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How do R&D factors affect total factor productivity: based on stochastic frontier analysis method

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ABSTRACT

Based on provincial panel data from 1998-2018, this paper estimates research and development (R&D) factors, and a stochastic frontier analysis (SFA) model is constructed to examine the effects of R&D factors on regional total factor productivity (TFP). The results show that both R&D capital stock and R&D personnel can significantly promote regional TFP, but the productivity-enhancing effect of R&D factors is different between regions. Specifically, R&D capital and R&D personnel can promote TFP in eastern and central provinces, and the promotion effect is not significant in western provinces. In addition, compared with investment-driven regions, innovation-driven regions are more likely to enhance TFP by R&D factors.

KEYWORDS

R&D capital; R&D personnel; Total factor productivity; SFA approach

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1. Introduction

The Chinese national 14th Five-Year Plan highlights the necessity to adhere to the innovation-driven development strategy, while the primary goal of the innovation-driven development strategy is to improve independent innovation capability and enhance TFP. Among them, sufficient R&D input factors (R&D capital, R&D personnel) are the guarantee for the implementation of China's innovation-driven development strategy. In fact, since the 21st century, China's R&D investment funds have maintained an average annual growth rate of more than 10%, exceeding the growth rate of GDP in the same period. And China's total R&D investment reached 2.21 trillion yuan in 2019, ranking second in the world. Meanwhile, China's R&D personnel has grown rapidly and reached 712.93 million people in 2019, with an average growth rate of over 5% since the 21st century. Then, a natural and realistic question is whether R&D factors can significantly contribute to regional total factor productivity growth? How does the impact of R&D factors on TFP differ between regions?

In this paper, the perpetual inventory method (PIM) is used to measures the R&D capital stock. And a heterogeneous stochastic frontier production (SFA) model is constructed to empirically test the effects of R&D capital, R&D personnel on regional TFP. Based on the empirical results, we propose policy implications for regional R&D investment strategies, talent policies and innovation-driven development planning.

The remainder of this paper is as follows. Section 2 provides measurement method and data collection. Section 3 presents the empirical model. Section 4 shows the empirical results and analysis. Section 5 concludes and provided the policy implication.

2. R&D factor inputs estimation

2.1. R&D capital stock

The PIM is applied to estimate the provincial R&D capital stock of China, and the specific process is divided into the following three steps

First, the R&D capital stock is measured by the classical PIM (Zhao et al., 2022).

$$K_{i,t} = K_{i,t-1} + I_{i,t} - R_{i,t} = \sum_{\tau=1}^{T} S_{i,\tau} I_{i,t-\tau} \tag{1}$$

i refers to the provinces in China, t represents the year, T represents the service life of R&D assets, $I_{i,t}$ denotes the comparable price investment of R&D investment in province i in year t, $R_{i,t}$ denotes the replacement demand of assets, and $S_{i,\tau}$ denotes the residual rate of R&D investment in province i at time point τ.

Secondly, we choose the bell-type decommissioning model widely used in international accounting, which means that assets gradually start to be retired from a certain time after installation and the decommissioning rate peaks near the average useful life, and its probability density function expression is showed as follow (Eq. 2, Eq. 3).

$$f_\tau = \frac{1}{\sqrt{2\pi}} \times \frac{1}{\tau} exp(-(ln\,\tau - \mu)|2\sigma^2) \tag{2}$$

$$\sigma = \sqrt{ln\left[1 + \frac{1}{(m/s)^2}\right]}, \mu = ln\,m - 0.5\sigma^2 \tag{3}$$

where f_τ denotes the proportion of R&D capital exiting at service age τ, σ and μ are the standard deviation and mean of the lognormal frequency distribution, respectively. m and s denote the standard deviation and mean of the normal distribution, respectively. When m is used as the average service life of the capital goods, s is generally set between $m/4$ and $m/2$ ($m/4$ is taken in this paper). At this time, the residual rate of R&D capital goods can be expressed as $S_{i,\tau} = 1 - f_\tau$。

At last, we identified the following indicators following Zhao et al. (2022). (1) The R&D investment sequence. (2) The service life and depreciation rate of R&D assets. (3) The R&D investment price index. (4) The initial capital stock of R&D.

2.2. R&D personnel

In this paper, the full-time equivalent of R&D personnel is chosen to represent R&D human capital. The full-time equivalent of R&D personnel is the sum of the number of full-time personnel plus the number of part-time personnel converted to full-time personnel according to the workload, which is an internationally comparable indicator for measuring technology manpower investment.

3. Empirical model and data description

3.1. Empirical model

The analysis in this paper is based on a stochastic frontier production function that inscribes the maximum output possible for the economy based on the available factor inputs (Pieri et al., 2018; Aldieri et al., 2021). The output frontier $\mathrm{Y}_{\mathrm{it}}^*$ can be expressed as follows:

$$Y_{it}^* = f(X_{it}; B)\exp(V_{it}), V_{it} \sim iidN(0, \sigma_v^2) \tag{4}$$

where i represents the different provinces, t represents the year of the study period, X_{it} represents a series of factor inputs, β represents the corresponding technical parameters, and V_{it} is a random error term that obeys an independent identical distribution, representing unobserved variables and measurement errors. The output of production units below the output frontier is characterized by a lower Y_{it} production efficiency, which we define as the output frontier Y_{it}^* multiplied by a technical efficiency term $exp(-u_{it})$ (Venturini, 2015).

$$Y_{it} = Y_{it}^* \exp(-u_{it}) = f(X_{it}; \beta)\exp(V_{it})\exp(-u_{it}), u_{it} \sim iidN^+(\omega, \sigma_v^2) \tag{5}$$

In this paper, we assume that the technical efficiency term is positive and follows a half-normal distribution ($u_{it} \geq 0, exp(-u_{it}) \in (0,1]$) and is independent of the random disturbance term.3 Under this assumption, the technical efficiency term ranges from （0,+∞）and the production unit is exactly at the output boundary when the null term is equal to 0.

The definition of Eq.6 contains three key attributes which are production function, the inefficiency term and uncertainty, and we focus on the regression results for inefficiency term. In this paper, we empirically study the TFP of each province using GDP as the output factor and physical capital, human capital as the input factors using with the C-D production function (Solomon, 2021). Ultimately, the stochastic frontier model with innovative factor inputs is constructed as follows.

$$\begin{cases} ln\, Y_{it} = \alpha_0 + \sum_n \alpha_n \, ln\, x_{nit} + v_{it} - u_{it} \\ u_{it} = \beta_0 + \beta_1 \, ln\, rd_{it} + \beta_2 \, ln\, rdp_{it} \\ \sigma_{it}^2 = \exp\,(\beta_0 + \beta_1 \, ln\, rd_{it} + \beta_2 \, ln\, rdp_{it} \end{cases} \tag{6}$$

3.2. Data description

In this paper, we select the GDP of each province as the output indicator (lnY). In terms of factor inputs, we choose the number of employed persons at the end of the year as the human capital input indicator (lnL); and we adopt the productive capital stock measured by the PIM as physical capital stock input indicator (lnK). Meanwhile, R&D capital stock (lnrd) and R&D personnel full-time equivalents (lnrdp) were chosen as proxy variables for R&D

investment and R&D human capital. Descriptive statistics of the relevant variables are shown in Table 1.

Table 1. Statistical description of the variables.

Variables	Explanation	Samples	Mean	Std. error	Max	Min
lnY	Regional GDP	630	8.651	1.114	10.996	5.394
lnK	Physical capital stock	630	9.786	1.256	12.453	6.210
lnL	Human Capital	630	7.534	0.823	8.820	5.541
lnrd	R&D capital stock	630	6.343	1.329	9.994	2.200
lnrdp	R&D Human Capital	630	3.647	1.260	6.636	-0.169

4. Empirical results and analysis

4.1. Benchmark regression results

Based on the model setting and testing ideas in this paper, the results are presented in Table 2. The regression results are divided into three panels in total, Panel A shows the estimation results of the production function, Panel B shows the estimation results of the inefficiency term, and Panel C shows the estimation of the uncertainty term, and we focus on the results of Panel B. Results (1) show the regression results without including any control variables, and result (2) and result (3) show the regression results for two time periods, 1998-2008 and 2009-2018. From the regression results of Panel A, the estimated coefficients of both capital input and human capital are significantly positive in the regression results of the production function, indicating that increasing regional capital input and human capital accumulation can effectively promote local economic growth. From the regression results of the inefficiency term of group B, both R&D capital stock and R&D human capital are significantly negative at the level of 10% or more, indicating that the increase of R&D capital and R&D personnel can significantly reduce the efficiency loss of economic growth and thus improve total factor productivity. From the regression results of the panel C uncertainty analysis, the estimated coefficients of R&D capital and R&D human capital are negative at least at the 5% level of significance, indicating that the accumulation of R&D investment can reduce the uncertainty of economic growth, which is due to the accumulation of R&D capital brings significant technological enhancement and provides sufficient endogenous impetus for economic growth, thus reducing the uncertainty of regional economic growth.

Table 2. Basic measurement results of stochastic frontier analysis.

	(1)	(2)	(3)
	SF	1998-2008	2009-2018
Panel A: Dependent variable: GDP			
lnK	0.527*** (28.141)	0.503*** (25.682)	0.323*** (8.952)
lnL	0.102*** (2.425)	0.185*** (4.042)	0.353*** (5.841)
Cons	2.702*** (5.661)	2.238*** (6.042)	2.862*** (11.573)
Panel B: Dependent variable: technical efficiency			
lnrd	-0.151*** (-4.972)	-0.123*** (-4.052)	-0.063** (-2.063)
lnrdp	-0.384*** (-11.105)	-0.321*** (-8.702)	-0.315*** (-9.361)
Cons	1.456***	1.739***	3.509***

	(3.391)	(5.662)	(8.191)
Panel C: Dependent variable: Uncertainty			
lnrd	-1.938*** (-4.325)	1.115** (2.317)	0.895*** (7.162)
lnrdp	-1.871*** (-4.621)	-1.329*** (-3.572)	-0.920*** (-9.961)
Cons	-10.855*** (-5.462)	-10.294*** (-4.521)	0.056 (0.070)
Samples	630	330	300
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes

*Note: *, **, *** represent 10%, 5% and 1% significance levels, respectively. Data in parentheses represent T values. Panel A represents the results of the production function regression, Panel B represents the results of the technical efficiency regression, and Panel C represents the results of the uncertainty regression. The following table is the same.*

4.2. Heterogeneity analysis

In this paper, the research sample is divided into eastern, central and western regions, and the heterogeneity stochastic frontier test is conducted respectively, and the estimation results are reported in Table 3. Results (1), (2), and (3) indicate the regression results of eastern, central and western regions. It can be found that the coefficients of R&D factors in the eastern and central region are negative at the significance level of 5% and above, which indicates that the R&D investment in the eastern region can significantly promote the growth of technical efficiency. The regression coefficients of R&D capital in the western region are significantly positive, while the regression coefficients of R&D personnel are not significant, which indicates that the western region lacks the support of R&D talents.

This paper classifies 30 provinces based on regional R&D intensity. Specifically, provinces with R&D capital stock per capita higher than the national level are innovation-driven regions; otherwise, they are investment-driven regions. Result (4) and result (5) indicate the regression results of innovation-driven regions and investment-driven regions. In Panel B, it can be found that the estimated coefficients of R&D capital and R&D personnel in innovation-driven regions are significantly negative. In investment-driven regions, the estimated coefficient of R&D capital is significantly positive, but the regression coefficients of R&D personnel are insignificant, which indicates that although investment-driven regions can enhance local TFP by increasing local R&D input, the contribution of R&D personnel in enhancing efficiency is low.

Table 3. Regression results of heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)
	Eastern	Central	Western	Innovation-Driven	Investment-driven
Panel A: Dependent variable: GDP					
lnK	0.221*** (12.144)	0.243*** (5.682)	0.345*** (2.921)	0.423*** (5.654)	0.334*** (8.442)
lnL	0.102*** (3.444)	0.142*** (3.042)	0.553*** (3.811)	0.444*** (4.042)	0.564*** (4.781)
Cons	2.702*** (5.661)	1.238*** (3.042)	2.552*** (3.523)	2.454*** (5.042)	3.264*** (5.573)
Panel B: Dependent variable: technical efficiency					
Lnrd	-0.631*** (-5.797)	-0.135** (-1.142)	-0.024 (-0.148)	-0.531*** (-5.794)	-0.135** (-1.145)
lnrdp	-0.608***	-0.241***	0.025	-0.608***	-0.011

	(-5.021)	(-2.872)	(0.313)	(-5.025)	(-0.038)
Cons	6.382*** (4.801)	-0.011 (-0.148)	-0.862*** (-3.464)	6.481*** (3.820)	3.257*** (3.121)
Panel C: Dependent variable: Uncertainty					
lnk	-1.050*** (2.582)	-0.072*** (2.402)	-5.818*** (-3.022)	-0.072*** (2.402)	-5.818*** (-3.022)
lnlabor	-1.174*** (-4.415)	-0.372*** (-2.951)	-1.648*** (-3.112)	-0.372*** (-2.915)	-1.648*** (-3.113)
Cons	-17.416*** (-3.653)	-4.741*** (-3.022)	1.279*** (3.222)	-4.741*** (-3.021)	1.279*** (3.222)
Samples	252	189	189	189	441
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes

5. Conclusions and policy implications

By applying the SFA method to assess the effects of R&D factor inputs on regional TFP, the main findings are as follows: (1) R&D capital stock and R&D human capital can significantly contribute to the growth of regional TFP. (2) By economic regions, both R&D capital stock and R&D human capital in eastern and central regions can significantly promote regional TFP growth, but western region can't promote regional TFP growth through R&D factors. (3) Innovation-driven regions can not only enhance TFP through the accumulation of R&D factors, whereas investment-driven regions can only rely on the accumulation of R&D capital stock to enhance TFP.

The policy implications based on the findings are as follows. First, Chinese government should continue to increase regional R&D investment, especially to raise the proportion of basic research in R&D investment. Secondly, the enterprises should pay attention to the proportion of researcher labor expenditure in R&D expenditure and play the role of innovation talent concentration in enhancing regional productivity. At last, local government should improve the mechanism and system of inter-regional factor flow mechanism and system, encourage the free flow of R&D factors, expand the spatial radius of knowledge spillover, and thus give full play to the knowledge spillover effect of R&D factor flow, which will be conducive to promoting the sustainable high-quality growth of China's regional economy.

Author contributions

Shikuan Zhao: Conceptualization, Writing - original draft, Writing - review & editing, Funding acquisition. Wen Tian: Software, Data curation. Abd Alwahed Dagestani: Supervision, Writing - review & editing.

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