The evolutionary characteristics and influencing factors of total carbon productivity: evidence from China

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Abstract
In order to systematically understand the evolution of total factor carbon productivity and explore its influence mechanism, based on panel data of 30 Chinese provinces from 2005 to 2019, the slacks-based measure of directional distance functions model and the Luenberger index are used to estimate the evolution of total factor carbon productivity, and the SYS-GMM model is constructed to explore the drivers of total factor carbon productivity and its influence effect. The results show that from 2005 to 2019, the overall level of total factor carbon productivity was low, but its growth index and decomposition term both showed an increasing trend; the development of total factor carbon productivity has regional differences. Only the eastern, northern, and middle Yellow River economic regions experience positive growth in total factor carbon production. The downward trend of total factor carbon productivity is most significant in the northwest and southwest economic regions, with $-2.577\%$ and $-1.463\%$, respectively; improvements in scale technology are the main reasons for improving total factor carbon productivity across time and regions; economic growth and environmental regulations contribute to total factor carbon productivity at 1% significance level, and industrial structure has a negative impact. Foreign direct investment inhibits total factor carbon productivity, but the effect is not significant. Based on these findings, this paper provides an effective reference for achieving the goal of low-carbon sustainable development and improving total factor carbon productivity.

Keywords Total factor carbon productivity · SBM-DDF model · Technological progress · Luenberger index · SYS-GMM model

Introduction

With the significant increase in energy consumption, greenhouse gas, and air pollutant emissions, climate change has become a common challenge for global sustainable development. According to the 2020 Emissions Gap Report, CO₂ is the major contributor to global warming and frequent extreme weather. Since the signing of the Paris Agreement, China has proposed the goal of “2030 carbon peak, 2060 carbon neutral” in 2020 in order to improve its independent contribution to global climate governance, and has incorporated carbon emission reduction into the overall layout of economic and social development, actively exploring effective paths for low-carbon economic development. However, after the normalization of the COVID-19, in 2021, the economic rebound has caused China’s carbon emissions to rise by 6.12% compared to the same period in 2019 (before the COVID-19). Meanwhile, the 2022 Global Environmental Performance Index (EPI) Report shows that China, the world’s second largest economy, ranks 20th from the bottom in EPI, with a large gap between environmental and economic levels. Based on self-organization theory, sustainable development emphasizes that development should neither overconsume resources causing ecological damage and economic instability, nor cause slow economic growth for optimal resource allocation. How to reduce the gap between economic development and carbon emissions is an issue that needs to be resolved for China to achieve its low-carbon sustainable development goals.
Kaya and Yokobori (1997) introduced the concept of carbon productivity, which is an indicator of the economic efficiency per unit of carbon emissions and can reflect the level of coordination between economic growth and carbon reduction. The higher the carbon productivity of a region, the more obvious the competitive advantage of economic and social development will be (Liang and Luo 2022). Therefore, under the Sustainable Development Goals, improving carbon productivity is the best way for China to deal with climate change issues and achieve high-quality economic development. The traditional carbon productivity only considers the relationship between carbon emissions and economic output. In fact, as carbon is an important factor in production activities (Zhuang et al. 2011), carbon emission is a complex system engineering which involves the input of multiple factors and the output of desired and undesired factors. Therefore, it is necessary to incorporate carbon emissions into the efficiency of production factor allocation. The carbon productivity measured in the total factor production framework with carbon emission reduction constraints is total factor carbon productivity (TCP) (Bai et al. 2019). TCP can be used as an important indicator to measure the efforts and effectiveness of a country or region to deal with climate change, and is of great significance to achieve regional low-carbon sustainable development. In the future competitive game, TCP can also be an evaluation standard for China to respond to international climate negotiations and to improve its low-carbon development strategy (Zhuang et al. 2011). Compared with previous studies, this paper innovatively combines the total factor productivity index decomposition method and dynamic regression model to explore the growth and drivers of TCP, which helps to deepen the understanding of the carbon productivity growth mechanism.

This paper has achieved the following contributions: In terms of research perspective, this paper considers carbon emissions as a kind of factor productivity. Based on the decomposition theory of productivity growth factors, this paper provides a more systematic analysis of TCP in China. Meanwhile, considering that TCP has economic connotations, this study further explores the LTCP of the eight integrated economic regions to more comprehensively verify the evolution of regional differences in TCP. In terms of research methods, most of the existing studies have used the slacks-based measure of directional distance functions (SBM-DDF) method or combined with the Malmquist-Luenberger index to measure carbon productivity, environmental efficiency, etc. (Li et al. 2018; Wang et al. 2019; Zhang and Xu, 2022). This paper combines the SBM-DDF and the Luenberger index to measure the spatial and temporal developmental changes of TCP in both static and dynamic dimensions, and chooses the SYS-GMM regression model to explore the influencing factors of TCP.

The rest of the paper is as follows: the second section is the “Literature review.” The “Method and data” section describes the methodology and data. The “Empirical results and analysis” section presents the empirical results and analyses. First, TCP and LTCP are analyzed in spatial and temporal dimensions, and the driving role of the decomposition term on LTCP is explored. Then a SYS-GMM model is constructed to explore the main influencing factors of TCP growth. The “Conclusions, policy implications, and future research” section summarizes the main findings and provides relevant implications for improving TCP.

**Literature review**

Productivity is the efficiency of unit factor input to material output and service output (Zhu, 2010). The input factors refer to the scarce resources that influence socio-economic development in a certain period, such as labor productivity and energy efficiency. As the constraints on carbon emissions output increase, the study of carbon productivity becomes particularly important. Kaya and Yokobori (1997) proposed carbon productivity, which reflects the economic benefits per unit of carbon emissions. The higher the carbon productivity, the more significant the effect of regional energy saving and emission reduction. As global climate and environmental problems become increasingly severe, improving carbon productivity is the key to achieving high-quality sustainable development and low-carbon transition in China (Wu and Yao 2021). The existing studies on carbon productivity have focused on the following three parts.

**The measurement of carbon productivity**

Scientifically accurate measurement of TCP is the basis of this study. Carbon productivity, as one of the efficiency indicators, is measured by the following two main methods: single-factor measurement and total-factor measurement. Under the single factor measure, carbon productivity is measured as the ratio of GDP per capita or the value added of GDP to CO₂ emissions. Because this method is easy to calculate and can visually evaluate the impact of carbon emissions on economic growth, many scholars have used it to explore the relationship between carbon productivity and economic development, industrial carbon productivity, etc. (Zhang et al. 2013; Zhang and Xu, 2016; Guo et al. 2021). Since production activities involve multiple input–output factors, the single-factor ratio method of measuring carbon productivity ignores the common effect of multiple factors and makes it difficult to portray its actual development trend. Therefore, more and more scholars have started to integrate total-factor indicators, such as capital and labor,
into the carbon productivity measurement index system to measure TCP. Data envelopment analysis (DEA), as a non-parametric method, can be measured directly for productivity with multiple input–output factors without setting a functional form, so it is the most widely used total factor measurement method. For example, Ma et al. (2021) used BCC model to measure the carbon emission efficiency of logistics industry, Wang et al. (2019) used directional distance function (DDF) and non-radial DEA to measure the environmental performance under economic growth objectives, and Zhou and Wang (2019) and Guo and Liang (2022) used super-efficient SBM method to measure the carbon emission rate from national and city levels to measure carbon emission rates.

All the above studies are static measurements. To explore the dynamic changes of TCP, Malmquist index and Malmquist-Luenberger (ML) index based on DEA model have become the main method to measure TCP growth. For example, Liu and Zhao (2016) and Cui and Zhang (2022) used the DEA-Malmquist index to measure TCP at the Yangtze River economic belt and provincial level, respectively. Han et al. (2022) constructed the SBM-ML model to measure regional TCP. The SBM-DDF can effectively solve the efficiency evaluation of non-desired outputs and the slackness of inputs or outputs (Fukuyama and Weber 2009). Therefore, in recent years, many scholars have combined SBM-DDF and ML index measures to analyze carbon productivity changes (Wang et al. 2019; Li et al. 2020a, b; Yang et al. 2021; Zhang and Xu, 2022). Chambers et al. (1996) extended the Luenberger productivity index. It is a proportional distance function with summation structure, which can consider both input reduction and output increase without the problem of choosing the measurement angle, and is more general than the ML index (Boussemart et al. 2003). Combining the above discussion, based on the studies of Liu and An (2012) and Zhu et al. (2021), this paper uses SBM-DDF and Luenberger index to measure total factor carbon productivity and its growth.

The development pattern of carbon productivity

China’s carbon productivity shows an upward trend at this stage (Niu et al. 2021), but there are significant regional differences and industry heterogeneity (Li et al. 2018; Zhong and Zhao 2021). For example, Pan and Zhang (2011) used the Thiel and decoupling indices to demonstrate that there are significant regional differences in China’s carbon productivity, with the eastern region performing the best. Xu et al. (2019) and Lan (2021) constructed convergence models to analyze the carbon productivity of manufacturing industries in Zhejiang Province and Chinese industries, respectively, and the findings showed significant absolute β convergence but not σ convergence in carbon productivity.

The analysis of factors influencing carbon productivity

Based on decomposition analysis and regression analysis methods, the existing studies can be divided into two categories. One category is the factor decomposition of carbon productivity based on time series data decomposition, such as Lu et al. (2018), Wang et al. (2019), Wang et al. (2020), and Guo et al. (2021) used LMDI factor decomposition to explore the effects of industrial structure, technology, and economic scale on the carbon productivity of manufacturing and industrial sectors. Lu et al. (2015) and Zang and Wu (2021) constructed a Laspeyres decomposition model, which showed that industrial structure contributes more significantly to carbon productivity compared to technological progress. Another category is based on regression models to explore the direction and extent of different factors on carbon productivity. Using the spatial lag model, Zhang et al. (2018) verified that import operations can significantly increase carbon productivity. From a socio-economic development perspective, it is a challenge to promote carbon reduction and economic growth at the same time. Wang et al. (2018) and Li and Wang (2019) showed that economic growth promoted carbon productivity and there was a non-linear relationship. Environmental regulation is an important tool for government environmental management. Based on the threshold regression model, Hu and Wang (2020) showed a U-shaped threshold relationship of environmental regulation on carbon productivity in China’s industrial sector, and the current strength of environmental regulation in China has not reached the threshold. According to Liu and Zhang (2021), industrial agglomeration and technological innovation are important mechanisms influencing industrial carbon productivity. Some scholars have also explored the effects of emissions trading (Zhou et al. 2020) and globalization strategies (Jahanger et al. 2022) on carbon productivity; however, most studies have focused on exploring the mechanisms of the relationship between single-factor economic development, industrial structure, environmental regulations, foreign trade, and carbon productivity.

In recent years, more and more scholars have started to focus on the study of carbon productivity, but the existing researches can be improved as follows. First, although there are literatures combining SBM-DDF and ML indices to solve the slackness of production factors, the Luenberger index is able to consider cost minimization and benefit maximization, and does not require the choice of measurement perspective. Therefore, this index is more suitable than the Malmquist index and ML index for measuring TCP growth. Second, studies on the influencing factors of TCP have mostly focused on the analysis of single-factor relationships such as technological progress and industrial structure (Yue et al. 2021; Wang et al. 2021a, b); the exploration of the
evolution and influence mechanisms of TCP is relatively weak. Based on the above studies, this paper combines the SBM-DDF model, which considers non-desired output and slackness, and the Luenberger productivity index to measure TCP and its growth in 30 Chinese provinces, analyzes the time evolution and spatial distribution characteristics of TCP, and explores the main decomposition dynamics driving its growth. After that, a SYS-GMM model is constructed to explore the effects of specific influencing factors on TCP.

Method and data

Total factor carbon productivity measurement model

DEA is widely used to analyze production efficiency because it can be used directly to process multiple factor inputs and outputs and is designed to measure efficiency constraints in a specific context (Zhang et al. 2011). In the DEA model, the DDF allows the effects of desired and undesired outputs to be considered separately. The DDF with ML index proposed by Chung et al. (1997) can solve the problem of productivity measurement based on non-expected output, but does not consider the slackness of input and output factors. Tone (2001) proposed the SBM model considering non-desired output and slackness, which can effectively solve the drawback of having zero slack in input–output factors. In view of this, Fukuyama and Weber (2009) proposed the SBM-DDF. It allows the desired output to expand toward the production frontier and the undesired output to decrease toward the production minimization frontier, which is consistent with the concept of sustainable production process. Therefore, this paper uses SBM-DDF to measure TCP from a static perspective. And the Luenberger productivity index does not have to consider the measurement perspectives of production factors; therefore, this method is used to measure the growth of TCP from a dynamic perspective.

In this paper, each province is considered a single decision-making unit (DMU). Referring to Ahmed (2020), the set of all possible outputs of a DMU (both desired and undesired outputs) constitutes the production possibility set \( P(x) \):

\[
P(x) = \{(k, l, e, g, b)| (k, l, e) \text{ can produce } (g, b)\}
\]  

In Eq. (1), \( x \) denotes the input factor and assumes that the input factor \( x = (k, l, e) \), \( k \), \( l \), and \( e \) denote the inputs of capital, labor, and energy, respectively. Through a series of production activities, the desired output \( (g) \) and undesired output \( (b) \) are obtained as gross regional product and carbon emissions, respectively. Based on production theory, the desired economic output is obtained with the joint output of carbon emissions. The directional distance function aims to increase the desired output while reducing the undesired output (Chung et al. 1997; Zhang et al. 2020). \( P(x) \) can be represented by the following linear programming:

\[
\bar{S}(x_t, g_k, b_k, d) = \sup \{ \beta : (g, b) + \beta d \in P(x) \}
\]  

\( x_t, g_k, b_k \) denote the input, desired output, and non-desired output indicators of province \( k \) in year \( t \), respectively. \( d = (g, -b) \), which indicates the increase in desired output and the decrease in undesired output. \( \beta \) is the ratio of the two outputs. Based on the above, the directional distance function is further introduced into the non-expected output SBM model. The SBM-DDF model constructed in this paper is shown below:

\[
\bar{S}(s'_{xt}, g', b', d', d) = \max_{s'_{xt}, g', b', d', d} \left\{ \frac{1}{N} \sum_{k=1}^{K} \frac{1}{M} \sum_{n=1}^{N} s'_{xkn} + \frac{1}{M} \sum_{i=1}^{N} s'_{yin} + \frac{1}{N} \sum_{n=1}^{N} s'_{dbn} \right\}
\]  

In Eq. (3), \( s'_{xk} \) denotes the weight of each cross-sectional observation. \( \bar{S} \) denotes the directional distance function under VRS. When the \( x_t \) constraint is removed, the directional distance function under CRS is denoted by \( \bar{S} \). \( (d', d', d) \) denotes the directional vector with positive input–output indicators. \( (s'_{xk}, s'_{yn}, s'_{db}) \) represents the input and output slack vectors, which reflect over-input, under-desired output, and over-undesired output, respectively.

Based on the SBM-DDF model, Chambers et al. (1996) proposed the Luenberger index, which can reflect the dynamic growth level of TCP. Therefore, in the total factor production framework with carbon emission reduction constraint, in order to emphasize the carbon emission factor, the Luenberger index is denoted as LTCP in this paper, and the expression of LTCP from period \( t \) to period \( t + 1 \) is as follows.

\[
LTCP_{t+1} = \frac{1}{2} \left\{ \bar{S}(x', g', b', d', d) + \bar{S}(x', g', b', d', d') - \bar{S}(x', g', b', d', d') \right\}
\]  

where \( \bar{S}(x', g', b', d', d') \) and \( \bar{S}(x', g', b', d', d') \) denote the directional distance function of the current period, which can be obtained directly by Eq. (3)
with the current period data. \( \overline{S}^{t+1} (x^t, g^t, b^t; d^t, d^h) \) denote the directional distance function across periods. For the cross-period direction distance measurement, under the production frontier surface in period \( t \), the directional distance function in period \( t+1 \) can be expressed by Eq. (5):

\[
\overline{S}^{t+1} (x_{kt}, g_{kt}^{t+1}, b_{kt}^{t+1}, d) = \max \left\{ \frac{1}{N} \sum_{n=1}^{N} \frac{c_n^{t+1}}{d_n} + \frac{1}{M} \sum_{m=1}^{M} \frac{c_m^{t+1}}{d_m} + \frac{1}{T} \sum_{t=1}^{T} \frac{d}{d^h} \right\}
\]

(5)

\[
\begin{align*}
&\sum_{t=1}^{T} \sum_{k=1}^{K} c_{k}^{t} x_{kn}^{t} + s_{n}^{t} = x_{kt}^{t+1}, \quad \forall n \\
&\sum_{t=1}^{T} \sum_{k=1}^{K} c_{k}^{t} y_{km}^{t} - y_{km}^{t} = y_{mt}^{t+1}, \quad \forall m \\
&\sum_{t=1}^{T} \sum_{k=1}^{K} c_{k}^{t} b_{ki}^{t} + s_{i}^{t} = b_{ki}^{t+1}, \quad \forall i \\
&\sum_{k=1}^{K} c_{k}^{t} = 1, \quad c_{k}^{t} \geq 0, \quad \forall k \\
&s_{n}^{t} \geq 0, \forall n \\
&d_{m}^{t} \geq 0, \forall m \\
&d_{i}^{t} \geq 0, \forall i
\end{align*}
\]

Similarly, \( \overline{S}^{t} \) denotes the directional distance function under VRS, and when the constraint \( \sum_{k=1}^{K} c_{k}^{t} = 1 \) is removed, \( \overline{S}^{t} \) is used to denote the directional distance function under CRS. For the directional distance function in period \( t \) under the production front surface in period \( t+1 \), it is sufficient to replace \( t \) with \( t+1 \) and \( t+1 \) with \( t \) in Eq. (5).

LTCP > 1 ( < 1) indicates an increase (decrease) in total factor productivity carbon. In the framework of sustainable development, the key to combat climate change is to improve carbon productivity. LTCP can reflect that a country or region has achieved significant results to combat climate change (He and Su 2009). To understand more about the dynamics of TCP, LTCP is divided into four components: pure technical efficiency change (PEC), scale efficiency change (SEC), pure technical progress (PTC), and scale technical change (STC). The decomposition process of LTCP requires solving four linear programs under two assumptions, CRS and VRS, respectively, including eight directional distance functions. These can be found by referring to Eqs. (3) and (5).

\[
TCP = PEC + SEC + PTP + STC
\]

(6)

\[
PEC_{t+1} = \overline{S} (x^t, g^t, b^t; d^t, d^h) - \overline{S} (x^{t+1}, g^{t+1}, b^{t+1}; d^t, d^h)
\]

(7)

\[
SEC_{t+1} = \frac{1}{T} \left\{ \frac{S_t^{t+1}}{T} \right\} (x^t, g^t, b^t; d^t, d^h) - \frac{1}{T} \left\{ \frac{S_t^{t+1}}{T} \right\} (x^{t+1}, g^{t+1}, b^{t+1}; d^t, d^h)
\]

(8)

PEC and SEC are technical efficiency change indices that measure the degree of convergence of each DUM toward the production frontier from moment \( t \) to moment \( t+1 \). PEC > 1 and SEC > 1 indicate that the technological advancement drives the growth of TCP. PTC and STC are indices of technological progress change, which reflect the movement of production technology in the direction of output increase from moment \( t \) to moment \( t+1 \). PTC > 1 and STC > 1 indicate that the movement of production frontier in the time period \( (t, t+1) \) has a positive impact on total factor productivity change.

**SYS-GMM regression model**

LTCP and policy variables may have lags. In order to weaken the time correlation of the productivity index and the problem of endogeneity of the variables, lagged terms of the explanatory variables and environmental regulations are introduced in the explanatory variables. Due to the use of lagged variables, ordinary least squares (OLS), fixed effects (FE), and random effects (RE) models inevitably produce errors (Wang et al. 2021a, b), whereas generalized moment estimation (GMM) can maximize the validity of variables and reduce standard errors, and it is the ideal model for this study, since SYS-GMM can simultaneously solve the endogeneity of lagged variables and improve the validity of estimation results (Cao et al. 2017). Therefore, based on the main influencing factors summarized in the second section of the paper “Literature review,” this study constructs a SYS-GMM regression model to analyze the influencing factors of carbon productivity.

\[
LTCP_{t+1} = \beta_1 TCP_{t,j-1} + \beta_2 EG_{kt} + \beta_3 ER_{kt,j-2} + \beta_4 FDI_{kt} + \beta_5 IS_{kt} + \alpha_k + \mu_{kt}
\]

(11)

\( LTCP_{t+1} \) denotes the average growth rate of TCP from year \( t \) to year \( t+1 \) in province \( k \). \( LTCP_{t,j-1} \) and \( ER_{kt,j-2} \) denote the lagged variables TCP and environmental regulations, respectively. \( EG_{kt} \), \( FDI_{kt} \), and \( IS_{kt} \) refer to economic growth, foreign direct investment, and industrial structure, respectively. \( \beta \) indicates the parameter to be estimated, \( \alpha_k \) represents the intercept of individual heterogeneity, and \( \epsilon_{kt} \) indicates the random perturbation term.
**Indicator selection and data description**

**Indicator selection**

1. **TCP.** Input indicators consist of three input factors: labor, capital, and energy: Labor input is expressed as the number of employees at the end of the year in the region; capital input is measured by the capital stock obtained according to the perpetual inventory method; energy input is characterized by the total energy consumption in each province. The expected output indicator is expressed in terms of gross regional product, and it is deflated based on the constant prices specified in 2000 in order to ensure the comparability of economic indicators. For carbon emissions, many previous studies have measured carbon emissions based on the low-level heat generation and carbon oxidation rate of end-use energy. Considering that the latest energy balance data is only updated to 2017, the timeliness of the measurement results is weak, so based on the 2006 IPCC Guidelines for Greenhouse Gas Inventories and the Guidelines for the Preparation of Provincial Greenhouse Gas Inventories, this paper constructs the following measurement formula:

\[
CO_2 = \sum_f E_{kf} \cdot \mu_f \cdot \gamma_f \cdot \frac{44}{12} \tag{12}
\]

where \(E_{kf}\) denotes the consumption of the \(f\)th end-use energy in province \(k\) in year \(t\), \(\mu_f\) and \(\gamma_f\) denote the \(f\)th energy standard coal conversion factor and carbon emission factor, respectively (Table 1). \(44/12\) represents the molecular ratio of carbon in \(CO_2\).

2. **Economic growth (EG).** Economic growth mainly refers to the increase of factor inputs or the improvement of utilization rate in a certain period, so that the economic scale can be effectively expanded. The balance between economic growth and carbon emissions is the key to achieve green and high-quality development, so EG is introduced to further explore the mechanism of the relationship between it and TCP. Considering that factors such as human capital can disturb the measurement of the real economy, this paper uses GDP per-capita growth rate to reflect EG (Shao et al. 2013).

3. **Environmental regulation (ER).** As an effective tool of government ecological governance, environmental regulation can stimulate the reallocation of factor resources such as technology and capital, which will influence TCP (Guo and Sun 2020). Considering the availability of data, referring to the indicator treatment of Li and Zou (2018), the combined values of pollutant-containing wastewater, \(SO_2\) emissions, and smoke (dust) emission indicators are derived based on the entropy value method, which can represent ER. Based on China’s national conditions, local governments have a certain time lag in implementing central policies, and the implementation effect of local producers tends to appear as the intensity of environmental regulation increases. Therefore, this paper chooses environmental regulation with a one-period lag as one of the explanatory variables.

4. **Foreign direct investment (FDI).** The technology spillover effect brought by the entry of foreign investors will increase the local carbon productivity, but at the same time, the carbon emission will also increase with the expansion of production scale. Therefore, in order to explore the effect of FDI on TCP, this paper measures FDI using the ratio of actual foreign investment to regional GDP.

5. **Industrial structure (IS).** A reasonable industrial structure is the basis for achieving a balanced development between economic growth and carbon emissions (Wang et al. 2021a, b). Theoretically, the higher the level of low-carbon technology of industrial structure, the more beneficial it is to improve carbon productivity. Therefore, this paper expresses IS using the proportion of secondary sector value added to regional GDP.

The descriptive statistics of the variables are shown in Table 2.

**Research subjects and data sources**

Considering the availability and continuity of data, this paper takes the panel data of 30 provinces in mainland China (except Tibet) from 2005 to 2019 as the research sample. Considering that the developmental evolution of industries, ecological environment, etc. has regional differences, in order to better reflect the relationship between economy and carbon emission space, this paper further explores the spatial

| End-use energy sources     | Coal   | Coke  | Crude oil | Gasoline | Kerosene | Diesel | Fuel oil | Natural gas |
|---------------------------|--------|-------|-----------|----------|----------|--------|---------|------------|
| Standard coal conversion factors | 0.7143 | 0.9714 | 1.4286    | 1.4714   | 1.4714   | 1.4571 | 1.4286   | 1.2150      |
| Carbon emission factors   | 0.7559 | 0.8550 | 0.5857    | 0.5538   | 0.5714   | 0.5921 | 0.6185   | 0.4483      |
and temporal evolution of TCP based on eight integrated economic Regions in China according to the Strategies and Policies for Coordinated Regional Development (Table 3).

In the regression analysis, to further reduce the possibility of total factor carbon productivity serial correlation, this paper divides the sample period of 2005–2019 into five growth intervals, 2005–2007, 2008–2010, 2011–2013, 2014–2016, and 2017–2019. Referring to Voitchovsky (2005) and, the variables are averaged over the corresponding time period, except for the variables TCP<sub>k, t-1</sub> and ER<sub>k, t-1</sub>, which take the initial values of the corresponding time period. For example, in the interval of 2005–2007, LTCP<sub>k, t-2</sub> is the average growth rate of Y variables from 2005 to 2007, LTCP<sub>k, t-1</sub> and ER<sub>k, t-2</sub> are distributed to represent the LTCP variables from 2005 to 2006 and the initial environmental regulation values in 2005, and other variables such as IS are taken as the average of 2005, 2006, and 2007. The raw data involved in this paper are taken from the China Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, and regional statistical yearbooks, and some missing data are processed by interpolation.

### Empirical results and analysis

#### Total factor carbon productivity evaluation

Based on a static analysis perspective, the SBM-DDF model was used to measure TCP in 30 Chinese provinces from 2005 to 2019. From Fig. 1, only 46.667% of provinces had annual average TCP greater than 1.00, among which Beijing and Shanghai had the highest TCP of 1.032. The level of TCP in Qinghai and Hainan provinces is 0.929 and 0.969, respectively, and the decreasing trend was more significant. In general, there is more room for improvement in China’s TCP; this is consistent with the findings of Hu and Wang (2020) and Bai and Sun (2021) for the analysis of TCP changes in China. Specifically, the provinces with lower or declining TCP are mostly located in the northwest and northeast regions with relatively backward development level, such as Ningxia, Qinghai, and Heilongjiang, while coastal regions such as Jiangsu, Shandong, Beijing, and other developed regions show an upward trend in TCP. Han et al. (2022) showed that adequate technology and capital in developed regions will undoubtedly improve resource utilization and carbon emissions more effectively. So improving TCP requires mutual collaboration of high-quality resource elements.

#### Time evolution of total factor carbon productivity

Based on the dynamic analysis perspective, this paper measured the LTCP of 30 provinces in China from 2005 to 2019 using the Luenberger index. From 2005 to 2019, LTCP grew at an average annual rate of 1.476%, and its decomposition terms efficiency change (PEC, SEC) and technology change (PTC, STC) also showed growth, especially the scale technology grew at an average annual rate of 2.276%. As can be seen from Fig. 2, a downward trend in TCP was observed.
from 2007 to 2009, and the STC decomposed from the changes in technological progress significantly contributed to this development trend. Although the country began to develop a series of emission reduction measures such as the Comprehensive Work Plan for Energy Conservation and Emission Reduction during the Eleventh Five-Year Plan, technical support for low-carbon industrial structure was still immature due to the long-term rough development model, and the problem of inefficient resource allocation was relatively prominent. As a result, the TCP continued to decline during the period, but the rate of decline was decreasing year by year.

TCP started to improve since 2010. In 2017–2018, the growth rate of TCP reached 6.079% and STC improved by 4.804%. STC is the main source of contribution to drive LTCP. Han et al. (2022) suggested that China’s TCP enhancement in this period is mainly driven by China’s new development concept. This may be due to the fact that since the 18th National Congress, China has been increasing its financial support for scientific research to stimulate green technological innovation, promoting high-quality industrial agglomeration and efficient allocation of production factors through policies, thus achieving the synergistic development of green technological progress and economic scale increment. Comparing the trend lines of LTCP and its decomposition terms, it can be concluded that the trend of STC changes is very similar to the trend of LTCP, which indicates that technological progress, especially the improvement of STC, is the key to drive LTCP. And the efficiency changes including PEC and SEC do not contribute much to LTCP.

**Regional differences in total factor carbon productivity**

As can be seen from Table 4, only the TCP of the eastern coast, northern coast, and the middle Yellow River region had increased, with growth rates of 2.408%, 1.425%, and 0.368%, respectively. The TCP of the other five integrated economic regions showed a decreasing trend. Inland areas are relatively lagging behind in terms of environmental productivity (Wang et al. 2016), especially the TCP of the northwest and southwest regions showed a significant decrease of 2.577% and 1.463%. Su and Lu (2019) pointed out that geographical location and economic development advantages bring innovative development environment and high-quality human resources. Therefore, effective technological advances in the northern and eastern coasts are able to meet the development needs of economies of scale while achieving optimal production scale, thus making the scale efficiency and scale technological effectively play a role in promoting carbon productivity. The LTCP is relatively low in the middle Yellow River due to the average decline of 0.212% in STC. Although the Northeast region achieved 0.045% growth in pure technological progress, SEC and
STC decreased by 0.272% and 0.368%, which directly affected the growth of TCP. This indicates a decreasing trend of economic scale payoffs in northeast China, technology and production do not advance in synergy, and technological change deviates from the optimal economic scale. For the middle Yangtze River region and the southern coastal region, SCT in the technological progress index is the main factor limiting the annual average TCP growth.

**Analysis of factors influencing total factor carbon productivity**

According to economic growth theory, LTCP can explain the effect on productivity in terms of both technical progress and technical efficiency, but this effect is caused by a combination of economic scale, industrial structure, and other factors. The econometric regression analysis can confirm the relationship between micro tangible factors and LTCP,
which is more useful in understanding the LTCP growth mechanism. Therefore, this paper further explores the drivers of TCP based on the SYS-GMM regression model. From the regression results, the Hansen test results accept the hypothesis that the instrumental variables are valid, and the SYS-GMM regression estimates fall between the estimates of mixed OLS and fixed effects. Furthermore, the direction of each variable’s effect on LTCP is the same with and without dividing the time period. Therefore, it can be verified that the regression results are reliable (Bond 2002). Considering the small sample size of this paper, the asymptotic standard error of the two-step SYS-GMM regression produces downward bias, so this paper focuses on the regression results of the one-step SYS-GMM in Table 5.

LTCP with a one-period lag plays a significant positive impact on the following year, which verifies that TCP is time-series correlated. For every 1 unit increase in economic growth at 1% significance, LTCP increases by 0.150; this is consistent with the findings of Guo and Sun (2020). On the one hand, because economic growth will stimulate market dynamics, production enterprises are going to vigorously develop green and clean technologies to improve their competitive advantage under the trend of reducing emissions and increasing efficiency; on the other hand, when economic growth meets people’s demand for material quality, the awareness of self-restraint and social supervision of energy conservation and emission reduction is greatly enhanced, which will inevitably reduce carbon emissions from production and life, and then enhance carbon productivity. At the 1% significance level, environmental regulation with a one-period lag is positively correlated with LTCP, the coefficient of 0.189; this is the same trend as the study by Wang and Wei (2020). Based on the Porter hypothesis, environmental regulation will promote the optimization of industrial structure over time by stimulating green technological innovation, which will significantly reduce the CO₂ emissions of production and life. For every 1 unit increase in the industrial structure, measured by the share of secondary value added in GDP, the LTCP decreases significantly by 0.014. Li et al. (2020a) showed that the increase in the share of secondary sector will lead to an increase in total energy consumption and waste, which is not favorable to reduce carbon emissions. Since the “Eleventh Five-Year Plan,” although the country has adjusted the industrial structure, due to the strong inertia of the old high-energy-consuming industrial development model, the actual situation of “adjusting but not fast” or even “rebonding after adjusting” still exists; as a result, the current industrial structure may inhibit LTCP. There is a negative correlation between FDI and LTCP; the coefficient is -0.014, but the effect is not statistically significant. This may be due to the fact that foreign direct investment is still mainly concentrated in manufacturing and production processing industries. The increased scale of production increases carbon emissions, which offsets the positive effect of technology spillovers on carbon productivity.

Table 5 Regression results

| Variables | LTCP (t, t+2) | LTCP (t, t+2) | LTCP (t, t+2) | LTCP (t, t+2) | LTCP (t, t+1) |
|-----------|--------------|--------------|--------------|--------------|--------------|
|           | POLS         | One step SYS-GMM | FE           | Two step SYS-GMM | One step SYS-GMM |
| L.LTCP    | 0.215**     | 0.124*       | 0.065**     | 0.125*       | 0.101*       |
|           | (1.78)       | (1.80)       | (1.28)       | (1.70)       | (2.07)       |
| EG        | 0.170*       | 0.150***     | 0.112**     | 0.158***     | 0.109**     |
|           | (1.63)       | (3.84)       | (2.95)       | (3.23)       | (2.99)       |
| LER       | 0.082        | 0.189***     | 0.238***    | 0.237***     | 0.166***    |
|           | (0.78)       | (3.47)       | (5.63)       | (4.68)       | (5.82)       |
| IS        | -0.232***    | -0.090**     | -0.063**    | -0.088***    | -0.064**    |
|           | (-4.47)      | (-4.16)      | (-3.34)     | (-3.49)      | (-2.73)     |
| FDI       | -0.013       | -0.014       | -0.054      | -0.019       | -0.038*     |
|           | (-1.22)      | (-0.28)      | (-1.08)     | (-0.27)      | (-0.79)     |
| Constant  | 0.511***     | 0.282***     | 0.350***    | 0.275***     | 0.342***    |
|           | (5.82)       | (5.09)       | (6.27)      | (3.89)       | (8.12)      |
| Year      | No           | Yes          | No           | Yes          | Yes         |
| AR (1)    | 0.002        | 0.014        | 0.119       | 0.073        | 0.750       |
| AR (2)    | 0.114        | 0.863        | 0.402       |              |             |
| Hansen test | 0.942     |              |              |              |             |

T-values in parentheses; *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.
Conclusions, policy implications, and future research

Conclusions

This paper combines the SBM-DFF model and the Luenberger index to evaluate TCP in different periods and regions from both dynamic and static dimensions, and further explores the specific factors influencing TCP based on the SYS-GMM model. The main findings are as follows:

(1) From the temporal analysis, the TCP is below 1 in most regions of China from 2005 to 2019, and there is more room for improvement. The development of TCP coincides with the degree of regional economic development, which is consistent with the findings of Han et al. (2022). LTCP can be decomposed into technical efficiency change index (PEC, SEC) and technical progress change index (PTC, STC). Among them, the average annual growth rate of STC reached 2.276%, and it is the main contributing source of TCP growth, which is closely related to China’s intensive promotion of green technology innovation for energy conversion and emission reduction. The effect of efficiency changes on TCP is not significant, which suggests that the current production activity has a weak ability to catch up to the optimal production frontier.

(2) From the spatial analysis, LTCP has obvious regional differences. The LTCP of the northwest economic region, where Ningxia and Qinghai are located, is obviously low, with a negative LTCP growth rate of 2.577%. The northern and eastern coastal economic regions have higher LTCP, achieving an average annual growth rate of 2.408% and 1.425%, respectively. The improvement of STC is the key to drive LTCP.

(3) From the results of the regression analysis, EG and L.ER can significantly promote LTCP, and the correlation coefficients are 0.150 and 0.189, respectively, which further confirms the findings of Li et al. (2020b). Meanwhile, this reflects that the current market economy environment and environmental governance tools in China are effective in promoting LTCP. IS is negatively correlated with LTCP, the coefficient is −0.090. Therefore, the current industrial structure needs to be optimized, and then to increase TCP. The effect of FDI on TCP is not significant. As shown by Song (2021), the interaction mechanism between FDI and carbon productivity improvement needs to be further strengthened.

Policy implications

Based on the main findings, the following policy implications are recommended in order to improve the TCP of the 30 provinces in China:

(1) First, the improvement of STC is the main contribution to drive LTCP, and there is room for improvement of TCP in most of China. In order to effectively increase carbon productivity, on the one hand, research and development investment in zero carbon and other green low-carbon technologies can be increased to achieve breakthrough innovation and application of energy saving and emission reduction. On the other hand, considering that LTCP has regional differences, for economic regions such as the northwest and northeast, a platform can be built for sharing scientific and technological resources related to carbon reduction with the eastern coastal economic regions, so as to promote the coordinated development of technological progress and economies of scale through advanced green and intensive production and management methods, and further contribute to the overall improvement of TCP.

(2) Second, current technical efficiency changes do not drive TCP significantly, so it is critical to optimize the factor allocation structure to accommodate technological progress. Secondary industry plays an important role in China’s socioeconomic development, but according to the above regression results, the higher the current proportion of secondary industry, the less beneficial it is to carbon productivity growth. Thus, it is crucial to adjust the production structure and optimize the internal structure of the industry to promote carbon reduction and efficiency in China. On the one hand, it can actively develop new energy and other low-carbon industries, and accelerate the development of industrial green transformation; on the other hand, the industry’s internal structure can be optimized. Incorporating emission reduction capacity into the capacity reduction replacement threshold will stimulate various industrial sectors to promote low-carbon intensive and high value-added production structures through green technology innovation. Third, the Chinese government has developed and implemented a series of environmental regulation instruments to achieve the goal of low-carbon sustainable development. The results from this paper show that ER can significantly contribute to LTCP. In order to further exploit the positive effects of environmental regulation, when developing environmental regulations, in addition to the goal of reducing carbon emissions, the impact of environmental regulations on the free disposal of production factors should be considered to maximize the economic efficiency of production. Meanwhile, in order to improve the administrative enforcement of environmental regulation, the ecological assessment system that includes the effectiveness of carbon reduction efforts should be improved. In addition, the level of greening of FDI introduction should be improved under the constraint of environmental regulation instruments, so as to play a positive role in promoting FDI on carbon productivity.
Research deficiencies and future research

There are some shortcomings in this paper, which can be improved in the future research. First, this study analyzes the level of development of TCP in China and its influence path, selecting panel data of provinces for empirical analysis with a limited sample size. In the future, the analysis can be attempted using micro data with larger sample size, and the obtained results can be compared with previous empirical results. Secondly, this paper is only a measurement analysis of the existing carbon productivity, and in the future research, we can try the long-term prediction of carbon productivity and further clarify the methodological paths that can improve TCP and expand the framework of TCP research ideas.

Author contribution
Shengnan Cui and Yanqiu Wang conceived and designed the research question. Shengnan Cui and Ping Xu constructed the models and analyzed the optimal solutions. Shengnan Cui wrote the paper. Zhiwei Zhu reviewed and edited the manuscript. All authors read and approved the manuscript.

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Data availability
The datasets generated and/or analyzed during the current study are property of the National Bureau of Statistics; they are available from the corresponding author who will inform the National Bureau of Statistics that the data will be released on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Consent to publish
Not applicable.

Conflict of interest
The authors declare no competing interests.

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