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Innovative Production Efficiency in Chinese High-Tech Industries During the 13th Five-Year Plan Considering Environmental Factors: Evidence from a Three-Stage DEA Model

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Abstract: Innovative production in high-tech industries is seen as a promoter of corporate profitability and a driver of China's economic growth. However, some scholars point out that high-tech industry is in its infancy and has insufficient innovative production efficiency, which severely restricts regional economic development. To explore this further, we studied the innovation production efficiency of China's high-tech industry during the 13th Five-Year Plan period (2016–2020). The three-stage data envelopment analysis (DEA) model was utilised to calculate the efficiency of the innovation production in this industry, and we initially employed the DEA-Banker-Charnes-Cooper (BCC) model to calculate the efficiency for 31 provinces and applied similar-stochastic frontier analysis regression to eliminate the potential influence of external environmental factors. The empirical results findings reveal significant inter-regional differences in the efficiency of innovation production, with the Eastern region is the most efficient in innovation production, the Western region has greater growth potential, and the Central region requires to improve its overall efficiency by increasing technological inputs. In addition, we attempt to provide recommendations to policymakers based on our conclusions.

Keywords: innovation production, efficiency, high-tech industries, 13th Five-Year Plan, regional economics

1. Introduction

Innovative production in high-tech industries is seen as a promoter of corporate profitability and a driver of economic growth (Hong et al., 2016). In the context of China's reform and rapid economic development, high-tech industries have played a crucial role and are viewed as essential for the country's economic development (Feng et al., 2020; Li, 2018). In recent years, the contribution of high-tech industries to national economic growth and employment has been increasing in the context of the authorities' policy shift from a large manufacturing country to a strong manufacturing country (Shan et al., 2018). However, on the whole, China's high-tech industry is in the initial stage, the innovation capacity is insufficient (Cao et al., 2020; Zhang et al., 2019), especially as Del Giudice et al. (2019) noted that the Chinese core technology lags behind the developed countries, which seriously restricts the development of high-tech. Hence, to address this issue, the report of the 19th National Congress of the Communist Party of China proposed accelerating the building of an innovative country, while the "13th Five-Year Plan" placed a strong emphasis on the urgent need to execute an innovation-driven development strategy.

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The efficiency measurement is of utmost importance for the innovative production in high-tech industries in China. The measurement of innovation efficiency in academia is primarily discussed using the data envelopment analysis (DEA) model, which utilises mathematical planning techniques to monitor efficiency frontiers; Banker et al. (1984) and Charnes et al. (1978) argued that generally all units should be able to maximise their output given specific input and output conditions. In practical application, Guan and Chen (2010) selected cross-sectional data from 26 Chinese provinces for 2002 and 2003 and applied the network-DEA method to measure the efficiency of the innovation production process. They argued that for some innovation-leading cities, increasing the level of innovation inputs may hardly improve their innovation output, while for some lagging cities, improving efficiency could improve the output and outcome performance of these provinces. In their follow-up study, Chen and Guan (2012) expanded the scope of their research to cover the period from 1995 to 2007 and focused on the Chinese region; the study revealed that a mere 20% of China's regional innovation system adhered to empirical best practices and remained at the forefront during the process of technology development to commercialisation. Another study endeavour examining the efficacy of innovations in technology within China's high-tech industries, Lin et al. (2021) utilised the DEA model to examine three distinct viewpoints, namely province, region, and industry.

And they concluded that there were large inter-regional differences in the efficiency of innovation production; the efficiency was consistently highest in the Chinese Eastern region. This conclusion is similar with Li et al. (2017); they use the dynamic DEA model to reach the same conclusion, and they further argued that the proportion of meta-technology in the West is rapidly increasing and showing a catch-up with the Eastern region. Other than that, DEA models have been used to measure innovation efficiency in some specific provinces or regions (Li et al., 2018; Yi et al., 2020; Zhang & Fu, 2022; Zhang et al., 2021).

However, the extant literature seems to take little consideration of the slackness of the variables, which may result in efficiency being overestimated, in addition to external factors and random errors that may interfere with the results of the calculations and distort the efficiency. As Fried et al. (1999, 2002) pointed out, the traditional DEA models have not taken into account the effects of environmental factors (including random noise and management efficiency) on the evaluation of the efficiency of decision-making unit (DMU), which may distort the results. Furthermore, within the existing literature, few scholars have used the 13th Five-Year Plan as a research period, during the Chinese government has implemented various policies aimed at promoting the establishment of high-tech enterprises, including the "Innovation-driven Development Strategy", the "Made in China 2025" plan, and the "Innovation of Social Justice Science and Technology System with Chinese Characteristics", which are theoretically conducive to improving the efficiency of innovation and production in high-tech industries.

Therefore, we purpose to investigate the efficiency of innovation production within China's high-tech industries throughout the 13th Five-Year Plan period (2016–2020). Specifically, the study aims to identify regional variations in innovation production efficiency across the Eastern, Central, and Western regions of China. In addition, the study seeks to explore the characteristics of each region and identify the factors that contribute to differences in innovation production efficiency. To achieve these objectives, we employ the approach developed by Fried et al. (1999, 2002) and use the DEA-BCC model to calculate the industry innovation efficiency in the first stage. We account for environmental factors by applying a similar-stochastic frontier analysis (SFA) regression. Finally, we determine the true efficiency using the DEA-BCC model and propose potential improvements based on our empirical results.

This study makes several contributions to the literature on innovation production in Chinese high-tech industries. First, it considers the potential impact of environmental variables and uses the similar-SFA model to adjust the efficiency evaluation, improving the reliability of the results. Second, unlike previous studies that focus on a limited number of regions, we examine 31 provincial-level administrative regions in China from 2016 to 2020, providing a more comprehensive study of trends and changes in the industry as a whole. Our in-depth analysis of innovation productivity in high-tech industries provides useful information for policymakers to make informed decisions and adjust resource allocation guidelines across regions in the "14th Five-Year Plan" or in future investment and development strategies.

To provide a clear structure for the remainder of this study, we have organised it as follows: Section 2 presents an overview of the research methodology and data sources used in this study. Section 3 describes the empirical results and provides corresponding discussions. In Section 4, we summarise our conclusions from the study, while Section 5 offers policy recommendations based on our findings.

2. Materials

The present section is bifurcated into two segments. In the first part, we formulate the empirical model for the study and describe the methodology for each of the three stages in detail. The second part expounds on the sources of the data and the configuration of the variables, including data descriptive statistics and the correlation coefficients of the input and output variables.

2.1. The first-stage DEA-BCC model

Charnes et al. (1978) proposed the constant returns to scale model as one of the relevant DEA models, although the CCR model is highly sensitive and effective in calculating DMU efficiency values (Golany & Thore, 1997; Roll & Golany, 1993; Toloo & Babaee, 2015), which is not always applicable in real-world situations. Banker et al. (1984) proposed the DEA-BCC model with variable returns to scale as a means of addressing the aforementioned limitation, thereby presenting an improvement over the CCR model. In this study, the input-oriented BCC model is preferred to ensure model sustainability and account for variable returns to scale. As the objective of this study is to investigate the efficiency of innovation production in China's high-tech industries across 31 regions, it is expected that the return to scale will vary across regions. Therefore, the variable returns to scale technology is adopted in the first stage to accurately evaluate the initial efficiency of each province.

The CCR model is a calculation of the relative efficiency between DMUs based on the premise of constant payoffs to scale. In this model, there are K same kind of DMUs, which contain m inputs and n outputs. x, y denote $m * k$ and $n * k$ order matrices. **Matrix (1)** represents the input and output data for all K DMUs.

$$
\begin{array}{cc|ccccc|cc}
DMU & & 1 & 2 & 3 & \cdots & k & & \\
V_1 & \rightarrow & x_{11} & x_{12} & x_{13} & \cdots & x_{1k} & & \\
V_2 & \rightarrow & x_{21} & x_{22} & x_{23} & \cdots & x_{2k} & & \\
V_3 & \rightarrow & x_{31} & x_{32} & x_{33} & \cdots & x_{3k} & & \\
\vdots & & \vdots & \vdots & \vdots & & \vdots & & \\
V_m & \rightarrow & x_{m1} & x_{m2} & x_{m3} & \cdots & x_{mk} & & \\
 & & y_{11} & y_{12} & y_{13} & \cdots & y_{1k} & \leftarrow & u_1 \\
 & & y_{21} & y_{22} & y_{23} & \cdots & y_{2k} & \leftarrow & u_2 \\
 & & y_{31} & y_{32} & y_{33} & \cdots & y_{3k} & \leftarrow & u_3 \\
 & & \vdots & \vdots & \vdots & & \vdots & & \vdots \\
 & & y_{n1} & y_{n2} & y_{n3} & \cdots & y_{nk} & \leftarrow & u_n
\end{array} \tag{1}
$$

Let V_i and u_r be x_{ij} $(i = 1, 2, 3, \ldots, m; j = 1, 2, 3, \ldots, k)$ and y_{rj} $(r = 1, 2, 3, \ldots, n; j = 1, 2, 3, \ldots, k)$ weights, for these two variables $V_i \geq 0$, $u_r \geq 0$. The efficiency of the DMU is calculated using equation (2)

$$h_j = \sum_{r=1}^{n} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \tag{2}$$

Consequently, its non-linear programming model is

$$
\begin{aligned}
& Max\ h_j = \sum_{r=1}^{n} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \\
& s.t \begin{cases} \sum_{r=1}^{n} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, j = 1, 2, \ldots, k \\ v_i, u_r \geq 0, i = 1, 2, \ldots, m.r = 1, 2, \ldots, n \end{cases}
\end{aligned} \tag{3}
$$

Charnes et al. (1978) considered that it is difficult to calculate DMU efficiency through a non-linear programming model; thus, they proposed to transform it into a linear programming model with the same role, referred to as Charnes–Cooper transformation as in equation (4).

Thus, we obtain the following linear programming model.

$$Max \sum_{r=1}^{n} u_r y_{rj}$$
$$s.t \begin{cases} \sum_{r=1}^{n} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, r = 1, 2, \ldots, n \\ \sum_{i=1}^{m} v_i x_{ij} = 1, \quad i = 1, 2, \ldots, m \\ u_r, v_i \ge 0, \ j = 1, 2, \ldots, k \end{cases} \tag{4}$$

Based on the duality theory of linear programming, equation (4) is transformed into the dual programming equation (5)

$$Min\ \theta$$
$$s.t \begin{cases} \sum_{j=1}^{k} \lambda_j x_{ij} + s_i^- = \theta x_{ij}, i = 1, 2, \ldots, m \\ \sum_{j=1}^{k} \lambda_j y_{rj} - s_r^+ = y_{rj}, r = 1, 2, \ldots, n \\ \lambda_j, s_i^-, s_r^+ \ge 0, j = 1, 2, \ldots, n \end{cases} \tag{5}$$

where, when θ denotes the technical efficiency of the DMU_j, and $0 \le \theta \le 1$, s^-, s^+ denote input and output slack variables. λ denotes the coefficients of the optimal DMU actual inputs and outputs.

When $\boldsymbol{\theta = 1}$, $\boldsymbol{s^- = s^+ = 0}$, the DMU_j is considered to be strongly TE. However, $s^- \ne 0$ or $s^+ \ne 0$, the DMU_j is considered to be weakly TE. Where $s^- > 0$ indicates input redundancy, $s^+ > 0$ indicates output deficiency. When $\theta < 1$, DMU_j is the technical ineffective.

The BCC model initially assumes constant returns to scale. However, it can be extended to accommodate variable returns to scale by introducing the following restrictions $\sum_{j=1}^{k} \lambda_j = 1$; thus, it is expressed as in equation (6):

$$Min\ \theta$$
$$s.t \begin{cases} \sum_{j=1}^{k} \lambda_j x_{ij} + s_i^- = \theta x_{ij}, i = 1, 2, \ldots, m \\ \sum_{j=1}^{k} \lambda_j y_{rj} - s_r^+ = y_{rj}, r = 1, 2, \ldots, n \\ \sum_{j=1}^{k} \lambda_j = 1, s_i^-, s_r^+ \ge 0, j = 1, 2, \ldots, k \end{cases} \tag{6}$$

where θ is expressed as the pure technical efficiency (PTE). We can calculate the results of the TE according to equation (6); the TE can be calculated by the formula TE = PTE × SE, where SE denotes scale efficiency, which measures the deviation between the current size of the DMU_j and the effective scale frontier.

2.2. The two-stage similar-SFA regression model

We utilise the method employed by Fried et al. (2002), by conducting a similar-SFA. In the first stage, we regress slack variables on both environmental variables and a mixed error term. The second stage involves using the SFA regression equation, with input slack and environmental variables as explanatory variables, as follows:

$$S_{ni} = f^n(Z_i; \beta^n) + v_{ni} + \mu_{ni}; i = 1, 2, \cdots, I; n = 1, 2, \cdots, N \tag{7}$$

The n observed environmental variables are denoted by $Z_i = (Z_1, Z_2, Z_3, \ldots, Z_k)$. The mode of effect of these variables on the input slack variables is represented by $f^n(Z_i; \beta^n)$, while the mixed error is given by $v_{ni} + \mu_{ni}$. Here, $v_{ni} \sim N^+(0, \sigma_{vn}^2)$ corresponds to the statistical noise, and $\mu_{ni} \sim N^+(0, \sigma_{un}^2)$ denotes the management inefficiency.

Assume v_{ni} and μ_{ni} are independent of each other. Equations are regressed using the maximum likelihood estimation method; each regression yields estimated parameters $(\beta^n, \mu^n, \sigma_{vn}^2, \sigma_{un}^2)$. When $\gamma = \sigma_{un}^2/(\sigma_{un}^2 + \sigma_{vn}^2)$ tends to 1, the effect of managerial inefficiencies dominates; when it tends to 0, statistical noise dominates.

According to the methodological scenario provided by Jondrow et al. (1982), we refer to Luo (2012) for the separation of managerial inefficiencies with the following equation:

$$E(\mu \mid \varepsilon) = \sigma_* \left[\frac{\phi\left(\lambda \frac{\varepsilon}{\sigma}\right)}{\Phi\left(\frac{\lambda\varepsilon}{\sigma}\right)} + \frac{\lambda\varepsilon}{\sigma} \right] \tag{8}$$

In this equation, $\sigma_* = \frac{\sigma_\mu \sigma_v}{\sigma}$, $\sigma = \sqrt{\sigma_\mu{}^2 + \sigma_v{}^2}$, $\lambda = \sigma_\mu/\sigma_v$.

Therefore, the composition error term $v_{ni} + \mu_{ni}$ is calculated as follows:

$$E[v_{ni} \mid v_{ni} + \mu_{ni}] = S_{ni} - f(Z_i; \beta_n) - E[\mu_{ni} \mid v_{ni} + \mu_{ni}] \tag{9}$$

2.3. The three-stage-adjusted DEA model

The goal of the similar-SFA regression is to remove the influence of environmental and random factors on efficiency measures. Following the methodology proposed by Aslani Khiavi & Skandari (2021) and García-Sánchez (2007), the original data are included in the random error term obtained in the second stage, which can be obtained using the following adjustment equation:

$$X_{ni}^A = X_{ni} + \left[max\left(f\left(Z_i; \hat{\beta}_n\right)\right) - f\left(Z_i; \hat{\beta}_n\right)\right] + \left[max(v_{ni}) - v_{ni}\right]$$
$$i = 1, 2, \cdots, I; n = 1, 2, \cdots, N \tag{10}$$

where X_{ni}^A is the adjusted input; X_{ni} is the pre-adjusted input; $\left[max\left(f\left(Z_i; \hat{\beta}_n\right)\right) - f\left(Z_i; \hat{\beta}_n\right)\right]$ is the adjustment for environmental factors; $[max(v_{ni}) - v_{ni}]$ is the adjustment of all DUMs to the same level of "luck".

2.4. Data sources and variable design

The data for this study are referenced from Huo and Wang (2022) and Liu and Sun (2021); from the EPS Database – China Science and Technology Database, the data cover the period of the 13th Five-Year Plan, which is 2016–2020. The scope of the sample is 31 administrative regions of China; thus, each variable contains 155 observations. The definitions and descriptive statistics of the input, output, and environmental variables for this study are provided in Table 1.

Regarding the selection of environmental variables, Dyson et al. (2001) argue that environmental variables are the economic and theoretical basis for the relevance of the study objects, and whether they can reflect external environmental factors of the study objects. Therefore, based on the consideration of representativeness, relevance, and availability, and taking into account the studies of Law et al. (2020), Liu and Lyu (2020), and Lei et al. (2013) we choose GDP per capita index, consumer price index (CPI), and average wage index (AWI) of employed persons as environmental variables in this study. These variables are commonly used economic indicators that are related to the development of high-tech industries and innovation production efficiency. Additionally, they can also reflect the external environmental differences across different regions.

We conduct correlation tests on the input–output variables to ensure that there is some correlation between the variables. Table 2 reports the Pearson's correlation test matrix for the input–output variables.

Table 2 shows positive correlation coefficients between input variables and output variables, passing the two-tailed test at the 1% level of significance. These results indicate a robust positive correlation between input and output variables, aligning with the principle of homogeneity and validating the variable selection.

Table 1
Variable definitions and descriptive statistics

Variable	Definition	Unit	Mean	Median	Std. dev.
Input variables					
RPF	R&D project funding	1×10^6 Yuan	15390.350	5402.570	34199.350
EN	Number of high-tech enterprises	Enterprises	539.645	159.000	1224.149
EM	In-service high-tech enterprise employees	1×10^3 Persons	1001.517	621.508	1322.283
HPS	High-tech project stock	Projects	3794.703	1810.000	6490.923
Output variables					
PAT	Patents obtained by high-tech enterprises	Patents	8552.013	2799.000	19272.880
NP	Net profit for high-tech enterprises in each province	1×10^6 Yuan	84709.500	38576.080	121695.600
CONT	Contracts obtained by high-tech enterprises	Contracts	13764.120	5850.000	18339.150
Environmental variables					
GDPPC	GDP per capita index	–	105.594	106.100	2.176
CPI	Consumer price index	–	102.118	102.100	0.585
AWI	Average wage index for employed persons	–	107.698	107.824	5.062

Table 2
Pearson correlation coefficients for input and output variables

	RPF	EN	EM	HPS	PAT	NP
RPF	1					
EN	0.9598***	1				
EM	0.9333***	0.9209***	1			
HPS	0.9237***	0.9373***	0.9297***	1		
PAT	0.9667***	0.9619***	0.9317***	0.9305***	1	
NP	0.8588***	0.8509***	0.967***	0.9058***	0.8561***	1

Note: *** indicates a significant correlation at the 0.01 level (two-tailed).

3. Empirical Results and Discussion

This section analyses the technical efficacy, pure technical efficacy, scale efficacy, and returns to scale of innovation production across 31 regions of China through the use of the DEA-BCC model. Moreover, this section presents the findings of the second stage of similar-SFA model regressions on slack variables relating to input variables and environmental disturbance terms. Furthermore, this section reveals the adjusted results of the third stage, and the outcomes of these empirical studies are thoroughly analysed.

By employing the DEA-BCC model and Deap 2.1 software, we assessed the TE, PTE, scale efficiency (SE), and return to scale of innovation production in 31 different regions across China. Table 3 shows the findings from our initial efficiency measurement stage.

According to Table 3, the average TE, PTE, and SE for innovation production in the Thirteenth Five-Year Plan are 0.853, 0.896, and 0.945, respectively. Without considering the effects of environmental factors, the empirical result of the first stage suggests that the overall SE of China is higher than the PTE, indicating that the factor of scale is dominated by the innovation production efficiency of provinces.

Regarding the SE of the provinces, Eastern China has higher values than Central and Western. The efficiency frontier contains 14 provinces: Anhui, Beijing, Shanghai, Shandong, Guangdong, Sichuan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. Among them, one of them is in the Central region, four by the Eastern region, and seven by the Western region, which indicates that these provinces are more efficient in innovation production, and the inputs and outputs are more reasonable. In contrast, Inner Mongolia has the lowest TE among the 31 provinces, with a score of 0.378.

While the first stage of efficiency measurement included environmental factors, the efficiency values obtained in this stage may not fully reflect the actual level of innovation production efficiency in each province. To address this, we conducted the second stage of analysis using Frontier 4.1 software following the approach of Fried et al. (2002). In this stage, we regress the slack variables of input variables and environmental disturbance terms using a similar-SFA model and adjusted the input terms to obtain

Table 3
The efficiency of innovative production for high-tech industries in stage I

Region	Province	TE	PTE	SE	Returns to scale	Region	Province	TE	PTE	SE	Returns to scale
Central	Shanxi	0.334	0.393	0.850	drs	Western	Inner Mongolia	0.378	0.519	0.728	drs
Central	Jilin	0.829	0.940	0.882	drs	Western	Guangxi	0.781	1.000	0.781	drs
Central	Heilongjiang	0.655	0.657	0.997	irs	Western	Chongqing	0.772	0.880	0.877	drs
Central	Anhui	1.000	1.000	1.000	–	Western	Sichuan	1.000	1.000	1.000	–
Central	Jiangxi	0.770	0.789	0.976	drs	Western	Guizhou	0.757	0.781	0.968	irs
Central	Henan	0.727	0.815	0.893	drs	Western	Yunnan	0.615	0.701	0.878	drs
Central	Hubei	0.951	0.951	1.000	–	Western	Tibet	1.000	1.000	1.000	–
Central	Hunan	0.839	0.939	0.894	drs	Western	Shaanxi	1.000	1.000	1.000	–
	Mean	0.763	0.811	0.937		Western	Gansu	1.000	1.000	1.000	–
Eastern	Beijing	1.000	1.000	1.000	–	Western	Qinghai	1.000	1.000	1.000	–
Eastern	Tianjin	0.952	0.953	0.999	drs	Western	Ningxia	1.000	1.000	1.000	–
Eastern	Hebei	0.560	0.776	0.722	drs	Western	Xinjiang	1.000	1.000	1.000	–
Eastern	Liaoning	0.927	0.940	0.987	drs		Mean	0.859	0.907	0.936	
Eastern	Shanghai	1.000	1.000	1.000	–						
Eastern	Jiangsu	0.897	1.000	0.897	drs						
Eastern	Zhejiang	0.974	1.000	0.974	drs						
Eastern	Fujian	0.913	0.913	1.000	–						
Eastern	Shandong	1.000	1.000	1.000	–						
Eastern	Guangdong	1.000	1.000	1.000	–						
Eastern	Hainan	0.809	0.821	0.986	irs						
	Mean	0.912	0.946	0.960		Average value		0.853	0.896	0.945	

Note: 1. TE, PTE, and SE indicate technical efficiency, pure technical efficiency, and scale efficiency.
2. irs, drs, and - represent increasing, decreasing, and constant returns to scale.

a more accurate level of efficiency. Table 4 presents the results of the second-stage regression of each of the four input variables on the three environmental variables.

From Table 4, it can be observed that almost all regression terms of environmental variables passed the 1%, 5%, or 10% significance tests; it demonstrates that input redundancy is influenced by external environmental factors. The LR one-sided test is performed with four input variables, yielding results of 19.068, 18.291, 19.296, and 16.899, all of which are greater than the one-sided critical value of 10.501 with 3 degrees of freedom at the 1% significance level; in addition, the values of γ in all four models are equal to 1.000 or close to 1.000, satisfying the 1% significance level. Thus, the null hypothesis of no inefficiency term is rejected, indicating that the proposed model in this study is reasonably constructed, and management efficiency is a significant factor in this cause.

Table 4
Results of SFA estimation in stage II

	RPF	EN	EM	HPS
	Coefficient	Coefficient	Coefficient	Coefficient
Constant term	2000.474***	1052.741***	9447.154***	4133.975***
	(2000.499)	(1052.769)	(9447.257)	(4128.879)
GDPPC	43.995***	1.295*	21.435***	−3.2121***
	(51.855)	(2.593)	(24.732)	(−16.522)
CPI	−54.582***	−11.920***	−122.619***	−38.033***
	(−63.124)	(−21.349)	(−139.153)	(−230.859)
AWI	−11.608***	0.147	6.261***	0.583***
	(−13.543)	(0.101)	(7.245)	(12.384)
σ^2	210768.980***	981.139***	262566.330***	6982.878***
	(210768.980)	(986.148)	(262566.330)	(6982.752)
γ	1.000***	1.000***	0.999***	0.999***
	(56414.278)	(15334.506)	(649.459)	(11448430.000)
Log-likelihood	−210.071	−127.227	−213.363	−158.342
LR one-sided Test	19.068	18.291	19.296	16.899

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

Fried et al. (1999) and Coelli et al. (2005) suggest that the presence of negative coefficients of environmental variables implies that the value of these variables reduces input slacks, whereas positive coefficients are detrimental to efficiency improvement. Therefore, we interpreted the results of our regression analysis in this stage accordingly:

1. GDP per capita index (GDPPC) coefficient is positive for all input slack variables except high-tech project stock (HPS), indicating that the level of regional economic development leads to an increase in the input redundancy of the regional high-tech industries in terms of R&D project funding (RPF), number of high-tech enterprises (EN), and in-service high-tech enterprise employees (EM) inputs. This means that an increase in regional GDP does not necessarily mean that all areas have become more efficient, whereas in this study the growth of redundant values of RPF, EN, and EM led to a decrease in the efficiency of these indicators. It is also consistent with the research of some scholars, who argue that China's GDP growth tends to come from labour-intensive manufacturing rather than high-tech R&D industries (Frankema, 2015; Hussin, 2013), and high economic growth makes more currencies inclined to flow into financial markets (Calderón & Liu, 2003; Garnaut et al., 2016; Wang et al., 2019); in addition, Wei et al. (2017) believe that state-owned enterprises receive the majority of RPF, which squeezes the viability of small private R&D institutions. This may be another reason why GDP growth has instead brought about redundant increases in RPF and EN inputs. For EM, Altbach and Pacheco (2012), based on the purchasing power parity theory, argue that in China the compensation of full-time researchers is low. During periods of high economic growth, individuals engaged in R&D may be tempted to leave their positions for other high-paying industries, resulting in an increase in input redundancy.
2. CPI has a negative effect on all input variables. This indicates that an increase in CPI leads to a decrease in input redundancy. Referring to Wang (2022), we consider that a rise in CPI would result in higher production costs for firms, which may seek ways to reduce costs and improve efficiency to maintain normal production and business activities. Additionally, the increase in CPI may lead to tighter financial policies, reduced currency liquidity, and higher financing costs for firms, which could prompt them to pay more attention to the allocation and utilisation of resources, thereby enhancing their productivity and technological innovation capabilities.
3. AWI for employed persons: the coefficient of RPF is significantly negative, while the coefficients of the remaining two input variables EM and HPS are significantly positive, although the coefficient of EN is also positive, but it is not significant. It indicates that the input efficiency slack of RPF, EM, and HPS is affected by AWI. This result can likewise be explained by the study of Wei et al. (2017) and Altbach and Pacheco (2012), where research funding flows to some state-owned research institutions during the 13th Five-Year Plan period, while regions that tend to be more economically developed have more dense research institutions; the slack in the RPF input variable decreases. However, the Matthew effect reveals that regions that do not receive research funding are less efficient in terms of AWI inputs, leading to an increase in the slack in the EM input variable. In addition, research institutions may reduce their investment in R&D projects by increasing employee wages in order to retain employees, which results in lower technological innovation capacity and thus lower input efficiency.

For the third stage of efficiency estimation, we adjusted the original input variables according to equation (10) to eliminate the influence of environmental variables and random errors. Subsequently, we applied the DEA-BCC model once more to determine the actual innovative production efficiency value, which is presented in Table 5. The table includes not only the efficiency values of the third stage but also a comparison with the results of the first stage. The analysis indicates that environmental factors and random errors in the first stage underestimate the TE value in 31 cities, which increases from an average of 0.853 in the first stage to

Table 5
The innovative production efficiency for high-tech industries in Stages I and III

		Stage I				Stage III			
	Province	TE	PTE	SE	Returns to scale	TE	PTE	SE	Returns to scale
Central	Shanxi	0.334	0.393	0.850	drs	0.477	0.490	0.974	irs
Central	Jilin	0.829	0.940	0.882	drs	0.925	0.943	0.981	drs
Central	Heilongjiang	0.655	0.657	0.997	irs	0.645	0.723	0.892	irs
Central	Anhui	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Central	Jiangxi	0.770	0.789	0.976	drs	0.793	0.793	1.000	–
Central	Henan	0.727	0.815	0.893	drs	0.794	0.821	0.967	drs
Central	Hubei	0.951	0.951	1.000	–	0.940	0.947	0.993	irs
Central	Hunan	0.839	0.939	0.894	drs	0.937	0.938	1.000	–
	Mean	0.763	0.811	0.937		0.814	0.832	0.976	
Eastern	Beijing	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Eastern	Tianjin	0.952	0.953	0.999	drs	0.934	0.937	0.996	irs
Eastern	Hebei	0.560	0.776	0.722	drs	0.720	0.783	0.920	drs
Eastern	Liaoning	0.927	0.940	0.987	drs	0.877	0.878	0.998	drs
Eastern	Shanghai	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Eastern	Jiangsu	0.897	1.000	0.897	drs	0.911	1.000	0.911	drs
Eastern	Zhejiang	0.974	1.000	0.974	drs	1.000	1.000	1.000	–
Eastern	Fujian	0.913	0.913	1.000	–	0.904	0.929	0.973	irs
Eastern	Shandong	1.000	1.000	1.000	–	1.000	1.000	1.000	–

(Continued)

Table 5
(*Continued*)

		Stage I				Stage III			
	Province	TE	PTE	SE	Returns to scale	TE	PTE	SE	Returns to scale
Eastern	Guangdong	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Eastern	Hainan	0.809	0.821	0.986	irs	0.512	0.688	0.743	irs
	Mean	0.912	0.946	0.960		0.896	0.929	0.958	
Western	Inner Mongolia	0.378	0.519	0.728	drs	0.588	0.685	0.859	irs
Western	Guangxi	0.781	1.000	0.781	drs	0.997	1.000	0.997	drs
Western	Chongqing	0.772	0.880	0.877	drs	0.885	0.888	0.997	drs
Western	Sichuan	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Western	Guizhou	0.757	0.781	0.968	irs	0.755	0.841	0.898	irs
Western	Yunnan	0.615	0.701	0.878	drs	0.799	0.799	1.000	–
Western	Tibet	1.000	1.000	1.000	–	0.713	1.000	0.713	irs
Western	Shaanxi	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Western	Gansu	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Western	Qinghai	1.000	1.000	1.000	–	0.956	1.000	0.956	irs
Western	Ningxia	1.000	1.000	1.000	–	0.736	1.000	0.736	irs
Western	Xinjiang	1.000	1.000	1.000	–	1.000	1.000	1.000	–
	Mean	0.859	0.907	0.936		0.869	0.934	0.930	
Average value		0.853	0.896	0.945		0.864	0.906	0.952	

Note: 1. TE, PTE, and SE indicate technical efficiency, pure technical efficiency, and scale efficiency.
2. irs, drs, and - represent increasing, decreasing, and constant returns to scale.

0.864 after eliminating these variables. This result suggests that the first stage may not accurately reflect the true level of innovative production efficiency.

The returns to scale for Jiangxi, Hunan, Zhejiang, and Yunnan are increasing in the first stage, while the returns to scale for these cities become constant after removing external factors. In contrast, Hubei, Fujian, Tibet, Qinghai, and Ningxia change from constant to increasing SE in the third stage. After adjustment, the number of cities reaching the efficiency frontier falls from 12 to 10, indicating that some cities' innovative production efficiency was overestimated in the first stage. Whereas comparing the average PTE and SE values of the three regions, it can be observed that the PTE and SE of the Eastern and Western regions decreases in the third stage, demonstrating that they are overestimated in the first stage, while the PTE and SE of the Central region have increased, for which we try to visualise in Figures 1–3.

Following the completion of the third stage of adjustment, the mean values of TE, PTE, and SE are calculated for all provinces, resulting in values of 0.864, 0.906, and 0.952, correspondingly. These outcomes propose a possibility for technical improvement throughout all provinces. In addition, since TE is calculated as the product of PTE and SE, we employed TE to symbolise innovative production efficiency and generated Figures 4 and 5 to illustrate

Figure 1
Efficiency values comparison between Stages I and III

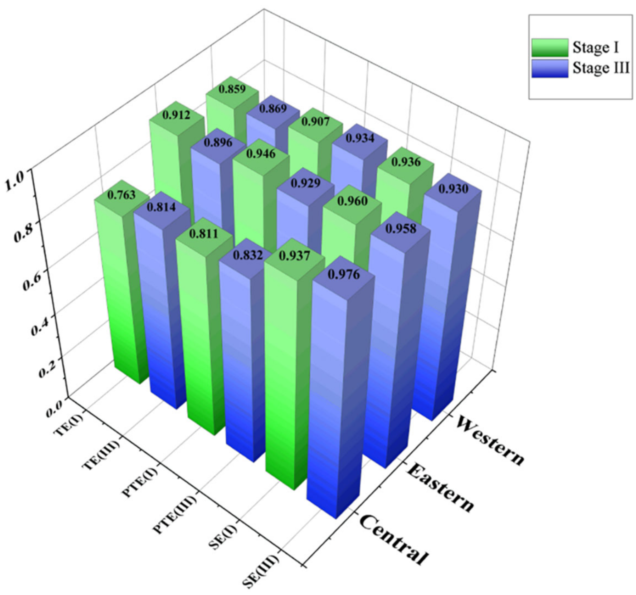


Figure 2
Pure technical efficiency comparison between Stages I and III

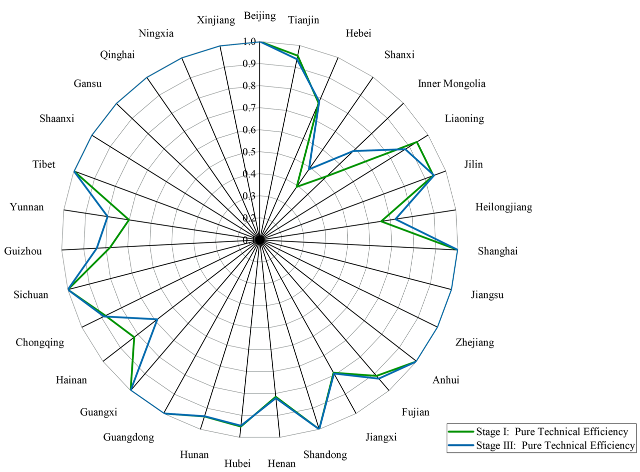
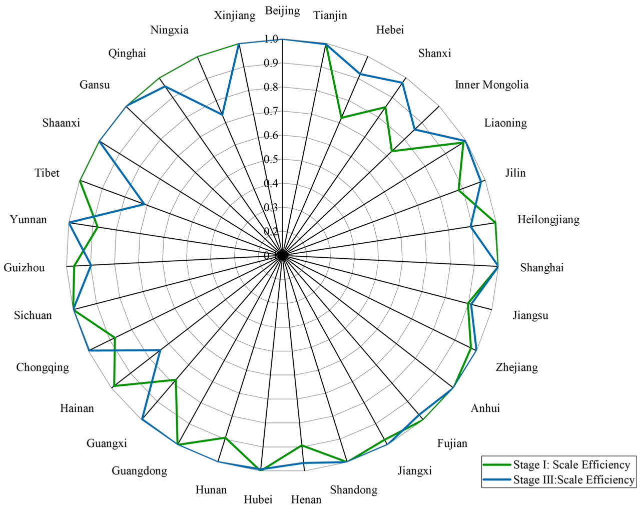


Figure 3
Scale efficiency comparison between Stages I and III



the comparison between Stage I and Stage III in various provinces of China.

The Central region displays lower PTE than the other two regions, with mean TE, PTE, and SE values of 0.814, 0.832, and 0.976, respectively. Nonetheless, the Central region is operating at a more optimal scale of production than the other two regions, implying that it has room for improvement in its PTE. It is noteworthy that Jilin and Henan exhibit decreasing returns to scale (drs), indicating that they are operating at a suboptimal level and might benefit from downsizing their operations. Conversely, Shanxi, Heilongjiang, and Hubei exhibit increasing returns to scale (irs), indicating that they are producing below their optimal size and could benefit from expanding their operations.

The mean TE = 0.896 in the Eastern region of China is higher than that in the Central (0.814) and Western (0.869) regions. As TE = PTE × SE, we utilise this metric to denote innovation production efficiency; these findings suggest that the high-tech industries in the Eastern region were relatively more efficient in generating innovative output. However, it is important to note that there were substantial variations in innovative production efficiency among the provinces within the Eastern region. Specifically, Beijing, Shanghai, Zhejiang, Shandong, and Guangdong demonstrated the highest levels of both PTE and SE in their innovative production, indicating that these provinces had effectively utilised their resources to achieve optimal innovative production efficiency. Conversely, Jiangsu had the lowest SE value, indicating a potential for further production scale to increase efficiency. Moreover, the province of Hainan had the lowest level of TE, indicating that the high-tech industries in this region were comparatively less efficient in generating innovative output. Given the Eastern region's status as one of the most developed regions in China, the high innovative production efficiency in the region suggests that the high-tech industries in the region have been playing a significant role in promoting China's economic growth. However, further improvements in TE and SE are still needed in Hebei and Hainan to fully utilise the potential of high-tech industries in the region.

The mean TE level in Western region of China is lower than in Eastern region, but higher than in Central region, suggesting that there is potential for improvement in terms of resource utilisation and adoption of advanced technologies. Nonetheless, the region displays a relatively high level of PTE, indicating that its high-tech industries need to increase their scale to increase innovation production efficiency. Given that the Western region is less developed than the other two regions, it has historically received significant investment in infrastructure and industry as part of China's development strategy. However, a closer examination of the data reveals that there is significant variation among the provinces within the Western region. For example, Inner Mongolia and Yunnan low PTE values indicate that their high-tech industries could benefit from improvements in both technical efficiencies. Conversely, Tibet demonstrates a high PTE value but low SE value, suggesting that its high-tech industries are

Figure 4
Regional differences in innovative production efficiency between Stages I and III

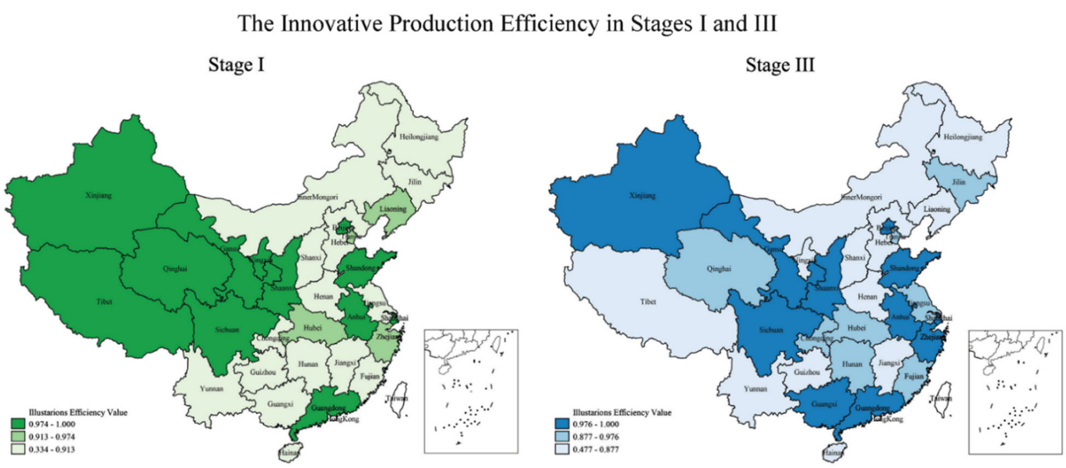
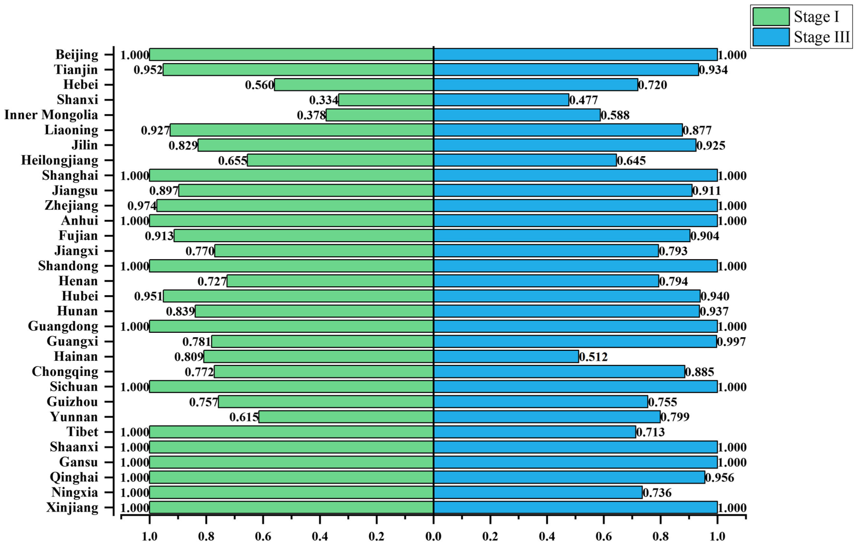


Figure 5
The innovation production efficiency of each province between Stages I and III.



operating efficiently at a small scale but may benefit from increasing the scale of production inputs.

Our result aligns with several scholars who have examined the efficiency of high-tech innovation in China and have observed ongoing improvements, though significant regional disparities persist (Lin et al., 2021; Liu et al., 2020; Xu et al., 2021; Zhuang & Ye, 2020; Zou et al., 2021). Specifically, our analysis supports the findings of Liang et al. (2020), Lin et al. (2021), and Zou et al. (2021) that the Eastern region exhibiting the highest levels of innovation and efficiency. Meanwhile, Dong et al. (2016) and Liu et al. (2020) believed that the Western region has great potential for development. Furthermore, studies suggest that the Central region would benefit from increased technology investment (Jin et al., 2019; Pan et al., 2022). Nevertheless, our study diverges from theirs; Zhong et al. (2011) analysed the first Chinese economic census data in 2004 with DEA model and concluded that the Western region has the lowest innovation efficiency. In addition, there have been evaluations highlighting the overall inefficiency of technological innovation in high-tech industries (Cao et al., 2020; Li et al., 2017; Zhang et al., 2019). Whereas we argue that there are three potential explanations for this outcome. First, their analysis may have underestimated innovation efficiency due to an oversight in accounting for external environmental factors. Second, the scale of investment in the Western region has increased in recent years. Third, we posit that the high-tech industry's efficiency as a whole has witnessed improvement during the 13th Five-Year Plan.

4. Conclusion

To examine the efficacy of innovation production in various Chinese provinces during the 13th Five-Year Plan (2016–2020), we collected data on four input variables, namely RPF, number of high-tech enterprises, in-service high-tech enterprise employees, and HPS. In addition, we gathered data on three output variables, including patents obtained by high-tech enterprises, net profits for high-tech enterprise employees, and contracts obtained by high-tech enterprises. To eliminate any potential impact of external environmental factors on efficiency, we employed a three-stage DEA model based on Fried et al. (1999, 2002). In the first stage, we calculated the initial efficiency of each province with the DEA-BCC model. In the second stage, we estimated a similar-SFA model with GDP per capita index, CPI, and AWI for employed persons as environmental variables to adjust the initial efficiency. Finally, in the third stage, we reapplied the DEA-BCC model to obtain the true efficiency values after removing environmental effects.

Based on our analysis, we have concluded the following:

1. China's high-tech industry is relatively efficient in innovation production. However, there are significant regional differences, with the average innovation production efficiency in the Eastern region being higher than that in the Western and Central regions.
2. There may be opportunities for growth and development in the Western region. Since it has a higher percentage of provinces with increasing returns to scale, indicating that the Western region will have great potential if more investment is made on R&D scale in the future.
3. High-tech companies in the Central region do not reach their maximum potential in converting inputs into outputs due to their relatively low level of pure technical inputs and thus increase efficiency by optimising their production technologies.

This study aims to investigate the efficiency of innovation production in China's high-tech industries during the 13th Five-Year Plan period (2016–2020). We argue that the study has important practical implications for policymakers in China's high-tech industries, as it illustrates the innovative production efficiency of high-tech industries and possible solutions for improvement. Simultaneously, this study reflects from the side that the focus on examining innovation production efficacy in various Chinese provinces during the 13th Five-Year Plan (2016–2020) provides a timely and relevant topic for research, as China is experiencing rapid economic development and technological advancement. The study employs a relatively robust methodology that attempts to eliminate the influence of external environmental factors on the final efficiency evaluation by considering the slackness of variables and environmental factors. Consequently, this methodology serves as a valuable reference for future research by scholars.

Nonetheless, the study has some potential limitations. First, the study focuses on only four input variables and three output variables, which may not be comprehensive enough to capture all dimensions of innovation and production in high-tech industries. Second, the study only used the DEA-BCC model, which may not be able to explain all the complexities of innovation and production in high-tech industries. Future research directions for scholars could focus on expanding the range of variables, using other models such as the Malmquist productivity index, and exploring other factors that may affect the efficiency of innovation and production in high-tech industries.

5. Policy Recommendations

Based on the conclusions of this study, we propose three policy recommendations for the improvement of innovation production efficiency.

1. Promote regional integration: The average efficiency is higher in the Eastern region than in the Central and Western regions. Governments could promote regional integration by creating infrastructure that facilitates transportation of goods and services between regions, which could help boost efficiency.
2. Encourage foreign investment: High-tech industries are often capital intensive, and foreign investment could help improve efficiency by providing capital, especially in the Western region, which can be made more efficient by increasing the scale of foreign capital inputs.
3. Rational allocation of state-owned resources: Policymakers could optimise the allocation of state-owned resources by providing more technical input to high-tech companies in the Central region. This could increase their efficiency in converting inputs into outputs and help them reach their maximum potential.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the authors.

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