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SCIENCE AND TECHNOLOGY INNOVATION EFFICIENCY IN GUANGDONG, HONG KONG AND MACAO GREATER BAY AREA BASED ON STATIC AND DYNAMIC DEA

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Abstract: In the context of the integration of science, technology, and finance, this study aims to scientifically assess the efficiency of science and technology innovation in the Guangdong-Hong Kong-Macao Greater Bay Area. To this end, a system of evaluation indexes, encompassing input-output dimensions, has been constructed based on panel data from 11 cities in the Greater Bay Area from 2019 to 2024. The DEA-Malmquist index method has been utilized in the construction of this system. The regional science and technology innovation efficiency is measured with precision through static efficiency measurement and dynamic total factor productivity decomposition. The reasons for the efficiency differences are revealed from the perspective of technological progress and efficiency changes. The findings of the study demonstrate that (1) the average value of the comprehensive efficiency of science and technology innovation in the Guangdong-Hong Kong-Macao Greater Bay Area exhibits fluctuations and increases, and (2) there are discrepancies in the magnitude of the fluctuations in the efficiency of science and technology innovation and the factors influencing it across different cities. (3) Considering the issue of the Guangdong-Hong Kong-Macao Greater Bay Area's high overall innovation efficiency, coupled with significant internal disparities, there is a compelling need to optimize resource allocation in a targeted manner.
Keywords: Guangdong-Hong Kong-Macao Greater Bay Area; DEA-Malmquist Index; Technology Innovation; Efficiency evaluation

1 INTRODUCTION

China's investment in technological innovation has been steadily rising in recent years. According to data released by the National Bureau of Statistics in 2025, the country's total research and experimental development (R&D) expenditure in 2024 reached RMB 3,613 billion, marking an 8.3% increase from the previous year. The R&D investment intensity reached 2.68%, an increase of 0.10 percentage points over the prior year, setting a new record. Evidence indicates that the contribution of high-tech and emerging industries to GDP growth has significantly increased. Nevertheless, despite the growth in the scale of innovation, it still faces deep-seated contradictions, such as inefficient resource allocation and insufficient coordination of innovation efforts. In 2019, an article titled "Building an International Science and Technology Innovation Centre with Global Influence," published by the Science and Technology Department of Guangdong Province, underscored that Guangdong, Hong Kong, and Macao have exceptional capabilities in technological research and development and the transformation of research outcomes. These regions have a solid foundation for establishing an international science and technology innovation center. The article emphasizes the need to concentrate on this strategic positioning, vigorously develop new technologies, industries, business forms, and models, and construct an economic system driven and supported by innovation. In this strategic context, enhancing the efficiency of technological innovation has become a key initiative to promote high-quality regional development. The current study employs the DEA-Malmquist index method, using panel data from 11 cities within the Guangdong-Hong Kong-Macao Greater Bay Area. This approach is used to systematically evaluate the regional technological innovation capability, conduct a comprehensive analysis of innovation efficiency levels and their core influencing factors, and provide a decision-making foundation for the optimization of the regional innovation ecosystem.

Fare et al. constructed a DEA-Malmquist model based on the theoretical framework of Data Envelopment Analysis (DEA). This model was innovative in its incorporation of the Malmquist index [1]. It systematically analyzes the dynamic evolution mechanism of production efficiency from multiple dimensions, such as technical efficiency changes and technological progress, by decomposing total factor productivity changes. This provides a scientific and effective analytical tool for exploring the intrinsic driving factors of economic growth. In their 2019 study, Chen Zhangxi and colleagues evaluated the land use efficiency of the Guangdong-Hong Kong-Macao Greater Bay Area and 11 other cities in the region. To this end, they constructed an input-output index system based on the DEA model [2].

In a 2020 study, Wen M and colleagues examined the efficiency of the marine economy of the Guangdong-Hong Kong-Macao Greater Bay Area. To this end, they employed the DEA-Malmquist model [3]. Han Xiaoteng and other scholars measured the research efficiency of eight universities within the Guangdong-Hong Kong-Macao Greater Bay Area from 2016 to 2019. The input-output perspective and the data envelopment analysis method [4] were utilized to achieve this objective. In the study by Wang Haonan, the logistics efficiency of the port system was evaluated and analyzed from 2012 to 2021 using the DEA model. The major ports in the Guangdong-Hong Kong-Macao Greater Bay

Area—Guangzhou, Shenzhen, and Hong Kong ports—were taken as examples [5]. Drawing upon the extended DEA model, scholars such as Chen Longfang have examined the degree of economic synergistic development within the Guangdong-Hong Kong-Macao Greater Bay Area. Their research has unveiled the spatial and temporal evolution characteristics of this development [6].

In summary, scholars both domestically and internationally have conducted further studies on various aspects of the Guangdong-Hong Kong-Macao Greater Bay Area using the DEA model. However, there are still shortcomings: there is a scarcity of literature on evaluating the efficiency of scientific and technological innovation in the Greater Bay Area cities of Guangdong, Hong Kong, and Macao using the DEA-Malmquist model. Consequently, based on panel data from 11 cities in the Greater Bay Area from 2019 to 2024, this paper employs the DEA-Malmquist index method to construct an evaluation index system that includes both input and output dimensions. The regional science and technology innovation efficiency is measured with precision through static efficiency measurement and dynamic total factor productivity decomposition. The reasons for the efficiency differences are explored from the perspectives of technological progress and efficiency changes.

2 MODEL CONSTRUCTION

In this paper, the CCR-DEA model and the Malmquist index are selected for the scientific analysis of the research and innovation efficiency of the cities in the Guangdong-Hong Kong-Macao Greater Bay Area. The CCR-DEA model has the capacity to accurately measure pure technical efficiency and scale efficiency, while the Malmquist index can dynamically assess changes in efficiency, thereby providing a comprehensive reflection of the dynamic evolution of regional research and innovation efficiency.

2.1 CCR-DEA Model

The CCR-DEA model (constant returns to scale) is an appropriate analytical framework for examining research and innovation efficiency in cities across the Guangdong-Hong Kong-Macao Greater Bay Area. This model enables both cross-sectional and longitudinal comparative analyses [7]. Horizontally, it allows for the assessment of the relative efficiency of R&D inputs (such as funding and personnel) and outputs (including patent grants and new product revenues) for each city in the same year, identifying areas where resource allocation can be improved. Vertically, it enables the tracking of each city's efficiency trajectory from 2019 to 2024, visually demonstrating the impact of policy implementation. Despite the significant differences in city sizes within the Greater Bay Area (for example, Shenzhen and Zhaoqing), the CCR-DEA model, based on the assumption of constant returns to scale and the creation of comprehensive efficiency indicators, can quantify the input and output efficiencies of cities in the context of scientific research and innovation as a whole. This provides a substantial database for understanding the current state of regional scientific research and innovation, thereby aiding in the development of collaborative growth strategies.

2.1.1 CCR-DEA Scale reward invariant model

In the DEA base model CCR, there are decision-making units (DMUs), denoted as DMUi $(\mathrm{i} = 1,2,\ldots,\mathrm{n})$ each containing m inputs and k outputs. The input vector is defined as $X_i = (X_{i1}X_{i2},\ldots X_{im})^T$ (where $\mathrm{X_{ij}}$ denotes, the j-input) and the output vector i s$Y_i = (Y_{i1},Y_{i2},\ldots Y_{im})^T$ (where $\mathrm{Y_{ij}}$ denotes the t-input). The weight vectors of the input and output metrics are denoted as $V = (V_1,V_2,\ldots V_m)^T$ and $U = (U_1,U_2,\ldots U_m)^T$, respectively,and are considered the evaluation indicators of DMUi.

$$H_i = \frac{U^T Y_i}{V^T X_i} = \frac{\sum_{s=1}^{k} U_S Y_{si}}{\sum_{t=1}^{m} V_t X_{ti}}, i = 1,2,\ldots,n \tag{1}$$

Refer to Equation (1), whose values are determined by the weight vectors U and V and satisfy $H_i \leqq 1$. When evaluating a specific unit $\mathrm{DMU_{i0}}$, it is denoted as $\mathrm{DMU_0}$ and its input/output vectors are X_0 and Y_0 respectively. Based on this, the CCR model can be formulated as follows:

$$\begin{aligned} &MaxH_{i0} = \frac{U^T Y_{i0}}{V^T X_{i0}} = \frac{\sum_{s=1}^{k} U_S Y_{s0}}{\sum_{t=1}^{m} V_t X_{t0}} \\ &s.t. \frac{\sum_{s=1}^{k} U_S Y_{si}}{\sum_{t=1}^{m} V_t X_{ti}}, i = 1,2,\ldots,n \\ &U \geqq 0, V \geqq 0 \end{aligned} \tag{2}$$

Eq. (2) is transformed into a linear programming model as (let $\mathrm{T} = \frac{1}{\mathrm{V^T X_0}}$; $\omega = \mathrm{tv}$; $\mu = \mathrm{tu}$):

$$\begin{aligned} Max \quad & \boldsymbol{\mu}^T Y_0 = H_{i0} \\ s.t. \quad & \omega^T X_i - \mu^T Y_i \geq 0 \; i = 1,2,\ldots,n \\ & \omega^T \boldsymbol{X}_0 = 1, v \geq 0 \\ & \omega \geq 0, \mu \geq 0 \end{aligned} \tag{3}$$

Solve for and introduce the slack variable $\mathrm{S}^{+}, \mathrm{S} \geq 0$ and then proceed with the solution.

$$Min\theta s.t.\sum_{i=1}^{n}\lambda_i X_i - S^- = \theta X_0$$
$$\sum_{i-1}^{n}\lambda_i Y_i - S^+ = Y_0 \tag{4}$$
$$i \geq 0, S^+ \geq 0, S^- \geq 0, i = 1,2,\ldots,n$$

As indicated by Eq. (4), within the CCR model, the integrated efficiency value of the decision unit $\mathrm{DMU_i}, \theta_i$ meets $0 \leq \theta_i \leq 1$. This signifies the minimum input ratio necessary when the output remains constant. Conversely, 1−θ_i represents the input redundancy rate, with its value being directly indicated by the radial optimization model $(1-\theta_i)\cdot X_i$ This model highlights the reduction potential of the various input elements, offering a precise direction for enhancing resource allocation optimization.

2.2 Malmquist Index

The limitation of the traditional DEA model is that it can only statically assess the relative efficiency of different decision-making units (DMUs) within the same time period, and it cannot capture the dynamic change of efficiency over time. To remedy this shortcoming, Fare and other scholars pioneered the integration of the Malmquist index theory with the DEA methodology in 1994, proposing the DEA-Malmquist model [3].

Assume that (x^t, y^t) and (x^{t+1}, y^{t+1}) denote the inputs and outputs of period t and period $\mathrm{t}+1$ respectively, where $D_c^t(x^t, y^t)$,$D_c^{t+1}(x^{t+1}, y^{t+1})$ are the output distance functions between the two periods under the constant returns to scale (CRS) assumption (subscript c denotes the CRS condition). Then the Malmquist index can be expressed by the following equation:

$$tfp = M^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D_c^t(x^{t+1},y^{t+1})}{D_c^t(x^t,y^t)} \times \frac{D_c^{t+1}(x^{t+1},y^{t+1})}{D_c^{t+1}(x^t,y^t)}\right]^{\frac{1}{2}} \tag{5}$$

If $M^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) > 1$, it means that total factor productivity has increased from period t to period $\mathrm{t}+1$, if $M^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) < 1$, it means that total factor productivity has decreased during this period, and when $M^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) = 1$, it means that total factor productivity has not changed significantly and is in a steady state. Further, under the assumption of constant returns to scale, the Malmquist index can be decomposed into the index of change in technical efficiency ($effch$) and the index of scientific and technological progress ($tech$), as shown in the following formula:

$$Effch = \frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)}$$

$$Tech = \left[\frac{D_c^t(x^{t+1}, y^{t+1})}{D_c^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_c^t(x^t, y^t)}{D_c^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}}$$

Where, $tfp = \mathrm{M}^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) = Effch \times Tec\ h$.And when the returns to scale are variable, the technical efficiency change index can be further decomposed into pure technical efficiency index (*pech*) and scale efficiency index (*sech*) as expressed:

$$pech = \frac{D_v^{t+1}(x^{t+1},y^{t+1})}{D_v^{t+1}(x^t,y^t)} \tag{6}$$

$$sech = \left[\frac{D_v^{t+1}(x^{t+1},y^{'+1})/D_c^{t+1}(x^{t+1},y^{t+1})}{D_v^t(x^t,y^t)/D_c^t(x^t,y^t)} \times \frac{D_v^{t+1}(x^{t+1},y^{t+1})/D_c^{t+1}(x^{t+1},y^{t+1})}{D_v^t(x^t,y^t)/D_c^{(}(x^t,y^t)}\right]^{\frac{1}{2}} \tag{7}$$

Where $D_v^{t+1}(x^{t+1}, y^{t+1})$ denotes the output distance function based on the technical conditions of the first $\mathrm{t}+1$ period in the case of variable returns to scale, and the subscript v denotes variable returns to scale. Then the index of technical efficiency change can be expressed as: *effch*= *pech* × *sech*.

Therefore, the total factor productivity, i.e., the efficiency of science, technology, and innovation, is calculated as:

$$tfp = Effch \times Tech = pech \times sech \times tech \tag{8}$$

3 SELECTION OF INDICATOR SYSTEM

The evaluation index system of science and technology innovation efficiency in the Guangdong-Hong Kong-Macao Greater Bay Area is the focus of this paper. The index is divided into two aspects: input index and output index. The number of R&D personnel and the internal expenditure of R&D funds by industrial enterprises above large scale are selected as input indicators, with reference to the research of Zhang Peng and other scholars. When analysing the efficiency of science and technology innovation in the Guangdong-Hong Kong-Macao Greater Bay Area based on the DEA-Malmquist model, the aforementioned scholars emphasised that R&D manpower and capital investment are the core dimensions for measuring the input of innovation resources [8].It is evident that financial support constitutes a pivotal propellant for the advancement of science and technology innovation [9]. Consequently, the proportion of S&T expenditures to general public budget expenditures is utilised as an input indicator, thereby reflecting the support of local governments for S&T innovation. Among the various output indicators, the number of patents applied and authorised is a significant metric for evaluating a nation's or region's technological innovation capacity and level. The sales revenue of new products by industrial enterprises above a certain scale is a key indicator of an economy's capacity for transformation through innovation. The selection of per capita GDP aligns with the research of Chen Ying [10], who considers it a pivotal indicator for comprehensively assessing innovation-driven economic development. Collectively, these indicators form a system for evaluating research and innovation efficiency, encompassing the input of R&D resources, policy support, technological output and economic effects. Input-output indicators for scientific and technological innovation efficiency can be seen in Table 1.

Table 1 Input-Output Indicators for Scientific and Technological Innovation Efficiency

Indicator Type	Indicator	Variable	Unit	Source
Input Indicators	R&D Personnel in Above-designated-size Industrial Enterprises	X_1	Hundred persons	Zhang Peng, Li Lin xin, and Zeng Yong quan (2021)
	Intra-expenditure on R&D in Above-designated-size Industrial Enterprises	X_2	Billion yuan	
	Proportion of S&T Expenditure in General Public Budget Expenditure	X_3	%	
Output Indicators	Number of Patents Granted	Y_1	Hundred units	
	Sales Revenue from New Products in Above-designated-size Industrial Enterprises	Y_2	Billion yuan	
	GDP per Capita	Y_3	Thousand yuan/Person	Chen Ying (2025)

4 EMPIRICAL RESEARCH

3.1 Dea Static Analysis

This study adopts the years 2019-2024 as its research period and selects nine mainland cities within the Guangdong-Hong Kong-Macao Greater Bay Area, along with the Hong Kong Special Administrative Region and the Macao Special Administrative Region, as its subjects. Data for the study is sourced from the China Statistical Yearbook, the Guangdong Statistical Yearbook, the Census and Statistics Department of the Hong Kong Special Administrative Region Government, the Statistics and Census Bureau of Macao, the Wind Database, and the statistical yearbooks of various cities. The current study aims to compare and analyze the pure technical efficiency, scale efficiency, and comprehensive efficiency of Science, Technology, and Innovation (STI) in the 11 cities of the Guangdong-Hong Kong-Macao Greater Bay Area. The objective is to identify internal factors influencing the efficiency of STI and to offer corresponding recommendations. The comprehensive efficiency values are calculated using software, with the STI efficiency of the 11 cities in the Guangdong-Hong Kong-Macao Greater Bay Area presented in Table 2.

Table 2 Comprehensive Efficiency of Science and Technology Innovation in the Guangdong-Hongkong-Macao Greater Bay Area

	2019	2020	2021	2022	2023	2024
Hong Kong	1.000	1.000	1.000	1.000	1.000	1.000
Macau	1.000	1.000	1.000	1.000	1.000	1.000
Guangzhou	1.000	1.000	1.000	1.000	1.000	1.000
Shenzhen	0.869	1.000	1.000	1.000	1.000	1.000
Zhuhai	0.625	0.678	0.968	1.000	1.000	1.000
Foshan	0.680	0.771	0.967	1.000	1.000	1.000
Huizhou	0.811	0.856	0.916	0.911	0.910	0.875
Dongguan	1.000	1.000	1.000	1.000	1.000	1.000
Zhongshan	1.000	1.000	1.000	1.000	1.000	1.000
Jiangmen	0.642	0.737	0.826	0.927	0.951	1.000
Zhaoqing	0.662	0.990	1.000	0.957	0.986	1.000
Average value	0.845	0.912	0.971	0.981	0.986	0.989

As shown in Table 2, the mean value of S&T innovation efficiency in the Guangdong-Hong Kong-Macao Greater Bay Area exhibits variability and peaks in 2024, with the mean value of S&T innovation efficiency sustaining a trajectory of steady growth after 2020. Recent studies have indicated that the average value of comprehensive technical efficiency in science and technology innovation in the 11 cities of the Guangdong-Hong Kong-Macao Greater Bay Area has ranged between 0.845 and 0.989 over the past six years. This indicates that the level is high and increasing annually. The findings suggest that the cities within the Greater Bay Area are more effective in converting scientific research

outcomes into practical applications, a consequence of the synergistic collaboration between government entities and innovation-oriented actors. Specifically, cities 5, 6, and 7 have a technical efficiency value of 1 in 2019, 2020, and 2021, respectively. Meanwhile, city 8 has a technical efficiency value of 1 in 2022 and 2023, and city 10 has a technical efficiency value of 1 in 2024. This coincides with an upward trend in the average value of the comprehensive efficiency of science, technology, and innovation. This upward trend is due to the sufficient and efficient investment of human and financial resources by these cities. The underlying reason for this phenomenon is that these cities have allocated sufficient and efficient investment in human and financial resources. The increase in the government's financial expenditure on science and technology has been identified as a key factor in enhancing the level of transformation of scientific and technological achievements. This, in turn, has been shown to contribute to the upward trend of the average value of technical efficiency. Consequently, this has led to an improvement in the efficiency of science, technology, and innovation in the city cluster of the Guangdong-Hong Kong-Macao Greater Bay Area as a whole.
In terms of individual cities, the five Greater Bay Area cities of Hong Kong, Macao, Guangzhou, Dongguan, and Zhongshan have maintained the DEA effective state over the past six years. This indicates that the technical and scale efficiencies of science and technology finance in these five cities have reached an optimal level, and the resource structure is reasonably configured. Shenzhen, a city with a dense concentration of high-tech enterprises, was in a non-DEA effective state in 2019, but has been in a DEA effective state in both 2020 and 2021-2024. The analysis indicates that Zhuhai and Foshan were in a non-DEA effective state from 2019 to 2021 and in a DEA effective state from 2022 to 2024. Jiangmen was in a non-DEA effective state from 2019 to 2023 and did not reach a DEA effective state until 2024. Zhaoqing was in a DEA effective state for the remainder of the years, with the exception of 2021 and 2024. Huizhou has been in a non-DEA effective state for the last six years. Comprehensive efficiency is composed of two constituent elements: technical efficiency and scale efficiency. It is evident that as the comprehensive efficiency value declines, the city's output exhibits a corresponding decrease when compared with other cities that have similar input levels. Years in which the value of comprehensive efficiency of science and technology innovation in the cities of the Greater Bay Area does not reach 1 indicate that the technical efficiency and scale efficiency in the transformation of scientific and technological achievements have not reached the optimal state. It is therefore necessary to improve the comprehensive efficiency, and to utilize the various input factors to the maximum extent. To this end, corresponding measures must be adopted to adjust and make it reach a relative equilibrium.

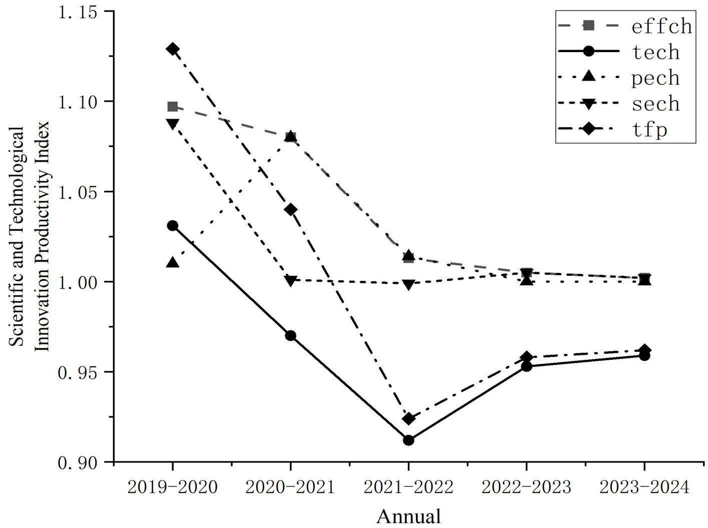
3.2 Malmquist Index Dynamic Analysis

Malmquist's methodology can be utilized to dynamically reflect changes in the efficiency of science and technology innovation within the cities of the Guangdong, Hong Kong, and Macao Greater Bay Area. The Malmquist index is used to decompose the productivity of science and technology innovation in the 11 cities of the Guangdong, Hong Kong, and Macao Greater Bay Area from 2019 to 2024. The following results have been obtained.

Table 3 Average Malmquist Index and Decomposition of Scientific and Technological Innovation in 11 Cities in the Guangdong-Hongkong-Macao Greater Bay Area from 2019 to 2024

	effch	*tech*	*pech*	*sech*	*tfp*
2019-2020	1.097	1.031	1.010	1.088	1.129
2020-2021	1.080	0.970	1.080	1.001	1.040
2021-2022	1.013	0.912	1.014	0.999	0.924
2022-2023	1.005	0.953	1.000	1.005	0.958
2023-2024	1.002	0.959	1.000	1.002	0.962
Average value	1.040	0.965	1.021	1.019	1.003

As shown in Table 3 and Figure 1, the average STI productivity index for the Guangdong, Hong Kong, and Macao Greater Bay Area from 2019 to 2024 is 1.003, with a 0.3% increase in Malmquist productivity. During the research period, the total factor productivity index exceeded 1 from 2019 to 2021, but fell below 1 from 2021 to 2024, indicating a gradual decline in STI efficiency. The STI inputs and outputs of the 11 cities in the Greater Bay Area reached optimal levels only between 2019 and 2021. Further decomposition of TFP into technical efficiency and technical progress indices reveals: (1) the highest TFP value from 2019 to 2020 was due to the combined effect of technical and scale efficiency, highlighting these factors as key drivers of STI efficiency improvement, while pure technical efficiency hindered progress; (2) the lowest TFP value from 2021 to 2022 was attributed to low technical progress and scale efficiency, suggesting that these factors are the primary causes of reduced total factor productivity. This insight can



guide government and enterprises to enhance scientific and technological innovation efficiency in the Greater Bay Area by increasing investment and scaling up innovation efforts.

The Malmquist Index and its decomposition of the efficiency of science and technology innovation of the cities in the Guangdong-Hong Kong-Macao Greater Bay Area are as follows table 4.

Figure 1 Guangdong-Hong Kong-Macao Greater Bay Area Science and Technology Innovation Productivity Index from 2019 to 2024

Table 4 Malmquist Index of Scientific and Technological Innovation Efficiency and Its Decomposition in Cities of the Guangdong-Hong Kong-Macao Greater Bay Area

	effch	*tech*	*pech*	*sech*	*tfp*
Hong Kong	1.000	0.986	1.000	1.000	0.986
Macau	1.000	0.952	1.000	1.000	0.952
Guangzhou	1.000	1.009	1.000	1.000	1.009
Shenzhen	1.030	1.036	1.000	1.030	1.074
Zhuhai	1.109	0.956	1.095	1.015	1.056
Foshan	1.084	0.955	1.084	1.001	1.034
Huizhou	1.016	0.927	1.001	1.015	0.938
Dongguan	1.000	0.945	1.000	1.000	0.945
Zhongshan	1.000	0.955	1.000	1.000	0.955
Jiangmen	1.083	0.945	1.049	1.047	1.033
Zhaoqing	1.101	0.951	1.000	1.101	1.047
Average value	1.039	0.965	1.021	1.019	1.003

As indicated in Table 4, only six cities – Guangzhou, Shenzhen, Zhuhai, Foshan, Jiangmen, and Zhaoqing – have a total factor productivity index greater than 1 from 2019 to 2024. In contrast, the total factor productivity of the five cities of Hong Kong, Macau, Huizhou, Dongguan, and Zhongshan, as depicted in Figure 1, is lower than 1. These observations suggest that the collective efficacy of science and technology innovation within the Guangdong-Hong Kong-Macao Greater Bay Area is on an upward trend. However, it is crucial to acknowledge that this efficiency still requires improvement, and there are noticeable differences in the rate of change across various cities. From the perspective of the decomposition analysis of the Malmquist index, the 11 cities can be classified as follows: (1) The technical efficiency of the five cities of Hong Kong, Macao, Guangzhou, Dongguan, and Zhongshan is all 1, indicating that technical efficiency does not contribute to the efficiency of science and technology innovation, and that technological progress hinders the improvement of the productivity of science and technology innovation; (2) The efficiency of science and technology innovation in Shenzhen has shown a 7% improvement. As illustrated in Figure 1, 43% of cities exhibit the highest level of technical efficiency, defined as the technical efficiency index being equivalent to the technical efficiency index. The technical efficiency index and the technical progress efficiency index increased by 3.0% and 3.6%, respectively, indicating that the increase in total factor productivity in Shenzhen is mainly due to technical efficiency and technological progress; (3) An examination of the STI efficiency of Zhuhai, Foshan, Jiangmen, and Zhaoqing reveals a varied picture, with increases of 5.6%, 3.4%, 3.3%, and 4.7%, respectively. The four cities demonstrate a positive effect on the technical efficiency index and technical progress. The findings indicate that while the technical efficiency index increases, the technical progress index decreases, and the pure technical efficiency index and the scale efficiency index work together to promote the enhancement of the technical efficiency index.

5 CONCLUSION

This paper presents the findings of an empirical study on the Science, Technology, and Innovation (STI) efficiency of 11 cities in the Guangdong-Hong Kong-Macao Greater Bay Area. The study concluded that: (1) The average value of the comprehensive efficiency of STI in the Guangdong-Hong Kong-Macao Greater Bay Area fluctuates and rises between 2014 and 2019, and then steadily grows after 2020, reaching a peak in 2024. The average value of the comprehensive technical efficiency is at a high level and is increasing year by year. (2) A number of differences have been identified in the magnitude of change and the factors influencing the STI efficiency of different cities. The five cities of Hong Kong, Macau, Guangzhou, Dongguan, and Zhongshan have demonstrated a consistent DEA effectiveness, while the five cities of Shenzhen, Zhuhai, Foshan, Jiangmen, and Zhaoqing have shown incremental improvement. Conversely, Huizhou has exhibited a persistent absence of DEA effectiveness. The Guangdong-Hong Kong-Macao Greater Bay Area has been found to demonstrate high levels of innovation efficiency overall. However, it is crucial to acknowledge the presence of significant internal disparities within the region. These disparities necessitate targeted interventions to ensure the optimization of resource allocation. The promotion of technological progress is an inherent feature of the concept of sustainable and efficient cities. In contrast, cities that are experiencing a decline in efficiency are required to enhance their scale efficiency.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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