Research on the Mechanism of Technological Innovation Investment and Innovation Performance

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***Abstract*—Utilizing meticulously gathered data from prominent laboratories at the state and provincial levels within Chinese publicly listed corporations, this study demonstrates that these laboratories significantly enhance the innovative outcomes of firms. Enterprises that have state- or provincial-level laboratories outperform their peers by generating a higher volume of patents and accruing more citations. This study utilizes sophisticated econometrics techniques and consistently confirm the robustness of our core results. Moreover, the analysis results show that key laboratories can promote innovation, especially in high-tech companies, companies led by CEOs with scientific or invention backgrounds, and companies in cities that strictly enforce intellectual property laws. In addition, key laboratories primarily drive innovation by augmenting scientific research capabilities, enhancing human capital, and fostering increased government subsidies for research and development. These insights affirm that key laboratories significantly contribute to the advancement of firms, benefitting their stakeholders and the broader public within China's dynamic market.**

Index Terms—Business scientific activities, Company-based research center, Innovation, R&D grant, Workforce capabilities

I. INTRODUCTION

SCIENCE and technology are universally recognized as pivotal drivers of corporate expansion and competitive advantage in the technology sector [1][2]. Due to the critical importance of innovation and its concentrated focus within scientific communities, a substantial body of theoretical and empirical research has been dedicated to this subject [3][4][5]. This research encompasses a wide array of analyses, each exploring distinct aspects of innovation dynamics.

At the micro level, scholarly investigations have delved into the influence of various factors on organizational outco-self-confidence [9], corporate governance architecture [10], and organizational culture.

At the industry level, research has explored the catalysts of innovation, focusing on determinants such as market competition [11], intra-industry competition in the banking sector [12], the enforcement of intellectual property (IP) rights [13], evaluations by financial analysts [14], the impact of corporate taxation [15], the influence of institutional investors [16], and credit accessibility [17].

Additionally, numerous studies have examined the institutional characteristics that foster innovation, covering legal and regulatory frameworks [18], regional cultural norms [19], the level of financial development at the national scale [20], the implications of policy uncertainty [21], and the impact of religious beliefs [22]. Despite these extensive inquiries, relatively few scholars have systematically investigated the contribution of primary research facilities—research centers funded by both private and governmental entities to produce pioneering fundamental knowledge—to innovation output [23].

Basic scientific research is fundamental to technological advancement in contemporary society [24], yet it often involves significant financial outlays and yields limited immediate returns. Moreover, asset specificity is very important for investment decisions in the private sector [25]. The primary outputs from leading laboratories, characterized by their non-exclusivity, are considered collective benefits. This non-exclusivity allows competitors to access and use newly developed knowledge without incurring the associated costs. As a result, firms may not capture full returns on their investments in scientific research.

Furthermore, the pursuit of scientific research may clash with a company's primary obgective of maximizing profits. When private companies encourage their researchers to carry out basic scientific exploration, problems related to the agency also come up.This shift in focus can reduce emphasis on technological innovation and business development, leading to increased participation in academic pursuits that extend beyond the organization's core objectives [26].

The Chinese government issued the Outline of the National Plan for Medium-and Long-term for Scientific and Technological Development in 2005 to motivate companies to invest in fundamental research, promote innovation, boost R&D expenditures, and build scientific research centers. This strategic blueprint provides corporations with comprehensive guidelines for establishing their own scientific research institutions. National and provincial-level corporate core laboratories have become important components of China's innovation ecosystem, crucially supporting fundamental scientific research for industrial application, talent development, and fostering scientific and technological exchanges. Their primary responsibilities include conducting cutting-edge research crucial to national

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industries, undertaking foundational studies, advancing the industrial application of key scientific discoveries, and establishing benchmarks at global, national, and industry levels.

To support these pivotal laboratories, the federal government has enacted various policies, including tax incentives, grants, funding initiatives, government procurement strategies, and regulations on intellectual property transactions. These measures are designed to foster the growth and development of these essential research centers.

The specific research results are as follows: We have analyzed the manually managed data sets of Chinese listed companies that have established core laboratories at the national or provincial level during 2013-2018, and gained some valuable insights from them. Companies with core research facilities have shown a significant increase in patent output and received a broader range of positive citations. In addition, these research facilities tend to adopt both exploratory and inventive approaches to innovation. The impact of these facilities is particularly pronounced in high-tech firms, those led by CEOs with scientific or inventive backgrounds, and those located in urban areas with well-established intellectual property protection frameworks.

Our research identifies three key mechanisms for enhancing innovation at these research facilities. And this paper has managed to fill a significant void in the existing literature. As far as we understand, this study is the first to explore the extent to which corporate core laboratories impact innovation outcomes comprehensively and systematically, and innovation achievements are measured by the number of patents and which are measured by the number of patents and the frequency of citation. The data of empirical study are sourced from Chinese publicly listed companies. Despite facing international criticism regarding technological constraints, particularly in basic scientific research, China predominantly allocates its national funding for such research to public institutions, including state-owned facilities and universities. In contrast, these publicly listed companies produce a significant volume of academic publications.

Consequently, most fundamental scientific research in China is predominantly carried out by government agencies, universities, and public research institutions. Despite the crucial role played by these entities, current research on the impact of corporate central research facilities at the national and provincial levels on innovation outcomes remains rather scarce. In addition, the relationship between enterprise core laboratories and the effectiveness achieved by innovative initiatives has not been fully and in-depth studied.

In exploring how corporate central laboratories influence innovation, this study also addresses secondary issues related to endogeneity. These issues primarily arise from unobserved latent variables, reverse causal links, or sample selection biases. Therefore, this paper enriches the literature on the role of enterprise central laboratories in promoting innovation, employing various identification methods to tackle the challenges posed by these approaches.

To address endogeneity concerns, our methodology employs multiple approaches. We include fixed effects for both industry and year, along with interactive fixed effects that combine these two dimensions. We carried out the first difference analysis as well, all variables in the baseline model were transformed into their first differences, effectively eliminating cross-sectional differences between companies. Two instrumental variables (IV) were used: the number of scholars hailing from the same hometown as the company's headquarters, and the laboratory facilities run by other enterprises located in the same city and in the same industry in the same year. Moreover, the specific policies issued by the central government to support corporate central laboratories were considered as exogenous policy shocks. Finally, we employed propensity score matching (PSM) techniques to further refine our analysis."To analyze the relationship of the enterprise central laboratories to innovation, we used these methods to improve the results' reliability.

In order to address the shortcomings present in the literature, we have extracted some alternative indicators from carefully collected information, aiming to delve into aspects that have been overlooked in the past. At the corporate level, the data derived from state and provincial key laboratories are used to analyze trends in corporate research publications and evaluate metrics for corporate innovative approaches. It is noteworthy that our research focuses on the economic effects that have yet to be thoroughly explored in the national and provincial key laboratories of the Chinese enterprise sector.""Unlike previous studies on innovation in Chinese enterprises, our dataset provides a comprehensive description of the forward and backward citation indicators for patents obtained by Chinese listed companies. This holistic approach allows for a more nuanced assessment of corporate innovation prowess and strategic orientation.

Moreover, the role of scientific publications by Chinese corporations, which serves as an essential indicator of their research advancements, has been notably overlooked. This study transcends the traditional analysis of patent quantity and quality, delving into the broader impacts of pivotal laboratories on corporate innovation strategies. This approach has made a significant impact in the field and has provided these entities with deeper insights into building a more comprehensive innovation environment.

Here is how this research is structured: In Section 2, the relevant academic literature is reviewed, in addition, this part presents some hypotheses and a theoretical framework. In Section 3, we briefly describe the sampling framework, explain the statistical methods employed, and delve into the relevant methodologies. In Section 4, this section mainly presents the actual research results. In Section 5, we deliberate on potential endogeneity issues, which are particularly crucial for ensuring the reliability and robustness of our research results. In Section 6, we conducted an in-depth analysis of the variability in cross-sections and further validated the stability we discovered, while also investigating potential mechanisms and reviewing other possible explanations. Ultimately, in Section 7, we made a significant contribution to the academic discussion on innovation in Chinese enterprises.

II. Literature Review and Hypothesis Formulation

A. Institutional background of corporate scientific research in China

The framework for scientific and technological advancement in China is deeply rooted in a planned economic system, with significant influences from the former Soviet Union. This influence is manifested in the relative independence of sectors engaged in scientific research and production. This independence has been pivotal in forming China's innovation structure. Over time, China has developed an innovation landscape predominantly led by the Chinese Academy of Sciences, universities, research entities associated with central government departments, regional research organizations, and sectors in science, technology, and industry that are dedicated to national defense[27]. Before the 1985 reform of the science and technology system, China includes many research institutions. Among them were 122 scientific institutes under the Chinese Academy of Sciences, which mainly concentrated on scientific and applied research. Moreover, there were 622 domestic research centers affiliated with different government departments, which were mainly involved in industrial research and development. Furthermore, 3,946 regional research facilities were responsible for regional research and development, engineering design, and technology transfer services [28].

The National Medium- and Long-Term Science and Technology Development Plan Outline in 2005 was designed to encourage private enterprises to take a central position in the nation's innovation landscape by setting up dedicated research and development (R&D) facilities. Meanwhile, the "Notice on Implementing Several Supporting Policies for the National Medium- and Long- Term Science and Technology Development Plan" highlights the significance of enterprises establishing independent research bases. Subsequently, the "Guiding Opinions on Building National Key Laboratories through the Transformation of Institutions and Enterprises" further elaborated on this matter. It clearly defined tasks, goals, principles, responsibilities, processes, and qualification criteria. Therefore, the Chinese government has rolled out some support measures, such as tax incentives, financial assistance, government procurement policies, and strategic technology planning. The aim of all these measures is to stimulate independent innovation within the private sector. Additionally, when the Office of Scientific Innovation is responsible for managing multiple national-level scientific projects, they will first consider the foundational research facilities of enterprises and provide support for the construction, management, and research of these laboratories.

In 2012, the "Interim Measures for the Management of National Key Laboratories" provide classified guidance and macro-control for various types of laboratories in China and outline a series of specific requirements, principles, and measures to further fortify the country's innovation framework and inspire enterprises to conduct fundamental research. In line with these guiding principles, several provinces have rolled out relevant policies to support firms in setting up provincial level key laboratories. As a result, enterprise primary research facilities have become integral to the country's innovation ecosystem, complementing the functions of university laboratories. The core responsibilities of these enterprise laboratories include conducting fundamental and advanced technological research, contributing to the establishment of global, national, and industry standards, developing skilled personnel, and driving technological progress across various sectors.

The administrative divisions for science and technology are responsible for overseeing corporate main research centers. Their primary duties include drafting administrative regulations, formulating directives and strategies, and implementing overarching development plans. These bodies also authorize the initiation, progression, modification, and termination of projects, conduct evaluations and inspections, and provide support for the construction, operational funding, and policy framework of these centers. Enterprises, in turn, are tasked with the development and operation of these research centers. Their specific responsibilities include planning the establishment of key laboratories, allocating human resources, finances, and infrastructure, appointing laboratory directors and academic committees, and conducting annual evaluations of the corporate main research centers.

B. Enterprise primary research facilities and innovation

The motivations for private companies to engage in foundational scientific study can be categorized into four primary groups. Firstly, conducting primary scientific research within a private corporation's laboratory can effectively enhance in-house R&D capabilities. Furthermore, setting up corporate core research centers enables private enterprises to attract and retain top-notch researchers and engineers, especially those regarded as star scientists. This attraction often arises from the preference of certain scientists for a strong academic reputation and research opportunities, rather than higher financial compensation. Additionally, these laboratories enable corporate scientists to actively participate in academic conferences and strengthen their ties with external academic communities. As a result, the creation of enterprise primary research facilities allows firms to acquire and integrate new knowledge, keeping them at the forefront of research and innovation advancements.

Secondly, enterprise primary research facilities have the potential to elevate the academic and public standing of firms, expand their networks, and strengthen collaborations with external research organizations, such as universities. These collaborations not only enhance the corporate image but also facilitate the exchange of ideas and resources, which is critical for advancing corporate research agendas.

Thirdly, a company's scientific research capabilities significantly contribute to the utilization and commercialization of innovative technologies, thus improving overall efficiency. Corporate core research centers act as strategic channels for innovation discovery, they speed up the dissemination of new technologies, empowering companies to secure a competitive edge in the market. This role is crucial in transforming research outputs into commercially viable applications that drive business growth and sectoral innovation.

Finally, the establishment of corporate main research centers not only bolsters a company's in-house R&D capabilities but also directly influences its capacity for innovation. This impact largely depends on the scientific advancements and breakthroughs facilitated by the central laboratory. By prioritizing technological efficiency and targeting untapped markets, scientific research plays a pivotal role in corporate strategy. Moreover, corporate scientists can collaborate with external researchers who are pioneers in innovative technologies, aiding in the adaptation to external technological advancements. Engaging in research publications and participating in scholarly conferences are essential strategies for maintaining active involvement in external scientific networks. Corporate publications are vital for advancing both fundamental understanding and practical applications. Furthermore, these laboratories are of crucial significance in improving the utilization and commercialization of emerging technologies, which in turn promotes productivity.

Consequently, we propose the following hypothesis:

Hypothesis 1a. Corporate main research centers have a favorable impact on innovation outcomes.

However, two potential factors may hinder the innovative outcomes of corporate research centers. The first factor is the effect of traffic congestion, primarily driven by the rising costs of wages and equipment. Unlike applied research, corporate research centers heavily rely on the expertise of highly qualified scientists when conducting scientific exploration. As a result, the salaries of these scientists often constitute a significant portion of the total research expenses for the company. Furthermore, most of these scientists hold doctoral qualifications, which necessitate relatively high salaries due to their specialized knowledge.

Equipment costs in enterprise primary research facilities are not only substantial but also prone to rapid increases. As a consequence, when a company dedicates a greater amount of resources to laboratory - based research endeavors, it might lead to a reduction in investments directed towards applied research undertakings, for example, patent - related activities. Additionally, individual scientists face inherent limitations regarding the time and attention available for conducting experiments, writing papers, and submitting patent applications. This situation underscores the critical role of company-provided incentives in guiding the efforts of these researchers. Therefore, when corporate incentives are predominantly aligned with laboratory-based scientific research, researchers involved in these projects are more likely to focus their time and energy on conducting experiments and publishing articles, rather than engaging in activities directly related to innovation and patenting.

Hegde and Bhaskarabhatta [29] concluded that scientists responded to changes in the incentive structure associated with their innovative achievements through IBM's analysis. IBM has a policy that allows scientists to keep 25 to 50 percent of their revenue in patent applications. This policy shift resulted in a significant increase in inventive activities among scientists, accompanied by a notable decline in the number of research publications. These findings highlight the direct impact of incentive structures on the balance between patenting and publishing within corporate research environments.

The second factor is that research conducted in corporate main research centers may not consistently foster innovation, as inventive projects often receive less recognition within corporate scientific endeavors. This trend is evident in observations suggesting that the link between innovation and scientific research is becoming increasingly tenuous. Arora et al [23] emphasized that many innovations emerging from corporate science are more closely related to novel business strategies or models than to direct scientific breakthroughs. For example, innovative initiatives such as code scanning payment systems, bike-sharing projects, and online retail platforms represent significant advancements in business models, optimizing the efficiency of payment processing, transportation, and retail, rather than deriving directly from fundamental scientific research.

Considering these discussions, this paper proposes the following hypotheses:

Hypothesis 1b. Corporate main research centers have an adverse impact on innovation outcomes.

C. Mechanisms: Corporate scientific practices, intellectual assets, and R&D grants

China's corporate research centers have emerged as an essential component within the nation's innovation ecosystem. These facilities play a vital role in driving forward fundamental scientific research within an industrial setting. They are instrumental in luring and nurturing high-caliber talents, as well as in fostering scientific and technological exchanges. In China, the key aims of these major corporate research centers are to carry out state-of-the-art, collaborative technological research that has immediate industrial applicability. They also focus on promoting the conversion and industrial application of basic research outcomes. Additionally, they strive to make contributions to the establishment of global, national, and industry-specific technical standards.

Moreover, the core research centers of enterprises have emerged as pivotal components of China's innovation system. Laboratories are of great significance in propelling fundamental scientific research in the industrial milieu. They are instrumental in drawing in top-notch talent and strengthening technological interaction. The primary objectives include conducting cutting-edge, collaborative research on fundamental industrial technologies, accelerating the transformation and industrial application of research results, and contributing to the formulation of global, national, and specific industry technical standards.

In China, when it comes to assessing a company's capability to conduct basic scientific research, the publication record often serves as a common yardstick. This publication record, in turn, plays a pivotal role in establishing benchmarks at both the national and industry levels. The national standardization system, comprising the government and selected companies, highlights that active participation in benchmark development can significantly enhance a company's reputation and attract potential collaborators for innovation. Studies indicate that companies involved in benchmark - setting frequently integrate their technical specifications or patents into standards, which is aimed at advancing their own interests. Highly competitive enterprises can utilize the establishment of benchmarks to enhance their market standing. In contrast, those with less competitiveness might strive to set standards that set them apart from their competitors. Additionally, companies in highly competitive environments often participate in collaborative innovation projects with other benchmark-setting entities. This involvement not only attracts high-quality innovation partners but also fosters information exchange, organizational learning, and idea sharing—key elements for driving innovation.

Hypothesis 2. Corporate main research centers encourage innovation by stimulating corporate scientific endeavors.

As noted, corporate main research centers significantly enhance a company's intellectual assets by attracting renowned scientists. These top-tier scientists bring new expertise and competencies, fostering innovative initiatives and creating pathways into professional and scientific networks. Through these networks, businesses can collaborate with other research teams, enhancing their innovative capacity. Additionally, promoting the publication of research articles boosts a company's reputation in the talent marketplace. Prospective employees, particularly those attracted by the presence of renowned scientists, may view these companies as valuing scientific expertise and offering opportunities for collaboration and professional growth.

Scientists often gravitate toward companies with prestigious laboratories, primarily for career advancement opportunities [41]. Working in these settings not only fulfills their intellectual curiosity but also aligns with their academic career goals, thereby opening further professional opportunities [53]. This engagement facilitates their ability to maintain strong connections with the academic community and establish a scholarly reputation. Research suggests that scientists risk losing visibility within academic circles if they fail to publish their findings promptly. Given that scientists are frequently driven by strong intrinsic motivation and may not require significant material incentives, companies with leading laboratories can more easily attract top talent.

Hypothesis 3. Corporate primary research centers can foster innovation by attracting intellectual resources.

Given the high uncertainty and inherent risks associated with innovation projects, many forward-thinking companies encounter financial constraints that significantly impact their R&D investments. Government-sponsored R&D subsidies are crucial in supporting corporate innovation efforts. Main research laboratories serve as conduits for companies to secure financial grants and direct government support for their scientific research activities. For example, in the relevant regulations promulgated by Guangdong Province, the ratio of new funds from provincial major companies research centers to provincial financial resources is greater than 2:1. On this basis, Guangdong Province will also subsidize the research facilities and equipment of key provincial research and development institutions and provide corresponding supporting policy assistance. Additionally, it is expected that relevant municipal agencies will offer at least 1:1.3 in additional funding support. The Annual Report of Hebei Key Laboratory for 2020 indicates that internal investment constitutes a substantial portion of funding for key laboratories, with government investment also playing an essential role.

Furthermore, corporate core research centers can substantially enhance a company's standing in both academic and industrial arenas. And this boosts its credibility regarding innovation capabilities, product quality, scientific contributions, and tacit knowledge. For small-scale, micro-sized enterprises and newly-founded startups, the establishment of such centers represents a strategic step towards luring prospective investors. Publishing scientific research plays a critical role in securing external grants, subsidies, or contracts, while a strong academic reputation can boost a firm's profitability and valuation, foster a favorable investment climate, and reduce capital costs. Reduced capital costs, in turn, enable companies to augment their R&D investments. Thus, we put forward the hypothesis 4 as follows:

Hypothesis 4. The main research centers of corporations are capable of spurring innovation by obtaining R&D grants for innovative projects.

III. Research Design

A. Data sources

This study analyzes some Chinese enterprises. According to the specific information provided by the inventors, there is an obvious time difference between the date of patent application and the date of grant, with the average time difference reaching two years [30]. Given that the coverage of this patent database is restricted to 2021, patent applications submitted in 2019 and 2020 may be insufficient, as this database only covers patents that have already been granted. This is because the database solely includes patents that have already been approved. Taking this limitation into account,"In accordance with the guidance from Chang et al. [30], we completed our sample extraction work by the end of 2018. In our analysis, we excluded publicly traded financial institutions due to their distinct financial statements and organizational structures. Additionally, companies undergoing specific treatments (such as ST, *ST, and PT) and those providing incomplete data were not considered. Once these screening criteria were adopted, the final dataset included 13,045 fixed annual observation data points.

In this analysis, the existence of a corporate central laboratory is regarded as a core variable. Within a fiscal year, if a company manages more than one such facility at the provincial level or above, it is considered to own such a laboratory. Data related to the company's flagship research laboratories are carefully compiled from the annual reports of listed companies and can be accessed on the official websites of the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The rest of the information can be obtained from the Science and Innovation Office, PRC and provincial science and technology departments, etc. The subsequent data collection work covered information from the official websites of well-known listed companies, such as Shanghai Pharmaceutical Holdings Co., Ltd., as well as the National Key Laboratory of Innovative Drugs and Drug Technologies.

In this analysis, the innovation results of listed companies are a variable influenced by other factors, assessed by the number of patents obtained. The information on patent authorization is obtained from the National Intellectual

Property Administration (CNIPA). We cross-checked the comprehensive data from three reliable sources: the Innojoy global patent database, Google Patents, and the WinGo database in order to assess the quality of the companies' innovation outcomes. These well-known platforms offer us profound perspectives on patents and their citation situations. As a result, this allows for a thorough evaluation of the innovation quality.

Moreover, the information concerning the financial and management indicators of enterprises is obtained from highly-regarded databases. This batch of data is sourced from multiple platforms, such as the China Stock Market and Accounting Research (CSMAR) database, the China Research Data Service Database, the WIND database, the RESSET database, the CnOpen CCER database, and the Baidu search function is also utilized for data collection when necessary.

B. Models

Using the empirical framework established in previous research [30][31], we investigate the enterprise flagship laboratory's impact on innovation outcomes with the subsequent fundamental regression model.

$$Ln(1+Innovations_{i,t}) = \alpha_0 + \alpha_1 Lab\_dum_{i,t} + \sum_{j=2}^{15} \alpha_j X_{i,t} + Industry + Year + Industry \times Year + \varepsilon_{i,t} \tag{1}$$

Where the reliant variable, $Innovation_{i,t}$, measures both the quantity and caliber of company i's innovation achievements during year t. The primary test factor is $Lab\_dum_{i,t}$, denoting the binary variable for the enterprise central laboratory at either the national level or the provincial level. Furthermore, several variables for control purposes are integrated into the model, encompassing *R&D*, *Size*, *Firmage*, *PPE*, *Sales*, *ROA*, *MB*, *Salesgrowth*, *Lev*, *Cashratio*, *Stockvolatility*, Stockreturn, *SOE*, *Institute*, *Industry*, *Year*, and *Industry×Year*.

C. Variables

In the following part, we'll detail where the data originated from and the methods employed to formulate the key variables for our analysis. Moreover, we offer an in - depth account of every variable presented in Supplementary Table I. This comprehensive elaboration guarantees transparency and promotes a lucid comprehension of the empirical basis underpinning our research.

Dependent variable: Creative productivity

Building upon the research findings presented by Gao et al. in their work [31], we employ a set of four distinct metrics to evaluate the innovation performance. The initial metric, denoted as Ln(Pat), is calculated in the following manner: we take the natural logarithm of the sum of the total number of patents a company both applied for and was ultimately granted during a specific year, and then we add one to this value. The second metric, designated as Ln(Cit), is computed by first determining the cumulative number of citations that all the patents held by the company have received over time. Then, we take the natural logarithm of this cumulative citation count and increment the result by one.

Newly granted patents typically attract fewer citations, which may lead to truncation bias.

In order to reduce this risk, this paper refers to the method proposed by Hall et al. [32]. The specific approach to adjusting our citation-technique metric is as follows: First, we need to determine the average frequency of positive citations a patent receives within its specific technical field, along with the year it was submitted. We will refer to this average as the average value for the type year. Next, we will calculate the average of all patent forwarding citations across all years within the same technical category, which we will record as the average value for the type. Following that, we constructed a citation correction factor to standardize citation count over time and interpreted the variations across different technical categories [54][55][56][57][58]. By adopting a type-average annual method for adjusting the annual averages, we calculated the relevant factors for each type of technology and the years of their application. In this paper, the inverse of the forward citation count is multiplied by the citation adjustment factor in order to enhance the accuracy of the citation count for each patent. In the final stage, we compiled all the adjusted patents granted to listed companies within a specific application year, along with their forward citations.

Furthermore, this research aims to assess the influence of key enterprise research centers on innovation results. These results are highly dependent on the contributions made by innovation-related experts like engineers and scientists. Based on this, we define the third indicator as Ln (PPt), and Ln (PPt) as the natural logarithm of the ratio of 1 to every 1,000 employees. And the fourth indicator is Ln (CPt). Ln(CPt) refers to the value obtained after taking the natural logarithm of the reference counts for every 1,000 employees.

Test variable: Company's leading research laboratory

Lab_dum is a binary variable. If a company possesses at least one national or provincial level central laboratory, it is assigned a value of 1; in the absence of such a laboratory, it is assigned a value of 0 in a given year. Notably, the standing of a company's flagship laboratory in China is subject to change. Additionally, we have introduced two supplementary binary variables."Lab_s_dum and Lab_p_dum. If a company has at least one flagship laboratory at the national level, Lab_s_dum takes the value of 1; if not, Lab_s_dum takes the value of 0. Likewise, when a company has a minimum of one provincial - level flagship laboratory, the variable Lab_p_dum is set to 1. In contrast, if the company doesn't have any provincial - level flagship laboratories, Lab_p_dum is set to 0.

Control factors

Current research highlights that numerous corporate attributes and external variables are important to corporate innovation [30][31]. Accordingly, we incorporate a comprehensive set of variables for adjustment to account for diverse influences, including Research and Development (*R&D*) expenses, Company Size, Firm Age, Property, Plant, and Equipment (*PPE*), Sales, Return on Assets (*ROA*), Market-to-Book Ratio (MB), Sales Growth, Leverage (*Lev*), Cash Ratio, Stock Volatility, Stock Return, State-Owned Enterprise Status (*SOE*), Institutional Affiliation (*Institute*), Industry Category, and Year, as well as an *Industry×Year* interaction term. Moreover, in order to guarantee robustness and reduce the influence of outliers, we apply data trimming methods to continuous variables, with a threshold set at 1%.

IV. Empirical Analyses

A. Descriptive statistics

Table I provides us with a detailed overview, illustrating the distribution of corporate primary research centers classified by year and industry. The figures in the first column correspond to the overall count of enterprises. The second column presents the quantity of key research facilities housed within these enterprises. As for the third column, it shows the percentage that these key research facilities account for within the companies. The extensive dataset comprises 13045 entries, spanning from 2013 to 2018. In 2013, only 5.75% of the companies possessed a laboratory, but this percentage increased to 14.51% by 2018. This upward trend highlights the influence of various government policies aimed at encouraging the establishment of laboratories and enhancing advanced scientific research within the private sector.

TABLE I
Distribution of the Dataset by Year and Industry

Panel A: Dataset by year and industry			
Year	(1)	(2)	(3)
2013	1802	134	5.75
2014	1802	70	4.52
2015	1946	299	13.06
2016	2120	224	11.24
2017	2257	288	13.95
2018	2266	305	14.51
Total	13045	1346	10.78
Panel B: Distribution of the sample across sectors			
Industry	(1)	(2)	(3)
Manufacture of special purpose machinery	855	85	9.55
Production of chemical base materials and chemical goods	978	121	12.23
Production of healthcare products	815	128	15.24
Manufacture of automobiles	478	69	13.95
Manufacturing of electrical machinery and equipment	993	165	16.28
Production of computers, communication devices, and related electronic equipment	1451	123	8.75
Manufacture of general-purpose machinery	578	81	14.54
Processing and forming of non-ferrous metals	345	45	16.35
Manufacture of rubber and plastics	296	42	12.55
Software and information technology services	642	48	7.84
Metal products	281	35	12.55
Nonmetal mineral products	345	32	9.71
Manufacture of measuring instruments	188	32	16.21
Food manufacturing from agricultural crops	176	26	14.27
Building projects	284	29	9.49
Textile industry	180	25	11.46
Food manufacturing	165	21	19.82
Refining and shaping of iron-based metals	158	23	16.52
Polytechnic services	112	18	17.48
Farming	46	12	25.52
Chemical fiber	120	11	9.16
Paper-making and paper products	145	12	11.25
Production of alcoholic beverages and refined tea products	185	14	9.85
Production of railway, maritime, aerospace, and other transportation-related machinery	163	18	10.26
Other	2415	121	4.87
Total	13045	1362	10.72

Panel B showcases the distribution of companies' key research facilities among different industries. The five sectors in which laboratories are most frequently present are as follows. The Electrical Equipment and Machinery sector has 165 companies, which represent 12.11% of the total number of enterprises within this particular sector. The Production of Medical Products sector includes 123 companies, accounting for 9.03% of the overall count in its sector.

Within the domains of computers, communications, and other electronic devices, 121 manufacturing-engaged companies are present, making up 8.88% of the quantity of companies within this industry. 121 companies are also involved in the production of chemical products, constituting 8.88% of the total production volume within this sector. Finally, 85 companies collectively make up the specialized machinery manufacturing sector, accounting for 6.24% of the total production volume in their respective fields.

Across panels A, B, and C, Table II presents the descriptive statistics of each variable. Regarding the key innovation indicators, the average value of Ln (Pat) is 1.256 and the standard deviation is 1.374. Meanwhile, for Ln(Cit), the mean stands at 1.885 and the standard deviation is 1.802. Additionally, the mean and standard deviation for Ln(PPt) and Ln(CPt) are 0.754 and 1.415, as well as 0.846 and 1.718. It is very clear that the quantity and quality of innovation output are very different between different enterprises. Lab_dum is 0.182 out of all the independent variables. This indicates that in 18.2% of the annual observation data of enterprises, there is a top-tier laboratory. The average values of Lab_s_dum and Lab_p_dum are 0.057 and 0.049, respectively. This data reveals that 5.7% and 4.9% of the observations are related to at least one major laboratory at the national and provincial levels.

TABLE II
Summary of Key Variable' Statistics

	Mean	Std. Dev.	P25	Median	P75
Panel A: Dependent variables					
Ln(Pat)	1.256	1.374	0.001	1.085	1.815
Ln(Cit)	1.885	1.802	0.000	1.632	3.012
Ln(PPt)	0.754	0.846	0.000	0.485	1.419
Ln(CPt)	1.415	1.718	0.000	0.945	2.856
Panel B: Independent variables					
Lab_ dum	0.182	0.384	0.000	0.000	0.000
Lab_s_dum	0.057	0.652	0.000	0.000	0.000
Lab_p_dum	0.049	0.225	0.000	0.000	0.000
Panel C: Control variables					
R&D	10.346	3.719	9.715	10.718	12.574
Size	14.521	1.419	13.245	15.365	13.625
Firmage	2.356	0.652	1.615	2.246	2.845
PPE	5.859	1.066	5.052	5.675	6.042
Sales	6.718	0.884	6.119	6.695	7.365
ROA	0.046	0.087	0.043	0.052	0.098
MB	0.916	1.021	0.345	0.595	1.419
Salesgrowth	0.188	0.384	-0.024	0.116	0.352
Lev	0.457	0.242	0.395	0.446	0.588
Cashratio	0.196	0.184	0.075	0.185	0.175
Stockvolatility	0.046	0.023	0.046	0.034	0.046
Stockreturn	0.158	0.585	-0.346	-0.023	0.393
SOE	0.375	0.499	0.002	0.001	1.004
Institute	0.419	0.246	0.195	0.416	0.815

Statistics for the control variables in panel C are given in Table II. The figures for R&D, company size, and the average age of the company stand at 10.346, 14.521, and 2.356 respectively. Additionally, the average value of property, plant, and equipment (PPE) reached 5.859, sales amounted to 6.718, the ROA was 0.046, the MB was 0.916, sales growth was 0.188, leverage (Lev) was 0.457, and the cash ratio was 0.196." The volatility of the stock is 0.046, the stock return rate is 0.158, the status of state-owned enterprises (SOE) is 0.375, while the value for institutional associations (research institutes) is 0.419. This batch of statistical data provides us with an in-depth insight into the distribution of the data and its characteristics.

B. Correlation examination

We calculated the correlation coefficients and observed notably strong positive correlations between our primary test variable, *Lab_dum*, and proxies for innovation output, including *Ln(Pat)*, *Ln(Cit)*, *Ln(PPt)*, and *Ln(CPt)*. These results imply a positive association between the existence of corporate main research centers and innovation output. Moreover, the majority of control variables display significant correlations with the dependent variables, which validates their incorporation into the analysis. It should be stressed that the level of association is comparatively low among the explanatory variables. This implies that the probability of multicollinearity occurring in our research is restricted.

C. Univariate analysis

Subsequently, we carried out a univariate analysis. Table III provides a comprehensive display of the results from univariate evaluations comparing companies possessing key laboratories and those lacking them. When considering those companies that do not possess key laboratories, the mean values calculated for the variables Ln(Pat), Ln(Cit), Ln(PPt), and Ln(CPt) are determined to be 1.045, 1.715, 0.652, and 1.352 in that order. In contrast, companies with key laboratories report mean values of 1.415, 2.316, 0.718, and 1.412 for these variables. These significant differences statistically highlight the connection between the existence of a core laboratory and higher quality innovative outcomes.

TABLE III
UNIVARIATE EXAMINATION OF THE DIFFERENCE IN MEANS BETWEEN THE PRIMARY DEPENDENT AND INDEPENDENT VARIABLES IN COMPANIES WITH AND WITHOUT A PRIMARY LABORATORY

	Without key laboratory		With key laboratory		Differences
	Obs	Mean	Obs	Mean	*T* value
Ln(Pat)	10,685	1.045	1349	1.415	-0.452***
Ln(Cit)	10,685	1.715	1349	2.316	-0.696***
Ln(PPt)	10,685	0.652	1349	0.718	-0.245***
Ln(CPt)	10,685	1.352	1349	1.412	-0.362***
R&D	10,685	10.847	1349	10.482	-1.152**
Size	10,685	14.126	1349	16.445	-0.985**
Firmage	10,685	2.346	1349	2.748	-0.046**
PPE	10,685	5.895	1349	5.958	-0.199**
Sales	10,685	6.613	1349	6.716	0.001
ROA	10,685	0.058	1349	0.043	-0.003**
MB	10,685	0.916	1349	0.912	0.035
Salesgrowth	10,685	0.284	1349	0.165	0.005
Lev	10,685	0.471	1349	0.425	0.009
Cashratio	10,685	0.416	1349	0.184	0.006***
Stockvolatility	10,685	0.049	1349	0.042	-0.000
Stockreturn	10,685	0.246	1349	0.095	0.045***
SOE	10,685	0.385	1349	0.415	0.002
Institute	10,685	0.715	1349	0.395	-0.002

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

D. Results of the multivariate analysis

Table IV presents the results of the multiple regression analyses for all the control variables. The coefficient of Lab_dum is remarkably significant, with a value of 0.294. This suggests that a single unit increase in Lab_dum is associated with a 29.4% increase in the quantity of patents. Moreover, statistically speaking, a positive relationship exists between a company's main research equipment and Ln(Cit). More specifically, for each additional unit of Lab_dum, the number of citations also increases by 45.8%. The values of the coefficients for both Ln(PPt) and Ln(CPt) are statistically significant, at 0.273 and 0.276 respectively. In fact, when the Lab_dum value changes from 0 to 1, on average, for every 1,000 employees, the quantity of patents experiences a 0.273 growth, while the quantity of citations sees a 0.276 increase. These research findings underscore the pivotal role of a company's primary research facilities in enhancing innovative outcomes.

TABLE IV
THE INFLUENCE OF ENTERPRISE PRIMARY RESEARCH FACILITIES ON INNOVATION PERFORMANCE

	Ln(Pat) (1)	*Ln(Cit)* (2)	*Ln(PPt)* (3)	*Ln(CPt)* (4)
Lab_dum	0.294**	0.458***	0.273***	0.276***
	(0.057)	(0.064)	(0.046)	(0.035)
R&D	0.086***	0.273***	0.058**	0.056***
	(0.006)	(0.091)	(0.003)	(0.043)
Size	0.473***	0.548***	0.054	0.049***
	(0.061)	(0.037)	(0.088)	(0.034)
Firmage	-0.076***	-0.088***	-0.046***	0.723***
	(0.091)	(0.094)	(0.038)	(0.091)
PPE	-0.084***	-0.376***	0.046***	0.024
	(0.016)	(0.094)	(0.017)	(0.066)
Sales	-0.037	-0.037	0.186***	0.736***
	(0.046)	(0.058)	(0.046)	(0.025)
ROA	0.946***	1.122***	0.739***	0.864***
	(0.258)	(0.364)	(0.253)	(0.734)
MB	-0.149**	-0.294*	-0.064***	-0.194***
	(0.050)	(0.046)	(0.057)	(0.028)
Salesgrowth	-0.027	0.028	0.078	0.046
	(0.094)	(0.054)	(0.096)	(0.033）
Lev	-0.158	-0.273	-0.736*	-0.312***
	(0.130)	(0.143)	(0.064)	(0.143)
Cashratio	0.191	0.176	0.376**	0.399***
	(0.188)	(0.219)	(0.145)	(0.186)
Stockvolatility	0.746	2.046	4.768***	6.045***
	(2.135)	(2.848)	(1.491)	(2.724)
Stockreurn	-0.003	0.027	0.058	0.061
	(0.049)	(0.046)	(0.046)	(0.046)
SOE	0.365**	0.394*	0.146**	0.246***
	(0.037)	(0.058)	(0.058)	(0.063)
Institte	-0.022	-0.058	-0.073	-0.273
	(0.058)	(0.146)	(0.011)	(0.064)
Constant	-6.763***	-8.512*	-1.046***	-2.764***
	(0.445)	(0.419)	(0.294)	(0.194)
FE	YES	YES	YES	YES
Obs	11,273	11,273	11,273	11,273
Adj_R^2	0.584	0.584	0.391	0.446

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

In terms of controlling variables, most coefficients show significance, consistent with previous research findings. R&D is considered a key factor in promoting innovative initiatives. For the four innovation output indicators, R&D shows a positive correlation in each case. Furthermore, elements like firm size, *ROA*, and the status of being a *SOE* all have remarkably positive coefficients. This implies that bigger enterprises, those boasting higher ROA, and state-owned firms are more inclined to generate a larger quantity of patents and citations. As a result, they can boost innovation output. However, for the two control variables, firm age and MB, both of them show a negative correlation with innovation output. This indicates that companies with a longer operating history and those having higher market-to-book ratios are likely to have less innovation output. The possible reason could be a reduction in the motivation for innovation.

V. Endogeneity Issues

The findings of the research suggest that the main research facilities within enterprises exert a positive influence in promoting innovation performance. However, it is crucial to acknowledge that these conclusions are susceptible to endogeneity issues, including the omission of relevant variables and potential biases due to reverse causality [58][59][60]. Despite the inclusion of various controls in our baseline model, there may still be omitted variables, as suggested by prior research, that could obscure the true effect of enterprise primary research facilities on innovation performance.

For instance, there could be unaccounted factors that influence the effectiveness of a key laboratory in driving innovation. Moreover, concerns about reverse causality suggest that the observed positive effects of corporate primary research facilities on innovation performance might be attributable to companies that are inherently more innovative and thus more likely to establish such facilities, possibly supported by governmental initiatives.

In this chapter, we employed various research methods to explore the causal relationships between corporate basic research facilities and how these relationships influence innovation performance. Initially, we integrate potential undisclosed factors into our regression model. Subsequently, we address the concern of endogeneity using techniques such as first-differencing, instrumental variable estimation, analysis of laboratory incentive policy shocks, and Propensity Score Matching (*PSM*).

A. Tests for variables possibly left out and assessments for reverse causation

While the government offers monetary incentives, establishing and maintaining a corporate key laboratory involves significant financial investments.

Therefore, in the environment of key laboratories [33], financial constraints become particularly critical, which also affects the funding of innovative projects. Consequently, we decided to include Kaplan and Company's [34] financial constraint index (KZ index) and the White and Wu [35] index (WW index) in our evaluation criteria, with the aim of gaining a deeper understanding of how financial restrictions impact innovation activities.

Once the baseline model was revised to incorporate these two indices, the positive coefficients of Lab_dum endured. In essence, the fundamental findings maintain their stability and robustness, even when financial constraints are taken into consideration. Moreover, as shown in Panel A of Table V, the KZ index and the WW index have a negative influence on innovation output.

TABLE V Assessments for Overlooked Factors and Reverse Causality (Panel A to Panel D)

	Ln(Pat)	*Ln(Cit)*	*Ln(PPt)*	*Ln(CPt)*
	(1)	(2)	(3)	(4)
Panel A: Addressing financial limitations				
Lab_dum	0.346***	0.586***	0.228***	0.389***
	(0.027)	(0.093)	(0.055)	(0.036)
KZ_index	-0.043***	-0.048	-0.035***	-0.007
	(0.008)	(0.023)	(0.009)	(0.064)
WW_index	-0.764***	-1.059***	-0.275	-0.172
	(0.649)	(0.655)	(0.482)	(0.336)
Obs	11,875	11,875	11,875	11,875
Adj_R^2	0.215	0.228	0.256	0.186
Panel B: Managing corporate governance				
Lab_dum	0.467***	0.456**	0.295**	0.284***
	(0.058)	(0.038)	(0.038)	(0.042)
G_index	0.046***	0.039**	0.046**	0.038**
	(0.024)	(0.090）	(0.038）	(0.035)
Board_size	0.023***	0.024**	0.045**	0.032***
	(0.037）	(0.028)	(0.003)	(0.028)
Duality	0.058	0.048**	0.015	0.098
	(0.027)	(0.037)	(0.065)	(0.042)
QFII	0.046***	0.086***	0.028***	0.058**
	(0.094)	(0.052)	(0.314）	(0.032)
Obs	11,875	11,875	11,875	11,875
Adj_R^2	0.456	0.423	0.295	0.286
Panel C: Accounting for regional economic expansion and innovation status at the local level				
Lab_dum	0.197**	0.429***	0.195***	0.985***
	(0.069)	(0.084)	(0.035)	(0.032)
Ln(local_gdp)	-0.086	-0.056	-0.058	-0.054
	(0.094)	(0.045)	(0.037)	(0.087)
GDP_growth	0.046***	0.059***	0.028***	0.38***
	(0.022)	(0.022)	(0.006)	(0.025)
Ln(local_patents)	0.076***	0.146***	0.028	0.072
	(0.058)	(0.063)	(0.039)	(0.056)
Ln(local_papers)	0.034	0.032	0.028	0.068
	(0.061)	(0.019)	(0.014)	(0.043)
Ln(tech_trans)	0.058	0.027	0.028	0.029
	(0.023)	(0.055)	(0.065)	(0.042)
Obs	11,845	11,845	11,845	11,845
Adj_R^2	0.374	0.446	0.286	0.395
Panel D: Taking government support for innovation into account				
Lab_dum	0.319***	0.404**	0.166***	0.299**
	(0.034)	(0.064)	(0.068)	(0.048)
IPP_index	0.002	0.001	0.002	0.009
	(0.022)	(0.002)	(0.003)	(0.002)
Ln(local_R&D_fee)	0.176	0.346***	0.078	0.345
	(0.273)	(0.173)	(0.028)	(0.363)
Local_R&D_ratio	0.003	-0.049	0.002	-0.008
	(0.063)	(0.046)	(0.046)	(0.022)
Ln(gov_R&D)	-0.058	-0.156	-0.035	-0.284
	(0.127)	(0.194)	(0.028)	(0.145)
Gov_R&D_ratio	0.003	0.027	0.006	0.008
	(0.025)	(0.027)	(0.003)	(0.002)
Obs	11,845	11,845	11,845	11,845
Adj_R^2	0.437	0.556	0.395	0.288

Notes. The model used in this article is consistent with the model in Table IV. In all regression analyses, all control variables were included. This brought stable effects for the industry, year, and the combination of industry and year. In simple terms, it only presented the estimated coefficients of the variables in the regression analysis. The standard errors are placed in parentheses and categorized by company. *, **, and *** exhibited significant significance at 10%, 5%, and 1% levels.

Previous studies have confirmed that one factor influencing innovation activities is the corporate governance structure. Given that the company's core research facilities are of high value, it is essential to recruit experts from various fields and establish collaborations with the government and universities to ensure effective management and internal monitoring of these laboratories. Therefore, in our benchmark model, we have included several governance indicators. These indicators include the Governance Index

(*G-Index*) formulated by Gao Bo et al. [36], the size of the board (Board_Size), the duality of the CEO, and the proportion of Qualified Foreign Institutional Investors (QFII) among the shareholders. After the model was re-implemented, the data in Table V, Panel B, shows that these management variables did not affect the main research findings.

TABLE VI ASSESSMENTS FOR OVERLOOKED FACTORS AND REVERSE CAUSALITY (PANEL E to PANEL H)

	Ln(Pat)	*Ln(Cit)*	*Ln(PPt)*	*Ln(CPt)*
	(1)	(2)	(3)	(4)
Panel E: Adjusting for innovation levels in local colleges				
Lab_dum	0.294***	0.446***	0.186**	0.394***
	(0.020)	(0.037)	(0.026)	(0.028)
Ln(coll_R&D_fee)	0.064	0.046	0.024	0.022
	(0.043)	(0.046)	(0.045)	(0.045)
Ln(coll_papers)	-0.027	0.046	0.028	0.008
	(0.089)	(0.141)	(0.018)	(0.095)
Ln(coll_patents)	0.027	0.098	0.002	0.008
	(0.053)	(0.037)	(0.035)	(0.035)
Ln(coll_patents_trans)	0.024	0.009	0.028	0.009
	(0.008)	(0.022)	(0.008)	(0.036)
Obs	11,845	11,845	11,845	11,845
Adj_R^2	0.436	0.437	0.284	0.253
Panel F: Taking local cultural factors into account				
Lab_dum	0.736***	0.446***	0.146**	0.298***
	(0.040)	(0.091)	(0.027)	(0.047)
Lottery_cul	0.064	0.084	0.019	0.028
	(0.063)	(0.064)	(0.046)	(0.055)
Religion_cul	-0.022	-0.008	-0.028	-0.046
	(0.069)	(0.066)	(0.009)	(0.032)
Confucian_cul	0.049	0.137	0.088	0.129
	(0.089)	(0.046)	(0.092)	(0.128)
Obs	11,845	11,845	11,845	11,845
Adj_R^2	0.422	0.449	0.292	0.246
Panel G: Accounting for urban and urban-year fixed effects				
Lab_dum	0.294**	0.273***	0.123***	0.955**
	(0.062)	(0.028)	(0.065)	(0.058)
Obs	11,321	11,321	11,321	11,321
Adj_R2	0.542	0.439	0.295	0.286
Panel H: Adjusting for prior innovation achievements				
Lab_dum	0.046***	0.273***	0.058***	0.062***
	(0.032)	(0.091)	(0.024)	(0.045)
Past innovation success	0.946***	0.762***	0.628***	0.519**
	(0.038)	(0.043)	(0.035)	(0.022)
Obs	9843	9843	9843	9843
Adj_R^2	0.673	0.542	0.527	0.528

Notes. The model used in this article is consistent with the model in Table IV. In all regression analyses, all control variables were included. This brought stable effects for the industry, year, and the combination of industry and year. In simple terms, it only presented the estimated coefficients of the variables in the regression analysis. The standard errors grouped by company are presented in parentheses. Significance is indicated by *, **, and ***, representing significance levels of 10%, 5%, and 1%, respectively.

The regional development and cultural characteristics of the province where the company operates can significantly influence the relationship between the company's primary research facilities and innovation output. Companies typically locate in areas with strong economic growth and high levels of innovation characteristics to better leverage local markets and innovation resources[37][38]. Therefore, we incorporate several regional variables into our baseline regression model. The variables consist of the following: the natural logarithm of the provincial regional GDP, denoted as Ln(local GDP); the year-on-year growth rate of the regional GDP of the province, called GDP growth; the natural logarithm of the total number of patents granted in the province, symbolized as Ln (Local_Patents); the natural logarithm of the total number of scientific papers published in the province (Local_Papers); and the natural logarithm of the total technology transactions within the province (Tech_Trans). Ln (Local_GDP) and GDP_Growth are applied to gauge the local economic growth level. In contrast, Ln (Local_Patents), Ln (Local_Papers), and Ln(Tech_Trans) serve as proxies for measuring local innovation levels. The results displayed on the C panel of Table V confirm that, even when taking into account local economic growth and innovation levels, our main findings remain robust.

We also consider the potential influence of government support on enterprise primary research facilities and technological innovation, which may have been previously overlooked [5][39]. To address this, we include indicators of government support in our analysis.These indicators consist of the following elements: the natural logarithm of the total R&D investment expenditure in the province is marked as Ln(Local_R&D_Fee); the proportion of provincial R&D investment to the regional Gross Domestic Product (GDP) is termed Local_R&D_Ratio; the natural logarithm of the provincial government's investment in R&D activities is denoted as Ln(Gov_R&D); the ratio of the provincial government's R&D investment to the total R&D investment is referred to as Gov_R&D_Ratio, and the provincial Intellectual Property Protection Index is called IPP_Index. As indicated by the results presented in Panel D of Table V, the positive effect of enterprises' primary research facilities on innovation output persists unchanged, even when the degree of government support is taken into consideration.

Enterprise primary research facilities are pivotal in conducting market-driven fundamental research and advancing application technologies, establishing a robust link with foundational research undertaken in academic laboratories [24]. Additionally, we integrate various indicators of local university innovation activities into our benchmark model. Upon reassessment of the expanded model, the findings confirm the enduring positive impact of enterprise primary research facilities on innovation output, thereby reinforcing our primary conclusions as outlined in Panel E of Table VI.

Prior research has demonstrated that local cultural factors exert significant influence on corporate innovation [4][40]. Therefore, in this model, we have integrated several culture-related proxy variables. Among these variables are the natural logarithm of provincial-level per capita lottery sales, which is denoted as Ln(Lottery_Cul); the natural logarithm of the number of temples of various religions in the province is referred to as Ln(Religion_Cul); moreover, the natural logarithm of the number of provincial-level Confucian temples is expressed as Ln(Confucian_Cul). The outcomes presented in Panel F of Table VI confirm that the positive impacts of enterprises' primary research facilities on innovation output still hold true, even after factoring in these cultural characteristics.

Furthermore, we broadened the scope of control variables. Specifically, we incorporated fixed effects for cities and the interactions of annual fixed effects for cities, as depicted in Figure g. Our key findings remained intact even after applying the improved regression model. Ultimately, we delved into the potential for reverse causality, particularly focusing on whether there is a mutual influence between firms' primary research facilities and their innovative outputs. To be more precise, we delved into whether enterprises that attach great importance to innovation are more likely to set up primary corporate research facilities [41].""In order to tackle this issue, we integrated variables derived from previous innovative achievements into the model and carried out the baseline analysis once again. As per Chang and his colleagues [30], the past innovative outcomes represent the average quantity of patents acquired from 2008 to 2012. As demonstrated in Panel H, the research outcomes concerning Lab_dum stay consistent and stable. This offers further evidence that our central findings have not been disrupted by issues associated with reverse causality.

B. Heckman's Two-Stage Sample Selection Model

TABLE VII
HECKMAN TWO-STEP ANALYSES OF THE ASSOCIATION BETWEEN ENTERPRISE PRIMARY RESEARCH FACILITIES AND INNOVATION PERFORMANCE

First-step regression		Second-step regressions				
	Lab_dum		*Ln(Pat)*	*Ln(Cit)*	*Ln(PPt)*	*Ln(CPt)*
	(1)		(2)	(3)	(4)	(5)
R&D	0.065** (0.025)	*Lab_dum*	0.289*** (0.060)	0.582** (0.034)	0.199*** (0.038)	0.260*** (0.065)
Size	0.047 (0.025)	*R&D*	0.157*** (0.063)	0.284*** (0.052)	0.0845*** (0.056)	0.283** (0.069)
Firmage	0.006 (0.058)	*Size*	0.586*** (0.023)	0.765*** (0.035)	0.0184** (0.035)	0.199** (0.057)
PPE	0.054*** (0.035)	*Firmage*	-0.058** (0.022)	-0.045 (0.058)	-0.045*** (0.028)	-0.285*** (0.068)
ROA	0.495 (0.368)	*PPE*	-0.054*** (0.025)	-0.027*** (0.022)	0.075*** (0.035)	0.098*** (0.061)
MB	-0.135*** (0.064)	*Sales*	-0.038 (0.045)	-0.045 (0.088)	0.195* (0.032)	0.345*** (0.031)
Salesgrowtn	-0.138** (0.055)	*ROA*	1.058*** (0.485)	1.859*** (0.394)	0.637*** (0.232)	1.285** (0.356)
Lev	0.022 (0.459)	*MB*	-0.298*** (0.034)	-0.058*** (0.035)	-0.198** (0.036)	-0.286*** (0.06)
Cashratio	-0.198 (0.233)	*Salesgrowth*	-0.088*** (0.033)	-0.048 (0.076)	-0.018 (0.022)	-0.095 (0.035)
SOE	0.084 (0.057)	*Lev*	-0.145 (0.159)	-0.185 (0.162)	-0.947** (0.098)	-0.475*** (0.285)
Institute	-0.133 (0.189)	*Cashratio*	0.005 (0.283)	-0.039 (0.256)	0.314* (0.058)	0.255 (0.193)
Ln(gov_R&D)	-0.008 (0.056)	*Stockvolatility*	0.495 (2.175)	1.945 (2.551)	4.638*** (1.559)	6.078** (2.185)
Ln(tech_trans)	-0.034 (0.098)	*Stockreturn*	-0.003 (0.033)	0.008 (0.063)	0.022 (0.035)	0.028 (0.069)
Ln(*coll_papers*)	-0.135 (0.186)	*SOE*	0.328*** (0.047)	0.456*** (0.058)	0.198*** (0.028)	0.356*** (0.065)
Ln(*coll_patents*)	0.086** (0.035)	*Institute*	-0.198 (0.032)	-0.276 (0.108)	-0.146** (0.074)	-0.256*** (0.033)
Peer_R&D_ratio	0.042*** (0.051)	*IMR*	1.054** (0.311)	1.391*** (0.560)	0.555*** (0.299)	0.475** (0.358)
FE	YES	FE	YES	YES	YES	YES
Obs	11,211	Obs	11,211	11,211	11,211	11,211
Pse_R^2	0.057	Adj_R^2	0.583	0.395	0.284	0.582

Notes. Standard errors, presented in parentheses, are clustered based on firm-level data. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table VII shows the result of the Heckman two-step method. After analysis, the establishment of key laboratories, R&D, PPE, Ln (Coll_Patents), and Peer_Ratio_R&D were positive, while MB and sales played a negative role. In order to surmount the potential sample selection bias, we are going to incorporate the inverse mills ratio (IMR) acquired from the first step into the regression model of the second step. In the columns of Table VI, the data from the second-step regression are presented. This data further demonstrates that the importance of critical laboratories for innovative output. Moreover, the regression coefficient of the IMR shows a significant positive value. The research reveals that the ambiguous factors affecting the establishment of key laboratories have a definite positive impact on the innovation activities of enterprises.

When assessing the impact of laboratories on innovation output, this study utilizes the Heckman Two-Step Method to better address the problem of self-selection bias caused by sample self-selection. In the initial stage, the Probit model is applied to judge whether a company has set up a key laboratory. Apart from the variables in the initial baseline model, such as R. D, company size, company age, etc., supplemental variables are incorporated as well. The supplementary variables consist of the investment of the provincial government in R&D activities, the overall provincial volume of technology transactions, the provincial quantity of papers published by university laboratories, the quantity of patents awarded to university laboratories in each province, and the enterprises' R&D intensity within the same industry.

They are respectively denoted as Ln (Gov_R&D), Ln(Tech_Trans), Ln(Coll_Papers), Ln(Coll_Patents), Peer_R&D_Ratio.

C. The instrumental variable approach

In an effort to tackle the possible biases stemming from reverse causality, we made use of the Instrumental Variable (IV) approach. Specific instruments were identified, related to the experimental variable Lab_dum, that are uncorrelated with the dependent variable. It's worth noting that being affiliated with the CAS and CAE, which are regarded as the top-tier institutions for scientific accomplishment in China, brings substantial influence and access to resources. For instance, scholars from these academies are typically well-positioned to secure substantial research funding for their institutions. As per Fisman et al [42], for institutions linked to members of the CAS or the CAE, in part, this facilitated a $9.5 million increase in annual research funding. Moreover, when applying for research grants from the Office of Scientific Innovation or other government agencies, the endorsement of CAS/CAE members is often pivotal. Moreover, the qualifications of the members of these academies often lead to positions where they take on leadership roles in multiple professional fields. Take Xiang Libin as an example. He is an academician of the CAS and has been formally named as the Deputy Minister of the MOST. Meanwhile, Zeng Yixin, a member of the academy, is presently holding the position of the Deputy Director of the NHC.

In the social changes of China, local relationships have played an undeniable role. We can clearly see, through the frequent interactions between members of the CAS and political leaders, that this connection is particularly due to the fact that they come from the same hometown. These kinds of ties frequently play a role in influencing academicians during the process of suggesting the locations for crucial laboratories, with them giving preference to their hometown areas. In order to quantify this phenomenon, we compiled the birthplace details of every researcher from the CAS and the CAE. The instrumental variable was the total quantity of researchers in the CAS / CAE with the company HQ in the same city. This was done with the intention of ascertaining the likelihood of the company establishing key laboratories. Furthermore, we incorporated a second-tier instrumental variable named Lab_Other. Specifically, the mean number of main facilities established by competitors in the same industry in the same city.

The estimated outcomes of the instrumental variable (IV) are presented in Table VIII. Moreover, we employed the 2SLS approach. The first column of Table VIII is the result of the analysis in the first stage. It's remarkable that a statistically significant correlation exists between the instrumental variables Local_CC_Fel and Lab_Other and the standard variable Lab_dum. The F- statistic, which has a value of 14.127 and is statistically significant, further validates the suitability of these instruments in dealing with the potential endogeneity of the variable being examined.

TABLE VIII
TWO-STEP INSTRUMENTAL VARIABLE REGRESSIONS EXAMINING THE CONNECTION BETWEEN KEY LABORATORIES AND INNOVATION OUTPUT

	First stage	Second stage			
	Lab_dum	*Ln(Pat)*	*Ln(Cit)*	*Ln(PPt)*	*Ln(CPt)*
	(1)	(2)	(3)	(4）	(5)
Lab_dum	N/A	3.765** (1.395)	4.046*** (1.738)	2.173*** (1.463)	1.274*** (0.796)
Local_CC_fel	0.007*** (0.013)	N/A	N/A	N/A	N/A
Lab_other	0.002*** (0.002)	N/A	N/A	N/A	N/A
Controls	YES	YES	YES	YES	YES
FE	YES	YES	YES	YES	YES
F-statistic	14.127	N/A	N/A	N/A	N/A
Hansen J	N/A	0.419 (0.376)	0.391 (0.761)	0.391 (0.437)	0.764 (0.581)
Obs	11,688	11,688	11,688	11,688	11,688

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

In Columns (2) through (5), the coefficients associated with Lab_dum are 3.765, 4.046, 2.137, and 1.274, respectively. These results indicate that enterprise primary research facilities significantly enhance innovation output, even after the application of Instrumental Variable (IV) estimation techniques. Furthermore, the overidentification tests conducted on all instruments show that the Hansen J statistics for each test are statistically insignificant. This result validates the exogeneity and effectiveness of the instrumental variables applied in the analysis. As a consequence, it strengthens the robustness of the research results.

D. Analysis of policy impact

In 2015, The incentives implemented by the Chinese government were far-reaching, so we studied its relationship with the construction of basic research facilities and used these measures as drivers of foreign policy. In that same year, the Fifth Plenum of the 18th CPC National Congress examined and ratified the "Proposals of the CPC Central Committee on Formulating the 13th Five-Year Plan for National Economic and Social Development." The proposals put forward the idea that enterprises ought to engage in fundamental and original innovative research, and commence the construction of basic research facilities. Subsequently, the "13th Five-Year" National Science and Technology Innovation Plan " elaborated the detailed measures for the construction of enterprise crucial laboratories.

Considering the expected growth in R&D subsidies, study undertakings, and policy support, after the policy change in 2015, the positive influence of primary research facilities on innovation output will be further enhanced, as predicted by us. In order to verify our hypothesis, we made use of a binary variable called Incentive_Policy2015. 1 is the value of this variable after 2015, and 0 for the remaining years. The enhanced regression model we constructed integrates Policy2015 and the interaction term Lab_dum×Policy2015. As presented in Table IX, the primary research facilities of enterprises exert a notably positive influence on innovation results. Moreover, after the 2015 policy was put into practice, this influence has been further enhanced.

TABLE IX
FINDING REGARDING THE ANALYSIS OF THE POLICY IMPACT

	Ln(Pat) (1)	*Ln(Cit)* (2)	*Ln(PPt)* (3)	*Ln(CPt)* （4)
Lab_dum	0.364*** (0.065)	0.374*** (0.023)	0.284*** (0.136)	0.316*** (0.064)
Policy2015	0.736 (0.467)	0.575 (0.439)	-0.764 (0.358)	0.046 (0.258)
Lab_dum×Policy2015	0.146*** (0.071)	0.737*** (0.085)	0.043 (0.051)	0.146*** (0.035)
Controls	YES	YES	YES	YES
FE	YES	YES	YES	YES
Obs	13,067	13,067	13,067	13,067
Adj_R^2	0.437	0.336	0.367	0.458

Notes. Standard deviations in brackets are clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

E. PSM procedure

Reverse causal relationships can lead to endogeneity, and we use the PSM method to reduce the overemphasis on it. This strategy is used to establish a stable comparison between companies with primary business research capabilities and those lacking such capabilities. Compute the propensity scores for the treatment group by Probit model initially. This calculation played a crucial role in enabling us to pinpoint a matching control group. Following this step, we assess the balance of covariates, confirming that the matched companies meet established economic and statistical criteria for evaluation. Post-matching, we observe a substantial reduction in percentage bias across all covariates, with all values falling below 10%. These results confirm the effectiveness of the balance tests conducted, thus reinforcing the validity of our matching procedure.

Subsequently, we used processed and matched control samples to reevaluate the baseline model, employing various propensity score matching (PSM) methods. The matching methods adopted encompassed one-to-one matching, neighborhood matching, radius (1:4) matching, radius matching, kernel matching, local linear regression, spline matching, as well as Mahalanobis matching. Across all these techniques, the coefficients constantly remained positively significant, which further validated the accuracy of the original baseline model (refer to Table X)

TABLE X
OUTCOMES OF PSM TECHNIQUES

PSM procedure	*Ln(Pat)* (1)	*Ln(Cit)* (2)	*Ln(PPt)* (3)	*Ln(CPt)* (4)
One-to-one matching	0.236*** (0.058)	0.464*** (0.094)	0.176*** (0.091)	0.246*** (0.066)
Neighbors matching	0.764*** (0.058)	0.376*** (0.091)	0.146*** (0.072)	0.246*** (0.058)
Radius (1:4) matching	0.137*** (0.059)	0.436** (0.060)	0.158*** (0.053)	0.463*** (0.046)
Radius matching	0.376*** (0.022)	0.369** (0.059)	0.367** (0.061)	0.246*** (0.095)
Kemel matching	0.736** (0.043)	0.735*** (0.058)	0.769*** (0.065)	0.766*** (0.022)
Local linear regression	0.167*** (0.058)	0.394* (0.036)	0.146** (0.064)	0.246*** (0.043)
Spline matching	0.376*** (0.086)	0.275*** (0.351)	0.736** (0.091)	0.496*** (0.073)
Mahalanobis matching	0.581*** (0.046)	0.491** (0.057)	0.156*** (0.011)	0.246*** (0.049)

Notes. Standard deviations in brackets are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

VI. FURTHER ANALYSES

A. Corporate key laboratory and innovation strategies

The basic research facilities of the company have been of vital importance in promoting innovation results viewed from the perspective of fundamental analysis. In this study, we further broadened our investigation to explore how key laboratories differentially impact various innovation strategies. We utilize a comprehensive set of indicators to capture the diversity of innovation approaches, which includes Exploration, Exploitation, Novelty, Universality, Non-Patent Citations, Reverse Citations, Patent Breadth, and Grant Lag. This array of metrics enables a thorough evaluation of how the presence of key laboratories influences distinct aspects of innovation practices.

The initial metric, Pioneering Innovation, measures the proportion of innovative activities focused on exploratory efforts. An innovation qualifies as pioneering if over 60% of its referenced innovation classification codes are unrelated to the company's existing portfolio of innovative products. Based on the frameworks set up by Benner & Tushman [43] and Sørensen & Stuart [44], this definition encompasses all the innovations that the company has developed and cited within the past five years. In contrast, Exploitative Innovations are those in which more than 60% of the innovation classification codes align with the company's current innovations, encompassing all innovations developed and cited within the same timeframe. The method for calculating the degree of development is determined by comparing the total amount of innovative development with innovation itself. The outcomes of the regression analysis regarding the influence of key laboratories on innovative exploration and the utilization of innovation are shown in Table XI. The findings reveal a significant positive correlation with the innovative innovation coefficient related to Lab_dum, indicating that the enhancement of pioneering innovation in a company's primary research facilities is disproportionately greater compared to exploitative research facilities, and its coefficient is also not significant.

TABLE XI
FINDINGS REGARDING THE CONNECTIONS BETWEEN THE PRIMARY STUDY VARIABLES AND VARIOUS INNOVATION TACTICS

	Exploration (1)	Exploitation (2)	Originality (3)	Generality (4)	Nonpat_cits (5)	Backward_cits (6)	Patent scope (7)	Grunt lag (8)
Lab_dum	0.046***	0.005	0.076***	0.006	0.076***	0.346***	0.364***	0.046***
	(0.030)	(0.005)	(0.016)	(0.003)	(0.064)	(0.076)	(0.036)	(0.004)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs	12,769	12,769	12,769	12,769	12,769	12,769	12,769	12,769
Adj_R^2	0.273	0.056	0.364	0.076	0.176	0.766	0.336	0.496

Notes. Standard deviations within parentheses are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

As per scholars like Trajtenberg et al. [45], originality is determined as the median value among all patent originality scores. This metric serves to gauge the extent to which innovation combines diverse knowledge sources. This metric evaluates how broadly a patent draws upon an array of patents from different technological fields, with higher originality scores indicating greater innovative output. In contrast, Generality is defined as the median of the generality scores of all patents. It assesses the impact scope of the patent on subsequent inventions by analyzing the diversity and categories (IPC) of the patents that cite this patent. Patents that are extensively cited across different technological domains are considered to have higher generality. The analysis, presented in Columns (3) and (4) of Table XI, reveals that enterprise primary research facilities significantly enhance Originality. However, their impact on Generality is not significant.

In line with the approach of Cassiman et al [46], Nonpat_cits is computed as the logarithm of the value obtained by adding 1 to the cumulative count of non-patent references cited in all patents. This metric serves as an indicator of the integration of scientific literature within patents, suggesting the use of more advanced knowledge. On the contrary, as defined by Harhoff et al [47], Backward_cits is calculated as the natural logarithm of the sum of 1 and the total number of patent and non-patent references cited in all the submitted patents. The specific survey results in columns (5) and (6) of Table XI indicate that enterprises which are equipped with crucial laboratories are more likely to quote patents and non-patent documents. This increasing citation behavior reveals that their patents hold greater value, thanks to their incorporation of more knowledge resources.

The scope of a patent measures the diversity among the first four IPC numbers granted for a patent. A greater score implies that the patent covers a broader and more profound range of categories [48]. Adopting the methods of Harhoff and Wagner [49] as well as R´egibeau and Rockett [50], Grant_lag is defined in the following way: It is calculated by subtracting from 1 the quotient obtained when the number of days between the patent application date and the authorization date is divided by the maximum number of days between these two dates for patents within the same IPC classification. Studies have revealed an inverse relationship between the quality of innovation and the duration from the patent submission to the receipt of the patent grant. Through an in-depth analysis in this paper, we found a clear positive correlation between the presence of primary research facilities in enterprises and the scope of their patents as well as Grant_Lag. This means,Organizations that possess core laboratories not only excel in quality but also contribute to a broader range of fields and demonstrate higher levels of innovation. The evidence corroborates the idea that key laboratories create an environment favorable for ground - breaking and innovative research undertakings.

B. Examination of cross-sectional diversity

High-technology enterprises are generally more inclined to adopt new technologies to enhance their competitive advantage, demonstrating a stronger commitment to scientific and technological advancement [51]. Therefore, the sample was divided into high-tech enterprises and low-tech enterprises by us. We hypothesize that compared to industries with lower technological levels, the positive impact of setting up key laboratories is more significant in high-tech enterprises. In Table XII, the data in Panel A show that Lab_dum's coefficient across different columns is significantly positive. In contrast, the coefficient for low-tech enterprises does not show significant statistical meaning. In addition, both the self-test and the permutation test convincingly reject the original hypothesis across all subsamples. Lab_dum's coefficient estimates always remain consistent. This analysis supports the conclusion that key laboratories significantly enhance innovation output predominantly in high-technology firms, while such effects are absent in low-technology firms.

CEOs who are actively engaged in inventing, referred to as inventor CEOs, bring unique competencies and insights to the evaluation, selection, and execution of innovative projects. Companies with inventor CEOs usually obtain a greater quantity and better quality of patents and citations. This indicates a robust connection between the participation of leadership in innovation activities and the intellectual achievements of the corporation [52]. Therefore, when a company establishes key laboratories under the leadership of an inventor CEO, the positive impact on innovative outcomes will be significantly amplified. Table XII, Panel B, delves into this phenomenon by dividing the samples into two distinct groups. The two groups are the companies led by inventor CEOs and non-inventor CEOs, respectively. The research findings reveal that, in the case of firms led by inventor CEOs, Lab_dum's coefficient is both economically and statistically significantly higher than that of companies led by non-inventor CEOs.

We further differentiate CEOs by categorizing them as scientist CEOs, defined as those who have held positions as university faculty members before assuming their current roles. This classification facilitates a segmented analysis into two distinct groups: firms led by scientist CEOs and those guided by non-scientist CEOs. By carrying out this categorization, we can conduct an in-depth comparative study of how key laboratories impact innovation output in these different types of companies. The results, presented in Table XII, Panel C, highlight that the presence of enterprise primary research facilities significantly enhances innovation output in companies led by scientist CEOs. This suggests that scientist CEOs may contribute a unique perspective and skill set that notably augments the benefits derived from key laboratories in driving innovation.

TABLE XII
THE DIVERSE IMPACTS OF ENTERPRISE PRIMARY RESEARCH FACILITIES ON INNOVATION ACROSS DIFFERENT CONTEXTS

	Ln(Pat)		*Ln(Cit)*	
Panel A: Heterogenous analysis by high- and low-tech firms				
	Low-tech	High-tech	Low-tech	High-tech
Lab_dum	0.086 (0.051)	0.598*** (0.045)	0.029 (0.156)	0.592*** (0.042)
Controls	YES	YES	YES	YES
FE	YES	YES	YES	YES
Obs	8458	3885	8458	3885
Adj_R^2	0.429	0.392	0.295	0.295
High-Low tech Prob.	0.002***		0.000***	
Panel B: Analysis of Variations by Firms Led by Inventor and Non-Inventor CEOs				
	Inventor	Non-scientist	Inventor	Non-scientist
Lab_dum	0.269*** (0.062)	0.194*** (0.036)	0.356** (0.058)	0.188*** (0.049)
Controls	YES	YES	YES	YES
FE	YES	YES	YES	YES
Obs	5298	6885	4850	6885
Adj_R^2	0.365	0.184	0.295	0.425
Inventor-Non CEO Prob.	0.002***		0.000***	
Panel C: Analysis of Variations by Firms with Scientist and Non-Scientist CEOs				
	Scientist	Non-scientist	Sdientist	Non-scientist
Lab_dum	0.558*** (0.285)	0.156*** (0.029)	0.584*** (0.395)	0.186*** (0.059)
Controls	YES	YES	YES	YES
FE	YES	YES	YES	YES
Obs	1869	11,284	1869	11,284
Adj_R^2	0.395	0.145	0.172	0.362
Scientist-Non CEO Prob.	0.002***		0.001***	
Panel D: Analysis of Variations by Firms in Cities with Strong and Weak IP Protection.				
	Strong IP protection	Weak IP protection	Strong IP protection	Weak IP protection
Lab_dum	0.295*** (0.061)	0.199 (0.136)	0.295*** (0.076)	0.955 (0.146)
Controls	YES	YES	YES	YES
FE	YES	YES	YES	YES
Obs	9485	2555	9155	2555
Adj_R^2	0.395	0.395	0.558	0.266
Strong-Weak IPP Prob.	0.000***		0.056**	

Notes. Standard deviations in brackets are clustered at the company level. *, **, and *** signify significance at the 10%, 5%, and 1% thresholds, respectively. Assessments of whether the coefficient estimates on Lab_dum are equivalent for various subgroups and the results from 1000 bootstrap iterations.

Drawing on the findings of Ang et al [53], which highlight the substantial differences in intellectual property (IP) protection among various regions in China, this study explores the relationship between intellectual property protection and innovation. We propose that enhanced IP protection could amplify the positive effects of corporate primary research facilities on innovation outcomes. To validate this hypothesis, we collected data on intellectual property (IP) litigation cases from the official Chinese judgment online platform. Subsequently, we categorized the samples into two groups: urban enterprises with strict intellectual property protection and regional enterprises with relatively weak intellectual property protection. As presented in Group D of Table XI, the coefficient of Lab_dum is significantly positive solely for the companies located in cities featuring more robust intellectual property protections. This finding reinforces the view that an environment with effective intellectual property enforcement. The beneficial impact of basic research facilities on innovation is even more pronounced.

C. Fundamental robustness examinations

In the course of this analysis, in order to verify the reliability of the study conclusions, we tested multiple stability. These tests involved the use of different model criteria and definitions of key variables. These tests uniformly support our initial conclusions across diverse settings, illustrating the reliability of our results.

The robustness checks include:

(a) Taking state key laboratories and provincial key laboratories as separate independent variables.

(b) Using the innovation indicators (derived from annual reports, management discussions, and text analysis) as the dependent variable.

(c) Employing standard innovation indicators as the dependent variable.

(d) Adjusting for the absent R&D dummy variables.

(e) Conducting negative binomial regressions.

(f) Employing innovation proxies that are measured with a one - year lead time (t + 1).

(g) Taking into account innovation proxies measured two years in advance (t + 2).

(h) Assessing innovation proxies measured three years in advance (t + 3).

(i) Taking patents that rank in the top 10% in terms of citation frequency as the dependent variables

(j) Using the average citation count per patent (counted five and seven years after patent filing, and up to the end of 2021) as the dependent variables.

(k) Only observations involving patents are incorporated into the analysis.

(l) Only observations that have at least one citation are included.

(m) Only the observations associated with academic journal publications are incorporated.

(n) Observations linked to their own academic journal publications are excluded.

(o) Firms involved in intellectual property lawsuits are excluded from the study.

(p) Firms that have experienced mergers and acquisitions in the past two years are excluded.

(q) Firms whose headquarters are located in major metropolises such as Beijing, Shanghai, Guangzhou, and Shenzhen are excluded.

(r) Firms located in National Scientific Center Cities, namely Beijing, Shanghai, Hefei, and Shenzhen, are excluded.

D. Mechanism examination

Our empirical research highlights the substantial role of key laboratories in enhancing innovation output, although the specific mechanisms underlying this effect remain to be fully explored. This section aims to examine potential pathways of influence, with a particular focus on corporate science. Within the scope of our study, corporate science denotes those research undertakings which are spearheaded by private companies and are both sanctioned and financed by government agencies. This kind of research mainly focuses on fundamental scientific exploration. Its aim is to build new knowledge systems and deal with long-term issues. Usually, it doesn't have short - term commercial goals in mind[23]. Such activities complement a company's R&D efforts by prioritizing basic research over projects aimed directly at application. A key indicator of corporate science's effectiveness is the publication of scientific articles by company researchers in prestigious academic journals, which plays a crucial role in advancing scientific knowledge and dissemination [26]. Previous studies have closely associated corporate science with the dynamics of innovation activities [41]. Our research results regarding the impact of corporate science on innovation mechanisms are shown in Panel A of Table XIII. In this distinctive analysis, we utilized the concept of Ln(Paper). It denotes the logarithm of the value obtained by adding 1 to the total quantity of academic publications. We used it as a valid proxy for a company's scientific research capabilities. The data in the first column reveals a positive correlation between Lab_dum and Ln(Paper), indicating that a company's primary research facilities significantly enhance its scientific research activities. Given this discovery,We decided to incorporate the scientific indicators of the enterprise into our benchmark model as an independent variable, facilitating subsequent validation work. The statistical results detailed in columns (2) to (5) show that the coefficients between the enterprise's primary research facilities (Lab_dum) and the enterprise's scientific indicators are significant, revealing the correlation between economics and statistics. These findings suggest that key laboratories not only directly increase innovation output but also indirectly enhance it by improving the firm’s scientific research capabilities. This dual influence—directly fostering innovation and indirectly strengthening research capacity—underscores the pivotal role of key laboratories in advancing firms' innovation potential.

In Table XIII, this study conducts an analysis of the role of an enterprise's human resources in promoting innovation in Panel B. Recognizing human capital as a critical driver of corporate innovation—encompassing not only the CEO and top management team, as identified by Custódio et al [7] and Chemmanur et al [8], but also non-executive staff [30]—we assess this dimension of influence. For this specific analysis, we incorporate Hum_cap, a variable that measures the quantity of employees possessing Master's and Doctorate degrees. Our research findings validate that key laboratories substantially enhance the human capital levels of firms. By incorporating Hum_cap as an independent variable into our baseline model, we observe that the coefficients for both Lab_dum and Hum_cap are significantly positive. This supports the assertion that enterprise primary research facilities influence innovation output not only directly but also indirectly by enhancing human capital, as evidenced by the recruitment and development of highly skilled personnel [61][62][63].

During our process of summarization and analysis, we placed special emphasis on the function that R&D subsidies play in improving innovation results. After a detailed review of government grant data allocated to Chinese listed companies over the past few years, we conducted an in-depth study of the portions specifically providing subsidies for R&D. In the core analytical model of our study, we utilize R&D_Sub, which represents the natural logarithm of the annual government funds a company obtains for R&D support. This variable has been incorporated into our analysis. In this way,We have the capability to assess the extent to which a company's core research facilities contribute to securing additional government R&D funding, thereby optimizing its innovation outcomes. The research of Group C revealed that augmenting government R&D subsidies can remarkably boost the innovation outcomes spurred by a company's own primary research facilities. This discovery highlights that government R&D subsidies have the potential to act as a catalyst, increasing the efficiency of primary research facilities in promoting firm-level innovation.

TABLE XIII
MECHANISM ANALYSIS

Panel A: Examination of the initial mechanism through the progression of corporate scientific exploration					
	Ln(Paper) (1)	*Ln(Pat)* (2)	*Ln(Cit)* (3)	*Ln(PPt)* (4)	*Ln(CPt)* (5)
Lab_dum	0.295**	0.259**	0.428***	0.256***	0.325***
	(0.049)	(0.026)	(0.061)	(0.029)	(0.094)
Ln(Paper)		0.156**	0.216***	0.084***	0.138***
		(0.053)	(0.044)	(0.059)	(0.028)
Controls	YES	YES	YES	YES	YES
FE	YES	YES	YES	YES	YES
Obs	12,764	12,764	12,764	12,764	12,764
Adj_R^2	0.584	0.365	0.295	0.395	0.298
Panel B: Examination of the second mechanism for enhancing the workforce					
	Hum_cap (1)	*Ln(Pat)* (2)	*Ln(Cit)* (3)	*Ln(PPt)* (4)	*Ln(CPt)* (5)
Lab_dum	0.256***	0.295**	0.598***	0.254***	0.356**
	(0.075)	(0.054)	(0.064)	(0.024)	(0.042)
Hum_cap		0.058***	0.084***	0.059***	0.059***
		(0.006)	(0.008)	(0.006)	(0.006)
Controls	YES	YES	YES	YES	YES
FE	YES	YES	YES	YES	YES
Obs	12,764	12,764	12,764	12,764	12,764
Adj_R^2	0.485	0.256	0.395	0.295	0.259
Panel C: Examination of the third mechanism by boosting research and development grants					
	R&D_Sub (1)	*Ln(Pat)* (2)	*Ln(Cit)* (3)	*Ln(PPt)* (4)	*Ln(CPt)* (5)
R&D_Sub	0.583***	0.286***	0.485***	0.149***	0.187**
	(0.146)	(0.059)	(0.024)	(0.036)	(0.059)
Controls	YES	YES	YES	YES	YES
FE	YES	YES	YES	YES	YES
Obs	12,764	12,764	12,764	12,764	12,764
Adj_R^2	0.045	0.598	0.584	0.395	0.395

Notes. Standard deviations within parentheses are clustered based on firm-level data. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

E. Investigations into possible competitive justifications

This section delves into potential competitive dynamics to clarify the nuanced effects of key laboratories on corporate innovation outcomes. Our investigation extends across various adjustments to account for unique corporate characteristics that might influence innovation outcomes, including:

(a) Adjusting for companies with university affiliations, recognizing the potential for enhanced research capabilities and resources.

(b) Adjusting for firms that host Centers for Post-Doctoral Studies, considering the impact of advanced research personnel on innovation.

(c) Adjusting for corporations that operate independent center research institutes, reflecting on their direct research contributions.

(d) Adjusting for businesses that have established Chief Scientific Officer roles, indicating a strategic focus on scientific innovation.

(e) Adjusting for the diversity index of firms' top management teams, linking management diversity to innovation breadth.

(f) Adjusting for companies led by CEOs with a proven track record in academic publishing, suggesting an inclination towards research-driven innovation.

(g) Adjusting for firms helmed by inventor CEOs, who bring unique insights and capabilities to the innovation process.

(h) Adjusting for companies led by CEOs with international education or professional experience, offering diverse perspectives on innovation.

(i) Adjusting for corporations with CEOs holding Ph.D. degrees, underlining the influence of high academic qualifications on innovation.

(j) Adjusting for companies led by founder-CEOs, considering their potential long-term commitment to innovation.

(k) Adjusting for businesses with CEOs who have political connections, recognizing the possible impact on innovation through regulatory and financial support.

(l) Adjusting for firms with overconfident CEOs, exploring how CEO confidence may drive innovation initiatives.

(m) Adjusting for companies with CEOs possessing financial backgrounds, considering the strategic allocation of resources to innovation.

VII. CONCLUSIONS

Innovation is broadly acknowledged as a crucial factor propelling economic advancement and conferring competitive edge upon both countries and companies. This underscores the importance of understanding the factors that determine corporate innovation. Our study focuses on the specific role of corporate key laboratories in enhancing innovation outcomes. Our research reveals that enterprises equipped with either state - level or provincial - level key laboratories consistently attain higher patenting rates and citation frequencies than their counterparts, which is in line with theoretical anticipations. Moreover, these facilities play a critical role in promoting both exploratory and groundbreaking innovation strategies. Key laboratories exert a notably beneficial impact on innovation output, especially in high-tech enterprises, companies led by CEOs with scientific or inventor backgrounds, and firms based in areas boasting strong intellectual property rights frameworks. Additionally, our research demonstrates how corporate research facilities act as catalysts for innovation by enhancing scientific activities, building human capital, and securing increased R&D subsidies. These interconnected mechanisms collectively boost firms' innovation capacities, highlighting the multifaceted role of key laboratories within the broader innovation ecosystem. This analysis not only confirms the significant value of key laboratories in driving corporate innovation but also offers practical insights for policymakers, industry leaders, and researchers aiming to foster environments that support innovative growth.

First, enterprises and governments looking to promote innovation will find our research particularly useful. A key insight from our findings is that while fundamental scientific research is typically seen as a public sector domain, it benefits greatly from the involvement of corporate research facilities. These facilities are pivotal in advancing technological innovation, reinforcing their importance within the innovation ecosystem. Although basic research offers broad benefits, private firms often face limited incentives to invest in these activities due to the public good nature of scientific discoveries. However, fundamental research is essential for boosting a firm’s innovation capacity. The establishment of key laboratories acts as a catalyst, enabling the conversion of cutting-edge scientific knowledge into technological advancements and commercially viable products. This transformation not only highlights the value of basic research to stakeholders but also provides firms with a strategy to secure sustainable competitive advantages. Our study emphasizes the need to create supportive environments that encourage corporate investment in research facilities. Such investments not only drive firm-level innovation but also contribute to broader economic and technological progress, benefiting both the private and public sectors.

Second, corporate research facilities are crucial for innovation in China, underscoring the need for a strategic approach that integrates fundamental research with applied technological research and product development. These facilities not only spur innovation but also reflect broader corporate governance and business philosophies. This contrasts with trends observed in European and American companies post-1980s, where shareholder-centric governance models led to reduced long-term investments in basic research. Notably, some leading American firms, despite their strong innovation capabilities, reduced their foundational research investments, outsourced basic research to universities, and redirected funds toward increasing shareholder returns and executive compensation. This shift has raised concerns about the sustainability of innovative ecosystems and underscored the need for governance models that prioritize technological advancement. Chinese firms have the opportunity to pursue a different path, one that avoids the short-termism seen in Western counterparts. By establishing and supporting corporate research facilities, Chinese firms can secure sustainable competitive advantages and maintain a continuous flow of technological innovations essential for global competitiveness. This commitment not only enhances corporate success but also aligns with China’s goal of becoming a leading global innovator, yielding benefits for society as a whole.

Lastly, this study offers important insights into innovation strategies, valuable to both policymakers and the business community. As China continues to deepen its reform process in the technological innovation system, the role of the private sector is becoming increasingly prominent. Currently, this sector accounts for over 75% of the national R&D funding. This change highlights the gradually rising core position of enterprises in China's innovation industry. Remarkably, privately-owned enterprises including Huawei, Alibaba, Tencent, and Baidu have achieved remarkable feats in advanced domains such as 5G and artificial intelligence. Their innovation capabilities have outpaced those of traditional academic organizations. Despite these advancements, Chinese firms have historically underinvested in basic research, which is critical for sustaining long-term innovation. For years, internal R&D budgets allocated to basic research have hovered around 5%, with over 90% of this funding coming from public sources and private sector contributions to scientific research financing remaining below 3%. Given these dynamics, there is an urgent need for policies that not only encourage but actively support private sector investment in fundamental research. Potential measures could include financial incentives, tax breaks, and strengthened public-private partnerships to increase resource allocation in this vital area. By creating a supportive environment for significant private investment in basic research, the government can ensure that Chinese firms not only participate in but also lead the global innovation race. This strategic pivot is essential for propelling China toward its goal of becoming a world leader in innovation, driving economic growth through technological advancements and research breakthroughs. It represents a strategic shift to leverage the private sector’s full potential in enhancing the nation’s innovation ecosystem, ultimately benefiting society at large.

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