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Driving effect of fiscal policy on regional innovation efficiency

Cui Li[a] and Yawei Qi[b]

[a]School of Intercultural Studies, Jiangxi Normal University, Nanchang, China; [b]School of Information Management, Jiangxi University of Finance and Economics, Nanchang, China

ABSTRACT

This study uses a network data envelopment analysis (DEA) approach to measure phased innovation efficiency to explore how fiscal technology innovation policy drives the development of regional innovation. A game model is constructed that includes governments, enterprises, universities, and research institutes to explain the influence mechanism. The innovation process is decomposed into the transformation stage of scientific research results and their commercial application. A Tobit model is used to explain the effect of fiscal policy on innovation efficiency. These methods led to novel conclusions: (1) the growth rate of innovation efficiency in the first stage is greater with smaller regional differences, with larger regional differences in innovation efficiency in the second stage; (2) the intensity of fiscal R&D funding in science and technology has a significant positive effect on overall innovation efficiency and phased innovation efficiency; and (3) the positive effect of fiscal R&D funding is greater on the commercial application of scientific achievements. The targeting effect of fiscal innovation policy on industry–university research (IUR) cooperation needs to be improved through resource sharing, joint participation, sharing of achievements, and risk sharing.

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1. Introduction

Against a background of changing regional innovation systems, the globalization of science and technology, and regional integration, it is inevitable that studies should examine regional innovation efficiency in depth. To formulate a new strategy to strengthening independent innovation and build an innovative country, all levels of government have vigorously supported technological innovation in high-tech industries. China's economy has transformed from extensive development to high-quality development, and the momentum has shifted from factor-driven and investment-driven growth to innovation-driven growth. Plenary sessions of the Central Committee and the National Congress of the Communist Party of China have in

CONTACT Yawei Qi qiyawei@jxufe.edu.cn

recent years demonstrated the central government's determination to support innovation-driven growth. The promotion of technological innovation in a country stems exclusively from financial support policies. Financial subsidies encourage enterprises to make suitable innovation and R&D investments to gain a competitive edge in the market (Becker, 2015).

According to the theory of innovative development, innovation is the main source of sustainable economic growth (Zizlavsky, 2016). Innovation-driven growth also ensures high-quality economic development. Total factor productivity provides a theoretical basis for quantitative research in innovation theory; however, there is no consensus on the impact of fiscal policy on innovation performance. This paper addresses the following issues: What is the theoretic basis for the role of fiscal policy in regional innovation activities? What role can government play in regional innovation? How should fiscal policy be used to improve the effectiveness of innovation activities? We construct a three-stage game model to describe regional innovation, and analyse the role of fiscal policy in promoting regional innovation efficiency by measuring two-stage innovation efficiency.

In this study, we examine fiscal policy's effect on regional innovation capacity from the perspective of staged innovation. The remainder of this paper is organized as follows. The following section reviews the literature, the third section presents an analysis of the underlying theoretical mechanism, the fourth section presents our empirical results, and the final section concludes the paper.

2. Literature review

2.1. Research on regional innovation efficiency

Measuring and analyzing innovation efficiency in China's regions provide insights into the input and output processes of high-tech industries in the high-quality development stage, and the overall direction of the regional innovation system's development. Zhou and Li (2011) considered the knowledge production function of knowledge stock and R&D expenditure, and used a data envelopment analysis (DEA) model to measure regional innovation efficiency and evaluate innovation ability. Bai et al. (2010) used DEA to measure innovation efficiency in the process of R&D innovation in different regions of China. Some scholars used the DEA model to study innovation in high-tech industries and attributed low efficiency in enterprises to the lack of research and development funds and investment in scientific research personnel (Chen et al., 2006). Yu (2009) used the DEA model based on slack variables to conduct a two-stage evaluation of the innovation efficiency of high-tech industries in 19 provinces in China from 1995 to 2009. Han et al. (2018) used two-stage DEA to analyse the efficiency of high-tech enterprises in the two stages of R&D and technology transformation, and found that most of the enterprises in most regions attached more importance to intermediate results and ignored the problem of commercial output, and put forward targeted countermeasures for technological innovation. Yang et al. (2017) used the shared investment two-stage DEA model to analyse R&D innovation efficiency in China's high-tech industries and found that R&D innovation efficiency has an inverted 'U' shape.

To summarize, when using DEA to analyse innovation efficiency in industries and regions, earlier studies have focused on technological innovation efficiency on an industry and enterprise level. Most of the research is based on a static analysis of the model's indicators and influencing factors, and relatively few studies have focused on regional innovation efficiency. Many studies also focused on changes in innovation efficiency in a specific period and regarded the two stages before and after R&D innovation as independent sub-stages.

This paper divides the two stages of R&D and innovation into two inter-related sub-stages: the realization of scientific and technological achievements and the commercialization of scientific and technological achievements. Taking 30 provinces and cities in China as the research objects, the network DEA method is used to measure the stage of innovation efficiency. The Malmquist productivity index(M index) is used to measure the rate of change in innovation efficiency and provides a basis for the formulation of government-related development policies.

2.2. Research on the effects of fiscal policy on regional innovation efficiency

Generally, countries utilize financial subsidy policies to promote technological innovation to boost regional innovation through R&D (Ivus et al., 2021). The fiscal policies adopted by governments to promote regional innovation focus on three aspects: tax incentives, direct investments in R&D projects, and financial subsidies and transfer payments (Miao et al., 2019). Among these, investment in R&D and tax subsidies are associated with policy sustainability (Liu & Bai, 2021), and provide better incentives for innovation than just tax subsidies (Neicu et al., 2016). Huang and Wu (2019) showed that a tax-based R&D incentive policy has a crowding-in effect on corporate innovation, and that this is more significant in the eastern region than in the western region. Li (2018) found that tax incentives increase R&D efficiency by eight to 10 percentage points. Tax reduction policies also play a significant role in promoting technological innovation (Zhang, 2021). Czarnitzki et al. (2011) used the propensity score matching (PSM) model to show that R&D tax relief can encourage the innovation output of subsidized enterprises. However, there is no consensus on the role of direct investment or government subsidies on technological innovation. Some scholars have found that the government's innovation subsidies for strategic emerging industries have a significant spill-over effect on regional innovation (Lu et al., 2014); while other scholars have shown that the government's loan discount policy has a crowding-out effect on corporate investment in technological innovation (Howell, 2017; Ye & Liu, 2020; Zhang & Zhen, 2018). Some scholars have shown that the positive and negative effects of government subsidies on enterprise innovation can coexist in an inversed 'U'-shaped relationship (Zhang & Sun, 2018).

To understand whether a government's fiscal policy can effectively drive the development of regional innovation or not, it is necessary to examine the periodic law of regional innovation and development (Lopez & Pineiro, 2020). In different stages of regional innovation, fiscal policy produces different types of innovation. According to Ye and Liu (2018), when the government supports scientific research and technological R&D, its effect and mechanism differ significantly. There are differences in the impact mechanism of the different types of innovation activities on economic growth, and there are differences in the method and intensity of government support for the different types of innovation activities (Tang & Xiao, 2012). Although the literature has discussed the necessity of fiscal support for scientific and technological innovation (Hong, 2013; Stiglitz, 2015), it has not examined the different stages of innovation or analysed the government's support at different stages of innovation. The sustainability and inter-provincial differences in fiscal policies on innovation efficiency have also not been considered.

This paper makes the following contributions. First, we use game theory to examine the relationship between enterprises, universities, scientific research institutes, and governments in the process of regional innovation to provide a better theoretical reference model for understanding the process of regional innovation. Second, this paper analyses the total innovation efficiency and the staged innovation efficiency of each region, and refines the research on innovation. Third, the study analyses the role of fiscal policy in improving total innovation efficiency and two-stage innovation efficiency, and explores the differences in their respective roles. The study not only inserts fiscal policy into the regional innovation efficiency system, but also provides a theoretical basis for building an innovation-driven policy system for regional innovation.

3. Theoretical analysis

3.1. Game model for fiscal policy driving innovation

Innovation activity is a systematic endeavour that involves many stakeholders and requires coordination from multiple links (Kleinschmidt & Cooper, 1991). Innovation ability has two aspects: an innovative agent and an innovative environment. Enterprises, universities, research institutes, and governments act as the direct innovative agents. The fiscal policies are the main components of the innovative environment, which can be improved by a series of financial support measures and preferential tax policies.

In this study, we focus on industry–university research (IUR) interactions that include cooperative economic activities such as scientific research and development, production, marketing, and consulting services carried out by various combinations of innovative agents and methods (Fang, 2021). The economic market mechanism can develop their complementary advantages. The support of the United States government allowed Silicon Valley to attract high-tech enterprises from different sectors and on scale, establish a number of famous universities and scientific research institutions, and form a large-scale, multi-level platform to exchange information, knowledge, and technology for IUR cooperation and innovation, which subsequently gave birth to numerous technological innovation achievements (Wang & Chen, 2020). The success of Silicon Valley is an illustrative example of how government, industries, universities, and research institutes can work together.

R&D innovation is also a systematic and dynamic process. Donaldson (1977) pointed out that R&D innovation transforms R&D investment to scientific and technological achievements to reap substantial economic benefits. A typical technological R&D innovation process can be divided into an upstream knowledge innovation stage and a downstream scientific and technological achievements commercialization stage (Guan & He, 2009). An et al. (2017) used the Stackerberg game method to study an interactive system and measure the efficiency of parallel interactive systems by finding the optimal solution in the interval. Zha and Liang (2010) used the Stackerberg framework to discuss optimal changes in efficiency at various stages in a non-cooperative form.

This paper divides R&D innovation into two interrelated sub-stages: the first stage is the realization of R&D efforts, and the second stage is the commercialization of R&D achievements. The research institutions is to realize the first stage of scientific and technological achievements, while the enterprises is to realize the second stage, namely the transformation of scientific and technological achievements into new products and services. The government plays a catalytic role in these innovation activities Therefore, we construct a three-stage dynamic game model with three subjects participating and analyse the driving mechanism of fiscal policies for different innovation agents at various stages of innovation.

3.2. The model

3.2.1. The model's assumptions

1. We assumed that there are two innovative modes for IUR cooperation: the technology transaction mode and the contractual cooperation mode. The technology transaction model refers to that the companies entrust scientific research institutions to carry out technological developments. The scientific research institution transfers the ownership of the patented technology to the enterprise for a fee. Contractual cooperation mode refers to a cooperative innovation mode in which IUR institutions jointly provide the funds, R&D equipment, and R&D personnel in the form of agreements or contracts. All the partners share the risks and the benefits.
2. There are three parties involved in the game model are: the enterprise, the academic research institute, and the government. The enterprise, which is abbreviated as 'F,' is the most critical innovation subject. The academic research institute (universities and other scientific research institutions), which is abbreviated as 'U,' is the preferred cooperative innovation mode. The government is the third participant in the game. Its main role is to promote the transformation of scientific and technological achievements.
3. Suppose the reverse demand function of an enterprise is $p = a - bq$, where, $a > 0$ is a constant, b is the reciprocal of the market demand sensitivity to price, p is the price of the enterprise products, and q is the output of the enterprise products.

The game process can be divided into three stages. In the first stage, the government subsidizes the innovation behaviour of enterprises while considering the maximization of social welfare. To encourage enterprises to increase their R&D investment, the government adopts a method of providing financial subsidies or tax incentives based on a certain percentage, λ $(0 \leq \lambda \leq 1)$ of R&D costs. The social welfare function is equal to the consumer surplus plus the profits of the enterprises and the institutions minus the total amount of government financial subsidies or tax incentives. The consumer surplus can be expressed as:

$$\int_0^q \mathrm{pdq} = \mathrm{aq} - 0.5\mathrm{bq}^2.$$

to obtain the following equation:

$$\mathrm{W} = a\mathrm{q} - 0.5\mathrm{bq}^2 + \pi_{\mathrm{F}} + \pi_{\mathrm{U}} - 0.5\mathrm{rx}^2$$

The second stage is the R&D stage. Assuming that the R&D activity is cost-saving, then the total R&D investment scale of the enterprise and the research institute is $\mathrm{x}(\mathrm{x} \geq 0)$, where the investment proportion of the enterprise is $\mathrm{k}(0 \leq \mathrm{k} \leq 1)$, and the research institute's investment proportion is $(1 - \mathrm{k})$. Next, we assume the knowledge spillover or sharing coefficient between enterprises and research institutes in the process of cooperative innovation is $\theta(0 \leq \theta \leq 1)$. The stronger the desire for knowledge sharing, the more successful the marketability of the scientific and technological achievements. Suppose that under the technology trading model, the value of the scientific and technological achievements is V, and under the contractual cooperation mode, the enterprises and the research institutes share the final product profits after marketing according to the proportion of investment. After deducting the government's R&D subsidy, the R&D cost of the enterprise is

$$\frac{1}{2} r(1 - \lambda)kx^2,$$

and the R&D cost of the research institute is

$$\frac{1}{2} r(1 - \lambda)(1 - \mathrm{k})x^2$$

where $\mathrm{r}(\mathrm{r} \geq 0)$ is the coefficient for innovation difficulty.

The third stage is the production stage. The initial cost of R&D activities at the current technology level can be presented as $\mathrm{A}(0 < \mathrm{A} < a)$. As the enterprise plans to carry out a technological innovation, the final R&D cost is c, which is jointly created by the enterprise and the academic research institute and can be presented as

$$\mathrm{c} = \mathrm{A} - \mathrm{kx} - \theta(1 - \mathrm{k})\mathrm{x}.$$

Based on the above assumptions, the respective profit functions of the enterprise and the academic research institute can be obtained as follows:

$$\pi_F = [a - bq - A + kx + \theta(1 - k)x]qk - \frac{1}{2} r(1 - \lambda)kx^2 \tag{1}$$

$$\pi_U = \left[a - bq - A + kx + \theta(1-k)x\right]q(1-k) - \frac{1}{2}r(1-\lambda)(1-k)x^2 \tag{2}$$

3.2.2. Solution

By using the backward induction method, the output of an enterprise is calculated when the correlation coefficient in Eq. (1) is known. Finding the first derivative of the company's output and equating it to zero, we get the equation:

$$q = \frac{a - A + Fx}{2b} \tag{3}$$

For the convenience of representation, the parameter F can be written as:

$$F = k + \theta(1-k).$$

Combined with Eq. (1), enterprise profit can be presented as:

$$\begin{aligned}\pi_F &= \left[a - \frac{a-A+Fx}{2} - AFx\right]\frac{a-A+Fx}{2b}k - \frac{1}{2}r(1-\lambda)kx^2 \\ &= \frac{(a-A+Fx)^2}{4b} - \frac{1}{2}r(1-\lambda)kx^2\end{aligned} \tag{4}$$

The value of x is obtained by equating its derivative to zero, and the optimal scale of R&D investment is given by:

$$x = \frac{F(a-A)}{2br(1-\lambda)k - F^2} \tag{5}$$

When the government offers financial subsidies or tax preferences to enterprises to encourage innovation and maximize social welfare, the first-order condition of the social welfare function can be presented as $\frac{\partial W}{\partial \lambda} = 0$ and the optimal subsidy rate as

$$\lambda^* = 1 - \frac{F^2a + 2(a-A)br}{brk(3a-A)} \tag{6}$$

Therefore, the equilibrium solutions for enterprises receiving government subsidies or tax incentives can be obtained as follows:

$$x^* = \frac{F(3a-A)}{4br - F^2} \tag{7}$$

$$q^* = \frac{2(a-A)br + aF^2}{b(4br - F^2)} \tag{8}$$

$$\pi_F^* = q^{*2}bk - \frac{1}{2}r(1-\lambda^*)kx^{*2} \tag{9}$$

$$W^* = aq^* + 0.5bq^{*2} - 0.5rx^{*2} \tag{10}$$

3.2.3. Analysis of the equilibrium solution

Under the previous assumptions, the following inferences can be made:

Corollary 1: Implementing the fiscal subsidies for innovation or the preferential policies will help enterprises to expand the scale of R&D investment. With the increase in subsidies, the output of enterprises and social welfare increase significantly.

Proof: From Eq. (5), we get the partial derivative:

$$\frac{\partial x}{\partial \lambda} = \frac{2brkF(a-A)}{[2br(1-\lambda)k - F^2]^2} > 0$$

According to the hypothesis, the scale of R&D investment is non-negative and $a > A > 0$. Therefore, we can infer from Eq. (5) that $2br(1-\lambda)k > F^2$. Meanwhile, due to fiscal subsidies for innovation or preferential tax rates, when $0 \le \lambda^* \le 1$, it can be inferred that:

$$F^2a + 2(a-A)br \le brk(3a-A)$$

Similarly,

$$\frac{\partial q}{\partial \lambda} = \frac{rkF^2(a-A)}{[2br(1-\lambda)k - F^2]^2} > 0$$

$$\frac{\partial W}{\partial \lambda} = \frac{rkF^2\left(a-A\right)\left[br(1-\lambda)k(3a-A) - (F^2a + 2(a-A)br)\right]}{[2br(1-\lambda)k - F^2]^3} > 0$$

Thus, from the above formulae, it is clear that the financial subsidies for innovation exert a positive impact on corporate R&D innovation input, output, and social welfare.

Corollary 2: Increasing the degree of knowledge sharing encourages companies to increase product/service output and expand their scale R&D investment. The impact of knowledge sharing on social welfare is affected by the proportion of profit distribution. At the same time, the policy subsidy rate is inversely proportional to the degree of knowledge sharing.

Proof: According to the aforesaid assumptions, we get following derivations:

$$\frac{\partial q^*}{\partial \theta} = \frac{4Fr(3a-A)(1-k)}{(4br-F^2)^2} > 0$$

$$\frac{\partial x^*}{\partial \theta} = \frac{(F^2+4br)(3a-A)(1-k)}{(4br-F^2)^2} > 0$$

$$\frac{\partial W^*}{\partial \theta} = \frac{Fr(3a-A)^2\left[4br(1-2k)-F^2\right]}{(4br-F^2)^3}$$

With the promotion of the cooperative relationship, the spillover and sharing effect of knowledge becomes more significant and encourages enterprises to increase R&D investment and product output. At the same time, when $\frac{\partial \lambda^*}{\partial \theta} < 0$, enterprises and research institutes cooperate closely with lower R&D costs, and the government can maximize social welfare without increasing subsidies. When $k > 0.5$ and $4br > F^2$, social welfare will decrease with an increase in the knowledge spillovers or sharing. When government subsidies are reduced and R&D costs increase, social welfare activities will decrease.

Corollary 3: The impact of the proportion of enterprises' investment in IUR cooperation innovation on the government's innovation subsidy rate will depend on the level of knowledge sharing between enterprises and academic research institutes.

Proof: By a partial differentiation of Eq. (6) we get

$$\frac{\partial \lambda^*}{\partial k} = \frac{abrF\left(3a-A\right)[k-\theta(1+k)]}{b^2r^2k^2(3a-A)^2}$$

In the above formula, when $\frac{k}{1+k} \le \theta \le 1$, we know $\frac{\partial \lambda^*}{\partial k} \le 0$; when $0 \le \theta \le \frac{k}{1+k}$, we know $\frac{\partial \lambda^*}{\partial k} \ge 0$. This indicates that when the degree of knowledge sharing between enterprises and research institutes is relatively high, a company's investment in cooperative innovation is proportional to its dominance and inversely proportional to the government's subsidy for innovation. Enterprises can therefore share the scientific and technological achievements of research institutes without relying on fiscal investment. When the degree of knowledge sharing between the enterprise and the academic research institute is low, the enterprise cannot fully absorb the scientific and technological achievements of the academic research institute for commercial application. As a result, fiscal policy for innovation plays a role in regulating enterprises and academic institutes' R&D investment, ensuring that enterprises can successfully achieve the transformation of scientific and technological achievements.

Corollary 4: The proportion of enterprises' R&D capital investment in cooperative innovation depends on the balance between the profits obtained from the technology transaction mode and the technology contract mode, as well as the degree of knowledge sharing between the enterprises and the academic research institutes.

Proof: Since

$$\frac{\partial x^*}{\partial k} = \frac{(F^2 + 4br)(3a - A)(1 - \theta)}{(4br - F^2)^2} > 0,$$

enterprises will continue to increase their share of R&D funds in cooperative innovation to receive more incentives to expand R&D investment. However, there is a principal–agent relationship between the enterprise and the academic research institute. To ensure the participation of the academic research institute in this endeavour, the profits distributed to the academic research institute should be greater than the value V. The constraint for the participation of the academic research institute is $\pi_U \geq V$. The formula can be written as follows:

$$1 - \mathrm{k} \geq \frac{2\mathrm{bV}(4\mathrm{br} - \mathrm{F}^2)}{\left(a - \mathrm{A}\right)\left[a\mathrm{F}^2 + 2(a - \mathrm{A})\mathrm{br}\right]}.$$

In other words, the minimum proportion of the enterprises' input in R&D is related to the degree of knowledge sharing between the enterprises and the research institutes.

4. Methodology

4.1. Innovation stage

Regional innovation activity is a typical multi-input and -output activity (Buesa et al., 2010). The input of innovation can be measured from two perspectives: the input of scientific and technological personnel and the input of scientific and technological funds (Carayannis et al., 2016). This paper uses full-time R&D personnel and internal expenditure on R&D to express the input index of the three major innovation subjects, namely, enterprises, universities, and scientific research institutions. Regional innovation output mainly refers to the transformation of knowledge into new products, new processes, or new services. The number of patent applications reflects the value of knowledge creation and innovation. In the first innovation-driven stage, academic institutions are mainly engaged in basic research and are responsible for the formulation of patents and publishing scientific papers.

In the second innovation-driven stage, enterprises are the main innovation subjects and convert knowledge innovation into technological innovation to produce new products, processes or services to create economic value. At the same time, the turnover of technology reflects the degree of activity in technology exchanges and is an indicator of the collaborative innovation achievements of IUR. Under the premise of limited innovation resources, the innovation efficiency analysis reflects the collaborative relationships of multiple innovation subjects in different innovation links.

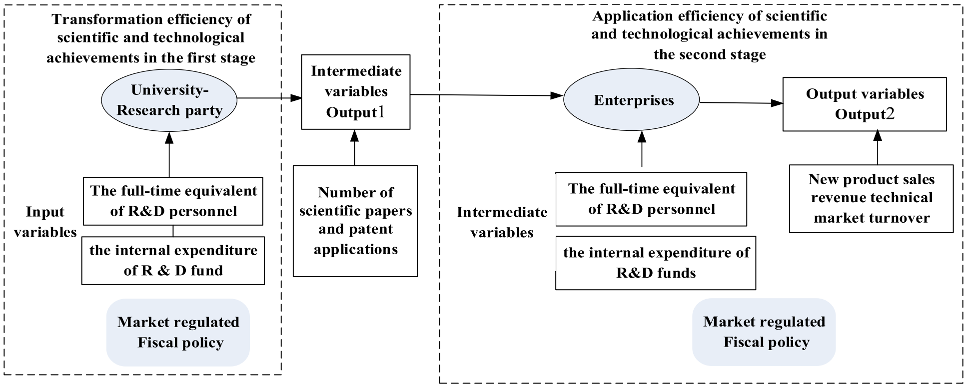

Figure 1. A flow chart of the two-stage innovation efficiency process.
Source: The authors.

Innovation efficiency can be understood as the inversion rate of regional innovation input–output. Since innovation is divided into different links, this paper mainly the transformation efficiency of scientific and technological achievements in the first stage and the innovation ability of enterprises to use their R&D resources in the second stage. .The two-stage innovation efficiency process advocated by Liu et al. (2012) and Zhang and Wu (2017) is depicted in Figure 1.

4.2. Network DEA

4.2.1. Measurement of the two-stage innovation efficiency

A DEA evaluates the relative effectiveness of input and output (Charnes et al., 1978). In this study, the innovation efficiency and growth rate of IUR institutions in 30 inland provinces and cities (the Tibet Autonomous Region was excluded due to a lack of data) are measured. They are furtherly decomposed into technology efficiency change and technology progress change.

Each province and city is regarded as a decision-making unit (DMU). Suppose there are N kinds of inputs in the first stage of innovation $X_N = (x_1, x_2, \ldots x_N) \in R_+^N$ to obtain M kinds of intermediate outputs $Y_M = (y_1, y_2, \ldots, y_M) \in R_+^M$. The intermediate output of the first stage is the input variable of the second stage and there are L kinds of intermediate inputs in the second stage, where $X_L = (x_1, x_2, \ldots, x_L) \in R_+^L$, to give O final output represented as $Y_o = (y_1, y_2, \ldots, y_o) \in R_+^o$. The two stages of innovation correspond to two nodes. Intermediate output Y_M and intermediate input $X_L$are the input variables of the second node $\mathrm{Z} = (\mathrm{Y_M}, \mathrm{X_L})$. That is X_N, Z, $Y_o$are the input variables, intermediate variables and output variables of the decision-making unit, respectively, and $\mathrm{a}, \mathrm{b}, \mathrm{c}$ are the weight vectors in the corresponding production process. In the first stage, the efficiency evaluation expression of the DMU is $\frac{b^T Y_M}{a^T X_N}$, while the constraint condition is $\frac{b^T Y_M}{a^T X_N} \leq 1$. In the second stage, the efficiency evaluation expression of DMU is $\frac{c^T Y_0}{a^T X_L + b^T Y_M}$ and the constraint condition is $\frac{c^T Y_0}{b^T X_L + b^T Y_M} \leq 1$. The two fractional plans can be presented as follows:

$$\max \frac{b^T Y_0}{a^T X_0} \text{ s.t.} \begin{cases} \frac{b^T Y_0}{a^T X_0} \leq 1 \\ a \geq 0, b \geq 0 \end{cases} \tag{11}$$

$$\max \frac{c^T Y_o}{b^T X_L + b^T Y_M} \text{ s.t.} \begin{cases} \frac{c^T Y_o}{b^T X_L + b^T Y_M} \leq 1 \\ c \geq 0, b \geq 0 \end{cases} \tag{12}$$

From Eqs. (11) and (12), the transformation efficiency of scientific and technological achievements in the first stage of innovation and the application efficiency of scientific and technological achievements in the second stage of innovation are obtained, respectively.

While simultaneously considering the efficiency of the first and second stage, the above two fractions jointly construct the multi-objective fractional programming as follows:

$$\max \left(\frac{b^T Y_0}{a^T X_0}, \frac{c^T Y_o}{b^T X_L + b^T Y_M} \right) \text{ s.t.} \begin{cases} \frac{b^T Y_0}{a^T X_0} \leq 1 \\ \frac{c^T Y_o}{b^T X_L + b^T Y_M} \leq 1 \\ c \geq 0, b \geq 0, a \geq 0 \end{cases} \tag{13}$$

Suppose the two stages of innovation are equally important, a two-stage network DEA model can be obtained to calculate overall innovation efficiency.

$$\max \lambda \frac{b^T Y_0}{a^T X_0} + (1 - \lambda) \frac{c^T Y_0}{b^T X_L + b^T Y_M} \text{ s.t.} \begin{cases} \frac{b^T Y_0}{a^T X_0} \leq 1 \\ \frac{c^T Y_o}{b^T X_L + b^T Y_M} \leq 1 \\ c \geq 0, b \geq 0, a \geq 0, 0 \leq \lambda \leq 1 \end{cases} \tag{14}$$

4.2.2. Calculation and decomposition of innovation efficiency

Based on Chung et al. (1997), this paper uses the M index to measure the change in the rate of innovation efficiency by using the following formula:

$$M_0^t = \frac{\overrightarrow{D}_i^t(x^t, y^t)}{\overrightarrow{D}_i^t(x^{t+1}, y^{t+1})} \tag{15}$$

The M index measures the rate of change rate in innovation efficiency from t to $t+1$ periods under the technical condition of t period. Among them,

$\overrightarrow{D_i^t}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, b^{t+1})$ is the mixed distance function representing the production status of phase $t+1$ with reference to technology in phase t. Similarly, under the technical condition of phase $t+1$, the M index is expressed as follows:

$$M_0^{t+1} = \frac{\overrightarrow{D_i^{t+1}}(x^t, y^t)}{\overrightarrow{D_i^{t+1}}(x^{t+1}, y^{t+1})} \tag{16}$$

To reduce the differences in measurement results caused by random period selection, the geometric mean values of (15) and (16) are usually used to measure the rate of change in total factor energy efficiency from period t to period $t+1$:

$$\begin{aligned} M_t^{t+1} = (M_i^t \times M_i^{t+1})^{\frac{1}{2}} &= \left\{ \frac{\overrightarrow{D_i^{t+1}}(x^t, y^t)}{\overrightarrow{D_i^t}(x^t, y^t)} \times \frac{\overrightarrow{D_i^{t+1}}(x^{t+1}, y^{t+1})}{\overrightarrow{D_i^t}(x^{t+1}, y^{t+1})} \right\}^{\frac{1}{2}} \times \left\{ \frac{\overrightarrow{D_i^t}(x^t, y^t)}{\overrightarrow{D_i^{t+1}}(x^{t+1}, y^{t+1})} \right\} \\ &= MTC_t^{t+1} \times MEC_t^{t+1} \end{aligned} \tag{17}$$

From Eq. (17), we conclude that the rate of change in innovation efficiency calculated by the M index can be divided into two parts: the technological progress rate MTC_t^{t+1} and the change in technological efficiency MEC_t^{t+1}. Among these, the technology progress rate MTC_t^{t+1} index measures the movement of the production possibility boundary between stage t and stage $t+1$. When $MTC_t^{t+1} > 1$, the production frontier moves outward, that is, phase $t+1$ has a higher innovation output than phase t. Whereas, the rate of technological efficiency change MEC_t^{t+1} index measures the actual change of innovation efficiency in each province from period t to period $t+1$, the change in the degree of catching up to the best possible output is indicated by the production possibility boundary. When $MEC_t^{t+1} > 1$ then innovation efficiency is improved. The input distance function $\overrightarrow{D_i^t}(x^t, y^t)$ in the M index can be solved by the following linear programming, while other distance functions can be solved by similar linear programming.

$$\overrightarrow{\mathrm{D}^t}(\mathrm{x}^t, \mathrm{y}^t) = \max\ \beta$$

$$\text{s.t.}\ \sum_{k=1}^{K} \lambda_k^t x_{kn}^t \le \beta x_k^t, n = 1, \ldots, N;$$

$$\sum_{k=1}^{K} \lambda_k^t y_{km}^t \ge y_{k'm}^t,\ \ m = 1, \ldots, M;$$

$$\lambda_k^t \ge 0,\ \ k = 1, \ldots, K$$

Table 1. Measurement results of innovation efficiency.

	Overall innovation efficiency			Innovation efficiency in the first stage			Innovation efficiency in the second stage		
Provinces	M	MTC	MEC	M	MTC	MEC	M	MTC	MEC
Beijing	1.155	1.113	1.044	1.292	1.181	1.123	1.077	1.077	1.000
Tianjin	1.016	0.929	1.143	1.072	1.060	1.086	0.979	0.859	1.223
Hebei	1.055	0.885	1.328	1.072	1.012	1.248	1.040	0.817	1.424
Shanxi	1.077	0.885	1.306	1.092	0.988	1.198	1.085	0.840	1.416
Inner Mongolia	1.151	0.937	1.281	1.153	1.032	1.147	1.149	0.898	1.453
Liaoning	1.037	0.920	1.182	1.084	1.022	1.107	1.016	0.869	1.289
Jilin	1.043	0.825	1.272	1.331	0.825	1.648	1.001	0.841	1.197
Heilongjiang	1.041	0.936	1.159	1.059	0.963	1.190	1.035	0.935	1.163
Shanghai	1.013	0.937	1.124	1.016	0.959	1.071	1.027	0.927	1.182
Jiangsu	1.114	0.946	1.280	1.096	1.004	1.134	1.118	0.889	1.620
Zhejiang	1.046	0.906	1.287	1.042	0.935	1.177	1.063	0.867	1.550
Anhui	1.080	0.886	1.331	1.128	0.978	1.342	1.058	0.840	1.401
Fujian	0.973	0.894	1.244	0.897	0.898	1.061	1.034	0.895	1.630
Jiangxi	1.212	0.900	1.476	1.305	1.025	1.409	1.160	0.833	1.578
Shandong	1.032	0.908	1.244	1.009	0.946	1.104	1.051	0.888	1.609
Henan	1.083	0.894	1.328	1.121	1.002	1.252	1.059	0.823	1.437
Hubei	1.119	0.911	1.301	1.163	0.977	1.278	1.090	0.866	1.335
Hunan	0.889	0.843	1.020	0.943	0.882	1.028	0.856	0.823	1.025
Guangdong	1.078	0.951	1.191	1.118	1.042	1.084	1.027	0.863	1.715
Guangxi	1.105	0.877	1.434	1.279	0.997	1.683	1.021	0.817	1.365
Hainan	1.344	0.891	1.635	1.380	1.005	1.696	1.352	0.884	1.721
Chongqing	1.042	0.887	1.257	1.130	0.933	1.261	0.998	0.855	1.311
Sichuan	0.965	0.877	1.163	1.087	1.001	1.265	0.925	0.874	1.154
Guizhou	1.142	0.869	1.502	1.363	1.048	1.552	1.033	0.797	1.498
Yunnan	0.995	0.875	1.200	1.116	0.940	1.394	0.946	0.878	1.138
Shanxi	1.135	0.967	1.210	1.285	1.025	1.281	1.044	0.938	1.158
Gansu	1.003	0.942	1.122	1.076	1.001	1.141	0.969	0.924	1.116
Qinghai	1.192	1.038	1.154	1.137	1.034	1.135	1.355	1.096	1.386
Ningxia	1.060	0.891	1.337	0.997	0.991	1.197	1.126	0.850	1.478
Xinjiang	1.154	0.871	1.495	1.160	0.934	1.438	1.144	0.851	1.546
Average	1.078	0.913	1.268	1.134	0.988	1.258	1.061	0.880	1.371
Ave. of the Eastern	1.088	0.935	1.246	1.098	1.006	1.172	1.071	0.894	1.451
Ave. of the Central	1.128	0.885	1.274	1.143	0.955	1.293	1.043	0.850	1.319
Ave. of the western	1.146	0.912	1.287	1.162	0.994	1.318	1.065	0.889	1.328
Standard deviation	0.087	0.055	0.139	0.040	0.065	0.050	0.094	0.086	0.173
Coefficient of variation	0.081	0.061	0.109	0.039	0.062	0.049	0.085	0.087	0.143

Note: As described in section 4.2.2, M measures the change rate of innovation efficiency. MTC measures the technological progress rate. MEC measures the change in technological efficiency.
Source: The authors.

5. Empirical analysis

5.1. The measurement results of innovation efficiency

According to the above analysis, the input variables selected in this paper are the full-time equivalent of R&D personnel and internal expenditure of R&D funds of the university research party, the intermediate output variables of the second stage are the number of scientific papers published and patents filed by academia, the intermediate input variables of the second stage are the full-time equivalent of R&D personnel and internal expenditure of R&D funds of industrial enterprises above scale, and the final output variables are the sales revenues of new products/services and turnover in the technology market. In this paper, the network DEA model and the M index based on constant investment orientation and return on scale are used to measure and decompose the rate of change in overall and staged innovation efficiency. The average growth rate of innovation efficiency 2009–2017 is shown in Table 1.

From Table 1, it is evident that overall innovation efficiency shows a growing trend. The first stage has the highest growth rate for innovation efficiency and the smallest regional difference. The regional difference in innovation efficiency growth in the second stage is the largest, and the slow growth in overall innovation efficiency is due to technological regression in the innovation process.

The growth rate in overall innovation efficiency and the first stage innovation efficiency in the eastern region is the smallest, but in the western region it is the highest. The second stage innovation efficiency in the eastern region is the fastest, which shows that although the innovation ability in the eastern region is the greatest, resources are still wasted in the process of realizing scientific and technological achievements, and many innovation resources are not fully utilized. In contrast, the perfect innovation environment and developed market in the eastern region promote the application of scientific and technological achievements with the highest degree of efficiency.

5.2. The role of fiscal policy in staged innovation

As an integral part of the innovation system, the regional innovation environment is the main factor affecting regional innovation ability and innovation efficiency in IUR cooperation. Since the range of innovation efficiency as an explained variable is [0, 1], the Tobit model is used to deal with limited dependent variables to analyse the impact of fiscal policy on innovation efficiency.

Innovation is a high-input and high-risk activity. Faced with the uncertainty of innovation performance, the enterprise may have insufficient investment funds. So, it needs the guidance and financial support of government investment to leverage R&D funds. In this paper, the intensity of the local government's financial investment in science and technology and education is selected to measure the effects of the government's financial policy.The financial investment intensity of science and technology is measured by science and technology expenditure's proportion of the local government's general budget. The financial investment intensity of education is expressed by regional financial education expenditure's proportion of the general budget. The enterprise tax burden is measured by net production tax's proportion of GDP. Since market-oriented reform introduces a competition mechanism in the process of economic growth. The exertion of a competition mechanism contribute to an improvement in innovation efficiency. The degree of marketization (MAR) is measured in terms of the marketization index as calculated by Fan et al. (2003).

In addition to domestic market-oriented reform, China has also actively implemented a policy of opening-up to the outside world. The international division of labour has improved the efficiency of regional innovation. In this paper, the ratio of total imports and total exports to GDP is used to measure the degree of openness. The corresponding data are converted into RMB based on the average annual RMB benchmark exchange rate. At the same time, the level of urbanization is expressed by the proportion of urban population in the total population; market demand is expressed by the level of economic development, that is, the value of per capita GDP.

Table 2. Empirical results of factors affecting the innovation efficiency.

	Overall innovation efficiency		Innovation efficiency in the first stage		Innovation efficiency in the second stage	
C	0.39***	−4.20***	0.34***	−2.61***	0.46***	−6.11***
	(11.90)	(−7.80)	(9.08)	(−4.69)	(9.84)	(−7.21)
Tech	0.26***	0.01	0.19***	0.01	0.39***	0.007
		(0.21)	(4.85)	(0.14)	(6.50)	(0.10)
	(6.51)					
Edu		0.15		−0.01		0.26*
		(1.53)		(−0.08)		(1.64)
Mar		0.08		0.03		0.24*
		(0.95)		(0.35)		(1.78)
GDP		0.72***		0.54***		1.04***
		(11.07)		(7.84)		(9.82)
Open		0.04**		0.04**		0.06*
		(2.27)		(1.96)		(1.70)
City		0.93***		0.70***		1.40***
		(4.35)		(3.15)		(4.11)

Note: ***, **, and * indicate significance level of 1%, 5%, and 10% respectively. The values in brackets refer to the statistical value of *t*.
Source: The authors.

The relevant data are collected from the China Statistical Yearbook (2010–2018) and the China Statistical Yearbook on Science and Technology (2010–2018).

Table 2 shows that the intensity of financial investment plays a significant role in promoting the overall innovation efficiency and phased innovation efficiency.The scientific and technological expenditure by the local government can make up for enterprises' lack of R&D funds. The intensity of financial investment in education significantly promotes innovation efficiency in the second stage, while it has no definite effect on the first stage. Because of the collinearity between the intensity of financial investment both in education and in science and technology, the two variables are observably reduced when they are introduced into the model at the same time.

The market-oriented process promotes the commercialized application efficiency of scientific and technological achievements in the second stage. Enterprises are the main body of the market. The acceleration of the marketization promotes innovation efficiency in the second stage.

The degree of dependence on foreign trade has a significant positive impact on overall innovation efficiency in all stages. Exchanges and cooperation between domestic and foreign universities, scientific research institutions, enterprises, and other innovative subjects will improve transformation efficiency and commercial application efficiency. The level of economic development plays a significant role in promoting the overall innovation efficiency, especially by promoting the commercialization of scientific and technological achievements. The level of urbanization also plays a significant role in improving overall and phased innovation efficiency. Urbanization concentrates innovation factors, provides sufficient capital and personnel for innovation.

6. Conclusions and suggestions

The above analysis reveals that China's fiscal policy has a positive effect on the regional innovation, which is similar with the conclusions of Lu et al. (2014) and Guo and Yuan (2020), however there are some differences.

First, the results of the network DEA calculations show a growing trend in overall innovation efficiency with regional heterogeneity. The superior innovation environment in the eastern region promote the application of scientific and technological achievements with the highest level of efficiency. However, the first stage innovation efficiency in the eastern region is the smallest. Innovative financial support for enterprises is exempted from income tax and pre-tax deduction of R&D expenses, whereas for research institutions and universities, it is a tax-free import of R&D equipment for scientific research projects. This kind of fiscal innovation funding policy may induce an over-investment by some innovation agents, resulting in low innovation efficiency.

Second, the empirical results of staged innovation show that the intensity of financial investment in science and technology plays a significant role in promoting overall innovation efficiency. The preferential tax policy in the innovation preparation phase is comprehensive, but it lacks pertinence and is biased towards large enterprises.

Third, the empirical results of the driving effect show that the fiscal innovation policy failed to consider the process of innovation. Innovation is a systematic process that involves multiple innovation subjects and links. Innovation by university research institutes appears mainly in the first stage, while innovation related to enterprises' commercialized application appears in the second stage. Enterprises should use these achievements to speed up the commercialization and industrialization of the knowledge created by universities and R&D institutions.

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ORCID

Cui Li http://orcid.org/0000-0002-2851-4500

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