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Regional Differences, Distribution Dynamics, and Convergence of the Green Total Factor Productivity of China's Cities under the Dual Carbon Targets

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Abstract: Economic development in China has been severely restricted by environmental problems such as carbon emissions. Improving green total factor productivity (GTFP) is an extremely important pathway to realizing carbon peak and carbon neutrality. Nevertheless, existing studies on China's urban GTFP under the carbon emissions constraint are still insufficient. In this context, this study adopts the directional distance function (DDF), includes carbon emissions in the undesirable output, combines the global Malmquist–Luenberger (GML) productivity index, and calculates the GTFP of China's cities. On this basis, the Dagum Gini coefficient, kernel density estimation, and convergence model are employed to explore the regional differences, distribution dynamics, and convergence in China and in three subdivision regions of east, center, and west. The core conclusions are as follows: (1) the average annual growth rate of GTFP in China's cities is about 0.7064%, which is relatively low, but there is great room for improvement. The growth trend of GTFP in the three subdivision regions of east, center and west is obvious, presenting a spatial distribution characteristic of "high in the east and low in the west"; (2) the regional differences in GTFP of these cities are enlarging, with the largest gap in the eastern region and the smallest in the western region. Intraregional difference is the primary source of regional differences; (3) the imbalance in urban GTFP in China is prominent, with noticeable gradient differences, making it difficult to achieve hierarchical crossing. The central and western regions even have multilevel differentiation problems; (4) there is an absolute β convergence and conditional β convergence of China's GTFP, but no σ convergence. As a result, it is necessary to comprehensively consider and actively implement the concept of shared development, enhance technological progress, focus on narrowing the differences in GTFP, and facilitate coordinated green development within the regions.

Keywords: dual carbon targets; green total factor productivity; regional differences; distribution dynamics; convergence

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1. Introduction

Global warming and other ecological crises have attracted worldwide attention, and carbon emission reduction has become an important measure to deal with global climate change. In this regard, China actively undertakes the international responsibility of building "A Community with a Shared Future for Mankind", puts forward the goal of carbon peak and carbon neutrality, and takes the high-quality development path of ecological priority and green development [1,2]. With the incremental challenges of resource environment and pollution to economic growth, green development has been regarded as an inevitable choice for China's current high-quality economic development [3]. Actually, China's economic development model is shifting from "scale and speed oriented" to "quality and efficiency oriented", guided by the concepts of innovation, coordination, green development, openness, and sharing. Against this backdrop, green total factor productivity (GTFP) has become a comprehensive indicator that considers economic welfare, ecological

welfare, and innovation welfare, which is also an important measure of economic quality [4]. Accordingly, improving GTFP is the key driving force for promoting high-quality economic development [5].

Current research on GTFP mainly focuses on theoretical interpretation, realistic logic, the implementation path, driving factors, influencing effects, and so on [6–8]. Currently, there is no in-depth exploration of the regional differences, distribution dynamics, and convergence of China's cities considering the constraints of the dual carbon targets. In other words, in the context of the dual carbon targets, the regional differences, distribution dynamics, and convergence of GTFP in China's cities have not received adequate attention.

Obviously, as an important criterion for both environmental protection and economic growth, GTFP has become a determinant of the competitiveness of countries around the world [9]. Given the significance of GTFP, the Chinese government attaches great importance to it and regards it as a long-term development task and goal. It is worth noting that the premise for fully leveraging the traction of GTFP is to measure the level and distribution dynamics of GTFP accurately and scientifically. Moreover, what is the level of GTFP in China's cities under the carbon emission constraints? Are there regional differences, and what kind of differences exist? What are the distribution characteristics, and is there a convergence characteristic? Such issues are of great importance, not only in helping to fully grasp the actual development status of China's GTFP, but also in providing a policy basis and decision-making reference for the improvement of GTFP.

In view of this, under the dual carbon targets, this study utilizes the directional distance function (DDF), combined with the global Malmquist–Luenberger (GML) productivity index, to scientifically measure the GTFP of Chinese cities from 2006 to 2020. On this basis, the Dagum Gini coefficient is adopted to reveal the regional differences and sources of GTFP, and then kernel density estimation is introduced to characterize the distribution and dynamic evolution. Finally, a convergence model is employed to test the convergence of GTFP in Chinese cities.

This study aims to scientifically measure the actual level of China's overall GTFP under the dual carbon targets, and furthermore elucidate the regional differences, distribution dynamics, and convergence of urban GTFP. In a theoretical sense, it could help toward comprehensively grasping the laws of China's green development; expand quantitative research on GTFP; reveal the main characteristics, current status, and development laws of GTFP in China's cities; effectively solve resource and environmental problems; provide theoretical support for the continuous improvement of urban ecological environment quality; and offer a decision-making basis for narrowing the gap in green development spaces. In a practical sense, it is of great significance to promoting China's green transformation and upgrading, regional coordinated development, and the continuous adjustment and improvement of existing green development policies.

The remainder of this study is as follows: Section 2 reviews the previous literature. Section 3 presents the DDF-GML method for calculating GTFP, the Dagum Gini coefficient for evaluating regional differences, the kernel density estimation method for analyzing the distribution dynamic, and the convergence model for exploring the convergence and divergence trend of GTFP in different regions. Section 4 describes the indicators and data resources. Section 5 calculates China's GTFP and its regional differences, distribution dynamics, and convergence. Section 6 summarizes the conclusions, makes some targeted policy suggestions, and proposes the research limitations and future research prospects in response to the above analysis.

2. Literature Review

In the wider public sector, efficiency is defined as the outcome of public sector activities [10], a manifestation of government productivity, the utilization of all available resources [11,12], and the ratio of output measures to input indicators related to public spending [13].

Most existing research on measuring public sector efficiency in a socioeconomic system have been conducted in two ways: One is by constructing comprehensive indicators to measure the efficiency, including the public sector efficiency index in policy areas of administration, education, infrastructure, and so on [14], and public service technology efficiency through the supplier and customer satisfaction opinion index [15], a comprehensive index combining the expenditure efficiency index and income efficiency index [16]. The other is using the DEA model to measure efficiency, such as the research and development efficiency of public and private sectors in EU countries [17], the Indian banking system's efficiency [18,19], 39 public sector entities operating efficiency in the province of Poland [20], and the effect of accrual accounting on efficiency of the state of Bavaria in Germany [21].

As an environmental performance indicator, GTFP incorporates energy consumption and pollution into traditional total factor productivity (TFP), which is also a comprehensive index of sustainable economic development [22,23]. The ecoefficiency of a sample of 171 rain-fed Spanish farms was analyzed [24]. The environmental performance of English arable and livestock farms was evaluated [25]. Present research on GTFP mainly is concentrated on the following three aspects:

From the perspective of GTFP measurements, Solow [26] first initiated the residual method, a typical parameter method that built on the endogenous growth theory by Arrow [27] and Romer [28] and was optimized by Cui et al. [29] and Zhang et al. [30]. Due to the strict prerequisites and the inability to decompose TFP, the scientific validity of the residual method has been questioned by many scholars. Subsequently, a large number of studies calculated TFP using the parametric method [31] represented by stochastic frontier analysis (SFA), the nonparametric method proposed as part of data envelopment analysis (DEA) [32], and its expanded indices, the Malmquist–Luenberger (ML) productivity index and GML productivity index. The SFA method is used to determine a specific functional form that can decompose TFP into technical efficiency and technological progress, and the existence of technical inefficiency makes it more closely related to the actual economic operation. After that, the nonparametric method, DEA, emerged, and its expansion indices, such as the ML and GML productivity indices, were gradually applied to a certain extent [30,33,34].

Among these approaches, DEA only needs specific data for statistical inference, rather than a specific production function. In this case, it can effectively avoid the errors caused by using parameter estimation and gradually becomes the primary method for GTFP measurement [7,35]. Rusiawan et al. [36] assessed the impact of GTFP on sustainable productivity growth in Indonesia. Ghosal et al. [37] computed the GTFP growth at the plant-level on Sweden by the ML productivity index. Alem [38] estimated the GFTP accounting for dairy farms' CH4 emissions in Norway by using a stochastic input distance function and a translog model. Tang et al. [39] introduced the DEA method to calculate GTFP and probed the impact of local government competition on GTFP. Peng et al. [40] adopted the DEA model to calculate the spatiotemporal variation characteristics of GTFP in the Yangtze River Delta region. Afterwards, Zhao et al. [41] explored the direction and extent of the impact of green innovation on GTFP by constructing the SBM-DEA model and combining it with the ML productivity index.

Moreover, a number of studies have focused on the selection of evaluation indicators for GTFP, including labor, capital and energy as input indicators, and actual GDP as desirable output [42–44]. As for undesirable output, the "three wastes", namely exhaust gas, wastewater, and waste residue, are often taken as measurement indicators. Qian and Wang [45] took three urban wastes as the undesirable output, which was combined with the background of industrial intelligence, and probed the impact of labor force increase on GTFP. Lee et al. [46] took the utilization rate of industrial wastewater, SO_2, and industrial solid waste as the undesirable output and examined the impact of environmental regulations and innovation capabilities on GTFP. Based on the data availability and the actual situation of pollution emissions in China, Zhao et al. [47] selected the total amount of wastewater

emissions, SO_2, and solid waste emissions as the undesirable output and analyzed the impact of China's digitization process on GTFP.

Regarding the spatiotemporal changes and convergence of GTFP, existing research has mostly been centered at the provincial level. As for the measurement of regional differences, most of the literature applied traditional approaches such as the Gini coefficient or Theil index [48,49]. Nevertheless, these methods cannot solve the problem of sample overlap and the source of overall differences. Xiao et al. [50] used the geographically and temporally weighted regression (GTWR) model to calculate the industrial GTFP of 30 provinces in China from 2003 to 2018, identified the driving factors and spatiotemporal heterogeneity, and found that the regional differences in GTFP gradually expanded over time. Huang et al. [51] conducted in-depth analysis of the spatiotemporal evolution characteristics and center shift of provincial GTFP and put forward that there were noteworthy differences in the east, west, and center regions, and that the spatial distribution pattern of China's interprovincial GTFP tended to be generally concentrated and stable. Zhu et al. [52] analyzed the driving forces, spatiotemporal differences, and convergence of agricultural GTFP growth rates in 31 provinces of China from 2000 to 2019, finding that the growth in agricultural GTFP came from the progress of green technology, and that there was absolute β convergence and conditional β convergence, but no σ convergence.

Compared with provincial-level research, few have focused on the city level. Zheng et al. [53] adopted the kernel density curve and proposed that the GTFP of cities in the Yangtze River Economic Belt in China was facing downward pressure, and the absolute difference in GTFP between cities was gradually narrowing. Liu and Zhu [54] employed kernel density estimation and the spatial Markov chain to explore the spatial–temporal evolution and spatial effects of GTFP in the coastal cities of eastern China.

From an industry perspective, recent research on agriculture [55], logistics [56], electricity [57], and hotels [58] has been further expanded upon; meanwhile, more and more subsectors have gradually been probed, such as the equipment manufacturing industry [59], chemical subsector [60], and so on.

As far as research solutions are concerned, the existing GTFP analysis means are relatively singlular. Beltrán-Esteve and Picazo-Tadeo [61] found that the distribution of green environmental efficiency in some EU countries has shifted to the right through kernel density function estimation, becoming closer to the distribution characteristics of green environmental efficiency in developed EU countries. Loganathan et al. [62] used quantile regression method to analyze the impact of total factor productivity of green tax in Malaysia on CO_2 emissions. Li et al. [63] used kernel density estimation to analyze the dynamic evolution of the GTFP of countries along the "the Belt and Road" and found that the GTFP of these countries increased from 2013 to 2017. Ahmed et al. [64] adopted data envelopment analysis to measure the agricultural green total factor productivity of 50 American states in the period 2005–2019. Goto and Sueyoshi [65] employed a convergence model and found that green economic growth in OECD countries did not converge as a whole between 1995 and 2014, but there was club convergence. Myeki et al. [66] used the GML index to calculate the agricultural GTFP (GATFP) of 49 African countries from 2000 to 2019. Through comparison, it was found that regional growth was mostly characterized by high GATFP and TFP except in southern Africa and east Africa. In addition, some scholars have explored the sources of differences promoting the growth in GTFP from the perspective of GTFP decomposition [38,67].

To sum up, despite the cumulative research on GTFP in recent years, the following issues still need to be further addressed: First, in the measurement process, although the DEA method is widely used in situations where pollution emissions such as wastewater, exhaust gas, and solid waste are considered undesirable outputs, it does not take into account the environmental issues caused by CO_2 emissions under the dual carbon targets, which may result in inaccurate measurements that are not in line with reality. Second, in terms of the research sample, provincial data is widely adopted while urban data is ignored. Third, the existing research on measuring GTFP based on carbon emission constraints is not

deep enough, and research on regional differences, distribution dynamics, and convergence is very rare.

Compared to the previous literature, this study endeavors to make the following innovations:

First, it incorporates carbon emissions and PM2.5 into the TFP analytical framework. In detail, it employs the DDF and the GML productivity index; takes carbon emissions and PM2.5 as the undesirable output; accurately calculates 271 cities' GTFP in China, which expands the scope of quantitative research on TFP; and implements the dual carbon targets in the calculation of GTFP.

It is innovative of this study to incorporate CO_2 emissions and PM2.5 into the calculation and analysis for the following reasons: Firstly, CO_2 is the main component of greenhouse gases, and controlling carbon emissions and promoting carbon reduction are the fundamental ways of achieving the dual carbon targets. Secondly, PM2.5 is the major cause of air pollution, seriously endangering human health and the sustainable development of society. Controlling PM2.5 is also an important task in environmental governance and should be included in the field of green development. It can be said that addressing climate change and controlling air pollution are the two primary challenges facing China today. Moreover, previous studies did not fully consider the impact of CO_2 and PM2.5 on GTFP. Based on this, this study brings CO_2 emissions and PM2.5 into the GTFP analysis framework, takes full account of the constraints of CO_2 and PM2.5 when measuring GTFP, and includes air pollution, represented by PM2.5, and greenhouse gas emissions, represented by CO_2, as undesirable outputs, which not only expands the quantitative research of GTFP, but also implements the dual carbon targets in the calculation of GTFP.

Second, this study extends GTFP research to the urban dimension, with a larger scope and more microscopic focus, resulting in more general and reliable research conclusions.

Third, it introduces the Dagum Gini coefficient to calculate the regional differences in China's GTFP and the three subdivision regions: eastern, central, and western, and probes the sources of regional differences by decomposing the Dagum Gini coefficient. The research results can provide feasible suggestions for solidly improving regional GTFP.

Fourth, this study introduces kernel density estimation to test the distribution dynamics, evolution process, and characteristic trends of GTFP in China and the three subdivision regions, and to provide a basis for enhancing the balance and sufficiency of China's GTFP.

Fifth, this study employs a convergence model to analyze the convergence characteristics and influencing factors of GTFP, explore their convergence laws, and provide quantitative support for the formulation of national and regional emission reduction and carbon reduction policies.

Sixth, it adopts the GML productivity index instead of the ML productivity index, which is noncircular, although widely applied in the past.

3. Methodology

3.1. DDF-GML for Calculating GTFP

Drawing on [68], this study adopts the DDF with GML productivity index to estimate urban GTFP in China considering the GML productivity index's advantages of transitivity and cyclic accumulation [69]. First, it combines the production possibility set and DDF to obtain the efficiency of each decision-making unit (DMU). DDF is commonly expressed as Equation (1) [70].

$$\vec{D_0}(x, y, d, g) = sup\{\beta : (y, d) + \beta g \in P(x)\} \quad (1)$$

In this formula, x represents the input, y denotes the desirable output, d indicates the undesirable output, g stands for the direction vector, and it is assumed that $g = (y, -d)$, indicating strict requirements for an increase in desirable output and decrease in undesirable output. $P(x)$ is the production possibility set of environmental technology functions. $G = (g_y, g_d)$ denotes the direction vector of the output extension.

Next, the DDF functions can be calculated from the following linear programming (LP) problem [71], and the calculation equations are as follows:

$$\overrightarrow{D_0^t}\left(x^t, y^t, d^t; y^t, -d^t\right) = \max\beta \tag{2}$$

$$s,t,\begin{cases} \sum_{j=1}^{J} z_j^t y_{jn} \geq (1+\beta) y_{j'n'}^t & p = 1,2,\ldots,P \\ \sum_{j=1}^{J} z_j^t d_{jk}^t \geq (1-\beta) d_{j'k'}^t & k = 1,2,\ldots,K \\ \sum_{j=1}^{J} z_j^t x_{jn}^t \leq x_{j'n'}^t & n = 1,2,\ldots,N \\ z_j^t \geq 0, & j = 1,2,\ldots,J \end{cases} \tag{3}$$

where j is the number of DMUs, p denotes the number of the desirable output, k represents the number of the undesirable output, n indicates the number of input indicators, z_j^t is the weight of period t, β stands for the largest proportion that leads to a decrease in undesirable output and an increase in desirable output.

Last, based on the DDF, the GML productivity index is further employed to describe urban GTFP under carbon emission constraints. Referring to the method in [72], this study constructs the GML productivity index covering the period t to $t+1$ as follows:

$$\begin{aligned} GML_t^{t+1} &= \sqrt{\frac{1+\overrightarrow{D_0^t}\left(x^t,y^t,d^t;y^t,-d^t\right)}{1+\overrightarrow{D_0^t}\left(x^{t+1},y^{t+1},d^{t+1};y^{t+1},-d^{t+1}\right)} \times \frac{1+\overrightarrow{D_0^{t+1}}\left(x^t,y^t,d^t;y^t,-d^t\right)}{1+\overrightarrow{D_0^{t+1}}\left(x^{t+1},y^{t+1},d^{t+1};y^{t+1},-d^{t+1}\right)}} \\ &= \frac{1+\overrightarrow{D_0^t}\left(x^t,y^t,d^t;y^t,-d^t\right)}{1+\overrightarrow{D_0^{t+1}}\left(x^{t+1},y^{t+1},d^{t+1};y^{t+1},-d^{t+1}\right)} \\ &\times \sqrt{\frac{1+\overrightarrow{D_0^{t+1}}\left(x^t,y^t,d^t;y^t,-d^t\right)}{1+\overrightarrow{D_0^t}\left(x^t,y^t,d^t;y^t,-d^t\right)} \times \frac{1+\overrightarrow{D_0^{t+1}}\left(x^{t+1},y^{t+1},d^{t+1};y^{t+1},-d^{t+1}\right)}{1+\overrightarrow{D_0^t}\left(x^{t+1},y^{t+1},d^{t+1};y^{t+1},-d^{t+1}\right)}} \end{aligned} \tag{4}$$

The GML productivity index is a growth rate that calculates the portion where the growth rate of the output exceeds that of the factor inputs. When GML > 1, it indicates an upward trend in GTFP; when GML < 1, it indicates a downward trend; when GML = 1, it means that GTFP remains unchanged. Because GTFP is the month on month growth rate, this study assumes that all GTFPs in the base period are 1 following the literature [73], and accordingly, the GTFP in the next period is calculated by multiplying the GTFP in the base period by the GML index in the next period, and by analogy, GTFPs for other years are obtained.

3.2. Dagum Gini Coefficient for Evaluating Regional Differences

Although the classic Gini coefficient and the Theil index can measure regional differences [74], they cannot solve the sample data overlap and intergroup differences, which can be solved by using the Dagum Gini coefficient [75]. It can reasonably decompose the sources of regional differences, that is, decompose regional differences into intraregional differences, interregional differences, and hypervariable density, thereby accurately distinguishing the contribution of regional differences from overall differences [76]. Specifically, the Dagum Gini coefficient between groups is defined as follows:

$$G_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|GTFP_{ji} - GTFP_{hr}\right|}{n_j n_h\left(\overline{GTFP_j} + \overline{GTFP_h}\right)} \tag{5}$$

where j and h represent two specific areas. n_j and n_h represent the number of cities in the corresponding area. $GTFP_{ji}$ and $GTFP_{hr}$ denote the GTFP of city i in region j and that of

city r in region h, $\overline{GTFP_j}$ and $\overline{GTFP_h}$ denote the mean value of GTFP of all cities in regions j and h, respectively.

If $j = h$, region j and h are in the same region, and the calculation result is the intragroup Gini coefficient G_{jj} or G_{hh} in region j or h, that is:

$$G_{jj} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|GTFP_{ji} - GTFP_{hr}\right|}{2n_j{}^2\overline{GTFP_j}} \text{ or } G_{hh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|GTFP_{ji} - GTFP_{hr}\right|}{2n_h{}^2\overline{GTFP_h}} \quad (6)$$

If all cities in the sample are considered as the same group, the intragroup Gini coefficient of that group is the overall Dagum Gini coefficient G of all the cities' GTFPs, as follows:

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|GTFP_{ji} - GTFP_{hr}\right|}{2n^2\overline{GTFP}} \quad (7)$$

In this formula, $\overline{GTFP}$ is the average GTFP of 271 cities, k denotes the number of regions divided, n represents the number of all cities.

Furthermore, the Dagum Gini coefficient is divided into the following three parts:

$$\begin{aligned} G &= \sum_{j=1}^{k} G_{jj}p_j s_j + \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}D_{jh}\left(p_j s_{h+} p_h s_j\right) + \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_j\right)\left(1 - D_{jh}\right) \\ &= G_w + G_{nb} + G_t \end{aligned} \quad (8)$$

where G_w is the contribution of regional disparities, G_{nb} denotes the contribution of regional disparities, G_t represents a supervariable density contribution. $p_j = n_j/n$ represents the proportion of the number of cities in region j to the total sample. $s_h = n_h\overline{GTFP_h}/n\overline{GTFP}$ indicates the proportion of GTFP in region h to GTFP of all cities in the sample. From the formula $\sum_j\sum_h p_j s_h = 1$, the overall Dagum Gini coefficient is the weighted average of pairwise combinations of intergroup (intragroup) Gini coefficient G_{jh} in all regions, and the corresponding weight is $p_j s_h$. D_{jh} denotes the relative influence between region j and h, and the calculation formula is as follows:

$$D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}} \quad (9)$$

$$d_{jh} = \int_0^{\infty} dF_j(GTFP)\int_0^{GTFP}(GTFP - x)dF_h(x) \quad (10)$$

$$p_{jh} = \int_0^{\infty} dF_h(GTFP)\int_0^{GTFP}(GTFP - x)dF_j(x) \quad (11)$$

It is necessary to adjust the number of the two regions to make $\overline{GTFP_j} - \overline{GTFP_h} \geq 0$ before calculating d_{jh} and p_{jh}. F_j (F_h) is the cumulative density distribution function of GTFP in areas j and h after adjustment. d_{jh} represents the overall influence between regions j and h, the mathematical expectations for aggregated values all the $GTFP_{ji} - GTFP_{hr} > 0$ in regions j and h. p_{jh} is the super variant first-order moment between regions j and h. D_{jh} represents the proportion of net influence $(d_{jh} - p_{jh})$ between regions to its possible maximum value $(d_{jh} + p_{jh})$. $D_{jh} = D_{hj}$, with the value range (0, 1). If, and only if $\overline{GTFP_j} - \overline{GTFP_h} = 0$, $D_{jh} = 0$; if, and only if there is no cross overlap between regions j and h, $D_{jh} = 1$.

It is worth noting that intergroup hypervariable density represents the regional development imbalance caused by regional overlap. The reason may be that a relatively high GTFP in a certain region can only reflect the overall high level of this region but cannot reflect that the GTFP of all cities in the region is at a high level. That is to say, if there is no cross overlap between different regions, the hypervariable density is 0.

3.3. Kernel Density Estimation for Analyzing Distribution Dynamic

This study selects the nonparametric estimation "kernel density estimation" to explore the dynamic distribution characteristics of urban GTFPs in China. It can be understood as a "smooth" histogram that describes the distribution characteristics of GTFP in China's cities using continuous density curves while also retaining the characteristics of the data itself. The horizontal position of the kernel density curve for a specific period represents the level of GTFP. The height and width of the curve peak denote the aggregation degree of GTFP within the region. The number of peaks describes the polarization degree of GTFP. The extensibility of distribution, i.e., the degree of tailing of the kernel density curve, represents the magnitude of the differences between the highest or lowest city in GTFP and other cities. The longer the tail, the higher the degree of difference within the region. From a horizontal comparison perspective, the kernel density curves of multiple regions depict their differences in the trajectory of GTFP changes. From a vertical comparison perspective, the kernel density curves of different periods in the same region depict the dynamic evolution process of the distribution characteristics of GTFP in the region. The kernel density curve function of GTFP in region j is calculated as follows:

$$f_j(GTFP) = \frac{1}{n_j h}\sum_{i=1}^{n_j} K\left(\frac{GTFP_{ji} - GTFP}{h}\right) \tag{12}$$

where $K(\cdot)$ denotes the kernel density function, choosing the Gaussian kernel function. h is the bandwidth, and the smaller the bandwidth, the more accurate the estimation. Nevertheless, correspondingly, the number of samples participating in the calculation within the region decreases, leading to an increase in estimated variance and a decrease in the smoothness of the kernel density curve. Therefore, this study determines the most suitable bandwidth based on the optimal bandwidth selection approach proposed in [77].

3.4. Convergence Model

This study introduces a convergence model to answer two questions: firstly, do the regional differences in GTFP in Chinese cities tend to converge or diverge, and secondly, can regions with low GTFP catch up with those with high GTFP at a faster pace?

3.4.1. σ Convergence

σ convergence refers to the process in which the dispersion of GTFP in various regions continuously decreases over time. This study employs coefficient of variation, and the calculation formula is as follows:

$$\sigma = \frac{\sqrt{\sum_{i=1}^{N_j}\left(GTFP_{ij} - \overline{GTFP_{ij}}\right)^2 / N_j}}{\overline{GTFP_{ij}}} \tag{13}$$

In this formula, $GTFP_{ij}$ represents the GTFP of city i in region j. $\overline{GTFP_{ij}}$ is the average value of GTFP in region j. N_j denotes the number of cities in region j. If the standard deviation of GTFP in different regions decreases over time, GTFP behaves as σ convergence.

3.4.2. Absolute β Convergence

β convergence refers to the fact that high GTFP regions are overtaken by low GTFP regions over time. The change rate of GTFP in different regions is negatively correlated with its initial level, resulting in a gradual decrease in the gap between the two and ultimately converging to the same steady-state level. Moreover, β convergence comprises absolute β convergence and conditional β convergence. The absolute β convergence only examines the convergence trend of the equalization level of GTFP itself, without considering a series of control variables. The model is as follows:

$$\ln\left(\frac{GTFP_{i,t+1}}{GTFP_{it}}\right) = \alpha + \beta\ln(GTFP_{it}) + \mu_i + \eta_t + \varepsilon_{it} \tag{14}$$

where i and t represent the city and year, respectively. $GTFP_{i,t+1}$ expresses the GTFP of city i in period $t+1$. $GTFP_{it}$ denotes the GTFP of city i in period t. Accordingly, $\ln\left(\frac{GTFP_{i,t+1}}{GTFP_{it}}\right)$ represents the growth rate of GTFP of city i during period $t+1$. β is the convergence coefficient, and $\beta < 0$ indicates that the regional GTFP has a convergence trend; that is, the growth rate of underdeveloped regions in the initial stage of GTFP is faster than that of developed regions, so all the regions will tend to the same steady-state level. When $\beta > 0$ and is significant, the GTFP in Chinese cities has divergent characteristics. The convergence speed $\nu = -ln(1-|\beta|)/T$. The half path convergence period can be approximated as $\ln 2/\nu$. μ_i, η_t, and ε_{it} are urban fixed effects, time fixed effects, and random disturbance terms, respectively. α is a constant term, μ_i represents a fixed effect of urban individuals, η_t denotes a fixed time effect, and ε is a random disturbance term.

3.4.3. Conditional β Convergence

Conditional β convergence refers to the final convergence of GTFP in various regions to their respective steady-state levels, controlling for a series of influencing factors. The model is as follows:

$$ln\left(\frac{GTFP_{i,t+1}}{GTFP_{it}}\right) = \alpha + \beta ln(GTFP_{it}) + \delta X_{i,t+1} + \mu_i + \eta_t + \varepsilon_{it} \quad (15)$$

In this formula, $X_{i,t+1}$ is a series of control variables that affect GTFP, δ is the parameter vector. Drawing on relevant research, this study selects financial development level (fin), government size (gov), urbanization rate ($urban$), market freedom ($market$), human capital (peo), and research and development investment (rd) as control variables. If β is significantly less than 0, the GTFP in Chinese cities is conditional β convergence. If β is significantly greater than 0, the GTFP in Chinese cities is not conditional β convergence. The meanings of other variables are consistent with Model (14).

4. Indicators and Data

4.1. Indicators

4.1.1. Selection of Input and Output Indicators for Calculating GTFP

Based on China's dual carbon targets, this study selects relevant evaluation indicators from both output and input levels and adopts MATLAB software to calculate the GTFP of 271 cities in China. The output indicators not only consider the maximization of desirable outputs such as economic development and so on, but also consider the constraints of undesirable outputs such as carbon emissions and PM2.5 on economic development. The investment indicators not only concern the labor, capital, and other investment indicators, but also concern the energy investment indicators.

(1) Input indicators

① Capital

Taking the year of 2005 as the base period, this study uses the whole social fixed assets investment price index to reduce the total fixed capital formation. Subsequently, the perpetual inventory method proposed in [78] is employed, and the specific calculation formula is as follows:

$$K_k^t = K_k^{t-1} + I_k^t - D_k^t \quad (16)$$

where t represents the time, k denotes the city, K is the capital, I expresses the investment, D denotes the capital depreciation, and the depreciation rate is 10.96% [79].

② Labor input

Given the data availability, this study employs the sum of unit employees and private individual employees at the end of the year in cities, which is the total number of employees in the city.

③ Energy input

This study takes the total electricity consumption of the city as an approximate indicator of energy input.

(2) Output indicators

① Desirable output

Due to the fact that economic development is an important output result of cities, the desirable output is the actual gross domestic product of each prefecture-level city, adjusted as constant prices in 2005 as the base period.

② Undesirable output

This study introduces CO_2 emissions and annual average PM2.5 concentration to measure the undesirable output for two reasons: First, CO_2 is the main component of greenhouse gases. Under the goals of carbon peak and carbon neutrality, controlling carbon emissions and achieving green development have become important goals for China's economic and social sustainable development. Second, PM2.5 is the main cause of air pollution, seriously damaging human health and hindering the transformation of economic development models. Controlling air pollution and addressing climate change are two major environmental challenges facing China today. For this reason, air pollution, represented by PM2.5, and greenhouse gas emissions, represented by carbon emissions, are both included in the undesirable output.

Up to now, there have been no authoritative official data on CO_2 emissions in China. Referring to relevant research [80], this study calculates urban carbon emissions by the sum of carbon emissions generated by direct energy consumption (such as natural gas and liquefied petroleum gas) and indirect energy consumption (such as electricity and thermal energy). The specific steps are as follows:

Firstly, this study introduces the relevant conversion coefficients provided by the IPCC (2006) to calculate the CO_2 emissions generated by direct energy consumption, "natural gas and liquefied petroleum gas".

Secondly, it estimates the indirect energy consumption, "the carbon emissions generated by electricity and thermal energy". The calculation steps for CO_2 generated by urban electricity consumption are shown below. According to [81,82], the Chinese power grid is divided into six regions, namely east China, central China, north China, south China, northeast China, and northwest China, and each region's power grid has released baseline emission factors. This study calculates the CO_2 emissions generated by urban electricity based on the total electricity consumption in each region and its baseline emission factors. The CO_2 emissions generated by urban thermal energy are measured by the amount of raw coal consumed for thermal energy. The specific steps are as follows:

In reality, cities use raw coal as a material for centralized heating, mainly the total amount of steam and hot water heating generated by boiler rooms and thermal power plants. Additionally, according to the provisions of "GB/T 15317-2009 [83] Energy Conservation Monitoring of Coal-fired Industrial Boilers", the thermal efficiency value is 70%. Subsequently, the quantity of raw coal is calculated by the heating capacity, thermal efficiency, and the average low calorific value of raw coal (20,908 kJ/kg), and is converted into the standard coal quantity. The formula for calculating urban carbon emissions is as follows:

$$CO_2 = \sum_{i=1}^{2} E_i \times CEF_i + \sum_{n=1}^{6} EC_n \times EF_n + \sum_{j=1}^{2} E_j \times NCV \quad (17)$$

In this formula, E_i denotes the energy consumption, CEF_i is the energy carbon content, i and j denote the natural gas and liquefied petroleum gas, respectively. EC_n is the total electricity consumption by region, EF_n is baseline emission factors for each regional power grid, n represents China's six major regional power grids. E_j represents total heat supply, mainly the total amount of steam heating and hot water heating, NCV is average low calorific value of raw coal.

4.1.2. Selection of Control Variables for Conditional β Convergence Analysis

(1) Financial development level (fin)

fin represents the proportion of deposit and loan balances of financial institutions to GDP. The level of financial development level reflects a city's economic development level

to a certain extent, while the economic development level is an important variable that affects the city's GTFP [84]. A healthy financial system provides not only capital support for urban development, but also funding sources for modern technological innovation of enterprises, which can enhance enterprise vitality and help long-term growth of enterprise benefits. Consequently, the level of urban financial development is directly related to GTFP.

(2) Government scale (*gov*)

gov represents the proportion of general public budget expenditure to GDP [85]. The size of the government exerts a certain impact on the improvement of total social welfare. The expansion of government size facilitates social welfare growth through a sound social security system, thereby increasing labor productivity. Therefore, government size may promote GTFP to a certain extent.

(3) Urbanization rate (*urban*)

urban is the proportion of the population in urban areas in relation to the total population of the city. Urbanization is the result of long-term accumulation of population and other factors, and its impact on urban GTFP is still uncertain. On the one hand, urbanization facilitates the concentration of capital, talent, technology, and other factors; optimizes resource allocation; enhances industrial structure upgrading and technological progress; and consequently boosts GTFP. On the other hand, urbanization means an increase in the scale of infrastructure construction, which leads to an increase in demand for energy-intensive products such as cement, causing environmental pollution and hindering the improvement of GTFP [86].

(4) Market freedom (*market*)

market shows the ratio of the difference between urban GDP and budgeted fiscal expenditure in relation to GDP. A competitive market structure is conducive to knowledge spillover and technology innovation among industries, thereby optimizing resource allocation. Certainly, if there is insufficient market freedom, that is, excessive government intervention, it is not conducive to fair market competition and also reduces production efficiency, exerting a negative impact on GTFP [87].

(5) Human capital (*peo*)

peo stands for the proportion of the population with a bachelor's degree or above in the total population of the city. Firstly, the level of human capital directly affects the innovation capacity of cities. Secondly, the higher the level of human capital, the more knowledge spillovers there are. The knowledge, production skills, and experience of a region can spread to other regions through knowledge spillovers, ultimately improving the productivity level of the entire region. Additionally, the matching of human capital with industrial structure encourages the effective utilization of resources and reduces pollution emissions. Finally, higher human capital enhances people's environmental awareness, optimizes residents' environmentally friendly behavior, and thus improves GTFP [88].

(6) R&D investment (*rd*)

rd means the proportion of fiscal scientific expenditure in relation to GDP. Increasing R&D investment can effectively upgrade the production level of enterprises, solve the problem of overcapacity, and consequently upgrade product quality. Meanwhile, the higher the R&D investment, the more conducive it is to promoting technological progress, boosting resource utilization efficiency, reducing energy consumption and carbon emissions, and enhancing GTFP [87].

4.2. Data Sources

Given the data availability and accuracy, this study selects the panel data of 271 cities from 2006 to 2020, which are mainly from the *China Urban Statistical Yearbook*, *China Urban Construction Statistical Yearbook*, *China Energy Statistical Yearbook*, and *Urban Power Statistical Yearbook*. Partially missing data have been filled in using interpolation and mean methods.

The sample in this study is 271 cities in China. The reason for selecting the sample is that there are about 300 cities in China, but due to the lack of some data, some cities, such as Shannan City, Nagqu City, and Hami City, have no official statistics. Therefore, such

cities need to be excluded from the sample. In addition, the 271 cities selected in this study account for over 90% of the total number of cities in China, and these cities are distributed in the 31 provinces, municipalities, and autonomous regions of China, covering the east, central, and western regions in China. They have good representativeness and reflect the overall characteristics of Chinese cities.

The sample period is from 2006 to 2020 for the following reasons: Before 2006, many statistical indicators in China had incomplete data. Since 2006, various statistical indicators have gradually been improved, and the latest data from the *China Urban Statistical Yearbook* are from the year 2020. Therefore, based on the availability and accuracy of sample data, this study selects the period from 2006 to 2020 as the sample period.

Based on the above, this study selects 271 cities as research samples, with a sample period from 2006 to 2020.

5. Results and Discussion

5.1. Calculation Results of China's GTFP

According to the GTFP calculated in Section 3.1, the annual changes in the average GTFP of the national, eastern, western, and central regions are shown in Figure 1.

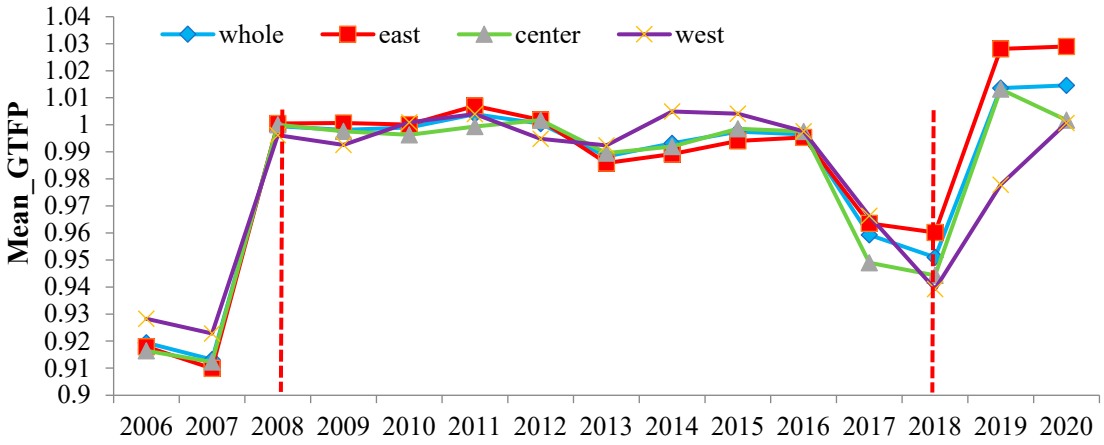


Figure 1. Annual changes in the average GTFP of the nation and the three regions.

It can be found that, firstly, GTFP exhibits a long-term positive trend and a distribution characteristic of east > center > west. Overall, the average national GTFP has gradually increased from 0.9194 in 2006 to 1.0146 in 2020, with an average annual growth rate of about 0.7064%, implying that China's GTFP has been remarkably optimized, and new breakthroughs have been made in the green transformation of China's economic development model. From the perspective of specific regions, the central region's average GTFP is the smallest, at 0.9832; the western region's average GTFP is centered, at 0.9815; the eastern region's average GTFP of 0.9855 is the highest and also higher than the national average level. In terms of the growth rate, the average annual growth rates of GTFP in the eastern, central, and western region are, respectively, 0.8134%, 0.6492%, and 0.5356%. The eastern region ranks at the top, owing to its policy advantages and industrial structure advantages. The central and western regions belong to economically underdeveloped provinces and have not properly handled the compatibility between economic growth and environmental protection. Secondly, from the time trend perspective, the GTFP of all the regions maintains an "N-shaped" change trend over the sample period. Taking the years 2008 and 2018 as nodes, GTFP can be divided into three stages. The first stage is from 2006 to 2008, during which the GTFP of the three regions showed a notable upward trend. The second one is from 2008 to 2018, a period with fluctuating decline. During this stage, the GTFP gradually declined, but remained higher than the level of the first stage, implying that although China's GTFP faced external shocks, it still developed in a "stable and positive" direction overall. The third one is the period after 2018, when the GTFP observably increased. In this

period, local governments attached great importance to ecological environment protection and continuously increased investment in ecological governance so that China's green and high-quality economic development achieved evident results.

5.2. Regional Differences in China's GTFP

The GTFP of China's cities shows a clear spatial pattern of high in the eastern region, low in the central and western regions, fast in the eastern region, and slow in the central and western regions. It is of necessity to measure the differences in GTFP among different regions and conduct in-depth analysis of their specific sources. Based on the calculation results of the Dagum Gini coefficient, the regional differences in GTFP are divided into intraregional and interregional differences.

5.2.1. Intraregional Differences

This study measures the degree of intraregional differences in urban GTFP among 271 cities in China and the three regions. The results from 2006 to 2020 are reported in Figure 2.

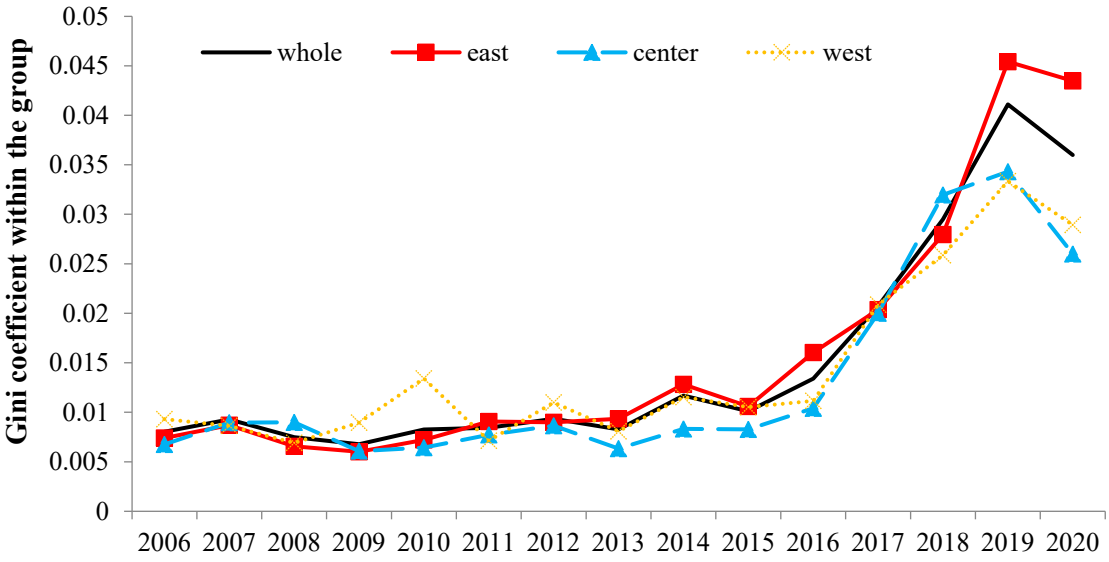


Figure 2. Changes in intraregional differences in GTFP.

Firstly, the overall Gini coefficient displays a steady upward trend. From a national perspective, the average Gini coefficient as a whole is 0.0152. From 2006 to 2020; the Gini coefficient showed a slightly fluctuating upward trend, rising from 0.0080 in 2006 to 0.0358 in 2020, with an average annual growth rate of nearly 11.31%. Especially after 2015, GTFP exhibited a jumping upward trend. This may be due to the implementation of the "strictest environmental protection law in history"—the "Environmental Protection Law" in 2015—which markedly boosted GTFP. At the same time, the overall Gini coefficient of GTFP covering the sample period only decreased within 4 years, indicating that the imbalance in GTFP in Chinese cities is obvious, and the trend is gradually deepening.

Secondly, from a regional perspective, the intraregional differences in GTFP among the three regions are gradually expanding. The Dagum Gini coefficient of GTFP in the eastern region is the highest, with an average of 0.0160 and an average annual growth rate of approximately 13.47%, which is basically higher than the national average and displays an "N-shaped" trend of "up–down–up" during the sample period. The intraregional differences in the eastern region show a slightly upward trend. As for the central and western regions, the Dagum Gini coefficients of GTFP in the two regions are lower than the national average level, especially in the central region, which is the smallest during the sample period, with an average of 0.0133 and an annual growth rate of about 10.1%. Compared

with the eastern region, the transformation and upgrading of the economic development model in the central and western regions are slightly slower, the improvement in GTFP is relatively slow, and there is a lack of sufficient green and high-quality development.

In summary, although the Dagum Gini coefficient of China's GTFP fluctuated during the sample period, it is generally in a continuous growth state, indicating that the imbalance within the region is gradually expanding, which requires the government to accelerate the implementation of the regionally coordinated development strategy, so as to achieve coordinated development and overall planning among all regions.

5.2.2. Interregional Differences

According to Section 3.2, this study calculates the intensity of differences in GTFP between the eastern, western, and central regions. The calculation results of some typical years are presented in Figure 3.

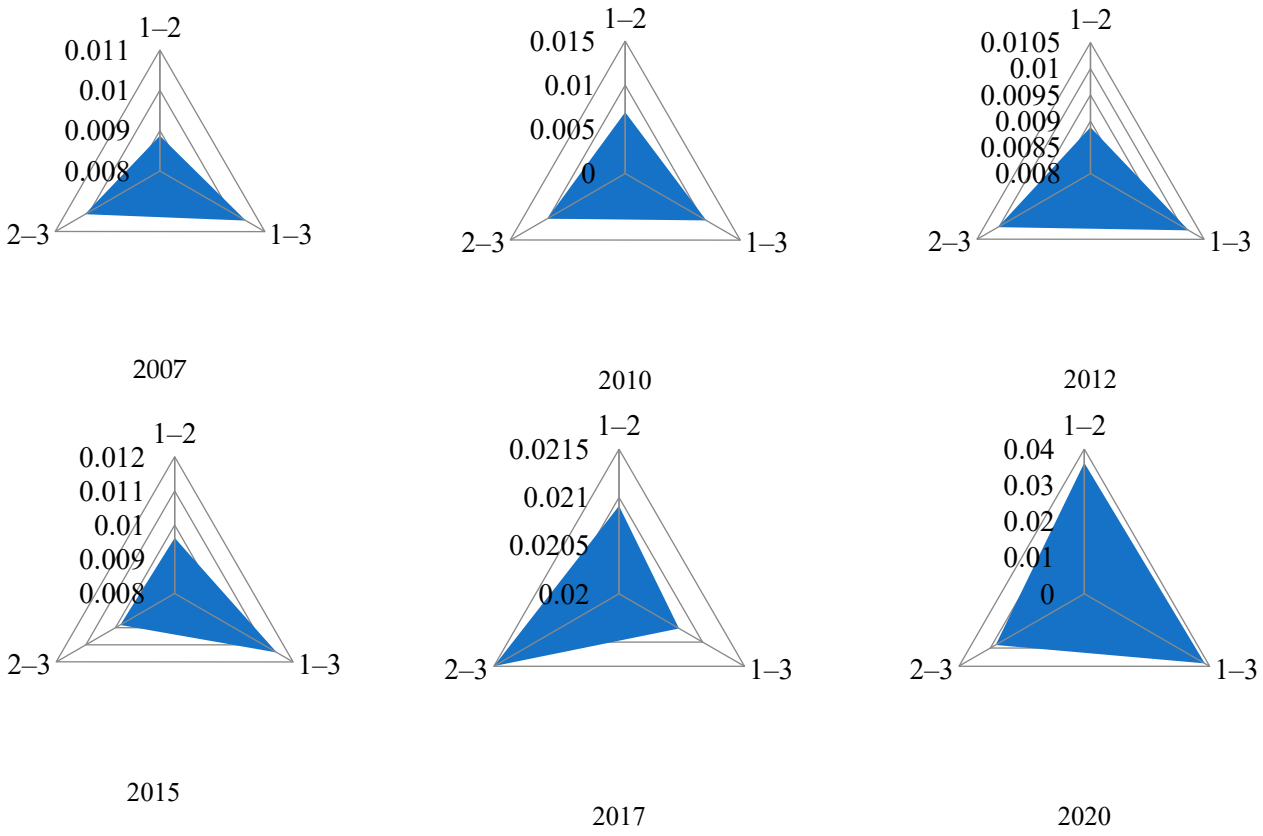


Figure 3. Gini coefficient between groups in some typical years.

In Figure 3, the blue shaded areas represent the differences between the eastern, central and western regions, with 1–2 representing the eastern and central regions, 1–3 representing the eastern and western regions, and 2–3 representing the central and western regions.

Firstly, from an overall point of view, the blue shaded area in Figure 3 is gradually expanding, and the interregional differences in China's GTFP show a significant upward trend of fluctuations, indicating that the differentiation trend in the three regions is significant.

Secondly, from the perspective of the Dagum Gini coefficient values, the coefficient between cities in the eastern and western regions is the highest; that is, the difference between the eastern and western regions is the greatest, with a sample mean of 0.0163. The difference between the central and western regions is the smallest, with a sample mean of 0.0146. The difference between the eastern and central regions is moderate, with a sample mean of 0.0150. It is basically consistent with China's current economic development pattern, indirectly verifying that the level of economic development and environmental constraints exert a constraining effect on GTFP.

Thirdly, from the perspective of time-varying trends, the Dagum Gini coefficients among the three regions maintain a gradual upward trend. The differences between the eastern, central, and western regions have almost synchronously increased, illustrating an evolutionary trend of up–down–up. From 2006 to 2015, there was a slow upward trend of fluctuations, and after 2015, there was a conspicuous increase trend. Among them, the growth rate of the Gini coefficient between the eastern and central regions is the most significant, with an average annual growth rate of 12.1%, followed by the eastern and western groups, with an average annual growth rate of 10.6%. The Gini coefficient between the central and western regions has the smallest average annual growth rate of 7.99%, indicating that the green and high-quality development processes in the central and western regions are temporarily lagging behind those in the eastern region.

5.2.3. Sources and Contributions of Regional Differences

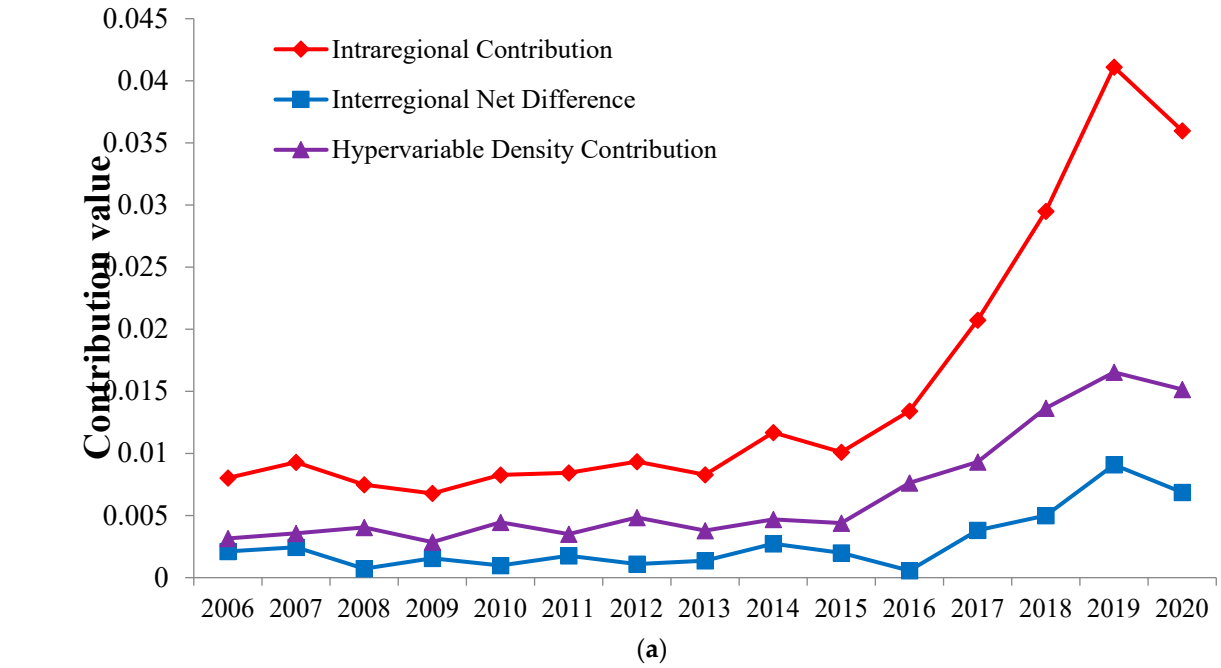
Furthermore, this study decomposes the overall differences in GTFP into three parts: intraregional contribution, interregional net difference, and hypervariable density contribution. The results are shown in Figure 4.

In Figure 4a, the contribution values of intraregional differences in GTFP among the three regions increase from 0.0080 in 2006 to 0.0360 in 2020, illustrating an overall fluctuating upward trend. Nevertheless, due to the larger difference in the green coverage rate in the eastern region compared to the overall sample data, the contribution rates of intragroup differences increase from 60.4458% in 2006 to 62.0380% in 2020. The contribution rate range is (60.4458%, 62.0883%), with an average annual contribution rate of 61.2283%, which is relatively stable overall. In other words, regional differences are the main source of overall differences in GTFP among the three regions, and the degree of impact is on the rise, consistent with the previous conclusion.

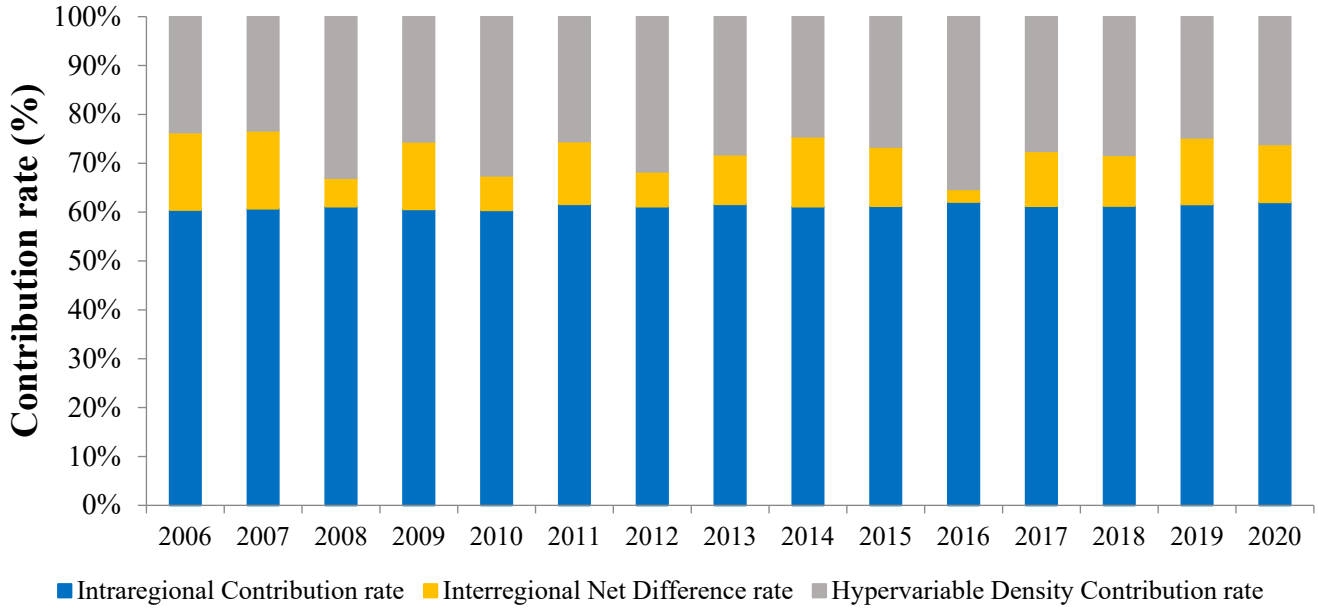
The contribution of interregional differences includes the net contribution of interregional differences and the contribution of interregional hypervariable density. Firstly, the net contribution of interregional differences maintain a fluctuating upward trend during the sample period, increasing from 0.0021 in 2006 to 0.0069 in 2020. Its contribution rate to the overall difference exhibits a conspicuous "V-shaped" characteristic. That is, from 15.8572% in 2006 to 2.6152% in 2016, it rapidly increases to 11.8399% in 2020, with an average annual contribution rate of 10.9854%. Hereby, reducing regional differences, especially in the eastern and western regions, is a meaningful task for China's future green and high-quality development. Secondly, the absolute value of interregional hypervariable density fluctuated and increases, from 0.0031 in 2006 to 0.0151 in 2020, with an average annual growth rate of 0.08%. The contribution rate of interregional hypervariable density fluctuates between 23.3159% and 35.2965%, showing an overall inverted "U-shaped" characteristic. That is, the contribution rate in 2006 is 23.6970%, which gradually increases to 35.2965% in 2016 and decreases to 26.1222% in 2020, with an average annual contribution rate of 27.7864%. Due to the fact that interregional hypervariable density represents the contribution of overlapping parts between different regions to the total difference and is relatively small compared to the intraregional differences, the division of the three regions can be used to reasonably distinguish cities with different levels of economic development.

5.3. Distribution Dynamics of China's GTFP

Although the Dagum Gini coefficient reveals the overall differences and sources of GTFP and depicts the relative change trajectory of GTFP in the eastern and western regions, it cannot accurately describe the time-varying evolution process of absolute differences in GTFP in the three regions. Then, according to Section 3.3, this study introduces the nonparametric kernel density estimation to describe the distribution characteristics and evolution trend of China's urban GTFPs in three regions, and data from 2006, 2011, 2016, 2020 are selected for analysis. The specific dynamic evolution characteristics are reported in Table 1 and the kernel density estimation results are presented in Figure 5, where the horizontal axis denotes GTFP and the vertical axis represents kernel density.



(**a**)



(**b**)

Figure 4. Spatial differences and sources of GTFP. (**a**) Contribution value. (**b**) Contribution rate.

Table 1. Dynamic evolution characteristics of GTFP in the eastern, western, and central regions.

Region	Distribution Location	Main Peak Distribution Pattern	Distribution Ductility	Peak Number
Whole	Right shift	Height descent and width increases	Right trailing, extension convergence	Single
East	Right shift	Height descent and width increases	Right trailing, extension convergence	Single
Center	Right shift	Height descent and width increases	Right trailing, extension convergence	Single or multiple
West	Right shift	Height first rises and then decreases, and the width increases	Right trailing, extension convergence	Single or multiple

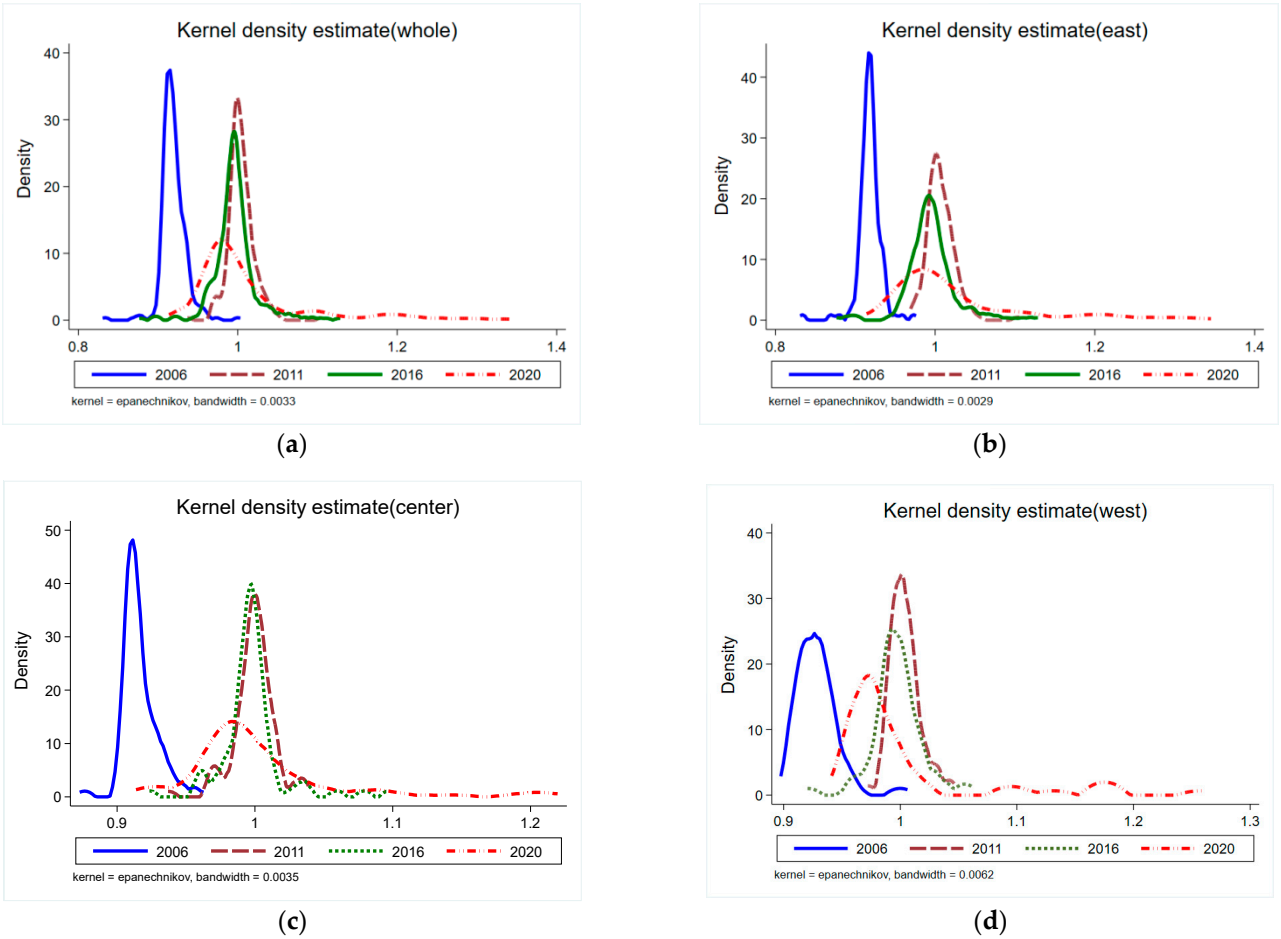


Figure 5. Dynamic evolution of GTFP. (**a**) Whole. (**b**) East. (**c**) Center. (**d**) West.

5.3.1. Distribution Location

Carbon emission reduction has become an essential goal for China's economic development since the 11th Five Year Plan. With the increasing call for high-quality economic development, the overall kernel density curve of GTFP at the national level has shifted to the right, indicating the continuous rise of China's GTFP, which is highly consistent with the previous calculation results. The concept of green development has forced local governments to accelerate the transformation and upgrading of industrial structures, change economic growth models, and promote high-quality development. Moreover, the center of the GTFP density function in the three regions displays a rightward shift trend with different degrees, indicating that cities in the eastern, central, and western regions have achieved evident results in terms of GTFP improvement, so as to achieve the dual carbon targets and green and high-quality development.

5.3.2. Main Peak Distribution Pattern

Firstly, from a national point of view, the kernel density curve of GTFP maintains a decrease in the height of the main peak and an increase in its width, showing an increase in the dispersion of GTFP. The difference in the growth rate of GTFP may be due to the noticeable differences in the economic foundation and environmental endowment of different cities, resulting in significant differences in the path and difficulty of achieving the dual carbon targets and high-quality development.

Secondly, due to the encouragement of some capable provinces and cities by the government to take the lead in reaching carbon peak, the performance of each region in improving GTFP varies observably without sufficient high-quality development experience in various regions. The peak height of the GTFP kernel density curve in the eastern region con-

tinues to decrease and the width increases, implying that the absolute difference in GTFP among cities in the eastern region has increased. Although the economic development level in the eastern region is relatively high, the degree of regional development imbalance is also severe. The peak height of the GTFP distribution curve in the central region maintains a fluctuating downward trend while the width gradually rises, suggesting that the absolute gap between cities in the central region has increased, illustrating that the implementation of the central rise strategy in recent years has exerted little effect on balancing regional development.

The height of the main peak of the kernel density curve of GTFP in the western region illustrates an overall fluctuation trend of "increasing–decreasing", with the width first becoming sharp and then flat, indicating that the absolute difference in urban GTFP in the western region is also expanding. The reason may be that, in recent years, with the implementation of the Western Development Strategy, some central cities in this region have prominently driven their GTFP with strong economic and policy support, greatly widening the development gap with other small and medium-sized cities, leading to a continuous widening of the absolute gap in GTFP in the western region.

5.3.3. Distribution Ductility

There is an obvious right tail phenomenon in the kernel density curves of the whole country and the three regions; that is, the GTFP of some cities is significantly higher than that of the others in the same region. At the same time, the right tail lengthens year by year, and the distribution ductility has a widening trend to a certain extent, meaning that the spatial gap of GTFP in the region is gradually expanding. There is a certain degree of left tail phenomenon in the eastern and central regions, implying that the GTFP of certain cities is far lower than that of the others in the same region.

5.3.4. Peak Number

During the sample period, except for the national and eastern regions, there are multipeak phenomena in the central and western regions; that is, there is a trend of multipolarization evolution in urban GTFP in the region. Specifically, the number of peaks in the central region displays an evolution trend of single peak–multipeak–single peak during the sample observation period, suggesting that the central region shows an evolution trend of convergence without differentiation to multilevel differentiation during the observation period, and there is an obvious polarization phenomenon, but the multipolarization characteristics tend to weaken on the whole, and the degree of differentiation in the region gradually decreases. The kernel density curve of western region only exhibits a multipeak shape in 2020, signifying that with the implementation of the Western Development Strategy, the GTFP of some cities in this region has increased remarkably, and the high-quality development has illustrated a more obvious multipolarization phenomenon. In the sample period, the kernel density curve in the eastern region has always maintained a single-peak shape without obvious polarization.

5.4. Convergence of China's GTFP

The above analysis reveals that the GTFP growths of cities in different regions of China are quite different, so whether the difference converges with time, and if so, whether the convergence model is the same, needs to be elucidated. In order to further explore the above problems, this study adopts σ convergence and β convergence to test the findings of Section 3.4.

5.4.1. σ Convergence

Figure 6 exhibits the GTFP σ convergence results of the overall cities and three regions. From an overall perspective, the σ value increased from 0.0160 in the early stage of the sample to 0.0755 in the late stage. Although the σ value decreased in some years, the overall trend was on the rise, indicating that the internal gap increased over time and,

consequently, there was no σ convergence trend. From a regional perspective, although the variation coefficients of GTFP in the three regions fluctuated to varying degrees, the overall trend was upward. The final value was greater than the initial one, and there was no σ convergence trend. The variation coefficient of GTFP in the central and eastern regions increased from 0.0155 to 0.0871, among which the one in the central region increased from 0.0131 to 0.0542 and the one in the western region increased from 0.0179 to 0.0669. This reflects that, over time, the GTFP in the three regions did not exhibit a σ convergence trend, making it difficult for cities with low GTFP to catch up with those with high GTFP. The gap in GTFP among the cities will become larger and larger.

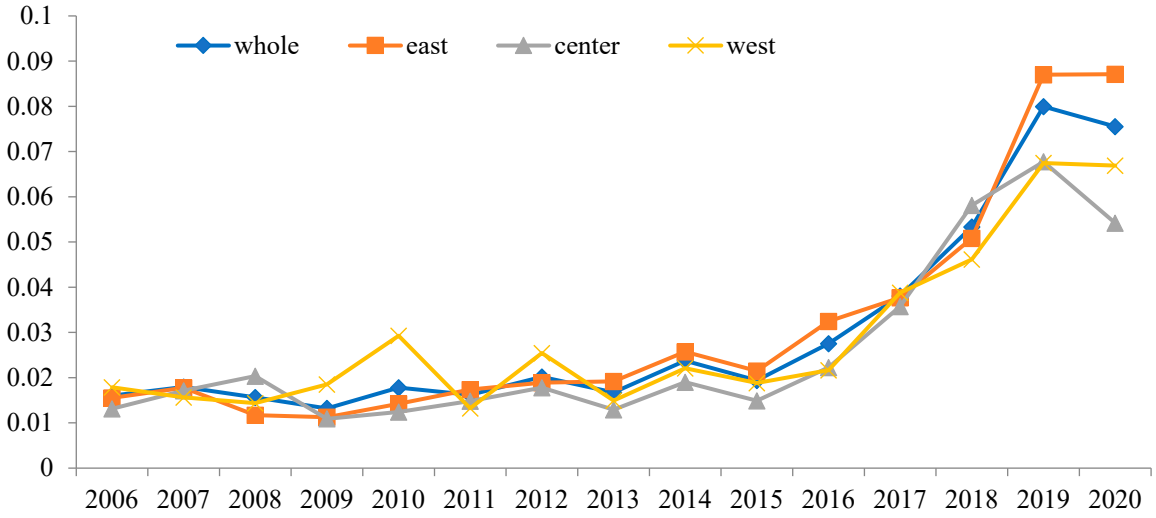


Figure 6. σ convergence of GTFP in the three regions.

5.4.2. Absolute β Convergence

Although σ convergence analysis is easy to understand and calculate, it does not take into account the initial level of environmental factors and the initial factor endowments of each region. Accordingly, in order to accurately master the convergence of GTFP, this study controls for time and the urban fixed effects and introduces the OLS panel model to analyze the β convergence according to Section 3.4.2. Table 2 presents the absolute β convergence results of GTFP in 271 cities and the three regions.

Table 2. Absolute β convergence test results of GTFP in China and three of its regions.

Zone	Whole	East	Center	West
β	−0.5402 ***	−0.5438 ***	−0.5521 ***	−0.5386 ***
	(−30.5774)	(−20.4179)	(−18.6976)	(−15.7696)
v	0.055497	0.056059	0.05737	0.05520
Half path convergence period $ln2/v$	12.49	12.36	12.08	12.56
Time fixed effect	√	√	√	√
City fixed effect	√	√	√	√
R^2	0.5570	0.5403	0.6434	0.2692

Note: t-statistics in parentheses. *** $p < 0.01$. √ is "control".

① There is absolute β convergence in the whole country and the three regions, eastern, central, and western. The coefficient β is significantly negative at the 1% level, indicating that the growth rate of GTFP is negatively correlated with its initial level. Within the same region, there is a catch-up effect between underdeveloped regions and developed ones. Without considering the influence of other economic and social factors, the GTFP of the whole country and the three regions will converge to their respective steady-state equilibrium values over time.

② The convergence speeds of GTFP in the whole country and the three regions are different. The convergence rate of the whole GTFP is 0.0555, which is lower than that in the central region, and the half path convergence period is 12.49 years. The possible reasons are as follows: with the in-depth implementation of the Strategy for the Rise of Central China, local governments have accelerated supply-side structural reforms, increased independent innovation, expanded opening up, promoted comprehensive strength and competitiveness, and achieved initial results in high-quality development. Thereby, the convergence rate of GTFP in the central region is the fastest. Specifically, the convergence rates from fast to slow are for the central, eastern, and western regions; the convergence speeds are 0.0573, 0.0560, and 0.0552, respectively; and the halfway convergence periods are 12.08 years, 12.36 years, and 12.56 years, respectively.

5.4.3. Conditional β Convergence

It is worth noting that the above absolute β convergence test is conducted under the assumptions of factor-level approximations, such as financial development level, government size, urbanization rate, market freedom, human capital, and R&D investment, but in reality, it does not necessarily follow this assumption. As a result, it is necessary to further test the conditional β convergence. Table 3 displays the conditional β convergence results of GTFP in 271 cities and the three regions.

Table 3. Results of conditional β convergence in the whole and three regions.

Zone	Whole	East	Center	West
β	−0.5453 ***	−0.5506 ***	−0.5670 ***	−0.5565 ***
	(−30.6804)	(−20.5158)	(−18.7277)	(−15.7663)
Control variable	√	√	√	√
v	0.056294	0.057131	0.059787	0.058076
Half path convergence period $ln2/v$	12.31	12.13	11.59	11.89
Time fixed effect	√	√	√	√
City fixed effect	√	√	√	√
R^2	0.5582	0.5419	0.6461	0.2997

Note: t-statistics in parentheses. *** $p < 0.01$. √ is "control".

① There is a conditional β convergence in the whole country and the three regions of the east, center, and west. The coefficient β is significantly negative at the 1% level, suggesting that after considering the financial development level, government size, urbanization rate, market freedom, human capital, R&D investment, and other factors, the trend of GTFP convergence at their respective steady-state levels in the whole country and the three regions still exists in the long run.

② The conditional β convergence speed of GTFP in the whole country and the three regions is basically consistent with the absolute β convergence speed, but compared with the absolute β convergence, the conditional β convergence speed is accelerated. Among them, the central and western regions have a larger increase in the convergence rate, and the eastern and national convergence rates have a smaller increase. Specifically, the convergence speed of the national GTFP has increased to 78.8117%, and the half range convergence period has correspondingly reduced to 12.31 years. The convergence rates of GTFP in the eastern, central, and western regions are 0.0571, 0.0598, and 0.0581, respectively, with half range convergence periods of 12.13 years, 11.59 years, and 11.89 years. It can be seen that there is spatial heterogeneity in the convergence rate of GTFP in the eastern, central, and western regions.

6. Conclusions and Policy Suggestions

6.1. Conclusions

Based on the DDF and GML productivity index, this study took 271 cities in China from 2006 to 2020 as samples, incorporated environmental pollutant variables such as carbon emissions and PM2.5 on the basis of traditional TFP, and measured the GTFP of Chinese

cities under the dual carbon target constraints. The Dagum Gini coefficient, nonparametric density estimation, and the convergence model were employed to investigate the regional differences, dynamic evolution, and convergence of GTFP in the whole country and the eastern, central, and western regions. The main findings are as follows:

Firstly, in terms of the time dimension, the overall level of GTFP in Chinese cities maintains a fluctuating growth trend. From the perspective of the spatial dimension, the GTFP level in the eastern region is leading, while those in the central and western regions are generally lower. This means that the development of GTFP in Chinese cities is showing an excellent trend but the phenomenon of spatial imbalance still exists, and there is an overall phenomenon of insufficient balance. The reason for the above phenomenon is that eastern cities have strong economic and technological strength, which can better cope with external uncertainty shocks; the weak comprehensive strength of the central and western regions leads to lower GTFP. Overall, there is remarkable room for efficiency improvement in all regions. Thereupon, it is essential to promote the balanced development of GTFP in various regions and provide a new explanatory perspective to solve the problem of low GTFP in Chinese cities.

Secondly, there are visible regional differences in the GTFP of Chinese cities, presenting a spatial distribution pattern of high in the east and low in the west, with obvious imbalanced characteristics. The intraregional difference is always the main source of the overall difference in GTFP, and the eastern region is the region with the largest intraregional difference. There is a demonstrable trend of GTFP differentiation in the three regions, with the largest difference between the eastern and western regions. There is an emphatic Matthew effect in GTFP across regions. In the process of GTFP improvement, it is material to pay attention to regional differences, especially intraregional differences. In the future, close attention needs to be paid to the potential loss of GTFP in underdeveloped areas. At the same time, the spatial distribution pattern of China's urban GTFP is conducive to clarifying the internal logic behind the formation of disparities, providing a scientific basis for alleviating the imbalance and inadequacy in urban green development.

Thirdly, from the perspective of dynamic evolution, the polarization characteristics of the central and western regions are obvious, and GTFP maintains a multipolar distribution trend, indicating that the central and western regions have the characteristics of high GTFP regional divergence and low GTFP regional convergence, making it difficult for states to shift between regions. Additionally, there is a certain degree of gradient development in China's urban GTFP, which requires heterogeneous governance measurements for different regions so as to narrow the polarization trend step by step and avoid the polarization problem caused by excessive agglomeration of resources. This provides policy implications for better guiding the healthy and orderly improvement of GTFP in Chinese cities.

Fourthly, from the perspective of convergence characteristics, there is no σ convergence in Chinese urban GTFP, but absolute β convergence and conditional β convergence exist. The GTFP of the three regions of the east, center, and west is slowly converging to its own steady-state level, and the catch-up effect is relatively slow, implying that narrowing the gap in GTFP between cities is a long-term and arduous task. This phenomenon is mainly caused by the gap in regional green resource endowment and economic and cultural heritage. In addition, the degree of linkage between China's regions is not high, and there is a certain gap in coordinated development. Cross-regional cooperation has considerable room for improvement. As a consequence, in the future, it is necessary to eradicate path dependence, gather the strength of all sectors of society, and jointly promote the improvement of urban GTFP.

In addition, the efficiency measurement tools used are applicable to the cities for the following two reasons: First, the DDF-GML model requires that each DMU has m inputs and s outputs. In this study, each city has three inputs (capital, labor, and energy) and three outputs (GDP, CO_2, and PM2.5), which is consistent with the requirements of the model. Therefore, regarding each city as a DMU in the model is scientific and in line with factual characteristics. Second, from the perspective of sample size, the model requires a prescribed

minimum of sample size more than three times the sum of inputs and outputs. The sample size at the city level meets the model requirements better than that of the provincial level, which has been extensively focused on in most of the existing literature. In this sense, the measurement results at the city level are more reliable and robust. In summary, the efficiency measurement tools used are applicable to cities.

6.2. Policy Suggestions

Based on the above research conclusions, some policy recommendations are put forward, as follows:

Firstly, strengthen the top-level design of the GTFP system and establish the concept of "one game of the whole country". Fully utilize the important role of top-level design and baton, upgrade the indicator system of GTFP, and incorporate it into local government performance evaluation and official performance evaluation. Establish an assessment, reward, and punishment system, and take the target results as an important basis for the appointment and dismissal of cadres. We should do a good job in environmental supervision and governance, strengthen coordinated environmental governance in various regions, strengthen incentives and constraints for green development through systems, and mobilize the enthusiasm of governments at all levels to facilitate GTFP. Additionally, it is imperative to guide enterprises to green production and innovation, advocate for low-carbon life for residents, enhance environmental awareness, promote green consumption approaches, and collaborate to expedite green development.

Secondly, build a collaborative cooperation mechanism for interregional GTFP. It was found that the GTFP of different regions in China cannot converge to the same steady state, the advanced experience and frontier technology of high GTFP regions cannot spread to low GTFP regions, and the catch-up effect of regional green development has not been formed. Consequently, it is essential to actively facilitate green and high-quality developed regions to actively help underdeveloped regions, strengthen regular exchanges and communication, expedite the free flow of factors and staff, break regional administrative barriers, build influential cross-regional cooperation zones, and promote regional market integration.

Thirdly, accelerate the development of green industries and support future economic development with green industries. The government needs to scientifically formulate the development plan of green industry; promote the development of green industry through fiscal and tax policies, land policies, trade policies, green finance policies, and other economic policies; and increase support for environmental protection industry, cleaner production, and green service industry. At the same time, vigorously accelerate the greening of lifestyles and consumption patterns on the consumer side, drive low-carbon transformation and upgrading of industries through green consumption, and achieve efficient utilization of various resources through conservation, recycling, and utilization.

Fourthly, keep a foothold on regional comparative advantages and implement a GTFP improvement strategy tailored to local conditions. For regions with high GTFP, it is necessary to focus on optimizing the industrial structure, implementing more stringent environmental protection measures, accelerating the pace of factor market integration, giving full play to the strategic role of high-end factors such as data and technology, and accelerating the digital transformation of the economy. For areas with low GTFP, it is necessary to strengthen the upgrading and transformation of traditional industries, vigorously develop characteristic and advantageous industries, moderately elevate environmental regulatory standards, increase the acceptance of industries in developed regions, and coordinate the relationship between development and protection.

Fifthly, strengthen technological innovation and leverage the carbon reduction function of technological progress. In the process of urban development, it is integral to pay attention to improving the technological innovation ability of enterprises and scientific research institutions, especially the R&D and innovation of green low-carbon technologies. At the same time, formulate reasonable incentive policies, optimize enterprise management models and organizational methods, expedite balanced development of technological

innovation in various regions, and actively promote the steady improvement of regional economic quality. The government should also establish and boost a green growth assessment mechanism, effectively benefiting all people with the results of high-quality economic development and achieving a comprehensive increase in GTFP.

6.3. Research Deficiencies and Prospects

This study utilized the DDF and GML model index to measure the GTFP at the urban level in China, measuring the relative efficiency of each decision-making unit. Future research could explore methods for measuring absolute efficiency and compare and analyze the measurement results to further enrich the research on GTFP. Moreover, due to the limitation that the Malmquist–Luenberger index does not directly incorporate dynamic intertemporal relations in the carryover variables, this manuscript only deals with static productivity changes. Future research should draw on the relevant research [89–91], combine the dynamic Luenberger indicator, and select appropriate carryover variables to calculate a GTFP that reflects the dynamic time relationship.

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