regression. The results of the first step regression results indicate that *R&D*, *PPE*, Ln(*coll_patents*), and *Peer_R&D_ratio* have a significant positive impact on the establishment of key laboratories by firms, whereas *MB* and *Salesgrowth* have a significant negative impact on the establishment of key laboratories. To mitigate the potential sample selection bias, we introduced the inverse Mills ratio (*IMR*) obtained from the first step regression into the second step of the regression model. Columns (2)–(5) in Table 6 present the second step regression results. Our findings indicate that the effect of key laboratories on the quantity and quality of innovation remains significantly positive at the 1% level, which is consistent with the main findings. Moreover, the regression coefficients of *IMR* are significantly positive, indicating that the unobserved factors that may influence firms' decision to establish a key laboratory also have a significant positive impact on firm innovation.

5.3. The instrumental variable approach

Subsequently, we apply the instrumental variable approach (IV) to address the possible bias caused by reverse causality. Thus, we construct specific instruments that are related to the test variable, *Laboratory_dummy*, but unrelated to the dependent variable. As the highest scientific honor in China, fellows of the Chinese Academy of Sciences (CAS)[21] and the Chinese Academy of Engineering (CAE)[22] have significant influence and resources. First, academicians can bring research funding to their institutions directly. Fisman, Shi, Wang, and Xu (2018) find that the membership of the CAS and the CAE generate approximately $9.5 million in research funding for their research institutions each year. Second, grants for research projects from the Ministry of Science and Technology or other government agencies often ask for the recommendation of academicians from the CAS or the CAE. Finally, CAS/CAE fellows have the potential to be appointed to leadership positions in some professional departments. For example, Xiang Libin, an academician at the CAS, has been appointed vice-minister of science and technology.[23] Zeng Yixin, an academician of the CAS, has been appointed the deputy director of the National Health Commission.[24]

Hometown ties play a central role in Chinese society (Chen & Chen, 2004). Prior studies have documented the essential role played by hometown ties of CAS/CAE fellows and political elites in China (Fisman et al., 2018; Fisman, Shi, Wang, & Wu, 2020). This hometown bond makes academicians more inclined to their hometown when recommending sites for state or provincial key laboratories. Therefore, we collect and compile information on the hometowns of all CAS/CAE fellows. We choose the number of CAS/CAE fellows in the city where the company headquarters are located (*Local_CAS/CAE_fellows*) as an instrumental variable for whether the company establishes a key laboratory or not. Additionally, we use a second instrument, *Laboratory_other*, which is defined as the average number of corporate key laboratories of other firms in the same industry and city in a given year.

Table 7 reports the empirical results of IV estimation. We also use a two-stage least squares (2SLS) methodology. The first-stage regression results are shown in Column (1). The two instruments, *Local_CAS/CAE_fellows* and *Laboratory_other*, are both significantly related to the test variable, *Laboratory_dummy*. Further, the F-statistic value is 15.290 and significant, indicating that the two instruments are relevant to the potentially endogenous variable.

Columns (2)–(5) show that the coefficients for *Laboratory_dummy* are 3.265, 4.161, 2.644, and 1.688, respectively. Hence, corporate key laboratory still has significantly positive effects on innovation output after applying IV estimation. As for the overidentification test of all instruments, all the four Hansen J statistics are insignificant, which indicates that all instrumental variables are exogenous and valid.

5.4. Policy shock analysis

We also introduce the Chinese government incentive policy on corporate key laboratories in 2015 as an exogenous policy shock. In 2015, the Fifth Plenary Session of the 18th Central Committee of the Communist Party of China (CPC) adopted the "Proposal of the CPC Central Committee on Formulating the 13th Five-Year Plan for National Economic and Social Development." At the central government level, enterprises were encouraged to conduct basic and cutting-edge innovation research, as well as to build corporate key laboratories.[25] The State Council then issued the "13th Five-Year National Science and Technology Innovation Plan," which further

[21] https://www.cas.cn/.
[22] https://www.cae.cn/.
[23] https://www.most.gov.cn/zzjg/bld/xlb/.
[24] http://www.nhc.gov.cn/wjw/wld/202202/cc6c50b250894ee2ae448c16b8920650.shtml.
[25] http://www.gov.cn/xinwen/2015-11/03/content_2959432.htm.

Table 6
Heckman two-step regressions on the relationship between corporate key laboratories and innovation output.

First-step regression		Second-step regressions				
	Laboratory _dummy		Ln(*Patent*)	Ln(*Citation*)	Ln(*PatentPt*)	Ln(*CitationPt*)
	(1)		(2)	(3)	(4)	(5)
R&D	0.077*** (0.018)	*Laboratory _dummy*	0.279*** (0.040)	0.410*** (0.054)	0.150*** (0.028)	0.270*** (0.045)
Size	0.055 (0.035)	*R&D*	0.145*** (0.023)	0.203*** (0.032)	0.085*** (0.017)	0.138*** (0.027)
Firmage	0.007 (0.045)	*Size*	0.563*** (0.034)	0.725*** (0.042)	0.039* (0.020)	0.114*** (0.031)
PPE	0.051** (0.025)	*Firmage*	−0.060* (0.034)	−0.077 (0.047)	−0.093*** (0.024)	−0.116*** (0.038)
ROA	0.357 (0.338)	*PPE*	−0.049* (0.027)	−0.068* (0.036)	0.059*** (0.020)	0.072** (0.031)
MB	−0.102*** (0.034)	*Sales*	−0.027 (0.028)	−0.034 (0.038)	0.175*** (0.025)	0.222*** (0.035)
Salesgrowth	−0.102** (0.049)	*ROA*	1.266*** (0.254)	1.997*** (0.370)	0.577*** (0.192)	1.148*** (0.309)
Lev	0.016 (0.139)	*MB*	−0.215*** (0.041)	−0.280*** (0.055)	−0.119*** (0.026)	−0.191*** (0.041)
Cashratio	−0.162 (0.203)	*Salesgrowth*	−0.097** (0.042)	−0.077 (0.060)	−0.034 (0.033)	−0.020 (0.052)
SOE	0.050 (0.062)	*Lev*	−0.121 (0.109)	−0.166 (0.152)	−0.223*** (0.080)	−0.327*** (0.125)
Institute	−0.127 (0.109)	*Cashratio*	0.008 (0.153)	−0.025 (0.209)	0.239** (0.122)	0.231 (0.183)
Ln(*gov_R&D*)	−0.009 (0.056)	*Stockvolatility*	0.407 (2.040)	1.879 (2.961)	4.507*** (1.553)	6.654*** (2.496)
Ln(*tech_trans*)	−0.044 (0.050)	*Stockreturn*	−0.002 (0.023)	0.010 (0.033)	0.015 (0.020)	0.020 (0.030)
Ln(*coll_papers*)	−0.104 (0.116)	*SOE*	0.344*** (0.050)	0.402*** (0.068)	0.179*** (0.036)	0.234*** (0.055)
Ln(*coll_patents*)	0.092* (0.050)	*Institute*	−0.119 (0.085)	−0.178 (0.118)	−0.141** (0.063)	−0.215** (0.097)
Peer_R&D_ratio	0.052* (0.031)	*IMR*	1.018*** (0.329)	1.279*** (0.460)	0.590** (0.251)	0.883** (0.390)
Industry FE	YES	Industry FE	YES	YES	YES	YES
Year FE	YES	Year FE	YES	YES	YES	YES
Industry×Year FE	YES	Industry×Year FE	YES	YES	YES	YES
Observations	11,991	Observations	11,991	11,991	11,991	11,991
Pseudo R^2	0.047	Adjusted R^2	0.439	0.404	0.273	0.270

Notes. Standard errors in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are shown in Appendix A.

introduced specific measures to support enterprises in building key laboratories.[26]

Given that companies expect to receive more R&D subsidies, research projects, and policy support, we argue that the promotion effect of corporate key laboratories on innovation output is more pronounced after this policy shock. To test this effect, we construct a dummy variable, *Incentive_Policy2015*. The value is 1 for 2015 and later and 0 for earlier. *Incentive_Policy2015* and *Laboratory_dummy×Incentive_Policy2015* are added in our augmented regression model. Table 8 presents the results of the policy shock analysis. We find significantly positive effects of corporate key laboratories and their enhancement effects after the incentive policy shock in 2015.

5.5. PSM procedure

To further address the endogeneity issue caused by reverse causality, we apply PSM. Our objective is to compare firms with corporate key laboratories to those without. To this end first, we need to select a control group. We estimate a Probit model and calculate a propensity score for the treatment group to identify and select a suitable control group. Second, we perform covariate balance checks to ensure that the matching results for these firms satisfy the economic and statistical requirements for the tests. All values of percentage bias drop significantly after the groups are matched and are below 10, as indicated in Online Appendix Table 4, suggesting that the balance test results are satisfactory.

Thereafter, we re-run the baseline model using the treatment and matched control samples, applying the following PSM

[26] http://www.gov.cn/gongbao/content/2016/content_5103134.htm; http://images.mofcom.gov.cn/www/201611/20161124110729907.pdf.

Table 7
Two-stage least squares regressions on the relationship between key laboratories and innovation output.

	First stage	Second stage			
	Laboratory_dummy	Ln(*Patent*)	Ln(*Citation*)	Ln(*PatentPt*)	Ln(*CitationPt*)
	(1)	(2)	(3)	(4)	(5)
Laboratory_dummy	N/A	3.265*	4.161**	2.644*	1.688**
		(1.655)	(1.968)	(1.493)	(0.787)
Local_CAS/CAE_fellows	0.006*	N/A	N/A	N/A	N/A
	(0.003)				
Laboratory_other	0.005***	N/A	N/A	N/A	N/A
	(0.001)				
R&D	0.006***	0.071**	0.047	0.013	0.043***
	(0.002)	(0.030)	(0.034)	(0.026)	(0.015)
Size	0.019***	0.400***	0.406***	−0.201**	−0.037
	(0.005)	(0.096)	(0.117)	(0.080)	(0.052)
Firmage	0.002	−0.076	−0.113	−0.389***	−0.134***
	(0.009)	(0.077)	(0.098)	(0.075)	(0.045)
PPE	0.010***	−0.100	−0.121	0.067	0.049
	(0.004)	(0.064)	(0.081)	(0.051)	(0.039)
Sales	−0.016***	−0.095	−0.049	0.147***	0.194***
	(0.005)	(0.065)	(0.078)	(0.052)	(0.039)
ROA	0.098	0.785	0.696	0.878**	0.367
	(0.069)	(0.518)	(0.697)	(0.360)	(0.410)
MB	−0.016***	−0.124	−0.187	−0.090	−0.120*
	(0.005)	(0.117)	(0.153)	(0.087)	(0.063)
Salesgrowth	−0.009	0.131	0.172	0.027	0.101
	(0.008)	(0.097)	(0.134)	(0.072)	(0.069)
Lev	0.000	0.625	0.664	0.273	0.065
	(0.023)	(0.424)	(0.540)	(0.443)	(0.231)
Cashratio	−0.005	−0.251	−0.177	0.489	0.130
	(0.021)	(0.314)	(0.402)	(0.295)	(0.220)
Stockvolatility	−1.208**	2.401	4.909	−3.222	5.675
	(0.562)	(8.106)	(9.560)	(5.443)	(4.164)
Stockreturn	−0.001	−0.089	−0.135	−0.079	−0.051
	(0.007)	(0.089)	(0.111)	(0.070)	(0.047)
SOE	0.018	−0.128	−0.199	−0.043	−0.093
	(0.012)	(0.248)	(0.285)	(0.223)	(0.132)
Institute	−0.018	−0.047	−0.034	−0.129	−0.145
	(0.022)	(0.285)	(0.360)	(0.238)	(0.156)
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry×Year FE	YES	YES	YES	YES	YES
F test of excluded instruments	15.290	N/A	N/A	N/A	N/A
	(0.000)				
Hansen J overid test	N/A	0.328	0.453	0.210	0.894
		(0.567)	(0.501)	(0.646)	(0.344)
Observations	11,991	11,991	11,991	11,991	11,991

Notes. Standard errors in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are shown in Appendix A.

procedures: one-to-one matching, neighbors matching, radius (1:4) matching, radius matching, kernel matching, local linear regression, spline matching, and Mahalanobis matching. All coefficients are positively significant, showing results that resemble those of the baseline model (Table 9).

6. Further analyses

6.1. Corporate key laboratory and innovation strategies

Our baseline model showed that corporate key laboratories promote innovation output. This section explores key laboratories' heterogeneous effects on innovation strategies. A set of heterogeneity proxies of innovation strategies is used, including *Exploration*, *Exploitation*, *Originality*, *Generality*, *Nonpat_cits*, *Backward_cits*, *Patent_scope*, and *Grant_lag*.

The first indicator, *Exploration*, represents the ratio of exploratory patents. Regarding definition of exploratory patents, if more than 60% of the patent classification numbers cited in a patent are not related to the patent portfolio of a company—including all patents invented and cited by the company in the preceding five years—it is classified as an exploratory patent (Benner & Tushman, 2003; Sørensen & Stuart, 2000). Regarding the definition of exploitative patents, if more than 60% of the patent classification numbers cited are equal to the combination of the existing patents of a company—including all patents invented and cited by the company during the preceding five years—it is an exploitative patent. We define *Exploitation* as a percentage of the total amount of exploitative patents

Table 8
Results for the policy shock analysis.

	Ln(*Patent*)	Ln(*Citation*)	Ln(*PatentPt*)	Ln(*CitationPt*)
	(1)	(2)	(3)	(4)
Laboratory_dummy	0.265***	0.274***	0.184***	0.204***
	(0.045)	(0.053)	(0.036)	(0.040)
Incentive_Policy2015	0.446	0.620	−0.304	0.041
	(0.497)	(0.449)	(0.307)	(0.178)
Laboratory_dummy×*Incentive_Policy2015*	0.138*	0.297***	0.054	0.145*
	(0.081)	(0.095)	(0.071)	(0.085)
R&D	0.114***	0.102***	0.070***	0.064***
	(0.008)	(0.009)	(0.006)	(0.006)
Size	0.547***	0.595***	−0.062***	0.037
	(0.030)	(0.034)	(0.022)	(0.023)
Firmage	−0.076**	−0.114***	−0.115***	−0.134***
	(0.038)	(0.042)	(0.031)	(0.032)
PPE	−0.106***	−0.128***	0.091***	0.045**
	(0.024)	(0.027)	(0.022)	(0.023)
Sales	−0.127***	−0.090***	0.200***	0.179***
	(0.031)	(0.034)	(0.029)	(0.030)
ROA	1.179***	1.200***	0.280	0.561**
	(0.281)	(0.300)	(0.230)	(0.235)
MB	−0.093***	−0.149***	−0.074***	−0.103***
	(0.033)	(0.037)	(0.021)	(0.022)
Salesgrowth	0.028	0.040	0.024	0.049
	(0.035)	(0.041)	(0.031)	(0.036)
Lev	0.184	0.101	−0.131	−0.164
	(0.121)	(0.130)	(0.098)	(0.102)
Cashratio	−0.236	−0.157	0.063	0.139
	(0.157)	(0.172)	(0.135)	(0.145)
Stockvolatility	−2.751	−1.685	3.174	3.128
	(2.371)	(2.656)	(1.967)	(2.113)
Stockreturn	−0.030	−0.060**	−0.019	−0.020
	(0.026)	(0.030)	(0.023)	(0.026)
SOE	0.147***	0.153***	0.034	0.048
	(0.052)	(0.056)	(0.040)	(0.042)
Institute	−0.031	−0.015	−0.169**	−0.136*
	(0.088)	(0.095)	(0.070)	(0.074)
Constant	−7.659***	−8.478***	−0.783*	−2.182***
	(0.483)	(0.477)	(0.415)	(0.331)
Industry FE	YES	YES	YES	YES
Industry×Year FE	YES	YES	YES	YES
Observations	12,024	12,024	12,024	12,024
Adjusted R^2	0.527	0.486	0.426	0.390

Notes. Standard errors in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 9
Results of PSM procedures.

PSM procedure	Ln(*Patent*)	Ln(*Citation*)	Ln(*PatentPt*)	Ln(*CitationPt*)
	(1)	(2)	(3)	(4)
One-to-one matching	0.255***	0.404***	0.131***	0.256***
	(0.066)	(0.088)	(0.041)	(0.066)
Neighbors matching	0.240***	0.367***	0.129***	0.242***
	(0.048)	(0.072)	(0.032)	(0.052)
Radius (1:4) matching	0.246***	0.375***	0.131***	0.245***
	(0.054)	(0.070)	(0.033)	(0.053)
Radius matching	0.252***	0.371***	0.137***	0.247***
	(0.035)	(0.045)	(0.022)	(0.035)
Kernel matching	0.268***	0.390***	0.130***	0.238***
	(0.036)	(0.049)	(0.025)	(0.034)
Local linear regression	0.221***	0.330***	0.130***	0.234***
	(0.033)	(0.046)	(0.024)	(0.037)
Spline matching	0.248***	0.364***	0.135***	0.243***
	(0.036)	(0.051)	(0.024)	(0.039)
Mahalanobis matching	0.305***	0.426***	0.128***	0.226***
	(0.034)	(0.049)	(0.024)	(0.039)

Notes. Standard errors in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are shown in Appendix A.

scaled by the number of patents filed (Benner & Tushman, 2003; Sørensen & Stuart, 2000). Table 10 shows key laboratories' regression effects on *Exploration* and *Exploitation*. We notice that the coefficient for *Exploration* related to the *Laboratory_dummy* is positive and significant, unlike for *Exploitation*. Therefore, corporate key laboratories show a more pronounced promotion impact on exploratory, rather than exploitative, patents.

Following Trajtenberg, Henderson, and Jaffe (1997), we define *Originality* as the median of all patents' originality scores. *Originality* refers to the importance of knowledge diversification to innovation and serves to measure whether the patent cites many patents from different knowledge sources; patents with higher originality scores produce more original outputs. Additionally, the proxy *Generality* is the median of all patents' generality scores. *Generality* is used to evaluate the technical scope of subsequent patents benefiting from a patent through the number of cited patents and the technology category (IPC) information. The more widely a patent is cited in the technical field, the higher its quality (Trajtenberg et al., 1997). Columns (3) and (4) in Table 10 show that corporate key laboratories have a significantly positive influence only on *Originality*, with their influence on *Generality* being insignificant.

Following Cassiman, Veugelers, and Zuniga (2008), when calculating *Nonpat_cits*, we use a logarithm based on 1 plus the number of non-patent studies cited by all patents. Patents that cite scientific papers may contain more complex knowledge. *Backward_cits* is defined as the natural log of 1 plus the total number of patent and non-patent studies cited in all filed patents (Harhoff, Scherer, & Vopel, 2003). Columns (5) and (6) in Table 10 show that firms with key laboratories tend to cite more patent and non-patent literature, reflecting that these patents have a higher value.

Patent_scope refers to the number of classes based on a patent's first four IPC classification numbers. The greater the patent scope value, the wider its range and the greater its value (Lerner, 1994). Following Harhoff and Wagner (2009) as well as Régibeau and Rockett (2010), *Grant_lag* is defined as 1 minus the ratio of the number of days between the applying date and the award date for a patent, divided by the maximum number of days between these two dates for a patent of the same IPC classification. Research shows a negative correlation between innovation quality and the period from patent application to award. Table 10 indicates that corporate key laboratories are positively associated with both *Patent_scope* and *Grant_lag*, suggesting that firms with a key laboratory have higher-

Table 10
Results for the relationships between the main study variables and different innovation strategies.

	Exploration	*Exploitation*	*Originality*	*Generality*	*Nonpat_cits*	*Backward_cits*	*Patent_scope*	*Grant_lag*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Laboratory_dummy	0.025**	0.002	0.059***	0.002	0.056***	0.334***	0.136***	0.022***
	(0.010)	(0.002)	(0.010)	(0.002)	(0.014)	(0.079)	(0.025)	(0.005)
R&D	0.011***	0.001***	0.016***	0.001***	0.013***	0.124***	0.051***	0.008***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)	(0.011)	(0.004)	(0.001)
Size	0.010*	0.000	0.021***	−0.002**	−0.001	0.167***	0.012	0.010***
	(0.006)	(0.001)	(0.005)	(0.001)	(0.007)	(0.045)	(0.014)	(0.003)
Firmage	−0.039***	0.001	−0.066***	−0.004***	−0.056***	−0.492***	−0.224***	−0.031***
	(0.008)	(0.001)	(0.008)	(0.001)	(0.012)	(0.065)	(0.024)	(0.004)
PPE	−0.002	−0.000	−0.007	0.001	0.002	−0.053	−0.005	−0.002
	(0.005)	(0.001)	(0.005)	(0.001)	(0.006)	(0.039)	(0.013)	(0.002)
Sales	−0.003	0.000	−0.008	−0.001	−0.005	−0.066	−0.033**	−0.006**
	(0.006)	(0.001)	(0.006)	(0.001)	(0.007)	(0.048)	(0.016)	(0.003)
ROA	0.146**	0.021**	0.293***	0.011	0.085	1.337***	0.823***	0.133***
	(0.057)	(0.009)	(0.059)	(0.012)	(0.085)	(0.484)	(0.167)	(0.026)
MB	−0.001	0.001	−0.007	0.001	−0.003	−0.040	−0.006	−0.005*
	(0.006)	(0.002)	(0.006)	(0.001)	(0.007)	(0.049)	(0.017)	(0.003)
Salesgrowth	−0.005	0.001	0.001	0.001	0.007	−0.025	−0.025	−0.006*
	(0.007)	(0.001)	(0.008)	(0.001)	(0.010)	(0.066)	(0.021)	(0.004)
Lev	−0.050*	−0.007	0.002	0.003	0.005	−0.203	0.030	0.002
	(0.026)	(0.005)	(0.025)	(0.005)	(0.032)	(0.199)	(0.073)	(0.012)
Cashratio	−0.013	−0.006	0.127***	−0.002	0.088*	1.007***	0.234**	0.029*
	(0.034)	(0.006)	(0.035)	(0.006)	(0.049)	(0.283)	(0.096)	(0.016)
Stockvolatility	−0.933*	0.100	−2.635***	−0.012	−2.577***	−11.347**	−8.389***	−0.731***
	(0.531)	(0.103)	(0.538)	(0.115)	(0.777)	(4.516)	(1.431)	(0.246)
Stockreturn	−0.020***	−0.001	0.002	0.001	−0.004	−0.095*	−0.033**	−0.006*
	(0.007)	(0.001)	(0.006)	(0.002)	(0.009)	(0.048)	(0.015)	(0.003)
SOE	0.038***	0.005**	0.036***	0.001	0.028*	0.239***	0.051	0.013**
	(0.011)	(0.002)	(0.011)	(0.002)	(0.014)	(0.089)	(0.031)	(0.005)
Institute	0.018	−0.001	0.010	0.001	0.024	0.197	0.063	0.010
	(0.018)	(0.003)	(0.019)	(0.003)	(0.026)	(0.153)	(0.049)	(0.009)
Constant	0.006	−0.016	0.046	0.042***	0.227**	−0.059	1.061***	0.009
	(0.089)	(0.019)	(0.074)	(0.013)	(0.103)	(0.651)	(0.202)	(0.037)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry×Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	11,991	11,991	11,991	11,991	11,991	11,991	11,991	11,991
Adjusted R^2	0.198	0.048	0.153	0.071	0.184	0.154	0.189	0.152

Notes. Standard errors in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are shown in Appendix A.

quality innovation output. Our results indicate that establishing a key laboratory encourages more exploratory, original, and creative innovations.

6.2. Cross-sectional heterogeneity checks

Generally, high-tech firms are more reliant on new technologies to increase their competitiveness, compared with low-tech firms, and have more incentives to implement scientific and technological innovation (Zhao, Li, & Yu, 2021). Hence, we separate our sample into two subgroups: high- and low-tech firms. We predict that having a key laboratory will have a more significant positive impact in high- than low-tech firms. Table 11 Panel A reports the regression results for these two subgroups. The coefficients for *Laboratory_dummy* in Columns (2) and (4), namely, for high-tech firms, are positively significant. However, the coefficients for low-tech firms are not significant. In addition, the bootstrap and permutation tests significantly reject the hypothesis that the coefficient estimates on *Laboratory_dummy* for the different sub-samples are equal, suggesting that key laboratories remain significantly positively related to innovation output in high-tech firms, while these positive effects do not exist in low-tech firms.

CEOs with hands-on experience in inventions (i.e., inventor CEOs) have a particular experiences and abilities in the evaluation, selection, and conduction of innovation projects, so the firms that they operate tend to obtain more and better patents and citations (Islam & Zein, 2020). Thus, if a firm with an inventor CEO establishes a key laboratory, the promotion impact of the laboratory on innovation output will be more pronounced. Table 11 Panel B provides the re-estimation results for the subgroups of firms with an inventor CEO and those with a non-inventor CEO. The coefficients for *Laboratory_dummy* are more significant for firms with an inventor CEO than those with a non-inventor CEO, both economically and statistically.

We also identify and define scientist CEOs, who are CEOs who have served as university faculty members. Then, we define two subgroups: firms with a scientist CEO and those with a non-scientist CEO. Once more, we compare key laboratories' effects on innovation output in these two subgroups. Table 11 Panel C shows the results of these comparisons, demonstrating that the impact of corporate key laboratories is more pronounced in companies with a scientist CEO and that their firms produce more innovation, both in quantity and quality.

The prior literature provides evidence on a substantial variance in IP protection level across different regions in China (Ang, Cheng, & Wu, 2014). Considering that IP protection plays a vital role in stimulating innovation, higher protection will enhance corporate key laboratories' positive impact on innovation output. Accordingly, we collect each city's IP lawsuit cases from the official website of China Judgements Online,[27] then separate our sample into two subgroups: firms in cities with strong IP protection and those with weak IP protection. Table 11 Panel D shows that all the coefficients for *Laboratory_dummy* are exclusively positively significant for firms in cities with strong IP protection—that is, corporate key laboratories impact innovation output only in firms located in cities with a strong IP protection.

6.3. Basic robustness checks

In this section, we conduct various robustness checks to ensure that our major conclusions hold true across various model settings and variable definitions. All robustness checks indicate that the main results do not change under any of the explored circumstances. For the sake of brevity, we only tabulate key variables' coefficients in Online Appendix Table 5.

The checks include: (a) using state key laboratory and provincial key laboratory as the independent variables; (b) using innovation indicators (based on annual reports, management discussion, text analysis) as the dependent variable[28]; (c) using standard indicators as the dependent variable[29]; (d) controlling for missing R&D dummy variables; (e) negative binomial regressions; (f) innovation proxies measured at $t+1$; (g) innovation proxies measured at $t+2$; (h)innovation proxies measured at $t+3$; (i) using patents that have top 10% citations as dependent variables; (j) using average citations per patent (after five and seven years, and by the end of 2021) as dependent variables; (k) only including observations that have patents; (l) only including observations with at least one citation; (m) only including observations that have academic journal publications; (n) excluding observations with their own academic journal publications; (o) excluding firms engaging in IP lawsuits; (p) excluding firms that have been involved in mergers and acquisitions during the last two years; (q) excluding firms with their headquarters at Beijing, Shanghai, Guangzhou, and Shenzhen; (r) excluding firms located in National Scientific Center Cities, namely, Beijing, Shanghai, Hefei, and Shenzhen.

6.4. Mechanism analysis

Our empirical evidence shows that key laboratories foster innovation output. However, the reason for this effect is unclear. In this section, we explore and test possible influence channels. Corporate science refers to discovery-driven research funded by private enterprises and recognized and supported by the government. The focus of corporate science is primarily on basic scientific research,

[27] https://wenshu.court.gov.cn/.

[28] Innovation indicators, also known as descriptive innovations, are text indicators that measure firms' level of innovation. Descriptive innovation indicators describe the input and output information related to technological innovation. Innovation, which is at the core of companies' competitiveness, is an important indicator for measuring enterprise value and sustainable development capability, and an important reference standard for investors' decision-making. http://www.wingodata.com/#/dash/index.

[29] http://openstd.samr.gov.cn/bzgk/gb/; https://c.wanfangdata.com.cn/standard.

Table 11
Corporate key laboratories' cross-sectional heterogenous effects on innovation.

	Ln(*Patent*)		Ln(*Citation*)	
Panel A: Heterogenous analysis by high- and low-tech firms				
	Low-tech firms	High-tech firms	Low-tech firms	High-tech firms
Laboratory_dummy	0.097	0.369***	0.041	0.411***
	(0.061)	(0.052)	(0.102)	(0.087)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry×Year FE	YES	YES	YES	YES
Observations	8005	3986	8005	3986
Adjusted R^2	0.410	0.481	0.250	0.261
High - Low tech Prob.	0.000***		0.000***	

Panel B: Heterogenous analysis by firms with inventor and non-inventor CEOs				
	Inventor CEO	Non-inventor CEO	Inventor CEO	Non-inventor CEO
Laboratory_dummy	0.272***	0.165**	0.320***	0.169*
	(0.075)	(0.081)	(0.089)	(0.088)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry×Year FE	YES	YES	YES	YES
Observations	4950	6978	4950	6978
Adjusted R^2	0.294	0.275	0.273	0.251
Inventor-Non CEO Prob.	0.020**		0.000***	

Panel C: Heterogenous analysis by firms with scientist and non-scientist CEOs				
	Scientist CEO	Non-scientist CEO	Scientist CEO	Non-scientist CEO
Laboratory_dummy	0.541***	0.162**	0.667***	0.163**
	(0.136)	(0.063)	(0.154)	(0.070)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry×Year FE	YES	YES	YES	YES
Observations	1661	10,288	1661	10,288
Adjusted R^2	0.265	0.284	0.252	0.259
Scientist-Non CEO Prob.	0.000***		0.000***	

Panel D: Heterogenous analysis by firms located in cities with strong and weak IP protection.				
	Strong IP protection	Weak IP protection	Strong IP protection	Weak IP protection
Laboratory_dummy	0.398***	0.158	0.318***	0.161
	(0.071)	(0.124)	(0.081)	(0.115)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry×Year FE	YES	YES	YES	YES
Observations	9285	2641	9285	2641
Adjusted R^2	0.270	0.262	0.259	0.279
Strong-Weak IPP Prob.	0.000***		0.050**	

Notes. Standard errors in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are shown in Appendix A. Tests of the hypothesis that the coefficient estimates on *Laboratory_dummy* for the different sub-samples are equal and the statistical results for 1000 bootstrap repetitions.

aiming to develop fundamental new knowledge and address long-term research problems that may not immediately lead to commercial applications (Arora et al., 2018). Corporate science complements the firm's R&D activities, but differs from them in that the latter are typically application-oriented. The key output of corporate science is scientific papers published by the firm's scientists in core journals, which highlights its importance in generating new knowledge and contributing to scientific progress (Simeth & Cincera, 2016). Prior studies have shown that corporate science is closely related to innovation activities (Hsu et al., 2021). Table 12 Panel A reports the results of mechanism analysis through corporate science. Ln(*Paper*), which equals the log of 1 plus the number of academic publications, was applied to quantify corporate scientific capacity.

Column (1) reveals that *Laboratory_dumm* is positively associated with Ln(*Paper*), indicating that corporate key laboratories can promote corporate science. Furthermore, we include these corporate science variables into the baseline model as explanatory variables and re-run the estimation. Columns (2)–(5) report the results. We find that the corporate key laboratories and corporate science variables' coefficients are both economically and statistically significant. This suggests that key laboratories can promote innovation by increasing firms' scientific research capacity.

In Panel B of Table 12, we explore whether corporate key laboratories promote innovation by increasing firms' human capital. Human capital is an essential driver of corporate innovation, including the CEO (Custódio et al., 2019), the top management team

Table 12
Mechanism analysis.

Panel A: First mechanism analysis by promoting corporate science

	Ln(*Paper*)	Ln(*Patent*)	Ln(*Citation*)	Ln(*PatentPt*)	Ln(*CitationPt*)
	(1)	(2)	(3)	(4)	(5)
Laboratory_dummy	0.273***	0.293***	0.422***	0.202***	0.315***
	(0.039)	(0.061)	(0.071)	(0.043)	(0.055)
Ln(*Paper*)		0.149***	0.270***	0.072***	0.169***
		(0.033)	(0.039)	(0.022)	(0.028)
Controls	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry×Year FE	YES	YES	YES	YES	YES
Observations	11,991	11,991	11,991	11,991	11,991
Adjusted R^2	0.446	0.272	0.252	0.226	0.199

Panel B: Second mechanism analysis for by increasing human capital

	Human_capital	Ln(*Patent*)	Ln(*Citation*)	Ln(*PatentPt*)	Ln(*CitationPt*)
	(1)	(2)	(3)	(4)	(5)
Laboratory_dummy	0.205**	0.323***	0.475***	0.213***	0.345***
	(0.085)	(0.062)	(0.074)	(0.044)	(0.057)
Human_capital		0.049***	0.097***	0.039***	0.083***
		(0.015)	(0.018)	(0.010)	(0.012)
Controls	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry×Year FE	YES	YES	YES	YES	YES
Observations	11,991	11,991	11,991	11,991	11,991
Adjusted R^2	0.339	0.270	0.248	0.228	0.202

Panel C: Third mechanism analysis by increasing R&D subsidy

	R&D_Subsidy	Ln(*Patent*)	Ln(*Citation*)	Ln(*PatentPt*)	Ln(*CitationPt*)
	(1)	(2)	(3)	(4)	(5)
Laboratory_dummy	0.678***	0.264***	0.385***	0.136***	0.246***
	(0.137)	(0.040)	(0.054)	(0.028)	(0.044)
R&D_Subsidy		0.020***	0.033***	0.019***	0.033***
		(0.004)	(0.006)	(0.003)	(0.005)
Controls	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry×Year FE	YES	YES	YES	YES	YES
Observations	11,991	11,991	11,991	11,991	11,991
Adjusted R^2	0.090	0.440	0.406	0.277	0.275

Notes. Standard errors in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are shown in Appendix A.

(Chemmanur et al., 2019), and other non-executive employees (Chang et al., 2015). We introduce *Human_capital* to test this influence channel. *Human_capital* is defined as the number of employees with Master's and Doctorate degrees. We first examine key laboratories' impact on human capital. As predicted, the results show that key laboratories can increase firms' human capital. Then, we augment our baseline model by including the human capital indicator as an explanatory variable; the results show that all coefficients for *Laboratory_dummy* and *Human_capital* are significantly positive. Hence, corporate key laboratories can drive innovation output by increasing human capital; this is accomplished by attracting and cultivating high-quality employees.

Finally, we explore the channel of R&D subsidy. By collecting the details of government subsidies received by Chinese listed companies over the years, we identify the items that belong to R&D subsidies. We define *R&D_Subsidy* as the natural log of a firm's R&D subsidy in a given year, and introduce it into our baseline model. We test whether corporate key laboratories promote innovation output by increasing R&D subsidies from the government. Panel C shows the results, wherein corporate key laboratory is shown to potentially increase R&D subsidies and stimulate innovation output.

6.5. Tests of potential competitive explanations

This section tests some potential competitive explanations to obtain corporate key laboratories' residual effects on innovation output. For the sake of brevity, we only tabulate key variables' coefficients in Online Appendix Table 6. These tests include: (a) controlling for firms that belong to universities (Hsu et al., 2021); (b) controlling for firms with a Center for Post-Doctoral Studies; (c) controlling for firms that own independent center research institutes; (d) controlling for firms that have Chief Scientific Officer positions; (e) controlling for firms' top management team diversity index (Cumming & Leung, 2021); (f) controlling for firms with a CEO with academic publishing; (g) controlling for firms with an inventor CEO; (h) controlling for firms with a CEO with overseas studying or working experience (Yuan & Wen, 2018); (i) controlling for firms with a CEO with a Ph.D. (He & Hirshleifer, 2022); (j) controlling for firms with a CEO who founded the company (Lee, Kim, & Bae, 2020); (k) controlling for firms with a CEO with political connections (Lin, Lin, Song, & Li, 2011); (l) controlling for firms with an overconfident CEO (Hirshleifer, Low, & Teoh, 2012); and (m) controlling for firms with a CEO with experience in finance (Custódio & Metzger, 2014).

7. Conclusions

It is widely known that innovation plays an essential role in stimulating countries' economic development and firms' competitiveness. Therefore, it is essential to have a deep understanding of corporate innovation's influencing factors. This study examines whether establishing a corporate key laboratory helps facilitate innovation output. Our results show that firms with key laboratories at the state or provincial levels produce more patents and citations than their counterparts, consistent with the theoretical predictions. Furthermore, corporate key laboratories contribute to the formation of explanatory and original innovation strategies. Key laboratories' promotion effects on innovation output are more significant when firms belong to high-tech industries, are led by an inventor or scientist CEO, and are located in cities with better IP protection environments. Corporate key laboratories also facilitate innovation, mainly by promoting corporate science, developing human capital, and attracting R&D subsidies for firms' innovation projects.

Firms and governments interested in supporting innovation will benefit from our findings. First, the results show that basic scientific research is not an activity supported exclusively by the public sector; corporate key laboratories also support such activities, and their role in the promotion of technological innovation is irreplaceable. Nonetheless, because basic research yields outcomes characterized as public goods, private companies have no incentive to invest in it. Simultaneously, basic scientific research is essential for improving firms' innovation capabilities, and having a key laboratory makes it easier for firm stakeholders to grasp the usefulness of cutting-edge scientific knowledge and transform it into technology or profitable products. This, in turn, forms the basis for companies to obtain sustainable advantages.

Second, corporate key laboratories are an indispensable part of innovation in China. Chinese private firms should focus on their long-term goals and balance the relationship between basic scientific research, applied technology research, and product innovation. It is also the external embodiment of corporate governance and business philosophy. After the 1980s, with the rise of the "shareholder supremacy" governance criterion in European and American firms, large American firms with strong innovation capacity began to reduce their long-term investments in basic research, divest research institutions, outsource basic scientific research to universities, and make firms' surplus flow to shareholders and executives. Firms in China should avoid this speculative tendency and explore the establishment of governance that encompasses technological innovation.

Finally, this study sheds light on innovation strategies for policymakers and enterprises. With the scientific and technological innovation system reform in China, the private sector now accounts for more than 75% of the total social R&D expenditure in the country. Hence, firms are becoming more significant in the national innovation system. In fact, across many emerging technological fields (e.g., 5G and artificial intelligence), the innovation strength of non-state-owned enterprises—for example, Huawei, Alibaba, Tencent, and Baidu—far exceeds that of colleges and universities. However, Chinese firms' basic scientific research, has been highly inadequate for a long time and needs improvements. The proportion of scientific research funds in the total internal R&D expenditure has remained at 5% for a long time, with more than 90% of these funds coming from public sources. Furthermore, private firm funds account for less than 3% of scientific research funds. Thus, the government should play a more active role in encouraging and supporting firms to conduct basic scientific research and invest money in this process.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chieco.2023.101954.

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