Human Capital Heterogeneous and Growth of Green Total Factors Productive

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Human Capital Heterogeneous and Growth of Green Total Factors Productive

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Abstract

Human capital improves the efficiency of GTFP has been established in research fields, but the heterogeneous effects of human capital on GTFP and its sustainable mechanisms are unclear. This study aims to examine the effects of human capital accumulation, education fiscal, and innovation on GTFP efficiency under diversity between spatial and temporal. Employing panel data from 30 provinces from 2001 to 2018 in China, We analyzed the dynamic and static efficiency of GTFP at different regions by three-stage DEA. We explored the heterogeneous effects of human capital on GTFP through Tobit regression. Results show that the average value of GTFP efficiency is inverted U-shape and having a significant geography difference. Then, human capital accumulation and education fiscal have positive effects on the GTFP efficiency; however, innovation negatively affects GTFP efficiency. At the same time, marketization growth decreases human capital and education positive influence on the GTFP efficiency. However, this effect was not seen on the innovation—the implication of these results concerning the human capital heterogeneous effects of GTFP efficiency in a different geography. Establishing a fair and transparent system is an available choice to reduce the endowments gap and effectively promote GTFP efficiency in developing countries.

Key words: Green Total Factor Productive; Human Capital; Heterogeneity; Tobit Model

JEL Code: R11; O44; Q57

1. Introduction

Large–scales urbanization in the world brought about a series of challenges for the human living environment (United Nations, 2016),[1] Such as extensive pollution, energy crisis, and ecological imbalance(Patwa N, Sivarajah U, Seetharaman A, et al. 2020). Under this new governance framework, resources can reconfigured to extract more value by reducing pollution emissions (Hobson, 2021). Ecological imbalance and high pollution emissions in developing countries have attracted international environmental concerns (Golini et al., 2017). As the largest developing country, China's total coal consumption reached 486 thousand tons, growing 4.3% year–on–year. Thus, China has been working on "high emission, high pollution, and low efficiency" (Sun J, Li G, Wang Z. 2019). Green Total Factor Productivity (GTFP) is an essential concept that requires reducing energy consumption and environmental pollution. Likewise, it is also an essential tool to measure the green economic performance of industries. Compared with traditional Total Factor Productivity (TFP) ignores the environmental pollution cost of GDP growth, GTFP accounts for energy consumption and environmental factors to analyze (Jin, Shen, & Li, 2020).

[1] United Nations. (2016). the world's cities in 2016 (Accessed 28 January 2019) http://www.un.org/en/development/desa/population/publications/pdf/urbanization/the_worlds_cities_in_2016_data_booklet.pdf.

The majority of the literature focuses on measuring the index of GTFP. Shuai Zhang and Dajian Zhu (2020) measured the GTFP through the dynamic panel GMM model. Chen et al. (2017) added industrial "three wastes" into the output factors, and then measured the environmental efficiency of 11 provinces in China's Yangtze River economic belt. Xiang Ji et al. (2019) adopted the DEA methods to find out that the efficiency of pollution treatment and waste disposal technology in Eastern China was the highest, while the technology levels in Western China were the lowest. Overall, the present literature focuses on exploring the measurement and evaluation of the development efficiency of GTFP while ignoring the relationship between the drive potential factors and sustainability path. To fill gaps, the paper measures the GTFP through a three-stage DEA model. Accounting for the heterogeneity includes spatial and temporal, we adopt data from province level from 2001 to 2018. Finally, combining comprehensive resource endowment, industrial structure, technological progress, trade flows, resources, environmental policies, and other variables, we investigate driving factors through Tobit regressions.

The paper contributes as follows: Firstly, we use three stages DEA to estimate the GTFP by excluding external factors and stochastic noise. Second, we account for the heterogonous between spatial and temporal in China. Third, our paper combined human capital and education fiscal to analyze the influence factors of GTFP.

The rest of the paper as follows. Section 2 describes literature and theoretical about GTFP; Section 3 describes the econometric method, includes data and variables. The empirical analysis in section 4; in section 5 further discusses the mechanism of GTFP; Section 6 sums up the conclusion.

2. Literature and Theoretical hypothesis

2.1 literature review

Numerous literature focuses on the micro or macro-economic policies evaluation, including trade policy

(Amiti & Konings, 2007; De Loecker, 2011; Yufan Jiang, 2021), and agglomeration industrial policy (Martin P, 2011). GTFP methods decompose mathematical programming techniques (Data Envelopment Analysis, DEA) or econometric modeling (Stochastic Frontier Analysis, SFA). Beeson and Husted (1989) use DEA to investigate the differences in the U.S. sector efficiency. There are also some studies evaluating GTFP in China. For example, Song et al. (2018) investigate the impact of China`s "new normal" economic development policy on environmental technology advancement and industrial land-use efficiency. They argue that weak environmental regulations have no significant impact on environmental technology advancement, while new normal economic policy improves industrial land efficiency. Other research measures the GTFP through enterprise microdata. Zhu et al. (2018) employ DEA to evaluating China`s mining and quarrying industry. They show that technical progress is the major driving factor to the production progress in this section.

Based on the above, we conclude that scholars are still interested in the topics about GTFP, especially in the policy evaluating and industrial production driving factors. However, few studies combine human capital and policy evaluation to analyze China provincial GTFP. This paper revises the input and output Factors in GTFP to explore the effects of human capital and education on the GTFP. Then, we use provincial-level data to measure spatial and temporal heterogeneity on GTFP efficiency. Finally, we integrated analysis influences of human capital and policy evaluation on the GTFP efficiency, which extend current literature about GTFP.

2.2. Theoretical Hypothesis

Overall, Fig.1 shows the sustainability mechanism of human capital on GTFP efficiency. This paper believes that human capital has an impact on GTFP from two paths: firstly, the direct mechanism is through human capital accumulation, education fiscal and innovation affect GTFP; secondly, the indirect mechanism is through system shock (like Foreign capital entry and increased marketization level) leads to competition effects which improve the human capital indirectly effects on the GTFP.

1. Human Capital Spillover Effects

In economic growth, the manifestation of human capital spillover effects includes higher labor productivity, rational allocation of labor resources, and decreasing the labor market mismatch. On the other hand, human capital and physical capital have substitution effects. It means the marginal return of human capital declines more slowly than material inputs. J B Ang et al. (2011) suggest that Human capital could improve productivity by optimizing other factor structures. Besides, this paper believes human capital directly influences GTFP by increasing labor productivity and other input factor productivity. However, this literature ignores the geography variety, particularly in China, a country with unbalanced economic development. Some literature shows that the level of human capital effects on GTFP varies greatly under the regional disparity (Jérôme Vandenbussche et al., 2006). Azomahou Theophile et al. (2009) emphasize that medium-quality human capital is more critical to the TFP than high-quality human capital in a relatively economically underdeveloped city. The possible explanation is that the improving TFP caused by imitating technical of economically development area, rather than innovation.

2. Education Fiscal Effects

China's regional diversity affects the disparity of GTFP between provinces for a long time. The central government has increased the fiscal education expenditures to introduce advanced technology and brain to reduce inter-regional variability. Some literature acclaim that R&D and education as the endogenous decision-making behavior of enterprises and residents are likely associated with fiscal education effects. It is perhaps that human capital and technological advancement in backward areas will promote economic growth and narrow the regional economic gap (Viaene & Zilcha, 2002; Glomm & Ravikumar, 2003). However, some literature finds that government education expenditure has a significant effect on economic growth in developed countries but has no significant impact on developing countries (Blankenau et al., 2007). China is a vast territory; whether education fiscal promote the GTFP in all provinces? The question is one of the focuses of the paper.

3. Innovation Effects

Innovation is one of the essential knowledge-intensive activities—enterprises through increasing R&D expenditures to obtain advanced technology. If technology coverage is fully maximized in the market, a technology monopoly can be realized, and help enterprises obtain surplus profits. This behavior promotes the improvement of regional innovation and achieving human capital accumulation. Simultaneously, enhancing the regional innovation level promotes enterprise technology competition to promote long-term social development. For example, the new technology application, artificial intelligence, and energy-saving technology have dramatically reduced energy consumption. Besides, material innovation promotes great resource productivity, which formats the sustainability loops of 'R&D-production-market-sales'.

Meanwhile, it also reduces the possible environmental pollutants during the organization's activity. Under the technology spillover effects, resource optimization urges enterprises to eliminate outdated production capacity and improve resource utilization efficiency, contributing to the regional green economics development—however, the technology with high investment and risky increasing threshold for the market. Because spillover effects may not affect the downstream and upstream chain, several weak technological enterprises may increase the resource investment to make up for their technological disadvantages. It results in a decline in the region's overall resource utilization efficiency, which is not conducive to circular economy development.

Drawing on the above, the hypothesis proposed as follows：Human capital, education fiscal, and innovation influence of GTFP.

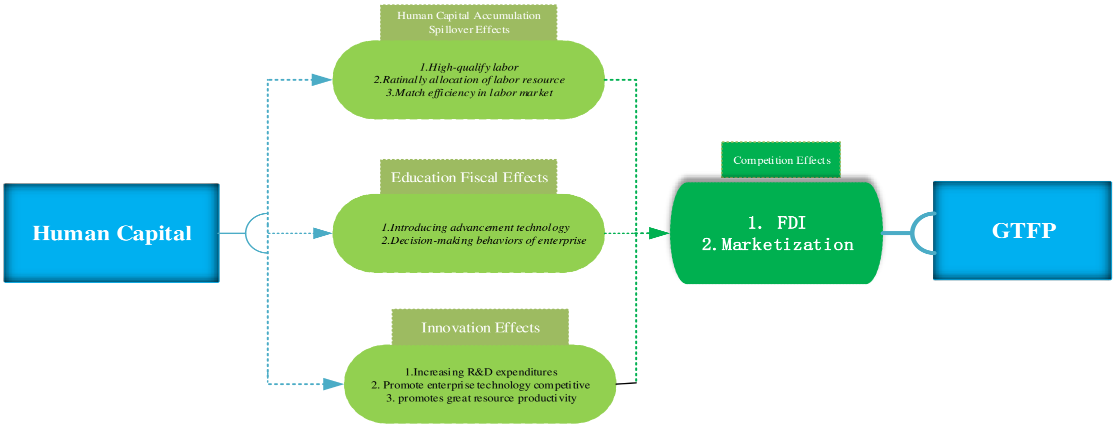

Figure 1: The Sustainability Mechanism of Human Capital on GTFP

3. Method, Variable and Data Source

3.1 Calculation of GTFP

Calculate these values to measure the principle-level evolution of the GTFP from 2001 to 2018 in China through Three-stages DEA models. Comparing with the Two-stages DEA model, the entry input-output system is a black box, making the specific production and operation processes ignored; the three-stage DEA explores the intersystem and distinguishes the different effects among factors. The model steps as follows: The first stage is the traditional DEA model. First, using the original input-output data to measure DEA efficiency and decompose the overall efficiency into two dimensions, pure technical efficiency, and scale efficiency.

Hence, the DEA-BCC model as follows:

$$\begin{cases} \min = \left[\theta - \varepsilon\left(\hat{e}^{T} S^{-} + e^{T} S^{+}\right)\right] \\ s.t. \sum_{j=1}^{n} \lambda_j X_j + S^{-} = \theta x_0 ; \sum_{j=1}^{n} \lambda_j y_j + S^{+} = \theta y_0 ; \sum_{j=1}^{n} \lambda_j = 1 ; \end{cases} \quad (1)$$

In equation (1); the $j=1,2\ldots n$ defined as the number of decision-making units. The input element and output element is X_j and Y_j respectively, and the valuable of λ_j defines as the combination coefficient of the decision-making unit; e^T is the unit row vector. θ is values of decision-making unit; S^+, S^- represent the surplus variable and slack variable ,respectively .if $\theta=1; S^+ \neq 0$ or $S^-=0$ the decision-making unit is efficient. If $\theta<1$ represent the decision-making unit is inefficient.

The second stage is SFA. Fried H O, Schmidt S (2002) claim that the decision-making unit affected by management inefficiencies, environmental effects, and statistical noise. The slack variable can reflect the initial low efficiency, construction the SFA model to regression of the first stage variables with environmental variables and the mixed error term, the SFA model as follow:

$$S_{ni} = f(Z_i ; \beta_n) + v_{ni} + \mu_{ni} ; i = 1, 2, \cdots, I ; n = 1, 2, \cdots, N \quad (2)$$

In formulation (2) S_{ni} represents the Decision-making unit i on the Slack value of n; and Z_i are environment variables; $\nu_{ni} + \mu_{ni}$ is the mixed error term; ν_{ni} represents a random variable. μ_{ni} Indicates management inefficiency. The random error term $\nu \sim N(0,\sigma_v^2)$ represents the influence of random interference factors on the input slack variable. μ represents the impact of management factors on the input slack variable, if μ obeys the normal distribution truncated at zero, the range equals $\mu \sim N^+(0,\sigma_\mu^2)$. All decision-making units can be adjusted to the same external environment. The adjustment formula is as follows:

$$X_{ni}^A = X_{ni} + [\max(f(Z_i;\hat{\beta}_n)) - f(Z_i;\hat{\beta}_n)] + [\max(\nu_{ni}) - \nu_{ni}] \quad i=1,2,L,I; n=1,2,L,N \qquad (3)$$

In formulation(3), X_{ni}^A and X_{ni} defined as the adjusted investment and investment before adjustment, respectivily; and $\max(f(Z_i;\hat{\beta}_n)) - f(Z_i;\hat{\beta}_n)$ presents the adjustment the external environmental, and $[\max(\nu_{ni}) - \nu_{ni}]$ is to place all decision-making units under the same environmental level.

The third stage: the adjusted input-output variable DEA efficiency analysis. Using the adjusted input variables to calculate the efficiency value of each decision-making unit again, which has eliminated the influence of environmental factors and random factors, hence the values relatively accurate.

3.1.1Mediation Effects Model

Analyzing the human capital factors of effects on GTFP efficiency through the Tobit regression. First, considering the total effect of human capital (Edu), education fiscal (Edu Fiscal), and regional innovation (patent) on GTFP, the regression model as follow:

$$GTFP_{it} = \beta_0 + \beta_1 X_{it} + \beta_3 Controls + \varepsilon_{it} \qquad (4)$$

Further considering the interaction effect of human capital accumulation level, education fiscal, FDI, marketization degree on GTFP; and the interaction effect of the level of regional innovation; the level of intellectual property protection on GTFP. The interaction model as follow:

$$GTFP_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_{it} + \beta_3 Z_{it} \times X_{it} + \beta_4 Controls + \varepsilon_{it} \qquad (5)$$

In equation (4) and (5). $GTFP_{it}$ Represents the efficiency with GTFP of the region "i" in year t; X_{it} defines the three explanatory variables in the article, including human capital accumulation, education fiscal expenditure, and the level of regional innovation. In addition, the values Z represents three variables: the degree of openness; marketization; and IPR protection; ε_{it} is a random error term.

The function with the interaction term of X and Z is to investigate hypothesis two. Besides, to reduce the endogenous problems caused by missing variables, we still control a series of variables that have been prove to have a significant impact on GTFP.

3.2 Variables

This paper investigates the effects of human capital on GTFP, the amount variables including two sectors. The first one is three-stage DEA variables, and the second variable is the mediation effects model through Tobit regression.

3.2.1 Variables of the three-stage DEA.

The section is to analyze GTFP and its decomposition. Therefore, the explained variable is GTFP, measured by three-stage DEA in section 3.1. In this paper, the input and output indicators are as follows, and the description of variables is in Table 1.

Input indicators: (1) the energy consumption inputs reflect the efficiency of green products, which represented by the amount of energy consumption. (2) The material capital input highlights the level of capital input in production progress, which usually represented by the increasing investment in fixed assets. (3) The labor input reflects the number of employees, which represented by the amount of employment at the enterprise.

Output indicators: (1) the desired output indicator is GDP, representing Per Capital GDP in each province. (2) The carbon emission is an undesired output indicator that highlights green production. At the same time, at the second stage, we need to eliminate those facts that affect the efficiency of GTFP and cannot be change in a short time.

Considering the large gap between provinces in China, particularly the economic gap, would affect the GTFP. We select the secondary industry's proportion in GDP and the full-time equivalent (FTE) of R&D as environmental factors.

Table 1: Describe of Variables.

Variable type	Variable name	symbol	Variable description	unit	Mean	Standard deviation
Input variable	Energy Consumption	EC	Total energy consumption	10,000 tons of standard coal	10,779.18	7702.263
	Material Capital	MC	Physical capital stock	(people/10,000 yuan) (price in 2000)	17.448	58.88
	Labor input	Lab	Number of employed persons	Ten thousand people	2,498.416	1,670.947
Output system	Economic development	Eco	per capita *GDP*	yuan(Price in 2000)	49.382	35.178
	Carbon Emission	Co_2	Carbon dioxide emissions	Ten thousand tons	27513.56	21,524.37

Environmental factor	Industrial development	Ind	The proportion of the secondary industry in GDP	%	46.437	7.778
	R&D investment level	Rd	Full-time equivalent of R&D personnel	Person year	73,569.85	90,715.93

3.2.2. Variables of Mediation Effects Model

This paper adopts Tobit regression to analyze the interaction effects of heterogeneous human capital on the GTFP efficiency. Traditional regression models may face bias issues between variables. This paper uses the Tobit model for the empirical analysis to eliminate the errors caused by the range from 0 to 1 GTFP variables, effectively solving explanatory variables' bias. The core explanation as following and the description of variables in Table (2).

Core explanation variable：(1) Human capital, represented by the average education years in labor. (2) Education fiscal expenditure is define as the ratio of expenditure on science and education to fiscal expenditure; it also emphasizes government attention. (3)Regional innovation, which is represented the number of domestic patent applications.

Explained variable: the purpose of this section is to analyze the effects of human capital on GTFP efficiency. Thus, the explained variable is GTFP, and the evaluation value of efficiency is to eliminate the environmental interference factors.

Control variables: (1) Economic development level (per capita GDP), per capita GDP direct reflects each province's economic level. A higher level of economic development in the region means that technology agglomeration improves the total green factor productivity. (2) Industrialization level (IGDP). From the perspective of the entire industry chain, the green technology level of the entire industry chain can help improve the green technology level. The industrialization level defined by the percentage of industrial production to the regional GDP. (3) Infrastructure construction level (Road). The road belongs to green industrialization and improves the efficiency of an economy. Infrastructure construction level represented by the urban road area per capita. (4)Urbanization level. A process with Urbanization brings about higher spillover effects on technology and human capital. We adopt the Proportion of urban population in the total population to represent the urbanization level. (5) Social investment in fixed assets. Total fixed-asset investment is a prerequisite for the development of regional GTFP. The investment in different regions determines the willingness of enterprises to update green technologies. The social fixed assets investment expressed as total investment in fixed assets of the whole society.

Mediate variables: (1) Foreign investment, Foreign direct investment through the human capital, competition effects, and knowledge spillover effects to improve the GTFP; we measure FDI through the index of annual foreign investment utilized in GDP. (2)The higher the marketization level means, the stronger wiliness to introduce green advancement technology and new talent. Considering the availability of data, we measure the variable of marketization index from Report on Marketization Index of China[2] (3) Intellectual Property Rights Protection. IPR protection level is the fundamental driving force for green technology innovation, conducive to stimulating enterprise enthusiasm for innovation and constructing an excellent innovation atmosphere. The measurement index is the ratio of technology transactions on the regional GDP.

In addition, we expect those variables may influence the efficiency of GTFP.

Table 2 The Descriptive variables of Tobit Model

Types of	Variable name	symbol	Variable description	unit	Mean	Standard deviation
Explained variable	Circular economy development efficiency	GTFP	Efficiency after removing environmental interference factors	-	0.89	0.15
Explanatory variables	Human capital level	Edu	Average years of education in labor	year	10.497	1.263
	education fiscal expenditure	EduF	Ratio of expenditure on science and education to fiscal expenditure	%	17.645	29.792
	Regional innovation	Patent	Number of domestic patent applications	Pieces/10,000 people	4.233	7.175
Control variable	The level of economic development	PGDP	GDP per capita	Yuan / person	49.382	35.178
	Industrialization level	IGDP	The added value of the secondary industry accounts for the proportion of regional GDP	%	46.437	7.778
	Infrastructure construction level	Road	Urban road area per capital	Square meter	12.069	4.336
	Urbanization rate	Urban	Proportion of urban population in total population	%	48.175	15.307
	Social investment level	SI	Total investment in fixed assets of the whole society	Ten thousand yuan	116286.7	139419.6

[2] Wang, X. L., Fan, G., & Hu, L. P. (2019). Report on Marketization Index of China by Province. Beijing, China: Social Science Literature Publishing House.

	Foreign investment level	FDI	Total foreign investment/gdp	%	0.434	0.542
Moderator	Marketization level	Market	Marketization index	-	6.642	2.083
	Protection of Intellectual property	TMR	The ratio of technology market transaction to regional GDP	%	1.008	2.091

Note:The education fiscal calculates using the (three science and technology expenses + education expenses) before 2006, while the education fiscal calculates using (education + science and technology expenditure) after 2006; the marketization index from the China's Marketization Index Report by Provinces.

3.3 Data source

Considering available data, we exclude the data from Tibet, Hong Kong, Macau, and Taiwan. Hence, the panel data from 30 provinces from 2001 to 2018. The primary data is calculated from the China Urban Statistical Yearbook and China's Energy Statistical Yearbook. The worth mention is the energy consumption data from the statistical Yearbooks of provinces and the marketization index measured from the Report with China's Marketization Index by Fan Gang(2019). The index of Carbon dioxide emissions collects from the eight types of energy consumption, including diesel consumption; coke consumption; coal consumption; kerosene consumption, gasoline consumption; fuel oil consumption; crude oil consumption; Natural gas consumption. Then evaluation the coefficient of energy conversion to the carbon. The inter-provincial material capital stock is calculated based on the relevant data and methods of Zhang Jun (2004), the equation is follows: $K_{it} = K_{it-1}\left(1-\delta_{it}\right)+I_{it}$.[3]

4. Results and Discussion

The following sections present the main analysis about GTFP efficiency and the influence factors in the various province. A full dynamic and static model to analyze the GTFP, the results expand four parts as follow:

4.1Analysis of the Dynamically GTFP

This paper takes materials capital, labor, and energy consumption as input variables, provinces GDP as the expected output, CO2 as the undesired outputs. The calculation of GTFP efficiency in 30 provinces through the three-stages DEA. That is because we can distinguish the different trends of spatial and time. According to the division method of Chinese administrative regions, the provinces divided into Northeastern, Eastern, Central, and Western China. The Northeastern provinces include Jilin, Liaoning, and Heilongjiang. The Eastern provinces include Hebei, Beijing, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan. In terms of Central provinces, including Henan, Hubei, Hunan, Anhui, Jiangxi, Shanxi. The Western includes Chongqing, Sichuan, Guizhou, Yunnan, Guangxi, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Inner Mongolia.

[3] Where i represents province, and t is year

As shown in Table 3, the Change trend of GTFP at the province level is significant. The results show that the general GTFP in China is 0.847 in 2001, and the value was 0.877 in 2018. It is indicating that the wave-like upward trend from 2001 to 2018. The average value of GTFP has seen a continuous and rapid increase from 2006 to 2008. In 2008, the average value of GTFP efficiency more than 0.9, the raise about 8%. The possible reason is that China government has focused on promoting green development, circular development, and low-carbon development to advocate the concept of the "Green Olympic" in the world. Since the government proposed the policy of "Beautiful China." The GTFP arrived at the peak value is 0.937 in 2013. However, it did not reach the production frontier and begin to decline after 2014. It shows that resource mismatch issues exist in the process of "Input-output" GTFP in China. In other words, the input resources have converted to output products inefficiently, and the scale of resource input has not yet reached the optimal production scale. As can be seen from Table 3, from 2001 to 2018, the values of GTFP were kept steadily in the production frontier were only in Beijing, Shanghai, Tianjin, Zhejiang, Guangxi, Hainan, and Qinghai. It indicates that those provinces can effectively transform input factors into output factors and match "Input-output." We also can find that only two provinces, Jiangsu and Fujian, have been at the forefront of GTFP for a long time. However, other provinces (such as Chongqing, Hunan, Hubei, Xinjiang) are at the non-frontier, which shows that most provinces in China still have to improve the GTFP efficiency.

The advantage of three-stages DEA is the further decomposition of GTFP. To analysis the difference among provinces, we compose provinces into four sections. Figure 2 shows the GTFP changing in four sections from 2001 to 2018. From 2008 to 2017, GTFP shows an upward trend. Besides, the changing trend of GTFP in the Eastern is significantly significant. The agglomeration of high-tech enterprises, human capital, and government finances in the Eastern region. It speeds up efforts to upgrade and optimize its industrial structure. What is more, the marketization of the eastern region has lower than other regions. It means that we can improve the value of GTFP by promoting the enthusiasm of economic entities and the rational allocation of factor resources.

Observing the trend efficiency results of provinces in the western region, we can see that the trend of GTFP is showing an upward trend, while it is still at the bottom of the four major sectors in China. It means that the advanced level of its industrial structure and technological innovation capabilities are relatively weaker than other regions, which will inevitably affect its GTFP. In terms of central regions, the changing trend of GTFP efficiency has the same as the national average, which shows an upward trend in volatility. The empirical results demonstrate that the values from 0.858 in 2001 to 0.975 in 2018 peaked in 2018. Two provinces, Hubei and Jiangxi, in the central region have potential development on the GTFP with abundant natural resources, convenient traffic conditions, and water resources. Implementing a "promote central region rising strategy" improves governments' enthusiasm for industrial transformation and upgrading, which has provided favorable conditions for developing a green economy. As seen from the Northeast region trend, the value of GTFP remains at a relatively high level. With the implementation of the Northeast revitalization strategy policy and the dilemma of surviving the economy cliff, local governments try to transform the economic development model by constructing the first chemical industry circular economy demonstration park.

Table 3 Green Total Productive of Province from 2001 to 2018

Province	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Beijing	0.868	0.872	0.925	0.887	0.887	0.935	0.947	0.928	0.987	0.995	1	1	1	1	1	1	1	1
Tianjin	0.878	0.901	0.846	0.857	0.857	0.834	0.896	0.915	0.893	0.896	0.947	0.958	0.929	0.92	0.904	0.887	0.877	0.875
Hebei	1	0.88	0.841	0.844	0.844	0.875	0.861	1	1	1	1	1	1	1	0.939	0.994	0.947	0.909
Shanxi	0.99	0.994	1	1	1	1	1	1	0.993	0.992	0.998	1	0.998	0.994	0.986	0.995	0.989	0.971
Inner Mongolia	0.908	0.904	0.861	0.847	0.847	0.901	1	0.921	1	1	1	1	1	1	1	1	1	1
Liaoning	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Jilin	0.936	0.889	0.797	0.808	0.808	0.811	0.877	0.873	0.913	0.919	0.931	0.959	0.938	0.875	0.899	0.846	0.835	0.768
Heilongjiang	0.877	0.948	0.898	0.912	0.912	0.901	0.955	0.961	0.984	0.996	1	1	1	0.989	0.997	0.984	0.915	0.88
Shanghai	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Jiangsu	1	0.993	0.998	1	1	1	1	1	1	1	0.939	0.96	0.966	1	1	1	1	1
Zhejiang	1	0.978	0.983	0.992	0.992	1	1	1	1	1	1	1	0.999	1	1	1	1	1
Anhui	0.888	0.937	0.906	0.921	0.921	0.901	0.96	0.974	0.989	0.997	0.997	0.997	0.994	0.988	1	0.991	0.942	0.948
Fujian	0.822	1	0.941	0.825	0.825	0.847	0.881	0.871	0.885	0.881	0.913	0.908	0.909	0.88	0.935	0.931	0.919	0.916
Jiangxi	0.591	0.836	0.74	0.73	0.73	0.743	0.809	0.809	0.807	0.794	0.838	0.823	0.824	0.78	0.78	0.785	0.799	1
Shandong	1	0.997	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.982
Henan	1	0.973	0.951	0.981	0.981	0.992	1	1	1	1	1	1	0.997	1	1	1	1	1
Hubei	0.904	0.948	0.916	0.943	0.943	0.926	0.971	0.977	0.991	0.998	1	1	1	0.998	1	0.997	0.987	0.982
Hunan	0.774	0.889	0.859	0.83	0.83	0.857	0.898	0.936	0.92	0.933	0.935	0.942	0.934	0.906	0.918	0.928	0.915	0.951
Guangdong	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Guangxi	0.838	0.871	0.82	0.837	0.837	0.851	0.933	0.938	0.939	0.907	0.953	0.993	1	0.964	0.995	0.974	0.947	0.882
Hainan	0.598	0.563	0.57	0.527	0.527	0.501	0.806	1	1	1	1	1	1	0.85	1	1	0.96	0.687
Chongqing	0.511	0.609	0.613	0.589	0.589	0.569	0.611	0.622	0.619	0.621	0.625	0.639	0.636	0.654	0.699	0.696	0.692	0.731
Sichuan	1	0.814	0.851	0.86	0.86	0.82	0.862	0.925	0.913	0.942	0.907	0.871	0.862	0.875	0.92	0.875	0.838	0.961
Guizhou	1	0.83	0.752	0.8	0.8	0.718	0.845	0.849	0.891	0.921	0.904	0.933	0.961	0.896	0.853	0.833	0.794	0.666
Yunnan	0.615	0.716	0.747	0.804	0.804	0.778	0.841	0.825	0.828	0.843	0.816	0.778	0.764	0.765	0.747	0.7	0.68	0.671

Shaanxi	1	0.793	0.759	0.853	0.853	0.799	0.908	1	0.971	1	1	1	1	1	1	1	0.936	1
Gansu	0.847	0.882	0.812	0.83	0.83	0.776	0.891	0.94	0.973	0.977	0.967	0.985	0.981	0.913	0.919	0.923	0.837	0.719
Qinghai	0.285	0.371	0.336	0.319	0.319	0.302	0.37	0.365	0.401	0.406	0.409	0.405	0.439	0.387	0.375	0.359	0.368	0.349
Ningxia	0.398	0.74	0.623	0.543	0.543	0.61	0.583	0.571	0.657	0.704	0.862	0.907	0.98	0.872	0.901	0.912	0.826	0.601
Xinjiang	0.871	0.858	0.745	0.764	0.764	0.78	0.824	0.838	0.869	0.948	0.989	1	1	1	1	1	1	0.859
Nationwide	0.847	0.866	0.836	0.837	0.837	0.834	0.884	0.901	0.914	0.922	0.931	0.935	0.937	0.917	0.926	0.92	0.900	0.877
East	0.917	0.918	0.91	0.893	0.893	0.899	0.939	0.971	0.977	0.977	0.98	0.983	0.98	0.965	0.978	0.981	0.970	0.937
Central	0.858	0.93	0.895	0.901	0.901	0.903	0.94	0.949	0.95	0.952	0.961	0.96	0.958	0.944	0.947	0.949	0.939	0.975
West	0.752	0.763	0.72	0.731	0.731	0.719	0.788	0.799	0.824	0.843	0.857	0.865	0.875	0.848	0.855	0.843	0.811	0.767
Northeast	0.938	0.946	0.898	0.907	0.907	0.904	0.944	0.945	0.966	0.972	0.977	0.986	0.979	0.955	0.965	0.943	0.917	0.883

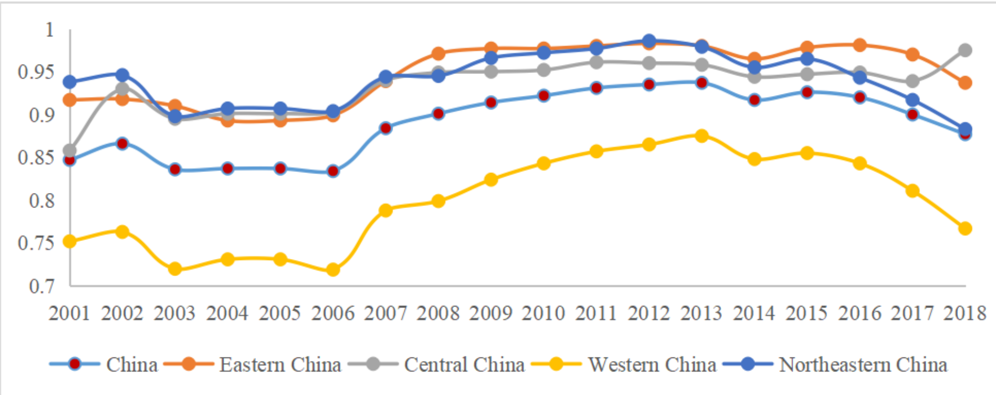

Figure 2 GTFP Variation Diagram at Four Sections

Table 4 and Figure 3 show the GTFP values of 30 provinces in China. Further, analyze the growth model of GTFP; this paper based on the average values of provinces` GTFP from 2001 to 2018 to divide provinces into four types, including low effective growth, weak effective growth, adequate solid growth, and highly effective growth. As shown in Table 4, the GTFP values with influential growth provinces are more significant than 0.916. Regarding weak and low effective growth, the values with weak and low influential growth model provinces are lower than 0.810.

From Figure 3, it also can be seen the spatial distribution difference of the growth model of GTFP from 2001 to 2018. Those provinces with high influential growth model provinces concentrated in eastern regions, such as Beijing, Shanghai, and Jiangsu. At some times, Sichuan and Hunan with locating in the central and western regions, and Northeast provinces of Guizhou, Gansu, Xinjiang, Guangxi, and Jilin in the Northeast, have belonged to the solid and effective growth model. Weak and low practical growth model major concentrated in the western region except for Hainan. It suggests that improving the value of GTFP can enhance the utilization efficiency of resources in the western region and achieving the convergence of the difference with the highly effective growth area.

Table 4 The growth model of GTFP efficiency

Growth type	Low effective growth (E＜0.629)	Weak effective growth (0.629≤E＜0.810)	Strong effective growth (0.810≤E＜0.916)	High effective growth (E≥0.916)
Provinces	Chongqing, Qinghai	Yunnan, Ningxia, Jiangxi, Hainan	Gansu, Xinjiang, Sichuan, Jilin, Guizhou, Hunan, Guangxi	Beijing, Shanxi, Inner Mongolia, Shanghai, Fujian, Jiangsu, Shandong, Henan, Liaoning, Hebei, Hubei, Anhui, Shaanxi, Guangdong, Heilongjiang, Tianjin, Zhejiang

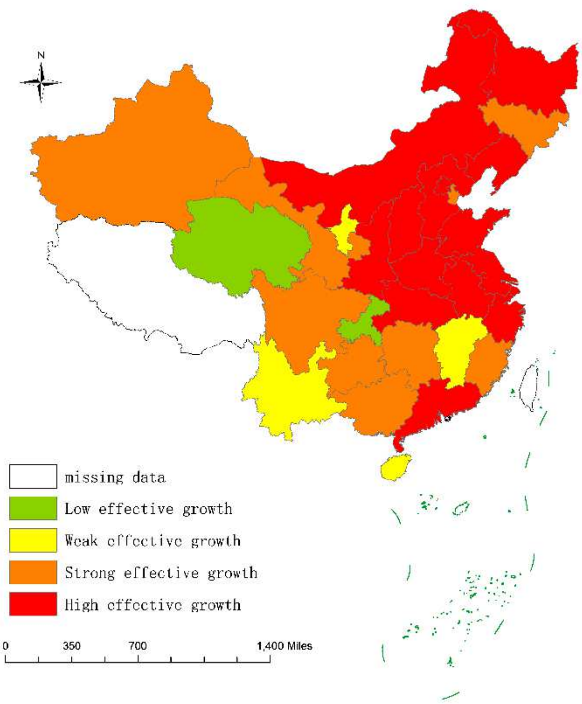

Figure 3 Spatial Distribution Diagram of GTFP

4.2 Analysis of GTFP and its Static Decomposing

In order to s analyze the efficiency of GTFP scientifically, this paper excludes environmental factors and random noise by a three-stage DEA model to obtain the GTFP static decomposing results, which include pure technology efficiency, scale technology efficiency, and return to scale. The initial DEA model results without considering the impact of environmental factors and random noise shown in Table 5. From the frontier's technological index in 30 provinces, the average GTFP efficiency is 0.79; the average technical efficiency is 0.889, and the average scale efficiency is 0.891. Specifically, the provinces include Beijing, Guangdong, Jiangxi, Inner Mongolia, Shaanxi, and Shanghai, which have reached the forefront of production, and those scale efficiency is 1. In terms of provinces in the eastern region, except for Beijing, Guangdong, and Shanghai reach the forefront of production, other provinces' values are all lower than 0.9, especially that Hebei is lower than 0.78. Overall, the eastern region's average efficiency is only 0.839; the average technical efficiency is 0.881, and the average scale efficiency is 0.857.

From the GTFP efficiency results of provinces in the central region, only Jiangxi is at the production frontier. Generally, the average efficiency of these provinces is 0.757, average technical efficiency is 0.776, and average scale efficiency is 0.975. From the western region results, two provinces, Inner Mongolia and Shaanxi have reached the production frontier. The average efficiency value of provinces in the western region is 0.789; the average value of technical efficiency is 0.980, and the average value of scale efficiency is 0.876. Specifically, provinces in the northeast region are not at the forefront of production. For example, the Northeast region's average efficiency value is 0.706, the average value of technical efficiency is 0.807, and the average scale efficiency is 0.89.

Observing the results of the first stage efficiency value indicates that the efficiency of GTFP is ineffective, and the scale efficiency is generally lower than the pure technical efficiency. On the other hand, the issues of insufficient resource utilization in GTFP remain in China. The eastern and western regions have redundant input variables, and the efficiency of scale inhibits the improvement of the efficiency of GTFP. In contrast, the efficiency of scale in the central and northeastern regions is generally higher than the pure technical efficiency. The reason may be the different levels of government governance and technical restrictions. To exclude the effects factors of socio-economic, regional development and random interference on the GTFP, this paper analyze the GTFP by second SFA regression as followed.

Table 5 GTFP and its decomposing of provinces in 2018

Provinces	TE	PTE	SE	VRS	Provinces	TE	PTE	SE	VRS
Beijing	1	1	1	-	Henan	0.686	0.703	0.976	drs
Tianjin	0.926	1	0.926	irs	Hubei	0.635	0.645	0.985	irs
Hebei	0.78	0.974	0.8	drs	Hunan	0.762	0.796	0.958	irs
Shanxi	0.717	0.732	0.98	irs	Guangdong	1	1	1	-
Inner	1	1	1	-	Guangxi	0.611	0.678	0.901	irs
Liaoning	0.626	0.636	0.985	drs	Hainan	0.788	1	0.788	irs
Jilin	0.784	1	0.784	irs	Chongqing	0.805	1	0.805	irs
Heilongjia	0.707	0.784	0.901	irs	Sichuan	0.779	0.801	0.972	irs
Shanghai	1	1	1	-	Guizhou	0.486	0.758	0.642	irs
Jiangsu	0.998	1	0.998	drs	Yunnan	0.538	0.799	0.673	irs
Zhejiang	0.829	0.835	0.992	drs	Shaanxi	1	1	1	-
Anhui	0.744	0.781	0.952	irs	Gansu	0.538	0.746	0.721	irs

Fujian	0.93	1	0.93	irs	Qinghai	0.427	1	0.427	irs
Jiangxi	1	1	1	-	Ningxia	0.79	1	0.79	irs
Shandong	0.925	1	0.925	drs	Xinjiang	0.921	1	0.921	irs

(1) TE=PTE×SE. (2) crs, irs and drs respectively represent constant returns to scale, increase return to scale and diminishing return to scale.

4.2.1 The Second Stage of SFA Regression

Based on the three input indicators in the first stage, the explained variables and the independent variables are the proportion of the secondary industry in GDP. The full-time equivalent of R&D personnel to establish an SFA regression model. Then, we analyze the GTFP through the Frontier4.1 software. Table 6 shows the SFA regression results, and it shows that the development of the secondary industry has a significant positive impact on the slack variables of energy consumption (3.37E+01), material capital input (6.34E-02), and labor input (2.07E+01).

Note that the likelihood of slack variables of energy consumption, material capital input, and labor input of -2.66E+02, -6.99E+01, and -2.39E+02 indicates the environmental factors and random interference factors significantly affect the efficiency of GTFP. The R&D investment positively affects the slack variable of energy input and labor input of 1.09E-03 and 7.01E-04. However, the R&D investment hurts the slack variable of material input of -3.12E-06.

Although the government has made great efforts to change the economic development model by regulating high pollution and supporting green enterprises, however, under the GDP assessment system, the waste phenomenon during the secondary industry's development process still exists. Considering the diversity of geography in China, the transfer of polluting industries from developed areas to inland provinces is increasingly common, which carry on industrial transfer without adequate supervision. Therefore, the more muscular the regional scientific and technological strength and the more emphasis on R&D investments and innovation, the more it can reduce material consumption and waste in economic development and rely on human capital and innovation capital to achieve intensive development. The input of R&D investment has not yet improved the input structure of labor and energy in the economic development system. The possible explanation is that excessive concentration of R&D investment and personnel leads to the internal waste of talent in these regions. While R&D investment also depends on industrial agglomeration, energy consumption will be higher in regions where many industries are concentrated.

Table 6: SFA regression

variable	Energy input slack variable	Material input slack variable	Labor input slack variable
Constant term	-2.14E+03	-2.88E+00	-1.32E+03
The proportion of the secondary industry in GDP	3.37E+01	6.34E-02	2.07E+01
R	1.09E-03	-3.12E-06	7.01E-04

sigma	1.37E+07	3.37E+01	2.22E+06
gamma	1.00E+00	1.00E+00	1.00E+00
likelihood	-2.66E+02	-6.99E+01	-2.39E+02
LR	1.78E+01	2.30E+01	1.75E+01

4.2.2 Adjustment results of DEA Model

The adjusted results with GTFP efficiency at 30 provinces in 2018 are shown in Table 7. Overall, after the adjustment, the average efficiency increase by 25%, and the average pure technical efficiency increase by 23%. However, it is interesting to observe that the scale efficiency fell by 0.82%. Table7 also shows the stripping away of environmental and random factors where provinces in the central region increase by 28% on the GTFP efficiency. The GTFP efficiency of eastern, northeast, and western provinces increases by 10%, 5%, and 3%, respectively.

It is well known that the environment is essential for GTFP in different regions, and the role of incentives for development efficiency is different. Nevertheless, the lower scale efficiency still causes the lower value of the adjusted GTFP. After the adjustment, each region's pure technical efficiency has increased significantly than the adjustment scale efficiency. Hence, after excluding the external environment and random error, the GTFP efficiency is still low. The main reason is the constraints of the scale efficiency.

Figure 4 shows the pre-and post-contrast evaluation for the GTFP. After the adjustment, the scale efficiency of the eastern and northeastern regions has declined. It means that there is potential for improving the scale efficiency of GTFP by improving the external environment. After the adjustment, the advantage is obviously on the provinces' scale efficiency in the central and western regions compared with other regions. Therefore, it is necessary to support the expansion of investment scale in those provinces, mainly focus on improving overall efficiency and technical efficiency. In terms of provinces in eastern and northeastern regions, it is necessary to avoid resource redundancy and waste caused by excessive investment.

Table 7 The Adjustment Range of First and Third Stage

	TE	PTE	SE
China	25.083%	23.967%	-0.824%
Eastern China	10.855%	12.494%	-1.586%
Central China	28.785%	28.838%	0.017%
Western China	3.505%	2.168%	1.295%
Northeastern China	5.102%	11.297%	-5.332%

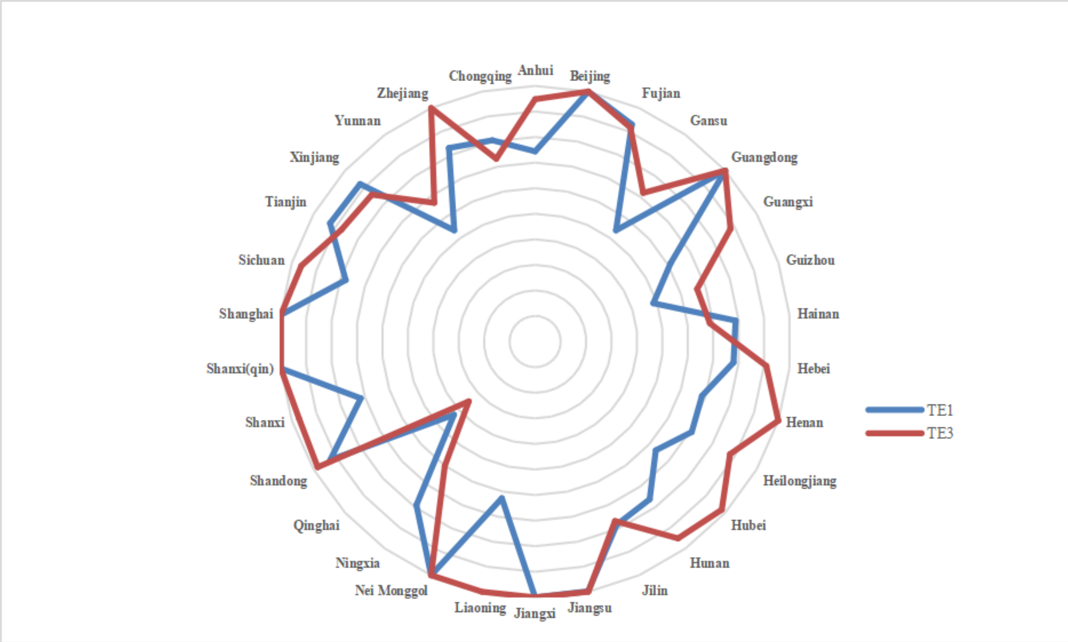

Figure 4 Pre- and Post-contrast evaluation for the GTFP efficiency

4.3 Analysis on the Effects of Human Capital on GTFP Efficiency

Accounting for the value of GTFP is a restricted dependent variable. The paper further analyses the mechanical effects of human capital on GTFP through the Tobit regression. Table 8 represents the results after control variables of investment rate, social investment, and industrial development. From Table 8, Models (1), (4), and (7) explore the effects of three human capital types, including human capital accumulation, fiscal education expenditure, and regional innovation, respectively, on GTFP efficiency. We find that the effects of human capital accumulation and education fiscal expenditure all positively affect the GTFP of 0.0231 and 0.484, respectively. From the micro perspective, the growth of human capital accumulation means that high-quality labor has a higher ability to allocate resources and absorb advanced technology, resulting in the mature "Labor cisterns." In other words, the more high-quality population in the "Labor cisterns," the greater probability that companies can hire high-quality workers at a lower cost and achieving growth of production efficiency under the fewer labor investment. From the Marco-perspective, the government's investment in education used as "lever Leverage," which means it can also increase education investment of microscopic entities, such as enterprises and families, which directly affects the labor quality.

On the other hand, financial science and education investment play an essential role in achieving the convergence of the regional economic development level gap. Considering that China's underdeveloped regions depend on infrastructure investment, the expansion of financial investment in education will cause "crowding out" effects, specifically, reduce the waste of resources by squeezing out the infrastructure construction of low repeat levels. However, the effects of the negative coefficients of regional innovation are -0.0439. The possible explanation is that the regional development gap is significant in China. Underdeveloped regions lag behind the developed regions in terms of innovation, lack of institutional environment, material capital accumulation, and insufficient infrastructure. It causes the "Erosion effect" on the innovation growth, then leading to the inefficient allocation of resources, and distorting the effect of innovation on total factor productivity.

Models (2), (5), and (8) have added the degree of openness, the human capital accumulation, and the fiscal education expenditure, respectively, to analyze heterogonous effects of openness on GTFP further. They are observing the results of models (2), (5), and (8), the cross-term coefficients between levels of openness with human capital accumulation, fiscal education expenditure, and innovation level of 0.0408, 1.919, and 0.000825, respectively. The results indicate that the growth of openness degree will increase the positive impact of high-quality labor and education fiscal expenditure on GTFP. On the contrary, it will weaken the influence of innovation on GTFP. FDI "overflow" effects caused by human capital accumulation, this effect is one of the main channels to improve the regional labor force's quality. Specifically, multinational companies with a perfect talent training system will be wiliness to export considerable skilled labor to the local market, enhancing the level of regional human capital. Especially for underdeveloped regions, the representative's medium-quality human capital can play a more critical role in the regional economy. They can achieve the model transformation to environment-friendly economic development by imitating advanced regions. Local enterprises can absorb advanced international technologies through cooperation with multinational enterprises from developed regions. Then, to realize the goals of technological catch-up, the cultivation of high quality, innovative talents, the imitating of advanced systems, and advanced concepts. Those all play an essential role in reducing the waste of resources.

Models (3), (6), and (9) have added the cross-term between marketization and human capital accumulation, fiscal education expenditure, and innovation. Analyze the heterogonous effects of marketization on GTFP. The cross-term coefficients between marketization levels with human capital accumulation, fiscal education expenditure, and innovation level of -0.00618,-0.236, and -0.00162, respectively. The results show that the marketization growth will reduce the positive impact of human capital and fiscal education expenditure on the GTFP. Since coastal areas have gotten rid of the influence of the planned economy and enjoying more institutional dividends, it caused geography differences in the level of marketization between coastal and western China. Therefore, the marketization differences lead to the agglomeration effects on talents and capital elements in coastal areas. The loss of high-quality resources will remain in underdeveloped areas when the marketization did not reach the "threshold." It will lead to low efficiency of GTFP and a severe waste of resources in underdeveloped areas.

Observing Model (10): exploring the heterogonous effects of intellectual property protection on GTFP. This paper adds the cross-term of innovation and intellectual property protection. The cross-term coefficients between intellectual property protection and innovation are 0.00000879.it means intellectual property protection improves the adverse effects of innovations on GTFP. Hence, the government should address the policy with intellectual property protection in developing cities.

Table 8 Tobit regression results

	(1)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)	(10)
edu	0.0231**	0.0320***	0.00859	te	0.484*	0.611**	0.511*	patent	-0.00439***	-0.00489***	0.00283	-0.00607***

	(2.24)	(2.95)	(0.71)		(1.86)	(2.40)	(1.96)		(-3.30)	(-3.24)	(0.91)	(-4.30)
fdi		0.0497***		fdi		0.0447***		fdi		0.0364**		
		(3.46)				(3.71)				(2.42)		
Edu*fdi		0.0408**		Te*fdi		1.919***		market			0.00195	
		(2.07)				(3.28)					(0.33)	
market			0.000900	market			0.000879	Paten*fdi		0.000825		
			(0.14)				(0.15)			(0.29)		
Edu* market			-0.00681***	Te*market			-0.236**	Patent* market			-0.00162***	
			(-2.61)				(-2.48)				(-2.63)	
								tmr				-0.0000781
												(-1.35)
								Patent*tmr				0.00000879**
												(2.10)
Control variables	Yes	Yes	Yes	Control variables	Yes	Yes	Yes	Control variables	Yes	Yes	Yes	Yes
_cons	0.436***	0.315***	0.632***	_cons	0.574***	0.526***	0.608***	_cons	0.698***	0.680***	0.709***	0.667***
	(4.02)	(2.70)	(4.48)		(8.46)	(7.74)	(8.86)		(11.66)	(11.32)	(11.60)	(10.95)
sigma_u	0.164***	0.166***	0.160***	sigma_u	0.162***	0.168***	0.155***	sigma_u	0.168***	0.168***	0.165***	0.166***
	(6.96)	(6.97)	(6.85)		(6.92)	(6.90)	(6.78)		(6.99)	(7.00)	(6.91)	(6.98)
sigma	0.073	0.072	0.0726	sigma	0.073	0.071	0.073	sigma_	0.0728	0.0719	0.0723	0.0709*

_e	5***	2***	***	_e	9***	6***	3***	e	***	***	***	**
	(23.86)	(23.82)	(23.85)		(23.88)	(23.87)	(23.86)		(23.86)	(23.84)	(23.89)	(23.31)
N	480	480	480	*N*	480	480	480	N	480	480	480	452

5. Robustness Test

This paper uses the variable substitution method and data substitution method to do the robust test. First, the variable substitution method uses a Two-way fixed OLS model. It adjusts the variables of CO2 emissions per GDP and COD emissions per GDP to measure the effects of human capital on GTFP efficiency. It can be seen from Table 9 that human capital, financial technology, and fiscal education expenditure still have adverse effects on the energy consumption scale and pollution discharge of -14.45 and -55.78, and the positive effects of innovation on the energy consumption scale and pollution discharge are 0.337. Secondly, the data substitution method removes extreme values; the robustness test shown in Table 10. From the robust results, we find that the coefficient of human capital, financial technology, and education expenditure on the GTFP is still significant, and the control variables result did not significantly change. Overall, two robust tests further verify that the selection of variables is reasonable and the model is robust.

Table 9 Robustness test results（Static panel model(Two-way fixed OLS model)）

Variables	CO_2_GDP			COD_GDP		
edu	-0.228**			-14.45**		
	(-2.39)			(-2.28)		
te		-2.996			-55.78	
		(-1.32)			(-0.37)	
patent			0.0496***			0.337
			(4.45)			(0.45)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
_cons	5.638***	4.007***	2.804***	364.7***	242.2***	229.0***
	(5.87)	(7.48)	(6.16)	(5.71)	(6.79)	(7.42)
N	510	510	510	510	510	510

Table10 Robustness test results（Removal of extreme values）

Variables	GTFP	GTFP	GTFP
edu	0.0181*		
	(1.66)		
te		0.516*	
		(1.92)	
patent			-0.00925***
			(-4.16)
Control variables	Yes	Yes	Yes
_cons	0.486***	0.568***	0.706***
	(4.42)	(8.21)	(11.91)
sigma_u	0.165***	0.162***	0.169***
	(6.97)	(6.93)	(6.99)
sigma_e	0.0736***	0.0738***	0.0721***
	(23.84)	(23.89)	(23.87)
N	480	480	480

6. Conclusion

The effects of human capital heterogeneity on GTFP and testing sustainable paths after excluding external factors and stochastic noise. Considering the heterogeneity between spatial and temporal, this paper adopts panel data from 30 provinces from 2001 to 2018 in China. Then verify two hypotheses about the heterogeneous effects of human capital through three-stage DEA and Tobit regression. The three types of human capital variables including human capital accumulation (Edu), education fiscal (Edu Fiscal), and regional innovation (patent). The main findings are as follows:

a) The average value of GTFP efficiency is inverted U-shape and has significant geography differences in China. The average efficiency of GTFP in eastern (0.916) is higher than in other sections. It notes that the average efficiency of GTFP in the western (0.810) is significantly lower than in other sections. In terms of the GTFP growth model, except the western provinces, including Guangxi, Guizhou, Gansu, Xijiang, and Sichuan, other provinces belong to a low-efficiency growth model.

b) The static decomposing for GTFP efficiency in 2018 shows that the average overall efficiency of GTFP rise 25% in China, and the average pure technical efficiency rise 23%. However, the scale efficiency decrease by 0.82%. Therefore, we must take into consideration in geography diversity of GTFP efficiency in the future.

c) Analyzing the heterogeneous human capital effects of GTFP efficiency, human capital accumulation, and education fiscal positively affect the GTFP efficiency. On the contrary, missed environment institutional, the inadequacy of resource capital, and insufficient infrastructure would lead to the "Erosion effect" for innovation, which negatively affects the GTFP efficiency.

d) FDI has positive effects on the GTFP efficiency. Specifically, FDI will increase the positive effects of human capital accumulation, education fiscal, and innovation on GTFP efficiency. However, under diverse geography in China, the growth marketization will weaken the positive impact of human capital and education on GTFP efficiency.

References

Auro Kumar Sahoo, Naresh Chandra Sahu, Dukhabandhu Sahoo, 2018. Impact of policy reforms on the productivity growth of Indian coal mining: A decomposition analysis [J]. Resources Policy.59: 460-467.

Azomahou Theophile, Diene Bity, Diene Mbaye, 2009. "Technology frontier, labor productivity and economic growth: Evidence from OECD countries," MERIT Working Papers, 059.

Beeson P E, Husted S. 1989. PATTERNS AND DETERMINANTS OF PRODUCTIVE EFFICIENCY IN STATE MANUFACTURING [J]. Journal of Regional Science.29 (1).

Chen, J., & Zhou, Q, 2017. City size and urban labor productivity in China: New evidence from spatial city-level panel data analysis. *Economic Systems, 41*, 165–178.

Cheng, J., Yi, J., Dai, S., & Xiong, Y., 2019. Can low-carbon city construction facilitate green growth? Evidence from China's pilot low-carbon city initiative. *Journal of Cleaner Production, 231*, 1158–1170.

Cheng Zhonghua, 2020. Green total factor productivity of extractive industries in China: An explanation from technology heterogeneity [J]. Socio-Economic Planning Science. 70(c)

Chuandi Fang, 2019.Defining and Measuring the Circular Economy: A Mathematical Approach [J]. Ecological Economics.157:369-372.

Collard-Wexler A, Asker Locker J D, (2012. Productivity Volatility and the Misallocation of Resources in Developing Economies [J]. NBER Working Papers.

Eskeland, Gunnar S.Harrison, Ann E, 2003. Moving to greener pastures? Multinationals and the pollution haven hypothesis [J]. Journal of Development Economics, 70(1):1-23.

Fried H O, Lovell C A K, Schmidt S S, et al, 2002.Accounting for Environmental Effects and Statistical Noise in Data Envelopment Analysis [J]. Journal of Productivity Analysis, 17(1-2):157-174.

Glomm G, Ravikumar B, 2003. Public education and income inequality [J]. European Journal of Political Economy, 19(2):289-300.

Gang Jin, Kunrong Shen, Jian Li, 2020.Inter jurisdiction political competition and green total factor productivity in China: An inverted-U relationship [J]. China Economic Review, 61.c.

James B. Ang, Jakob B. Madsen, Md. Rabiul Islam, 2011. The effects of human capital composition on technological convergence. Journal of Macroeconomics, 33(3), pp. 465-476.

Jérôme Vandenbussche, Philippe Aghion, Costas Meghir, 2006. Growth, distance to frontier and composition of human capital [J]. Journal of Economic Growth, 11(2): 97-127.

Jiang Y, Wang H, Liu Z, 2021.The impact of the free trade zone on green total factor productivity ——evidence from the shanghai pilot free trade zone [J]. Energy Policy, 148.

Kersty Hobson, 2021.The limits of the loops: critical environmental politics and the Circular Economy [J]. Environmental Politics, 30(1-2): 161-179.

Malin Song, Shuhong Wang, Kaiya Wu, 2018. Environment-biased technological progress and industrial land-use efficiency in China's new normal [J]. Annals of Operations Research, 268(1-2): 425-440.

MARY, AMITI, JOZEF, et al., 2007. Trade Liberalization, intermediate Inputs, and Productivity: Evidence from I Indonesia [J]. American Economic Review.97 (5):1611-1638.

Martin P, Mayer T, Mayneris F, 2011. Spatial concentration and plant-level productivity in France [J]. Journal of Urban Economics, 69(2):182-195.

Patwa N, Sivarajah U, Seetharaman A, et al., 2020. Towards a circular economy: An emerging economies context [J]. Journal of Business Research,

Reppelin-Hill V, 1999.Trade and Environment: An Empirical Analysis of the Technology Effect in the Steel Industry [J]. Journal of Environmental Economics & Management.38 (3):283-301.

Sun J, Li G, Wang Z, 2019. Technology heterogeneity and efficiency of China's circular economic systems: A game meta-frontier DEA approach [J]. Resources Conservation and Recycling, 146:337-347.

Viaene J M, Zilcha I, 2002. Public education under capital mobility [J]. Journal of Economic Dynamics and Control.226 (12):2005-2036.

William F Blankenau, Nicole B Simpson, Marc Tomljanovich, 2007. Public Education Expenditures, Taxation, and Growth: Linking Data to Theory [J]. American Economic Review.97 (2): 393-397.

Xiang Ji et al., 2019. Using a hybrid heterogeneous DEA method to benchmark China's sustainable urbanization: an empirical study [J]. Annals of Operations Research.278. (1-2): 281-335.

Xuehong Zhu, Ying Chen, Chao Feng, 2018. Green total factor productivity of China mining and quarrying industry: A global data envelopment analysis [J]. Resources Policy. 57: 1-9.

Yufan Jiang, 2021.The effect of the free trade zone on green total factor productivity ——evidence from the shanghai pilot free trade zone [J]. Energy Policy.148:112-120.

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Declarations

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Not applicable.

Consent for publication

We have read the author`s guide, rules and ethics for publication in Environmental Science and Pollution Research. All authors agree for the manuscript to be published in Environmental Science and Pollution Research.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflict of interest

The authors declare that they have no competing interests.

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h Xiao: Methodology; Software; Data curation

jialu You: Writing;Original draft; Visualization; Writing;Reviewing and Editing

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