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Government Funding and Regional Innovation: The Role of Openness and Economic Development in Chinese Pharmaceutical Manufacturing Industry

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Abstract

The government plays a significant role in the National Innovation System (NIS) by allocating diversified resources, and government funding is one of the important instruments. This study focuses on the relationship between government R&D funding and regional industrial innovation performance by analyzing the innovation performance of the Chinese pharmaceutical manufacturing industry. The study divides the pharmaceutical manufacturing industry's innovation process into the lab R&D and new product development (NPD) stages. A two-stage slacks-based measure (SBM) DEA model is applied to measure the Chinese pharmaceutical manufacturing industry's innovation efficiency from 2009 to 2019. Whereafter, it investigates the impact of government funding on pharmaceutical manufacturing industry innovation performance. It is found that government funding has more effects on the lab R&D stage's performance than the NPD stage's performance. Meanwhile, in the open and economically developed regions, the effect of government funding will be weakened.

Keywords

Government funding; Innovation performance; Pharmaceutical manufacturing industry; Two-stage DEA; Tobit regression

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1. Introduction

Government funding plays a critical role in shaping regional innovation, particularly in technology-intensive and high-risk sectors such as pharmaceutical manufacturing. In the context of intensifying global and regional competition, effective public investment can serve as a catalyst for strengthening regional innovation systems (RIS) by enhancing knowledge flow, facilitating technological diffusion, and enabling the integration of innovation resources. The pharmaceutical manufacturing industry, characterized by its dependence on sustained innovation and substantial R&D investment, is especially sensitive to the quality and scale of government support. Regional Innovation Systems provide a valuable analytical framework for examining how government funding interacts with local economic conditions and industrial structures to influence innovation outcomes. As Fritsch (2002) and Furman *et al*. (2002) have noted, regional disparities in innovation performance often stem from differences in policy environments, economic development, and openness to external knowledge. This study explores the role of government funding in promoting regional innovation in China's pharmaceutical manufacturing industry, focusing on how regional openness and economic development mediate this relationship.

The innovation of the Chinese pharmaceutical manufacturing industry is essential for the national economy and people's livelihood. Firstly, the Chinese pharmaceutical manufacturing industry has experienced rapid growth and has made a significant contribution to the economy (Song *et al*., 2019). Its total revenue jumped from 90.3 billion RMB in 1995 to 2500.9 billion RMB in 2023, a nearly thirtyfold increase over thirty years. China has now become the second-largest pharmaceutical market globally (Wu and Hsu, 2018). Secondly, as highlighted in the Chinese pharmaceutical manufacturing industry *Development Planning Guidelines*, the pharmaceutical manufacturing industry is closely linked to public health and quality of life, attracting substantial attention from the government. The sudden public safety incidents caused by the coronavirus in 2003 and 2020 have tested China's capacity for pharmaceutical manufacturing innovation.

From the perspective of industrial development theory, the pharmaceutical manufacturing industry is both knowledge-intensive and capital-intensive, with technological innovation serving as the core engine of its long-term competitiveness and sustainable growth (Gambardella, 1992). In the context of rising global economic competition and increasing public health challenges, the development of China's pharmaceutical manufacturing industry holds strategic significance for national health security and international industrial positioning (Song *et al*., 2019). Therefore, government industrial policy plays a guiding role by influencing the direction of technological progress, setting R&D priorities, and promoting structural optimization and industrial upgrading.

From the perspective of government-market relations, the need for government funding becomes particularly pronounced in sectors where market mechanisms alone are insufficient to ensure efficient resource allocation. The pharmaceutical R&D process is characterized by high levels of uncertainty, long development cycles, and significant sunk costs, often leading private actors to underinvest due to risk aversion and information asymmetries. This mismatch between social returns and private incentives exemplifies a classic case of market failure. In China's pharmaceutical manufacturing industry, R&D investment remains at approximately 2% of sales revenue, considerably lower than in advanced economies (Sun *et al*., 2008). In addition, the persistent disconnect between R&D input and innovation output highlights inefficiencies in the innovation system (Ni *et al*., 2017).

As the pharmaceutical manufacturing industry is an innovative industry and innovation activities

have the characteristics of externalities and public goods, it is ineffective to allocate the resources solely relying on the market mechanism. Government funding can effectively make up for the shortcomings of market mechanisms in resource allocation, especially in areas with externalities and public goods characteristics (Lerner, 2002). Government intervention, such as funding, subsidies, taxes, tariffs, trade restrictions, etc. may effectively correct the market failure and promote the development of innovative activities through risk sharing, signal transmission and resource integration (Hong *et al*., 2016).

However, the effect of government funding is not always positive, and its effect is affected by a variety of factors, including the scale, method of funding, and the regional economic environment (Guan and Chen, 2012). In the pharmaceutical manufacturing industry, the impact of government funding on innovation performance is particularly complex. On one hand, government funds can alleviate the financial constraints of enterprises and promote basic research and early R&D activities; on the other hand, excessive reliance on government funding may lead to insufficient innovation motivation for enterprises and even lead to inefficient resource allocation (Hong *et al*., 2016).

There are still significant theoretical and practical gaps in existing research when exploring the impact of government funding on the innovative performance of pharmaceutical manufacturing. From the theoretical perspective, innovation in the pharmaceutical manufacturing industry is a complex systematic project involving multiple links such as basic research, clinical trials, results transformation, and marketing promotion. The impact of government funding investment and allocation methods on innovation performance may vary significantly (Ni *et al*., 2017). However, the existing literature focuses on the impact of government funding on general innovation in enterprises, and lacks in-depth analysis of the special industry of pharmaceutical manufacturing. From a practical perspective, the pharmaceutical manufacturing industry has unique attributes such as high R&D investment, long R&D cycle, and high risks. The effect of government funding may be affected by regional heterogeneity factors. Existing research often ignores the role of these heterogeneity factors, resulting in inaccurate assessment of the effectiveness of government funding.

This study focuses on China's pharmaceutical manufacturing industry and explores the impact of government subsidies on the innovative performance of pharmaceutical manufacturing from the perspective of regional innovation system. Using a two-stage slacks-based measure (SBM)-DEA model, the research evaluates the innovation efficiency of the Chinese pharmaceutical manufacturing industry from 2009 to 2019 and further explores the impact and mechanisms of government funding on innovation performance across different regions. The innovation points of this study are: (1) using the two-stage SBM-DEA model to systematically evaluate the efficiency of different innovation stages of the pharmaceutical manufacturing industry, filling the gap in stage analysis of existing research; (2) introducing regional openness and economic development level as regulatory variables to explore its heterogeneous role on government subsidies, providing a new perspective for understanding the effect of government funding in different regional environments; (3) combining the actual background of China's pharmaceutical manufacturing industry, empirical support is provided for the formulation of more effective industrial policies.

The rest of this study is organized as follows. Section 2 reviews the previous literature and develops the hypotheses. Section 3 introduces the methods and data used in this study. Section 4 gives the results of the evaluation of the Chinese pharmaceutical manufacturing industry's regional innovation performance and measurements of the Tobit regression. Conclusion and discussion are displayed in Section 5.

2. Literature Review and Hypotheses Development

To initiate this study, it is necessary to first clarify the regional unit concerned, second present the characteristics of the pharmaceutical manufacturing industry, third define the proper indicator for measuring innovation performance, and finally discuss the potential factors that influence the innovation performance and propose the hypotheses.

2.1. Regional innovation systems and analytical units

Previous literature on regional innovation agrees that innovation activities are unevenly distributed across different areas. The uncertainty, complexity, and hidden form of new knowledge determine that it can only be transferred between areas through personal interaction. Geographical proximity can help promote interactive learning and knowledge flow, and regional boundaries impact transfer flow. Based on those traits, regional innovation systems are an adequate approach for analyzing innovation activities (Fritsch, 2002). In China, provinces are independent administrative and economic geographic areas and have obtained autonomy in the formulation of economic and social development policies (Liu and White, 2001). Meanwhile, dialects, customs, and culture have distinct local meanings and regional characteristics. These "special social capitals" are rooted in a region and affect the process of innovation and development in that region.

In recent years, research on RIS has gradually deepened. Scholars generally believe that regional innovation systems are not only affected by geographical factors, but also by a comprehensive influence of various factors such as policies, economic environment and culture. For example, Furman *et al*. (2002) pointed out that innovation systems in different regions exhibit significant heterogeneity, which is not only due to differences in economic development levels and industrial structures, but is also closely related to policy environment and cultural background. Research shows that China's regional innovation system has significant differences between the eastern coastal areas and the central and western regions. This difference is reflected not only in innovation input and output, but also in innovation environment and policy support (Wang *et al*., 2016).

In addition, the effectiveness of regional innovation systems is also affected by regional openness. The higher the regional openness, the faster the diffusion of technology and knowledge flow, and the higher the innovation efficiency (Yanikkaya, 2003). For example, Sbia *et al*. (2014) research shows that the improvement of trade openness can significantly promote the improvement of regional innovation efficiency. In China, the eastern coastal areas are usually more active in innovation activities due to their high openness, while the central and western regions are relatively lagging behind. The differences between these regions make it practical feasible and distinctive to analyze problems from the perspective of regional innovation system.

Although clarifying the borders of the regional innovation system may be quite complicated and controversial, the concept of the regional innovation system is essentially useful in helping researchers formulate hypotheses and presumes. So, we selected administrative provincial regions in China as the units of analysis.

2.2. Technological innovation in the pharmaceutical manufacturing industry

The pharmaceutical manufacturing industry, as a major subordinate industry in the high-tech industry sharing the same operational process with other sub-sectors (Zhang and Chen, 2019), has

unique characteristics and is widely studied. The literature regarding the pharmaceutical manufacturing industry's technological innovation is conducted at three levels, i.e., macro, meso, and micro levels.

The macro-level literature focuses on the national innovation environment of the pharmaceutical manufacturing industry, covering issues such as innovation-related laws and policies. For instance, Acemoglu *et al*. (2006) investigate how Medicare affects pharmaceutical innovation. Kinch and Hoyer (2015) review four American Acts regarding drug development and the related economic trends in the biomedicine industry. Song *et al*. (2019) introduce the impact of China's medical products regulatory system reform on its pharmaceutical innovation.

The Meso-level literature analyzes multiple aspects of industry-level pharmaceutical innovation. Some studies investigate the productivity and innovation patterns of the pharmaceutical manufacturing industry. For example, González and Gascón (2004) studied 80 pharmaceutical laboratories operating in Spain from 1994 to 2000 and found that pure technical efficiency change and scale change are the main drivers of improving productivity. Some focus on the specificity of the pharmaceutical manufacturing industry compared to other industries. For example, Ciliberti *et al*. (2016) compare the drivers of innovation in the Italian pharmaceutical manufacturing industry and the food industry and find that the pharmaceutical sector relies more on internal R&D activities owing to its high R&D intensity. Additionally, others analyze the interactions and cooperation in the pharmaceutical manufacturing industry, including external information to the innovation (Gambardella, 1992), technology spillovers (Feinberg and Majumdar, 2001), outsourcing of R&D (Higgins and Rodriguez, 2006), organizational modes for open innovation (Bianchi *et al*., 2011), and the process of innovation internationalization (Zhao *et al*., 2019).

The micro-level literature further explores the R&D activities in the pharmaceutical manufacturing industry, including the relationship between R&D activities and the pharmaceutical production process, R&D efficiency measurement, and the pharmaceutical firms' R&D activities and corporate strategies. For example, Saranga and Phani (2009) find that higher R&D investments lead to the long-term operational efficiency of Indian pharmaceutical firms. Schuhmacher *et al*. (2016) measure pharmaceutical companies' R&D efficiency from the cost perspective and indicate the reasons for the decline in R&D efficiency and the necessity of innovation strategy adjustments. Toole (2012) finds that both industry R&D investment and potential market size positively affect innovation in the pharmaceutical manufacturing industry.

2.3. Performance assessment of pharmaceutical innovation

Different measurement methods have been proposed for different indicators of innovation output (Bronzini and Piselli, 2016; Tavassoli and Karlsson, 2015). In previous studies, patent data and financial data are the most common proxies of innovation performance. Patents have traditionally been used as a proxy for technological innovation output and new knowledge output (Chen and Guan, 2011). The use of the patent as a proxy has both advantages and disadvantages. On one hand, not all inventions can be measured by patent, and the quality of patented inventions varies greatly. On the other hand, compared to other proxies, patents are more objective and reasonable as they are less influenced by personal or subjective factors (Acs *et al*., 2002; Bronzini and Piselli, 2016). Meanwhile, the primary target of firms initiating innovation activities is to enhance their economic return. Therefore, innovation should better meet customer needs and generate more economic profits (Chen and Guan, 2011). Financial data, related to sales of new products, are considered as proper indicators of economic innovation performance (Guan and Yam, 2015). In addition, financial data can directly reflect the contribution of innovation output to economic growth in China.

This research attempts to study deeper and not be solely restricted by the simple innovation output represented by patents or economic profits. It first disassembles the innovation activities in the pharmaceutical manufacturing industry into several processes. The new medicine innovation process is a "pipeline", including drug discovery, pre-clinical studies, human clinical development, and application for approval. The human clinical stage can be further divided into phases I, II, and III (DiMasi *et al*., 2003). There are differences and connections between these stages. DiMasi *et al*. (2003) find that the average R&D cost of phases II and III is much higher than phase I. Higgins and Rodriguez (2006) indicate that more later-stage products in the pipeline will lead to a higher possibility of receiving FDA approval. Nishimura and Okada (2014) divide the pharmaceutical innovation process into two parts, where the pre-clinical and phase I are called the early stage, and all the phases after are called the late stage.

As the outputs of each stage are all public knowledge (Girotra *et al*., 2007), the knowledge generated from the previous stage is supposed to enter the next stage as an intangible input. Thus, this study proposes a two-stage structure of the pharmaceutical manufacturing industry's innovation process, including the lab R&D stage and the new product development (NPD) stage (Fig. 1). The two stages have a corresponding internal relationship with the drug pipeline. The lab R&D stage contains the "basic research" and "pre-clinical studies", and the NPD stage contains "clinical development", "FDA approval" and "after-approval research" (DiMasi *et al*., 2016).

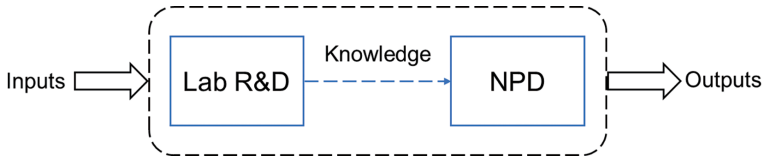


Fig. 1. The innovation process of the pharmaceutical manufacturing industry.

Since innovation is a complicated process involving multiple factors, as the two-stage structure discussed above, it is improper to evaluate innovation performance by using simple inputs or outputs as proxies.

Among all input-output methods, Data Envelopment Analysis (DEA) is a linear programming method to measure the input-output efficiency of different decision-making units (DMUs), first proposed by Charnes *et al*. (1978). Over the past 40 years, DEA has become a widely used tool for performance assessment in various fields (Emrouznejad and Yang, 2018). Its effectiveness has been consistently demonstrated in numerous studies. For instance, DEA has been extensively applied to measure the innovation efficiency of China's high-tech industry. A typical approach is to apply the two-stage DEA model and assess the performance of each innovation stage, where shared inputs (Wang *et al*., 2020), dedicated inputs (Chen *et al*., 2018), and shared outputs (An *et al*., 2020) are all considered, and the different provinces in China are selected as samples. Besides, Zhang and Chen (2019) view the high-tech industry as a hierarchical system with several inner levels and apply a multiplicative network DEA technique. Chen *et al*. (2021) further expand the innovation process of the high-tech industry into a three-stage structure and incorporate cooperative games. With the results of DEA efficiency measurement, some scholars analyze the time-evaluating characteristics (Lin *et al*., 2021) and the influencing factors of the high-tech industry's innovation efficiency (Liu *et al*., 2020). Given its proven effectiveness and reliability in these contexts, this study uses the two-stage DEA model to assess the different innovation stages of the Chinese pharmaceutical manufacturing industry.

2.4. Government funding's effects on the Chinese pharmaceutical manufacturing industry's innovation performance

The relationship between government funding and innovation performance remains inconclusive in previous literature. There are multiple correlations between government funding and innovation performance.

First, government funding can mitigate the companies' capital constraints in the innovation process. Innovation is risky and uncertain, so it often needs substantial resources and investment. It is widely believed that companies with abundant financial resources are more likely to initiate and promote innovation activities. Government funding can effectively stimulate innovation in high-tech industries by providing additional financial support (González and Pazó, 2008).

Second, the companies that receive government funding will be encouraged or even compelled to cooperate with research institutions, and national and local centers, especially state laboratories and universities. Through this collaboration, recipients of government funding have a better chance to obtain scientific achievements and R&D resources (Bedu and Vanderstocken, 2020; Hu and Hassink, 2017). Compared to companies that do not receive government funding, these high-tech companies are more integrated into the national and regional innovation system and often benefit from the overflow of knowledge in the local ecosystem of innovation (Lee, 2011).

Third, providing government funding to high-tech companies sends a prominent signal to the entire society. This signal can be considered a "stamp of approval", which means that the company must process enough capacity to receive government support (Guerini and Quas, 2016). Consequently, the companies that gain the government's support will attract additional investments from the financial market (Lerner, 2002).

However, it would be unwise to assume that there is a simple positive correlation between government funding and innovation performance. It is not a "the more, the better" scenario in this process. Pharmaceutical companies that receive too much government funding may have mediocre performance in terms of innovation compared to those with relatively low levels of public financing (Hong *et al*., 2016). Because the government is not a professional financial manager, which means it lacks the necessary management skills and specialized knowledge to effectively lead and coordinate innovative activities, especially in the pharmaceutical manufacturing industry where innovation is seen as a risky and uncertain process (Colombo *et al*., 2016). In this sense, having a large amount of government funding may not be beneficial. It is reasonable for pharmaceutical companies to attract government funding, but they should not excessively rely on them which may put the company at risk (Huang and Xu, 1998).

Both positive and negative correlations coexist, which leads to the uncertainty of the overall relationship between government funding and innovation performance. Some studies indicate that government support influences firms' behavior and decisions (Hemmert *et al*., 2016) and positively affects innovation activities (Doh and Kim, 2014). In contrast, some scholars indicate that government support harms innovation performance due to a lack of government regulation (Hong *et al*., 2016), crowding out private R&D spending (GÖRg and Strobl, 2007), or an imperfect inner structure of the regional innovation system (Bai and Li, 2014). Others also propose a U-shaped relationship between government support and innovation efficiency (Huang *et al*., 2016).

In China, the government can and is motivated to allocate resources and make policies to improve the local industries' innovation performance (Zhang *et al*., 2019). Furthermore, the Chinese pharmaceutical manufacturing industry relies heavily on government support more than other sub-sectors of the high-tech industry due to the high R&D risk (Hong *et al*., 2016). Qiu *et al*. (2014) also indicate that public funding plays a vital role in the R&D investment of the Chinese pharmaceutical manufacturing industry.

Thus, we propose that government financial support positively affects the lab R&D performance of the Chinese pharmaceutical manufacturing industry. Nevertheless, because the NPD activities are closer to profit-oriented business behavior, they may not be significantly affected by government support. Additionally, it is hypothesized that government funding has a positive effect on overall innovation performance.

The following hypotheses are given based on the previous discussion.

Hypothesis H1 (a): Government funding has a positive relationship with lab R&D efficiency.

Hypothesis H1 (b): Government funding has no significant relationship with NPD efficiency.

Hypothesis H1 (c): Government funding has a positive relationship with overall efficiency.

Multiple factors influence the pharmaceutical manufacturing industry's innovation performance. Regional openness is an essential characteristic of the macroeconomic environment and impacts the national innovation system's innovative performance (Guan and Chen, 2012). Regional openness positively affects technological innovation by promoting the diffusion of technology among different countries (Yanikkaya, 2003), improving the communication of knowledge (Wang *et al*., 2015), and facilitating the adoption of more advanced technology (Sbia *et al*., 2014).

Regional openness may affect the two stages of pharmaceutical innovation differently. Innovation within laboratories tends to operate as a relatively closed and self-sufficient system, where the impact of regional openness is mitigated by internal high specialization and technological barriers. Laboratory innovation may rely more heavily on the domestic research environment and policy support rather than on inter-regional openness. Therefore, it is proposed that regional openness has no significant relationship with the Lab R&D performance. In contrast, the development of new products is more market-oriented, necessitating rapid responses to market demands and shifts. Consequently, increased regional openness can provide a wealth of market intelligence, customer feedback, and collaborative opportunities, all of which are conducive to the successful development of new products. Regional openness may foster transnational cooperation and international competition, bringing to the pharmaceutical manufacturing industry advanced managerial knowledge, marketing strategies, and customer service expertise. These elements are integral to the successful development of new products. Above all, it is proposed that regional openness has a positive relationship with NPD performance. Additionally, it is hypothesized that regional openness has a positive effect on overall innovation performance.

The following hypotheses are given based on the previous discussion.

Hypothesis H2 (a): Regional openness has no significant relationship with lab R&D efficiency.

Hypothesis H2 (b): Regional openness has a positive relationship with NPD efficiency.

Hypothesis H2 (c): Regional openness has a positive relationship with overall efficiency.

Though regional openness plays a positive role in promoting innovation performance according to most previous literature opinions, the moderating effect of regional openness on the impact of government funding on innovation performance might turn out to be negative. On one hand, a higher regional openness level usually represents a prosperous regional market. In a more developed market environment, the company's R&D funds are mostly invested from the private sector. Accordingly, the proportion of government funding will be lower, and the impact of government funding on innovation performance will be weakened. On the other hand, regional openness may also expose domestic products to greater competition from foreign products in developing countries. Considering the Chinese pharmaceutical manufacturing industry is still weak in the global medicine innovation network (Chan and Daim, 2018), companies pursuing economic value have their own decision: purchasing potential

new knowledge, techniques, or products from other regions may be a more properly choice instead of initiating their innovation activities. Thus, the innovation performance of regional companies may be lower than expected due to these trade actions.

Therefore, this study proposes Hypotheses as follows:

Hypothesis H2 (d): Regional openness has a negative moderating effect on the impact of government funding on lab R&D efficiency.

Hypothesis H2 (e): Regional openness has a negative moderating effect on the impact of government funding on NPD efficiency.

Hypothesis H2 (f): Regional openness has a negative moderating effect on the impact of government funding on overall efficiency.

Previous literature indicates that innovation activities directly or indirectly promote economic development through other macroeconomic factors. At the same time, innovation activities are also influenced by macroeconomic factors such as economic development (Furman *et al*., 2002). This implies that in practice, economic development and innovation activities mutually influence each other, and there may be a feedback relationship between economic development and innovation activities. These viewpoints can be summarized by the feedback hypothesis (FBH). The FBH reveals a bidirectional causal relationship between economic growth and innovation activities (Guloglu and Tekin, 2012; Pradhan *et al*., 2016). Studies indicate that, in most cases, using different innovation indicators, there is a long-term relationship between innovation and per capita economic benefits. Studies also manifest that there is both a unidirectional and bidirectional causal relationship between innovation and per capita economic growth.

Thereafter, we assume that the degree of regional economic development positively correlates with innovation performance, represented by all three regional pharmaceutical efficiencies: lab R&D efficiency, NPD efficiency, and overall efficiency. The following hypotheses are given based on the previous discussion.

Hypothesis H3 (a): Economic development has a negative moderating effect on the impact of government funding on lab R&D efficiency.

Hypothesis H3 (b): Economic development has a negative moderating effect on the impact of government funding on NPD efficiency.

Hypothesis H3 (c): Economic development has a negative moderating effect on the impact of government funding on overall efficiency.

Besides the direct positive correlation between economic development and innovation performance, economic development meanwhile has a moderating effect on the impact of government funding on innovation performance. According to the feedback correlation theories, regions that have achieved more advanced economic development tend to have higher levels of innovation. The innovation activities can be categorized into high-quality innovation and low-quality innovation based on the quality of firms' innovation activities (Chen *et al*., 2020). High-quality innovation is more challenging and generates higher value, while low-quality innovation is characterized by stronger imitation capacity, lower innovation difficulty, and lower value. For enterprises focused on high-quality innovation, there is no existing source of innovation, so they have to choose autonomous innovation, which often relies on idea collision, knowledge exchange, and intense market competition. On the other hand, low-quality innovation can be achieved through imitation, and external investments play a more significant role in simulating innovation in this case (Liu *et al*., 2023). The different characteristics of these two types of innovation will

lead to different reactions to government policies. Mahmood and Rufin (2005) argue that when innovation progress occurs through imitation, it can be stimulated innovation through centralized economic and political control provided by the government. Therefore, innovation activities are strongly influenced by government support in low-quality innovation scenarios. However, high-quality innovation has high production value, but it is uncertain and has an unclear direction of development. The improvement of high-quality innovation requires pioneering in the relevant field and contributing to subsequent technological innovation. Regions that choose to engage in high-quality innovation activities rely more on factors and information flows and less on government behaviors. Thus, we assume that economic development has a negative moderating effect on the impact of government funding on innovation performance.

The following hypotheses are given based on the previous discussion.

Hypothesis H3 (d): Economic development has a negative moderating effect on the impact of government funding on lab R&D efficiency.

Hypothesis H3 (e): Economic development has a negative moderating effect on the impact of government funding on NPD efficiency.

Hypothesis H3 (f): Economic development has a negative moderating effect on the impact of government funding on overall efficiency.

3. Methods and Data

3.1. Two-stage slacks-based measure (SBM) DEA method

3.1.1. Theories and formulae of SBM-DEA method

Assume there are n *DMU*s (j=1, ..., n), $m^{(1)}$ kinds of initial inputs (denoted as $x_i^{(1)}$), $m^{(2)}$ kinds of additional inputs (denoted as $x_i^{(2)}$), h kinds of intermediates (denoted as z_p), and the final outputs y_r, r=1, 2, ..., s (Fig. 2).

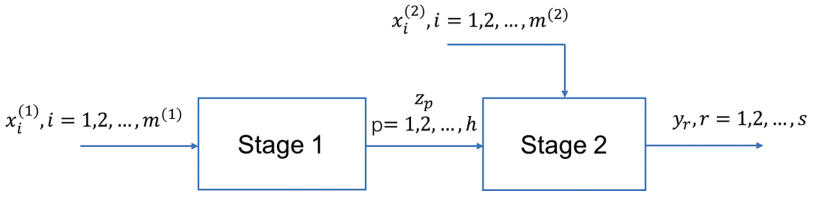


Fig. 2. The two-stage DEA model.

This study follows Kao (2014) and applies a slacks-based measure (SBM) DEA method under the constant return to scale assumption. The production possibility set of the DMU under evaluation (denoted as DMU_o) can be defined as:

$$P = \left\{ (x,y,z) \left| \begin{array}{l} \sum_{j=1}^{n} \eta_j^{(1)} x_{ij}^{(1)} \le x_i^{(1)}, i = 1,\ldots,m^{(1)}; \sum_{j=1}^{n} \eta_j^{(2)} x_{ij}^{(2)} \le x_i^{(2)}, i = 1,\ldots,m^{(2)}; \\ \sum_{j=1}^{n} \eta_j^{(1)} z_{pj} \ge z_p, p = 1,\ldots,h; \sum_{j=1}^{n} \eta_j^{(2)} z_{pj} \le z_p, p = 1,\ldots,h; \\ \sum_{j=1}^{n} \eta_j^{(2)} y_{rj} \ge y_r, r = 1,\ldots,s; \eta_j^{(1)}, \eta_j^{(2)} \ge 0, j = 1,\ldots,n \end{array} \right. \right\} \quad (1)$$

where $\eta_j^{(1)}$ and $\eta_j^{(2)}$ are the intensity variables.

For DMU_o, the efficiencies of its two stages can be defined in a slacks-based form as:

$$E_o^{(1)} = \frac{1 - \frac{1}{m^{(1)}} \sum_{i=1}^{m^{(1)}} \frac{s_i^{(1)-}}{x_{io}^{(1)}}}{1 + \frac{1}{h} \sum_{p=1}^{h} \frac{\hat{s}_p^+}{z_{po}}} \tag{2}$$

$$E_o^{(2)} = \frac{1 - \frac{1}{m^{(2)} + h} \left[\sum_{i=1}^{m^{(2)}} \frac{s_i^{(2)-}}{x_{io}^{(2)}} + \sum_{p=1}^{h} \frac{\hat{s}_p^-}{z_{po}} \right]}{1 + \frac{1}{s} \sum_{r=1}^{s} \frac{s_r^+}{y_{ro}}} \tag{3}$$

Then, the flexible weights of the two stages are used:

$$\alpha^{(1)} = \frac{1 + \frac{1}{h} \sum_{p=1}^{h} \frac{\hat{s}_p^+}{z_{po}}}{\left[1 + \frac{1}{h} \sum_{p=1}^{h} \frac{\hat{s}_p^+}{z_{po}}\right] + \left[1 + \frac{1}{s} \sum_{r=1}^{s} \frac{s_r^+}{y_{ro}}\right]} \tag{4}$$

$$\alpha^{(2)} = \frac{1 + \frac{1}{s} \sum_{r=1}^{s} \frac{s_r^+}{y_{ro}}}{\left[1 + \frac{1}{h} \sum_{p=1}^{h} \frac{\hat{s}_p^+}{z_{po}}\right] + \left[1 + \frac{1}{s} \sum_{r=1}^{s} \frac{s_r^+}{y_{ro}}\right]} \tag{5}$$

Thus, we can obtain the system efficiency of DMU_o as $E_0=\alpha^{(1)}E_0^{(1)}+\alpha^{(2)}E_0^{(2)}$. Then, through programming (6), the optimal weights and slacks can be obtained as well as the best system efficiency:

$$E_o = \min \frac{\left[1 - \frac{1}{m^{(1)}} \sum_{i=1}^{m^{(1)}} \frac{s_i^{(1)-}}{z_{io}^{(1)}}\right] + \left[1 - \frac{1}{m^{(2)} + h} \left[\sum_{i=1}^{m^{(2)}} \frac{s_i^{(2)-}}{x_{io}^{(2)}} + \sum_{p=1}^{h} \frac{\hat{s}_p^-}{z_{po}} \right]\right]}{\left[1 + \frac{1}{h} \sum_{p=1}^{h} \frac{\hat{s}_p^+}{z_{po}}\right] + \left[1 + \frac{1}{s} \sum_{r=1}^{s} \frac{s_r^+}{y_{ro}}\right]}$$

$$\begin{aligned}
s.t. \quad & \sum_{j=1}^{n} \eta_j^{(1)} x_{ij}^{(1)} + s_i^{(1)-} = x_{io}^{(1)}, i = 1, \ldots, m^{(1)} \\
& \sum_{j=1}^{n} \eta_j^{(2)} x_{ij}^{(2)} + s_i^{(2)-} = x_{io}^{(2)}, i = 1, \ldots, m^{(2)} \\
& \sum_{j=1}^{n} \eta_j^{(1)} z_{pj} - \hat{s}_p^+ = z_{po}, p = 1, \ldots, h \\
& \sum_{j=1}^{n} \eta_j^{(2)} z_{pj} + \hat{s}_p^- = z_{po}, p = 1, \ldots, h \\
& \sum_{j=1}^{n} \eta_j^{(2)} y_{rj} - s_r^+ = y_{ro}, r = 1, \ldots, s \\
& \eta_j^{(1)}, \eta_j^{(2)}, s_i^{(1)-}, s_i^{(2)-}, \hat{s}_p^+, \hat{s}_p^-, s_r^+ \geq 0
\end{aligned} \tag{6}$$

As the program (6) is nonlinear, it can be linearized by the technique introduced in Charnes and Cooper (1962).

3.1.2. Indicators and data

Proper inputs and outputs for the DEA model should be selected to obtain accurate and reasonable results. We review previous literature regarding innovation efficiency measurement using two-stage DEA methods.

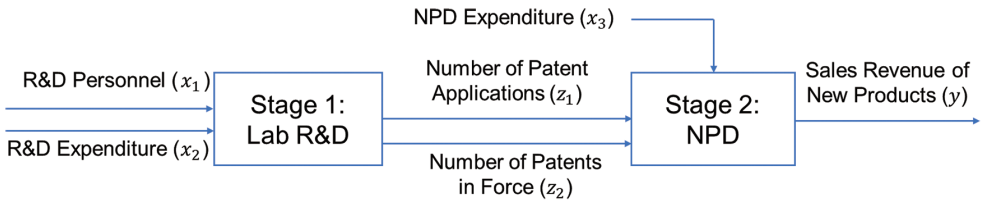


Fig. 3. The logical model of this study.

As Cruz-Cázares *et al*. (2013) emphasized, the input and output indicators related to the innovation process are selected. In the logical model (Fig. 3), *R&D Personnel* and *R&D Expenditure* are two initial inputs and the essential human and financial resources allocated to laboratory R&D activities. Then, the knowledge produced in the lab R&D stage is proxied by the *Number of Patent Applications* and *Number of Patents in Force* (two intermediates).

The additional input, *New Product Development Expenditure*, measures the resources devoted to the NPD stage. According to the *National Statistics Yearbook of Science and Technology*, the conception of a "new product" incorporates both creative innovation and improved innovation. Considering the comprehensiveness, we apply the final output *Sales Revenue of New Products* to proxy the value of the innovation in the pharmaceutical manufacturing industry. The details of the selected inputs and outputs are listed in Table 1.

Table 1
Specifications of inputs and outputs.

Types	Variables	Notations	Units	Definitions
Initial inputs	*R&D Personnel*	x_1	Man-year	The full-time equivalent of R&D personnel
	R&D Expenditure	x_2	10 thousand RMB	The actual expenditure for internal R&D activities during the reporting year.
Additional input	*New Product Development Expenditure*	x_3	10 thousand RMB	The expenditures for research and development of new products.
Intermediates	*Number of Patent Applications*	z_1	Piece	The number of patent applications filed by domestic and foreign intellectual property administrations.
	Number of Patents in Force	z_2	Piece	The number of invention patents owned by enterprises as patentees as authorized by the domestic and foreign intellectual property administrations.
Output	*Sales Revenue of New Products*	y	10 thousand RMB	Refers to the sales income realized by the company from the sale of new products.

The data set of this study consists of the provincial aggregational data of 29 provinces in the Chinese mainland during the period from 2009 to 2019 (Tibet and Qinghai are excluded due to missing data), obtained from the *National Statistics Yearbook of Science and Technology* of the corresponding year. All the monetary terms have been deflated to the 2009 value.[1]

[1] *R&D expenditure* and *NPD expenditure* are deflated by Consumer Price Indices; *Sales Revenue of New Products* is deflated by Health Care Consumer Price Indices. The two indices used are obtained from the website of National Bureau of Statistics of China. http://data.stats.gov.cn/english/easyquery.htm

Besides, the time-lag effect should be considered here (Hashimoto and Haneda, 2008; Toole, 2012). As there is no widely accepted time lag, for generality, we adopt a one-year lag for both the lab R&D stage and the NPD stage (Liu *et al*., 2019).

3.2. Tobit regression

3.2.1. Theories and formulae of Tobit regression

The innovation efficiency values calculated by the DEA model are mostly between 0 and 1. Only a few DMUs have the innovation efficiency value reaching the boundaries, which means the values equal to 1. The innovation efficiency values, as the dependent variables, are limited, and the parameter estimates obtained using ordinary least squares (OLS) regression will be biased and inconsistent, while the Tobit regression is a limited dependent variable model that can effectively process the censored dependent variable data. Therefore, this study uses the Tobit regression to investigate the impact of influencing factors on innovation efficiency values, referring to some literature (Song *et al*., 2019). The Tobit regression equations are as follows:

$$y_i^* = x_i\beta + \varepsilon_i,\ \varepsilon_i \sim \mu(0, \sigma^2) \tag{7}$$

$$y_i = \begin{cases} 0, \text{ if } y_i^* \le 0 \\ y_i^*, \text{ if } 0 < y_i^* < 1 \\ 1, \text{ if } y_i^* \ge 1 \end{cases} \tag{8}$$

In basic equations (7) and (8), β is the regression parameter, x_i and y_i are the independent and dependent variables, respectively, and ε_i is the random perturbation term that obeys normal distribution $N\sim(0, \sigma^2)$. Equations (9)-(11) are the specific regression models employed in this study. We use the interactions to measure the moderating effect between variables.

$$LabEff = \alpha_0^{\,l} + \alpha_1^{\,l}Gov + \alpha_2^{\,l}Gov \times Open + \alpha_3^{\,l}Open + \alpha_4^{\,l}Gov \times Pgdp + \alpha_5^{\,l}Pgdp + \alpha_6^{\,l}Gov \times Open \times Pgdp + \beta_1^{\,l}Env + \beta_2^{\,l}Grad + \beta_3^{\,l}Age + \varepsilon_1 \tag{9}$$

$$NPDEff = \alpha_0^{\,N} + \alpha_1^{\,N}Gov + \alpha_2^{\,N}Gov \times Open + \alpha_3^{\,N}Open + \alpha_4^{\,N}Gov \times Pgdp + \alpha_5^{\,N}Pgdp + \alpha_6^{\,N}Gov \times Open \times Pgdp + \beta_1^{\,N}Env + \beta_2^{\,N}Grad + \beta_3^{\,N}Age + \varepsilon_2 \tag{10}$$

$$OverEff = \alpha_0^{\,0} + \alpha_1^{\,0}Gov + \alpha_2^{\,0}Gov \times Open + \alpha_3^{\,0}Open + \alpha_4^{\,0}Gov \times Pgdp + \alpha_5^{\,0}Pgdp + \alpha_6^{\,0}Gov \times Open \times Pgdp + \beta_1^{\,0}Env + \beta_2^{\,0}Grad + \beta_3^{\,0}Age + \varepsilon_3 \tag{11}$$

where $\beta_0^{\,l}$, $\beta_0^{\,n}$, $\beta_0^{\,o}$ are the constant terms and ε_1, ε_2, ε_3 are disturbance terms.

3.2.2. Variables and data

This study calculates the innovation performance by applying the two-stage DEA method, gives estimation through Tobit regression, and uses the interaction terms to measure the moderating effect. The variables are divided into four categories: dependent variables, independent variables, moderating variables, and control variables.

(1) Dependent Variables

There are three dependent variables, *Lab R&D efficiency, NPD efficiency*, and *Overall efficiency*. These three variables are all generated by the two-stage SBM-DEA method introduced in Section 3.1.2.

(2) Independent Variables

The independent variable is government funding intensity, measured by the ratio of government funding to total R&D expenditure. This indicator captures the extent of financial support provided by the government to the pharmaceutical manufacturing industry and reflects the degree of reliance of pharmaceutical firms on public funding for their R&D activities.

On one hand, an appropriate level of government funding intensity indicates that public support plays a complementary and guiding role in stimulating corporate R&D investment, thereby contributing to a more efficient allocation of innovation resources and improved R&D productivity. However, a low funding intensity may suggest insufficient engagement of government resources or weak absorption capacity on the part of enterprises. On the other hand, a disproportionately high dependence on government funding could lead to over-reliance, potentially crowding out private investment and dampening firms' internal incentives and capabilities for innovation.

(3) Moderating Variables

There are two moderator variables: *Regional openness* and *Economic development*. *Regional openness* is represented by the percent of total imports and exports to the GDP. *Economic development* is represented by per capita GDP.

(4) Control Variables

There are three control variables: *Environmental regulation, Quality of human capital*, and *Degree of aging*. *Environmental regulation* can be either incentive or voluntary, including taxes, subsidies, tradable sewage permits, etc. In this study, the local government's investment in environmental pollution treatment is used to represent the strength of local environmental regulation. The *Quality of human capital* is represented by the number of college graduates. The *Degree of aging* is represented by the proportion of the population over the age of 65.

Detailed information on different variables is presented in Table 2.

Table 2
The variables and data sources.

Types	Variables	Abbreviation	Definition	Data sources
Dependent Variables	Lab R&D efficiency	LabEff	Efficiency of the lab R&D stage.	Two-stage DEA model
	NPD efficiency	NPDEff	Efficiency of the NPD stage.	
	Overall efficiency	OverEff	Efficiency of the whole two-stage innovation process.	
Independent Variables	Government funding intensity	Gov	Government funding/Total intramural R&D expenditure.	China Statistics Yearbook on High Technology Industry
Moderator Variables	Regional openness	Open	Total imports and exports/Each province's GDP.	China Statistical Yearbook
	Economic development	Pgdp	Per capita GDP	China Statistical Yearbook
Control Variables	Environmental regulation	Env	Total investment in the treatment of environmental pollution/ Each province's GDPs.	China Environment Yearbook
	Quality of human capital	Grad	the number of college graduates	China Statistical Yearbook
	Degree of aging	Age	Percentage of the population over the age of 65.	

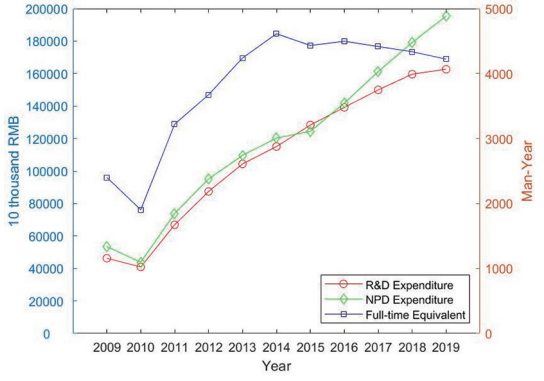
4. Results

4.1. Efficiency measurement results and analysis

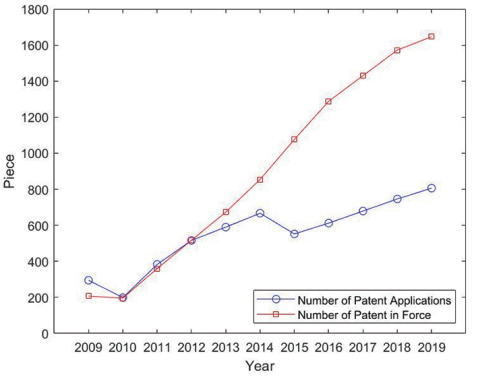
The descriptive statistics of the indicators are displayed in Table 3. The scale of the pharmaceutical industries varies among different provinces. The variation trends of the indicators are depicted in Fig. 4, where the continuous growth and development of the pharmaceutical manufacturing industry in China in recent years can be revealed. Specifically, there is more expenditure on NPD than lab R&D activities in most years. A difference exists between the *Number of Patents in Force* and the *Number of Patent Applications* in both the growth rate and the total amount.

Table 3
The descriptive statistics of inputs and outputs in the two-stage DEA model.

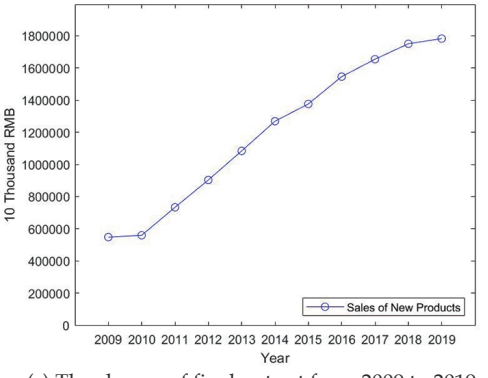
Variables	N	Mean	SD	Min	Max
R&D Personnel	319	3,815	4,148	6	18,588
R&D Expenditure	319	126,077	178,824	78	1,226,803
Number of Patent Applications	319	613.7	704.8	4	4,989
Number of Patents in Force	319	1,051	1,264	1	7,515
New Product Development Expenditure	319	158,385	225,165	138	1,791,773
Sales Revenue of New Products	319	1,859,446	2,716,886	1,656	24,720,969



(a) The change of external inputs from 2009 to 2019.



(b) The change of intermediates from 2009 to 2019.



(c) The change of final output from 2009 to 2019.

Fig. 4. The variation trends of the different types of input and output indicators.

Several characteristics of the Chinese pharmaceutical manufacturing industry's innovation performance are observed.

Perspective (1): Characteristics of the two innovation stages of the Chinese pharmaceutical manufacturing industry.

The change in three efficiencies during 2009-2019 is shown in Fig. 5. It can be found that the average NPD efficiency score has a more stable trend than lab R&D efficiency before 2016. The average lab R&D efficiency changed from 0.51 to 0.72, while the NPD efficiency changed from 0.65 to 0.42. The average efficiency of the NPD stage is higher than the lab R&D stage most of the time. More than 80% of the provinces' average NPD efficiency is higher than lab R&D efficiency from 2009 to 2019. In 2011, the average efficiency of NPD had a significant descent. During 2012-2016, three efficiencies changed slightly and showed a tendency to converge. From 2017 to 2019, the average lab R&D efficiency and the overall efficiency both had a sudden decrease.

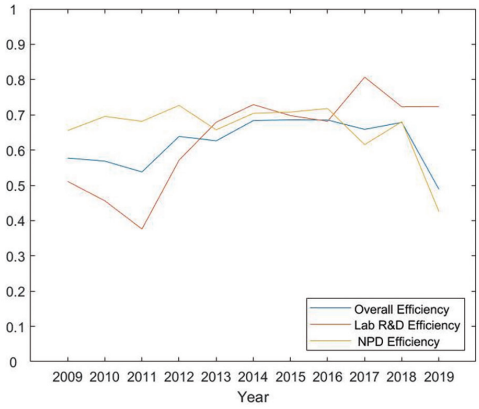


Fig. 5. The change in the average efficiencies during the period 2009 to 2019.

Perspective (2): The evolution path of the provincial innovation performance of the Chinese pharmaceutical manufacturing industry.

Based on lab R&D efficiency and NPD efficiency, the distribution of sample provinces from 2009 to 2019 is depicted in Fig. 6. The scatters of different years show that lab R&D efficiency has an obvious growth from 2009 to 2019. In 2009, only 9 provinces' lab R&D efficiency scores were higher than their NPD efficiency scores. In 2019, 27 provinces' lab R&D efficiency scores were higher than their NPD efficiency scores. This indicates that from 2009 to 2019, there was an overall improvement in lab R&D efficiency within the Chinese pharmaceutical manufacturing industry, while the enhancement in NPD efficiency was less pronounced.

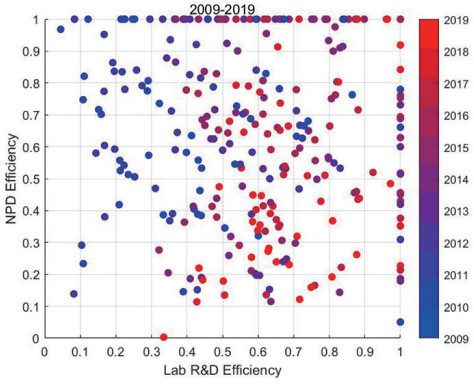


Fig. 6. The change in the distribution of sample provinces during the period 2009-2019.

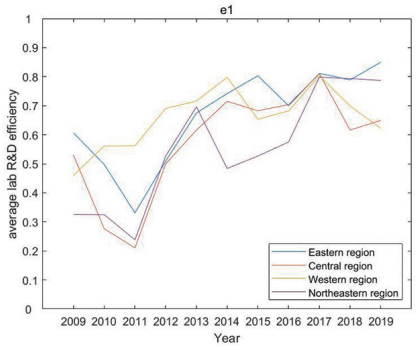
Perspective (3): The trend of regional innovation performance of the Chinese pharmaceutical manufacturing industry.

According to the *China Statistical Yearbook*, the provinces (and autonomous regions and municipalities) in the Chinese mainland can be divided into four major regions, i.e. eastern, central, western, and northeastern.[2] The change in the aggregating innovation efficiency scores of the four regions during 2009-2019 is depicted in Fig. 7.

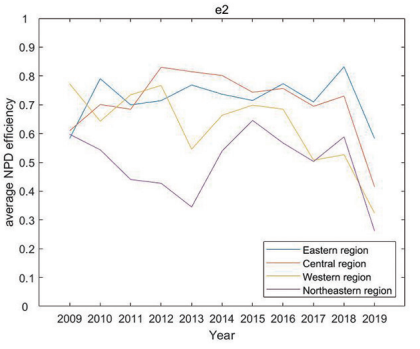
Fig. 7 (a) indicates that all four regions have achieved overall progress in lab R&D efficiency. The western region shows the potential for further improvement in lab R&D efficiency because it is the only region that keeps progressing from 2009 to 2019. In 2011, the four regions' average efficiencies of lab R&D had a significant descent, which combined with the previous national average lab R&D efficiency results.

In Fig. 7 (b), the four regions' NPD efficiency evolution processes are different. The northeastern region witnessed the most significant decline in NPD efficiency and had the most minor average NPD efficiency from 2009 to 2019. The northeastern region still falls behind the other three regions (Fig. 7 (c)). As for the other three regions, the overall efficiencies are close and have similar trends from 2009 to 2019.

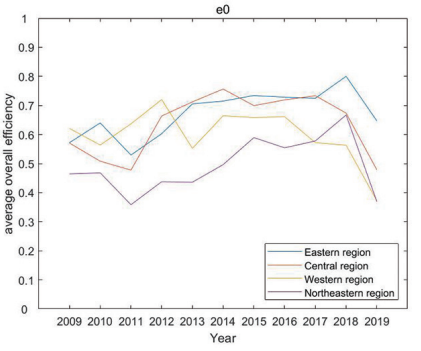
In 2019, the four regions' average NPD efficiency and overall efficiency had a sudden decline, which combined with the previous national results.



(a) The change in average lab R&D efficiency.



(b) The change in average NPD efficiency.



(c) The change in average overall efficiency.

Fig. 7. The change in average innovation efficiencies of different regions in China from 2009 to 2019.

[2] http://www.stats.gov.cn/tjsj/ndsj/2019/indexeh.htm

4.2. Estimation results

The descriptive statistics of variables in Tobit regression are displayed in Table 4. Table 5 reports the Pearson correlation coefficients of the major variables used in the analysis. Except for the correlation coefficients between OverEff and LabEff, OverEff and NPDEff are higher than 0.5, which are bound to be correlated. The correlation coefficient between open and pgdp is 0.566, which represents a medium-level correlation. All other correlation coefficients are lower than 0.5. There is no strong correlation between variables.

Table 4
The descriptive statistics of inputs and outputs in the Tobit regression.

Variables	N	Mean	SD	Min	Max
Lab R&D efficiency	319	0.62	0.23	0	1.00
NPD efficiency	319	0.63	0.26	0.04	1.00
Overall efficiency	319	0.66	0.28	0	1.00
Government funding intensity	319	0.06	0.044	0.01	0.39
Regional openness	319	0.27	0.29	0.03	1.46
Economic development	319	0.59	0.20	0.04	1.01
Environmental regulation	319	0.01	0.01	0.001	0.09
Quality of human capital	319	1.27	0.31	0.21	1.78
Degree of aging	319	0.10	0.02	0.05	0.16

Table 5
Correlation coefficient between variables.

Variables	1	2	3	4	5	6	7	8	9
1. LabEff	1.000								
2. NPDEff	0.115**	1.000							
3. OverEff	0.551***	0.874***	1.000						
4. gov	0.095*	0.007	0.022	1.000					
5. open	0.044	0.077	0.103*	-0.067	1.000				
6. pgdp	0.257***	0.171***	0.276***	-0.340***	0.566***	1.000			
7. env	-0.055	0.106*	0.036	0.091*	-0.256***	-0.144**	1.000		
8. grad	0.022	0.038	0.071	-0.255***	0.143**	0.209***	-0.374***	1.000	
9. age	0.266***	0.018	0.154***	-0.293***	0.037	0.388***	-0.306***	0.466***	1.000

Note: ***, ** and * denotes significance at the 1%, 5% and 10% level respectively.

The Tobit regression results, indicating the different regressions of innovation performance in different stages, are displayed in Tables 6-8. In the design of the moderating effect interaction plot, we adopt the overall mean of each variable plus or minus half the standard deviation to represent the scenarios of high and low levels, respectively.

Table 6
Results of Lab R&D Efficiency Tobit regression.

(LabEff)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
gov		1.4749***	3.0168***	8.1426***	8.1826***	8.7165***
		(0.4341)	(0.6664)	(1.3491)	(1.3600)	(1.4545)
gov×open			-5.3594**		1.6010	-2.4537
			(2.6196)		(2.9403)	(4.7623)
open			0.1630	-0.1495**	-0.2419	-0.3310
			(0.1675)	(0.0721)	(0.1844)	(0.2015)
gov×pgdp				-12.9202***	-13.6385***	-14.6837***
				(2.5478)	(2.8843)	(3.0531)
pgdp			0.5457***	1.3191***	1.3592***	1.3439***
			(0.1180)	(0.1934)	(0.2078)	(0.2074)
gov×open×pgdp						7.5168
						(6.9956)
env	0.0353	0.3482	-0.0566	-0.0311	-0.1147	0.0796
	(2.1463)	(2.1162)	(2.1149)	(2.0480)	(2.0538)	(2.0562)
grad	-0.1433**	-0.1115*	-0.0662	-0.0687	-0.0766	-0.0671
	(0.0644)	(0.0640)	(0.0637)	(0.0603)	(0.0620)	(0.0625)
age	4.5263***	5.1423***	2.8254***	2.7430***	2.8872***	2.8400***
	(0.9129)	(0.9161)	(1.0119)	(0.9457)	(0.9818)	(0.9803)
_cons	0.3833***	0.1813	-0.0115	-0.3326**	-0.3384**	-0.3286**
	(0.1120)	(0.1249)	(0.1279)	(0.1447)	(0.1453)	(0.1451)
var(e.LabEff)	0.0875***	0.0846***	0.0778***	0.0731***	0.0731***	0.0727***
	(0.0081)	(0.0079)	(0.0072)	(0.0067)	(0.0067)	(0.0067)
N	319	319	319	319	319	319

Note: ***, ** and * denotes significance at the 1%, 5% and 10% level respectively.

Table 6 and Fig. 8 report the empirical results of lab R&D efficiency. First, we examine the direct effect of the government funding intensity. In Model 2, the coefficient of the government funding intensity is significant and positive, indicating that government funding promotes lab R&D efficiency, which supports H1(a). Representing in Fig. 8, all functions exhibit positive slopes. This result is consistent with the conclusion of Qiu *et al*. (2014), indicating that public funding plays a vital role in the R&D investment of the Chinese pharmaceutical manufacturing industry.

The parameter of regional openness in Model 3 is not significant, confirming H2(a), which means there is no significant relationship between regional openness and lab R&D efficiency. As a moderating variable in Model 3, the coefficient of the interaction term between regional openness and government funding is significant and negative, which supports H2(d). In other words, higher regional openness leads to domestic products facing greater competition from foreign products in developing countries. Considering that the Chinese pharmaceutical manufacturing industry is still weak in the global medicine innovation network (Chan and Daim, 2018), Chinese pharmaceutical firms may prefer to purchase critical technologies form foreign companies instead of initiating their innovation activities. That process suppresses the impact of government funding on lab R&D efficiency, therefore, heightened regional openness is indicative of lower slopes in Fig. 8(a).

Regarding the role of economic development, the coefficient of economic development in Model 4 is significant and positive, supporting that the direct effect of economic development on lab R&D efficiency is positive (H3(a)). The parameter of the interaction term between economic development and government funding indicates statistically significant with a negative effect, which confirms H3(d). According to the discussion on low-quality and high-quality innovation ahead, high economic development leads to high-quality innovation activities that depend more on intelligence and information flows and less on government funding. Thus, the impact of government funding on lab R&D efficiency is negatively moderated by regional economic development. In Fig. 8(b), higher level of economic development suggests lower slopes of the functions.

Model 5 and Model 6 incorporate both the moderating effects of regional openness and economic development concurrently. The coefficient of the gov×pgdp interaction term is significant and negative, but the coefficient of the gov×open interaction term is no longer significant. One possible explanation for this outcome is the presence of certain multicollinearity between regional openness and economic development. To address this issue, a least squares estimation was designed. The least squares estimation aims to verify the robustness of Tobit regression and to calculate the variance inflation factor (VIF) between variables. The result suggests that all explanatory variables have passed the collinearity test. Detailed results are displayed in the discussion of the robustness analysis. The other explanation is that one moderating effect is relatively smaller in terms of its marginal effect compared to the other. In this case, the moderating effect of higher economic development is much stronger so the moderating effect of regional openness has been covered and absorbed. As depicted in Fig. 8(c), an increase in regional openness does not result in a slope difference, whereas an increase in economic development leads to a decline in the slope. In Model 6, the three-way interaction term's parameter is not significant. This implies that the two moderating effects do not compound each other. The slopes in the Fig. 8(c) representation further support this conclusion.

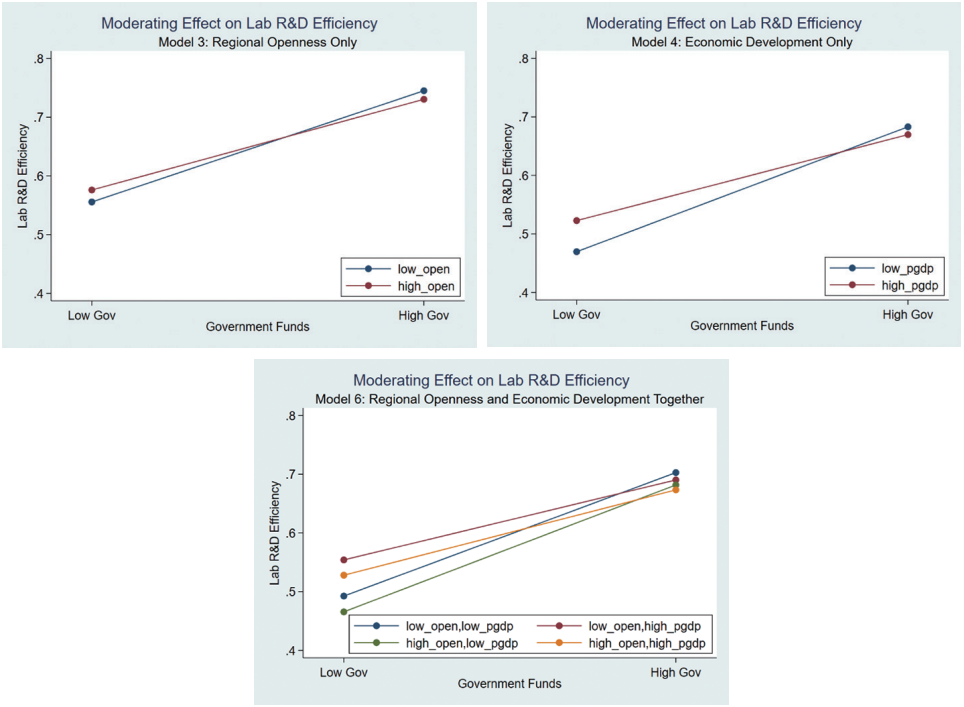


Fig. 8. Moderating effect diagrams on Lab R&D Efficiency.

Table 7
Results of NPD Efficiency Tobit regression.

(NPDEff)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
gov		0.4334	3.2786***	7.2142***	7.2276***	8.3715***
		(0.5401)	(0.8387)	(1.6364)	(1.6081)	(1.7776)
gov×open			-12.2064***		-6.4262*	-14.1967**
			(3.2854)		(3.6812)	(5.9573)
open			0.6335***	-0.0716	0.2968	0.1113
			(0.2093)	(0.0944)	(0.2306)	(0.2557)
gov×pgdp				-13.7453***	-11.0436***	-13.2742***
				(3.1720)	(3.4697)	(3.7653)
pgdp			0.5370***	1.3459***	1.1976***	1.1829***
			(0.1521)	(0.2487)	(0.2586)	(0.2589)
gov×open×pgdp						14.7343*
						(8.9161)
env	7.1524***	7.2336***	7.8675***	7.5676***	7.8265***	8.1787***
	(2.7367)	(2.7381)	(2.7160)	(2.7068)	(2.6871)	(2.6832)
grad	0.0516	0.0619	0.1412*	0.0957	0.1291	0.1462*
	(0.0822)	(0.0832)	(0.0822)	(0.0797)	(0.0814)	(0.0816)
age	0.5771	0.7639	-2.1579*	-1.4885	-2.0989	-2.1820*
	(1.1464)	(1.1695)	(1.2895)	(1.2346)	(1.2747)	(1.2701)
_cons	0.4937***	0.4328***	0.1508	-0.1110	-0.0972	-0.0853
	(0.1413)	(0.1602)	(0.1630)	(0.1856)	(0.1837)	(0.1834)
var(e.NPDEff)	0.1359***	0.1359***	0.1234***	0.1222***	0.1203***	0.1192***
	(0.0136)	(0.0136)	(0.0123)	(0.0122)	(0.0120)	(0.0119)
N	319	319	319	319	319	319

Note: ***, ** and * denotes significance at the 1%, 5% and 10% level respectively.

Table 7 and Fig. 9 report the empirical results of NPD efficiency. In Model 2, the correlation between the government funding intensity and NPD efficiency is not significant, which supports H1(b). This result supports the discussion that the NPD activities are closer to profit-oriented business behavior and NPD efficiency is not significantly affected by the strength of government support.

In Model 2, before adding moderating variables and the interactions, the coefficient of government funding is not significant in the regression of NPD efficiency. In the subsequent models, after adding moderating variables and the interaction terms, the coefficients of independent variables, moderating variables, and interactions are significant. It indicates that in these models, independent variables produce effects on dependent variables under the role of moderating variables.

Specifically, in Model 3, regional openness plays the role of a moderating variable. In this case, government funding positively affects NPD efficiency under the role of regional openness. The coefficient of regional openness is significant and positive, supporting H2(s) which means regional openness directly

promotes the NPD efficiency. Moreover, higher regional openness has a negative moderating effect on the impact of the government funding intensity on NPD efficiency, confining H2(e). A higher regional openness level usually represents a prosperous regional market. A strong regional market may crowd out the effect of government funding and the moderating effect of regional openness is significantly negative as shown in Fig. 9(a).

When economic development is posited as a moderating variable in Model 4, the direct effect of economic development is positive, supporting H3(b), and the moderating effect of it is negative, supporting H3(e). Like the lab R&D efficiency, the innovation quality mechanism equally functions on the NPD efficiency, bringing a negative moderating effect. Fig. 9(b) also shows the moderating effect of economic development is significantly negative.

In Model 5, when two moderating variables are in the same model, both coefficients are significant and negative. The moderating effect of regional openness is strong enough to avoid being covered by the moderating effect of economic development. The collinearity test for multicollinearity between two variables was examined again in this regression. Both moderating effects had a negative influence on the impact of the government funding intensity on NPD efficiency.

In Model 6, the triple interaction coefficient is significant and positive. Higher levels of regional openness and economic development would bring a negative moderating effect separately. In the joint model, the positive triple interaction coefficient indicates both two variables reinforce the negative moderating effect of each other. As depicted in Fig. 9(c), an increase in regional openness or economic development leads to a decline in the slope. As for the three-way interaction term is significantly positive, the main effect's slope is lower at instances when both regional openness and economic development are at high levels, compared to the other three conditions where at least one of these factors is not at a high level.

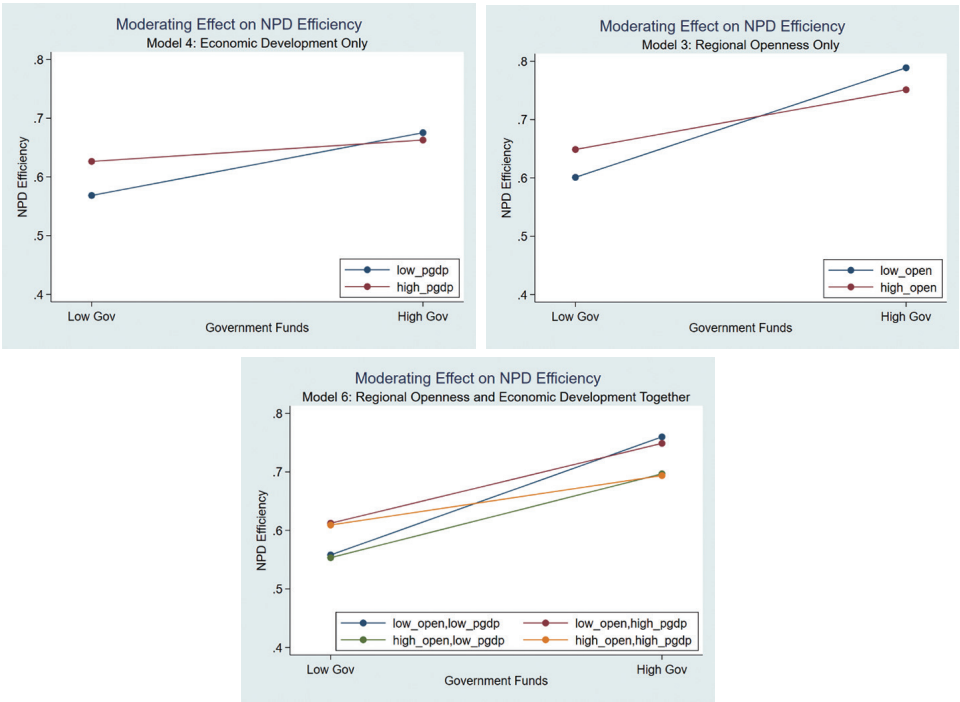


Fig. 9. Moderating effect diagrams on NPD efficiency.

Table 8
Results of Overall Efficiency Tobit regression.

(OverEff)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
gov		0.6074*	2.9107***	6.2690***	6.2860***	7.3934***
		(0.3485)	(0.5275)	(1.0111)	(0.9973)	(1.0924)
gov×open			-9.6759***		-4.6177**	-12.3449***
			(2.0945)		(2.3226)	(3.7100)
open			0.4880***	-0.0709	0.1942	0.0064
			(0.1337)	(0.0591)	(0.1456)	(0.1606)
gov×pgdp				-11.3921***	-9.4786***	-11.6495***
				(1.9587)	(2.1534)	(2.3188)
pgdp			0.4844***	1.1515***	1.0469***	1.0285***
			(0.0952)	(0.1521)	(0.1589)	(0.1582)
gov×open×pgdp						14.7237***
						(5.5588)
env	2.9165	3.0463*	3.5042**	3.2597*	3.4935**	3.8818**
	(1.7748)	(1.7715)	(1.7113)	(1.6803)	(1.6701)	(1.6589)
grad	0.0008	0.0145	0.0809	0.0488	0.0727	0.0914*
	(0.0533)	(0.0537)	(0.0517)	(0.0495)	(0.0506)	(0.0505)
age	2.0569***	2.3267***	-0.2339	0.2473	-0.1933	-0.2810
	(0.7499)	(0.7635)	(0.8191)	(0.7739)	(0.7992)	(0.7914)
_cons	0.3813***	0.2957***	0.0597	-0.1613	-0.1522	-0.1399
	(0.0926)	(0.1045)	(0.1033)	(0.1159)	(0.1148)	(0.1139)
var(e.OverEff)	0.0607***	0.0603***	0.0519***	0.0502***	0.0493***	0.0483***
	(0.0053)	(0.0052)	(0.0045)	(0.0043)	(0.0043)	(0.0042)
N	319	319	319	319	319	319

Note: ***, ** and * denotes significance at the 1%, 5% and 10% levels respectively.

Table 8 and Fig. 10 report the empirical results of overall efficiency. In Model 2, which is the baseline regression, the coefficient of the government funding intensity is significant and positive, indicating that the government funding intensity has promoted overall efficiency, which supports H1(c). This result is in line with the theory that the Chinese pharmaceutical manufacturing industry relies heavily on government support more than other sub-sectors of the high-tech industry due to the high R&D risk (Hong *et al*., 2016).

As the moderating variable in Model 3, regional openness has a positive direct effect on overall efficiency, which supports H2(c). As for the significant and negative coefficient of the interaction term, it implies that regional openness has a negative moderating effect on the impact of the government funding intensity on the overall efficiency, which confirms H2(f).

As the moderating variable in Model 4, economic development has a positive direct effect on overall efficiency, supporting H3(c). The parameter of the interaction term is significant and negative, revealing that economic development has a negative moderating effect on the impact of the government funding

intensity on the overall efficiency, confirming H3(f).

Fig. 10 reports the moderating effects diagrams of overall efficiency. All results are consistent with those presented in Table 7 and Fig. 9, with the only modification being the substitution of "NPD efficiency" with "overall efficiency" in the conclusion.

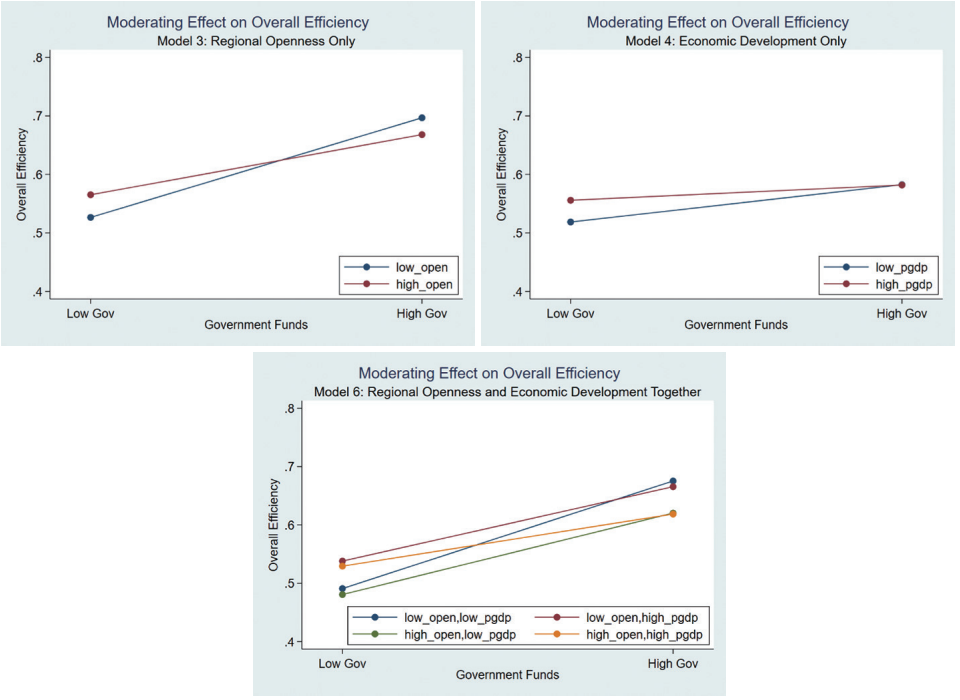


Fig. 10. Moderating effect diagrams on overall efficiency.

4.3. Robustness check

To verify the robustness of the findings, we conducted the first robustness check by employing a bootstrap resampling method. The basic idea of the bootstrap method is to construct multiple resamples by repeatedly sampling data from the original sample. By observing the distribution of the bootstrap samples, we can observe that the bootstrap regression results closely resemble those obtained using Tobit regression. In the bootstrap robustness check, we chose a random seed for the bootstrap robustness check, setting up 2000 resample times, to test the robustness of the results of lab R&D efficiency, NPD efficiency, and overall efficiency. Significant and the direction of correlations are all consistent throughout. This suggests that the results obtained using Tobit regression are robust. The results of the bootstrap robustness check are represented in Table 9.

Table 9
Results of Bootstrap robustness check (resample times = 2000).

(LabEff)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
gov		1.4749***	2.3714***	8.0139***	8.1826***	8.7165***
		(0.5059)	(0.7745)	(1.6235)	(1.6675)	(1.7988)
gov×open			-4.6868*		1.6010	-2.4537
			(3.0375)		(3.0489)	(5.2847)

Table 9. (continued)

(LabEff)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
open			0.3373*		-0.2419	-0.3310
			(0.1876)		(0.1879)	(0.2088)
gov×pgdp				-12.8953***	-13.6385***	-14.6837***
				(2.9287)	(3.2020)	(3.4284)
pgdp				1.1701***	1.3592***	1.3439***
				(0.2018)	(0.2352)	(0.2383)
gov×open×pgdp						7.5168
						(7.8355)
env	0.0353	0.3482	1.2162	1.0760	-0.1147	0.0796
	(2.2886)	(2.2046)	(2.3082)	(1.9579)	(1.9779)	(1.9371)
grad	-0.1433**	-0.1115**	-0.0894	-0.0824	-0.0766	-0.0671
	(0.0567)	(0.0542)	(0.0567)	(0.0518)	(0.0560)	(0.0560)
age	4.5263***	5.1423***	4.7151***	3.3773***	2.8872***	2.8400***
	(0.8828)	(0.8984)	(0.9480)	(0.8913)	(0.9921)	(0.9840)
_cons	0.3833***	0.1813*	0.1135	-0.3402**	-0.3384**	-0.3286**
	(0.1050)	(0.1084)	(0.1106)	(0.1464)	(0.1526)	(0.1553)
var(e.LabEff)	0.0875***	0.0846***	0.0836***	0.0741***	0.0731***	0.0727***
	(0.0080)	(0.0076)	(0.0074)	(0.0070)	(0.0069)	(0.0068)
N	319	319	319	319	319	319

Note: ***, ** and * denotes significance at the 1%, 5% and 10% levels respectively.

(NPDEff)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
gov		0.4334	2.6345***	7.1306***	7.2276***	8.3715***
		(0.7298)	(0.9023)	(2.2398)	(2.1015)	(2.1413)
gov×open			-11.4417***		-6.4262*	-14.1967**
			(3.0059)		(3.7749)	(7.0284)
open			0.7986***		0.2968	0.1113
			(0.1969)		(0.2389)	(0.2147)
gov×pgdp				-13.6808***	-11.0436***	-13.2742***
				(3.5097)	(4.1170)	(4.0782)
pgdp				1.2698***	1.1976***	1.1829***
				(0.2632)	(0.3185)	(0.3072)
gov×open×pgdp						14.7343
						(9.1863)
env	7.1524	7.2336	9.0663	8.0901	7.8265	8.1787
	(5.4669)	(5.4702)	(5.7922)	(5.0518)	(5.1979)	(5.3905)
grad	0.0516	0.0619	0.1196	0.0896	0.1291	0.1462
	(0.0960)	(0.0983)	(0.0977)	(0.0938)	(0.0955)	(0.0948)

(continued)

(NPDEff)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
age	0.5771	0.7639	-0.3303	-1.1840	-2.0989	-2.1820
	(1.2712)	(1.2932)	(1.2915)	(1.2143)	(1.4083)	(1.4079)
_cons	0.4937**	0.4328*	0.2760	-0.1131	-0.0972	-0.0853
	(0.2124)	(0.2344)	(0.2419)	(0.2650)	(0.2583)	(0.2538)
var(e.NPDEff)	0.1359***	0.1359***	0.1283***	0.1223***	0.1203***	0.1192***
	(0.0131)	(0.0130)	(0.0125)	(0.0123)	(0.0118)	(0.0117)
N	319	319	319	319	319	319

Note: ***, ** and * denotes significance at the 1%, 5% and 10% levels respectively.

(OverEff)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
gov		0.6074	2.3322***	6.1957***	6.2860***	7.3934***
		(0.5390)	(0.6475)	(1.6393)	(1.5419)	(1.4642)
gov×open			-9.0351***		-4.6177*	-12.3449**
			(2.2133)		(2.8044)	(5.1852)
open			0.6418***		0.1942	0.0064
			(0.1405)		(0.1731)	(0.1467)
gov×pgdp				-11.3510***	-9.4786***	-11.6495***
				(2.5530)	(3.0959)	(2.8477)
pgdp				1.0791***	1.0469***	1.0285***
				(0.1891)	(0.2322)	(0.2208)
gov×open×pgdp						14.7237**
						(6.5036)
env	2.9165	3.0463	4.6698	3.7840	3.4935	3.8818
	(3.2142)	(3.2084)	(3.4333)	(2.8153)	(2.8545)	(3.0345)
grad	0.0008	0.0145	0.0602	0.0427	0.0727	0.0914
	(0.0576)	(0.0583)	(0.0582)	(0.0543)	(0.0567)	(0.0559)
age	2.0569**	2.3267***	1.4500*	0.5421	-0.1933	-0.2810
	(0.8269)	(0.8424)	(0.8319)	(0.7752)	(0.8841)	(0.8765)
_cons	0.3813***	0.2957**	0.1692	-0.1642	-0.1522	-0.1399
	(0.1345)	(0.1475)	(0.1507)	(0.1736)	(0.1698)	(0.1660)
var(e.OverEff)	0.0607***	0.0603***	0.0561***	0.0503***	0.0493***	0.0483***
	(0.0056)	(0.0054)	(0.0050)	(0.0047)	(0.0045)	(0.0043)
N	319	319	319	319	319	319

Note: ***, ** and * denotes significance at the 1%, 5% and 10% levels respectively.

To verify the robustness of the Tobit regression method, we implemented an OLS regression for the second robustness test. The results of the regression are largely in agreement with those of the Tobit regression. Additionally, a Variance Inflation Factor (VIF) test was conducted, with the highest VIF

value among all the independent variables being 2.05, indicating no severe multicollinearity among the predictors. The results of the OLS regression robustness check are presented in Table 10.

Table 10
Results of OLS regression robustness check.

(LabEff)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
gov		1.0390***	1.6250***	3.9486***	4.0445***	4.4996***
		(0.3330)	(0.5244)	(0.7429)	(0.7468)	(0.8404)
gov×open			-3.0744		0.2166	-3.3631
			(2.1974)		(2.3994)	(3.8704)
open			0.2351*		-0.1322	-0.2187
			(0.1371)		(0.1496)	(0.1666)
gov×pgdp				-6.0127***	-6.1196***	-7.0139***
				(1.5752)	(1.7967)	(1.9494)
pgdp				0.6868***	0.8089***	0.7953***
				(0.1207)	(0.1418)	(0.1422)
gov×open×pgdp						6.8029
						(5.7736)
env	-0.1523	0.0621	0.7843	0.5833	-0.3411	-0.1453
	(1.7692)	(1.7465)	(1.8006)	(1.6675)	(1.7307)	(1.7376)
grad	-0.1111**	-0.0869	-0.0720	-0.0696	-0.0611	-0.0522
	(0.0532)	(0.0531)	(0.0548)	(0.0507)	(0.0524)	(0.0530)
age	3.9493***	4.4348***	4.1420***	3.0571***	2.5967***	2.5562***
	(0.8828)	(0.8984)	(0.9480)	(0.8913)	(0.9921)	(0.9840)
_cons	0.3745***	0.2245**	0.1748	-0.0464	-0.0396	-0.0318
	(0.0926)	(0.1032)	(0.1068)	(0.1093)	(0.1091)	(0.1092)
N	319	319	319	319	319	319
adj. R^2	0.0755	0.1004	0.1040	0.1825	0.1875	0.1885

Note: ***, ** and * denotes significance at the 1%, 5% and 10% levels respectively.

(NPDEff)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
gov		0.1601	1.9055***	3.5597***	3.8053***	4.5114***
		(0.3862)	(0.5948)	(0.8685)	(0.8703)	(0.9777)
gov×open			-9.2616***		-6.7136**	-12.2673***
			(2.4922)		(2.7963)	(4.5027)
open			0.6490***		0.3593**	0.2250
			(0.1555)		(0.1744)	(0.1938)
gov×pgdp			-9.2616***		-6.7136**	-12.2673***
			(2.4922)		(2.7963)	(4.5027)
pgdp				0.7458***	0.6415***	0.6205***

(continued)

(NPDEff)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
				(0.1411)	(0.1653)	(0.1654)
gov×open×pgdp						10.5545
						(6.7168)
env	4.7376**	4.7707**	6.4542***	5.3419***	5.5495***	5.8533***
	(2.0214)	(2.0256)	(2.0422)	(1.9494)	(2.0170)	(2.0215)
grad	0.0743	0.0781	0.1273**	0.0982*	0.1363**	0.1502**
	(0.0608)	(0.0615)	(0.0621)	(0.0593)	(0.0611)	(0.0616)
age	0.3216	0.3964	-0.5577	-1.0322	-1.8015*	-1.8643*
	(0.8541)	(0.8741)	(0.9046)	(0.8870)	(0.9679)	(0.9665)
_cons	0.4671***	0.4439***	0.3205***	0.1494	0.1508	0.1630
	(0.1058)	(0.1197)	(0.1211)	(0.1278)	(0.1271)	(0.1270)
N	319	319	319	319	319	319
adj. R^2	0.0092	0.0066	0.0537	0.0828	0.0941	0.0983

Note: ***, ** and * denotes significance at the 1%, 5% and 10% levels respectively.

(OverEff)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
gov		0.4097	1.9408***	3.8932***	4.1140***	4.9504***
		(0.3044)	(0.4651)	(0.6599)	(0.6601)	(0.7372)
gov×open			-8.1117***		-5.2102**	-11.7893***
			(1.9488)		(2.1208)	(3.3952)
open			0.5757***		0.2438*	0.0848
			(0.1216)		(0.1322)	(0.1461)
gov×pgdp				-7.3249***	-5.4423***	-7.0860***
				(1.3992)	(1.5880)	(1.7101)
pgdp				0.7826***	0.7361***	0.7113***
				(0.1072)	(0.1253)	(0.1247)
gov×open×pgdp						12.5031**
						(5.0648)
env	2.6208	2.7053*	4.2400***	3.3030**	3.1975**	3.5575**
	(1.5973)	(1.5965)	(1.5970)	(1.4811)	(1.5297)	(1.5243)
grad	0.0210	0.0306	0.0731	0.0512	0.0836*	0.1001**
	(0.0480)	(0.0485)	(0.0486)	(0.0451)	(0.0463)	(0.0465)
age	1.8146***	2.0061***	1.1792*	0.4834	-0.2545	-0.3289
	(0.6750)	(0.6889)	(0.7074)	(0.6739)	(0.7341)	(0.7288)
_cons	0.3730***	0.3138***	0.2025**	0.0049	0.0079	0.0224
	(0.0836)	(0.0943)	(0.0947)	(0.0971)	(0.0964)	(0.0958)
N	319	319	319	319	319	319
adj. R^2	0.0226	0.0252	0.0860	0.1636	0.1768	0.1901

Note: ***, ** and * denotes significance at the 1%, 5% and 10% levels respectively.

5. Discussion and Conclusion

5.1. Discussion

In this study, we figure out a framework for the measurement of innovation efficiencies and investigate the factors that are significant in shaping these efficiencies. The results indicate that these efficiencies show spatial and temporal imbalances and are affected by government funding and other factors.

First, our findings show that lab R&D efficiency, NPD efficiency, and overall efficiency demonstrate spatial and temporal imbalances in the 29 provinces from 2009 to 2019. From the perspective of provincial efficiency changes, lab R&D efficiency manifests an overall augmentation, indicating that the industry's foundational research and early development capabilities have been steadily improving over the past decade. However, NPD efficiency and overall efficiency exhibit fluctuations over time, suggesting that the transition from research to marketable products and the entire innovation process face challenges and uncertainties. From the perspective of regional disparities, the Eastern region generally maintains a leading position, whereas the Northeast region is relatively lagging. This is consistent with the findings of Zhang (2023), who highlighted that the Eastern region's innovation efficiency is higher than other regions due to its advanced economic development, abundant resources, and favorable innovation environment. The performance of the Northeast region is attributed to its economic transition difficulties, insufficient innovation inputs, and underdeveloped regional innovation system. Furman *et al*. (2002) indicated that innovation systems in different regions exhibit significant heterogeneity, which is not only due to differences in economic development levels and industrial structures but is also closely related to policy environment and cultural background. Our findings provide empirical evidence for this view.

Second, we explore and examine the government funding's effects on the pharmaceutical manufacturing industry's innovation performance using Tobit regression. Government funding exhibits a more pronounced facilitative effect on lab R&D efficiency than on NPD efficiency. Especially in the baseline regression analysis, government funding has a significant positive impact on lab R&D efficiency, whereas its explanatory capacity for NPD efficiency is not statistically significant. Gambardella (1992) noted, the pharmaceutical manufacturing industry exhibits typical characteristics of being knowledge-intensive and capital-intensive, with technological innovation being the core driving force behind its sustainable development. Our findings further indicate that government funding can effectively alleviate the financial constraints of enterprises in the early stages of innovation, supporting basic research and early development activities. However, in the NPD stage, innovation activities are closer to market applications, requiring enterprises to possess strong market-oriented capabilities and rapid responses to market demands. Government funding alone may not effectively stimulate innovation performance in this stage due to its potential inefficiencies and lack of market sensitivity. This is consistent with the point of Hong *et al*. (2016), who argued that excessive reliance on government funding may lead to insufficient innovation motivation for enterprises and even trigger inefficient resource allocation.

Third, we introduce regional openness and economic development into the regression model to estimate these regional characteristics' moderating effect of government funding on innovation performance. It is found that in regions with higher regional openness, the positive impact of government funding on innovation performance is diminished. Similarly, in regions with advanced levels of economic development, the effectiveness of government funding is also attenuated. This can be explained by the regional innovation system theory, which suggests that open and developed regions tend to have

more developed market economies and higher levels of technological diffusion. As Sbia *et al*. (2014) demonstrated, the improvement of trade openness can significantly promote the improvement of regional innovation efficiency. Our results indicate that enterprises in open regions may have easier access to external technologies and innovative resources through international trade, technology introduction, and cross-border collaborations. Consequently, they may exhibit lower reliance on government funding and a reduced incentive to engage in independent innovation. Similarly, in economically advanced regions, enterprises are more likely to pursue high-quality innovation that relies on advanced technologies, skilled talent, and information flows. As Chen *et al*. (2020) pointed out, high-quality innovation is more challenging and generates higher value, while low-quality innovation is characterized by stronger imitation capabilities, lower innovation difficulty, and lower value. Our findings show that government funding tends to have a weaker impact in regions with advanced economic development, where high-quality innovation dominates.

5.2. Conclusion

Our study finds firstly, the lab R&D efficiency of the Chinese Pharmaceutical Manufacturing Industry increases stably, while the NPD efficiency and overall efficiency fluctuate overtime; the efficiencies of the Eastern region are higher than other regions. Secondly, the government funding positively impacts lab R&D efficiency but has a weaker effect on NPD efficiency. However, the positive effects are reduced in regions with higher openness and advanced economic development. Our study contributes to three aspects. First, we seek to divert more attention from the direct effects of government funding to the moderating effects of regional openness and economic development, which is not commonly researched in previous literature. Second, we provide empirical results of the Chinese pharmaceutical manufacturing industry, thereby extending the theoretical framework of the open national innovation system. Third, those empirical results also bring valuable contributions to the empirical research of innovation performance across distinct geopolitical landscapes.

Based on discussion and conclusion, we propose three policy implications. First, given the imbalances in innovation efficiencies arising from regional disparities and the differential stages of research and application within the innovation process, the government should take a holistic view to foster a robust pharmaceutical manufacturing industrial ecosystem. Specific policy implications could encompass financial and advisory assistance for small and medium-sized enterprises (SMEs) in the pharmaceutical sector, aimed at strengthening their market positions and enhancing their innovation capacities. The development of stable and secure supply chains for essential raw materials and components is crucial, which may reduce dependence on international markets and mitigate risks related to geopolitical uncertainties. In a well-structured pharmaceutical manufacturing innovation ecosystem, innovation activities can be conducted consistently and robustly, which also guarantees that government policies sustain a certain degree of effectiveness in the face of external disruptions.

Second, government policies aimed at fostering innovation activities in the Lab R&D stage and NPD stage should be differentiated. For the Lab R&D stage of innovation performance, government funding can serve as an effective incentive. The government can increase fiscal funding for R&D activities, targeting strategic areas of pharmacy that promise significant advancements and economic returns, or introduce tax incentives for businesses investing in R&D, including tax credits for R&D expenditures and reduced tax rates for revenues derived from patented technologies. However, for the innovation performance at the new product stage, government funding tends to be relatively ineffective; a shift

towards industrial policies and other measures may be more conducive. For example, government can develop policy frameworks that facilitate public-private partnerships, encouraging collaboration between academic institutions, research centers, and industry players to translate scientific research into commercial applications. Meanwhile, the government should establish innovation clusters and incubators to nurture startups and small businesses specializing in high-potential biotechnology sectors, providing them with the necessary infrastructure and resources to grow.

Third, the government should adopt a more proactive and positive attitude within the realms of international trade and technological communication. On one hand, the results highlight the importance of enhancing the transnational diffusion of technology and knowledge communication with foreign countries, so that the government should establish bilateral and multilateral partnerships with other countries. For example, China can take advantage of the Belt and Road corridors, focusing on joint ventures, technology exchange, and mutual market access. On the other hand, the negative moderating effect of regional openness suggests that the pharmaceutical manufacturing industry should actively confront the international pharmaceutical market's challenges. Such policy implications could encompass establishing platforms for dialogue and collaboration between Chinese and international companies to facilitate knowledge transfer and joint R&D projects. Additionally, negotiating trade agreements with provisions tailored to the pharmaceutical sector is essential to ensure favorable conditions for the export and import of medical products.

Our study has a few limitations. The first is that the present DEA model does not consider the undesirable output of pharmaceutical innovation and production processes, such as air pollution or other negative externalities, which will be incorporated in the future model. Second, the findings are currently on account of the Chinese pharmaceutical manufacturing industry which can be generalized to other countries and industries in the future study.

Conflicts of interest

The authors declare no conflict of interest.

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