Available online at www.sciencedirect.com

ScienceDirect

Advances in Climate Change Research 13 (2022) 266−278

www.keaipublishing.com/en/journals/accr/

Dynamic changes and convergence of China's regional green productivity: A dynamic spatial econometric analysis

Xu-Quan ZHAI[a], Rui XUE[b], Bin HE[c,*], Dong YANG[d], Xiang-Yu PEI[e], Xian LI[f,**], Yuli SHAN[g]

[a] Research Center for Socialism with Chinese Characteristics, Zhejiang University, Hangzhou 310058, China
[b] Centre for Corporate Sustainability and Environmental Finance, Department of Applied Finance, Macquarie University, Sydney 2109, Australia
[c] China Center for Public Sector Economic Research, Jilin University, Changchun 130012, China
[d] School of Statistics, Southwestern University of Finance and Economics, Chengdu 611130, China
[e] School of Economics, Jilin University, Changchun 130012, China
[f] College of Textile, Donghua University, Shanghai 201620, China
[g] Integrated Research on Energy, Environment and Society (IREES), Energy and Sustainability Research Institute Groningen, University of Groningen, Groningen 9747 AG, the Netherlands

Received 16 September 2021; revised 18 November 2021; accepted 28 January 2022
Available online 7 February 2022

Abstract

Low-carbon economic development is at the heart of the post-pandemic green recovery scheme worldwide. It requires economic recovery without compromising on the environment, implying a critical role that green productivity plays in achieving the carbon neutrality goal. Green productivity measures the quality of economic growth with consideration for energy consumption and environmental pollution. This study employs the slacks-based measure directional distance function (SBM-DDF) approach and the Malmquist-Luenberger (ML) index to calculate green productivity and its components of 30 provinces in China between 2001 and 2018. Using a spatial panel data model, we empirically analyzed the conditional β-convergence of China's green productivity. We found that overall, since 2001, China's green productivity has demonstrated a continuous upward trend. When taking into account spatial factors, China's green productivity demonstrates a significant conditional β-convergence. In terms of regional effects, the results indicate that the green productivity of the eastern and western regions demonstrates club convergence, implying a more balanced green economic development. Moreover, the convergence rate of China's green productivity increases with the addition of environmental regulation variable, and so the corresponding convergence time decreases. It indicates that environmental regulations help to facilitate the convergence of China's green productivity, narrowing the gap between the regional green economic development. The findings provide guideline for achieving a low-carbon development and carbon neutrality from a regional green productivity perspective.

Keywords: Green productivity; Slacks-based measure of directional distance function (SBM-DDF); Malmquist-Luenberger (ML) index; Conditional β-convergence; Spatial econometrics; Carbon neutrality

1. Introduction

During the COVID-19 pandemic, although the demand for fossil fuels has decreased dramatically, the demand for green energy has demonstrated an increasingly growing pattern (Wan et al., 2021; Tian et al., 2022). It is thus not surprised that instead of a pure economic recovery like economic stimulus scheme after 2008 global financial crisis, many

* Corresponding author.
** Corresponding author.
E-mail addresses: hebin1979@jlu.edu.cn (HE B.), lixian@dhu.edu.cn (LI X.).
Peer review under responsibility of National Climate Center (China Meteorological Administration).

https://doi.org/10.1016/j.accre.2022.01.004

countries have proposed and implemented green recovery schemes (Barbier, 2020; Liu et al., 2021b) in which low-carbon development is the primary goal (Liu et al., 2021c). China has been pioneering and leading the low-carbon recovery (Xu et al., 2021), e.g., on September 22, 2020, the Chinese government has announced the aim to "have CO_2 emissions peak before 2030 and achieve carbon neutrality before 2060", highlighting China's strong commitment to the carbon neutrality (Huang and Zhai, 2021). Moreover, China's national carbon emission trading scheme (ETS) began formal trading from July 2021. As the world's largest ETS, the carbon market currently covers more than 4 Gt of annual emissions, more than two thousand coal-fired and gas-fired power generation firms in the first stage, and plans to include other high energy-consuming and high-polluting industries such as steel and chemical industry in the next few years. China's rapid industrialization has long been characterized by 'high input, high energy consumption, and high discharge' and by an environmental practice of 'pollution first and remediation later'. This development model has compromised on the environment and resources (Shao et al., 2021), and has continuously increased the gap between energy supply and demand. The reason for the widening gap between energy supply and demand is mainly due to China's energy consumption structure.

Moreover, it has aggravated the cost of environmental degradation and the loss due to ecological damage (Jie et al., 2021). Ma et al. (2019) reported that the total cost due to environmental degradation and ecological damage was 1538.95 billion and 441.7 billion CNY, accounting for 3.5% and 1.0%, respectively, of the 2014 China's gross domestic product (GDP). From 2004 to 2014, the annual growth rate of the total costs in terms of environmental degradation and ecological damage was 13.7% and 9.6%, respectively. Realizing that economic growth dependent on high input and discharge is harmful and not sustainable, the Chinese government has adopted a series of policies and regulations to tackle the increasingly severe environmental issues.

Resources and the environment are not only rigid constraints to the scale and speed of economic development but also endogenous variables of economic growth (Giddings et al., 2002; Lin et al., 2020). Traditional measurements of total factor productivity (*TFP*) do not consider undesirable outputs resulting from resource and energy consumption. The traditional approaches of analyzing and assessing economic performance only consider *TFP* and omit the constraining effect of resources and the environment. Therefore, these approaches have a possible bias (Hailu and Veeman, 2000; Long et al., 2015). In comparison, green productivity (*GP*), or green total factor productivity (*GTFP*), considers energy consumption and environmental pollution and can measure the quality of economic growth more accurately (Liu et al., 2021c). Therefore, it is an important indicator for assessing the economic growth modes and the sustainable development of a country or region (Liu et al., 2021a). As a new type of productivity measurement, green productivity builds on the traditional total factor productivity measurement and incorporates energy and environmental constraints into the measurement framework, thereby embodying green and sustainable economic development principles (Zhu et al., 2020).

The core issue is how to incorporate energy consumption and environmental pollution into the classical measurement framework of total factor productivity. Prior research usually adopts the following four approaches. The first approach treats energy consumption and environmental pollution as input factors (Hailu and Veeman, 2001) and employs input distance functions to measure the productivity that incorporates environmental factors. The second approach performs certain algebraic transformations of the undesirable outputs by using two methods: the first method takes the reciprocals of the undesirable outputs as desirable inputs (Scheel, 2001; Lovell et al., 1995); and the second method converts the undesirable outputs into desirable inputs through a linear monotone decreasing transformation (Seiford and Zhu, 2002). The third approach employs the metafrontier technique to measure eco-efficiency (Picazo-Tadeo et al., 2014; Sáez-Fernández et al., 2012), which defines all the feasible combinations of economic value added (EVA) and environmental pressures as the 'pressure generating metatechnology set (PGMT)'. The fourth approach employs the directional distance function (DDF). Färe and Grosskopf (2010) further combined the DDF and slacks-based measure (SBM) and proposed the SBM-DDF. This approach can measure productivity from multiple aspects and can also measure the impact when inputs or outputs have none-zero slacks. In comparison with the first three approaches, the advantage of the SBM-DDF is that, it incorporates both desirable and undesirable outputs into the measurement without any algebraic transformation, thus retaining the original data of undesirable outputs and reflecting a PPS that is better aligned with the actual green production process (Arabi et al., 2015; Halická and Trnovská, 2021). Meanwhile, the model meets the convexity requirement and can be solved via linear programming. Therefore, a large volume of research has adopted the DDF and its extension methods to study the GP of different countries or regions.

Moreover, analyzing the convergence of regional *GP*, whether it is converging or diverging, is critical to identifying differences in regional economic growth and to enhancing the coordinated development of regional economies (Gerschenkron, 1962; Grossman and Helpman, 1991; Young, 1995; Easterly and Levine, 2001; Islam, 2003). The existing research proposes two types of convergence: absolute convergence, in which productivity converges at the same level, and conditional convergence, in which productivity converges at different levels. Typical absolute convergences mainly include the σ-convergence and absolute convergence (Baumol, 1986; Barro and Sala-I-Martin, 1995), while conditional convergence includes the conditional β-convergence (Miller and Upadhyay, 2002). The implication of absolute convergence is that underdeveloped regions can eventually catch up with and surpass developed regions and reach the same stable level, whereas conditional convergence means that underdeveloped regions and developed regions can reach their respective stable states but underdeveloped regions cannot surpass the developed regions.

During recent years, some scholars began to study whether energy efficiency and *GP* in different countries and regions converge. For instance, Miketa and Mulder (2005) examined the convergence of energy productivity of 10 manufacturing sectors in 56 developed and developing countries between 1971 and 1995; the empirical results showed that the cross-country energy productivity demonstrates certain degrees of convergence. Mulder and De Groot (2012) studied the convergence of the energy intensity of 50 sectors of manufacturing and services in 18 OECD countries during the period 1970–2005 and found that for most sectors, lagging countries are catching-up with leading countries in terms of energy intensity; it is noted that the convergence rate of energy intensity in the service sectors is higher than that of the manufacturing sectors. Huang et al. (2018) used China's city-level data to test the regional convergence of energy productivity. Their results of the generalized method of moments (GMM) model indicated that China's regional energy productivity has three different types of club convergence and that the regional resource endowment and differences in institutional arrangements are major reasons for the differences in the convergence of regional energy productivity. To control trade-flow related spatial effects, Wan et al. (2015) applied the spatial panel data model and examined the energy productivity of the manufacturing sector of 16 European Union (EU) countries. The results indicated that the energy productivity has both σ- and β-convergence. It is noted that the tests of the convergence of regional productivity discussed above tend to use regional data; but they fail to consider the fact that regional data usually have a significant spatial correlation.

Existing research has examined the influencing factors of green productivity, however, little attention has been received for the convergence of regional green productivity. This is important because understanding the convergence pattern of China's regional green productivity is advantageous for coordinating regional ‘green’ development and so has important implications for high-quality economic development. Although existing studies have tried to use the SBM-DDF method to measure China's green productivity, they fail to investigate the spatial pattern and time-varying pattern of China's regional green productivity and its components. Ignoring regional *GP*'s spatial correlation has serious impacts on the test results for convergence and considerably reduces the effectiveness of the empirical analysis.

Therefore, using the panel data of China's 30 province-level administrative divisions (hereafter referred to as provinces) from 2001 to 2018, this study employs the slacks-based measure directional distance function (SBM-DDF) approach and the Malmquist-Luenberger (ML) productivity index to calculate China's regional *GP* and its components. Moreover, the global spatial autocorrelation technique is applied to test whether the *GP* and its components among different regions have significant spatial correlations. Building on the spatial correlation test, we constructed a spatial panel data model and empirically analyzed the conditional β-convergence of China's *GP* and its components. Last but more important, it is particularly imperative to analyze China's regional *GP* and its convergence from the perspective of reducing regional development gaps, promoting the coordinated development among regions. As such, we further examined whether environmental regulations affect the conditional β-convergence of China's *GP*.

This paper makes contributions to the existing literature from three aspects. Firstly, this paper applies the SBM-DDF method to calculate the green productivity and its decomposition components in China, and so analyzes the spatial characteristics and changing patterns of China's regional green productivity and its components. Second, we contribute to the green productivity literature by applying the spatial econometric models to examine the convergence of China's regional green productivity. Third, considering the importance of institutional factors in China, we contribute to the literature by demonstrating dynamics between environmental regulation and the convergence of China's regional green productivity. When different regions intensify environmental regulation, the differences of green productivity among regions will be reduced, resulting in the convergence of regional green productivity.

2. Method and data

2.1. SBM-DDF model

Based on Färe et al.'s (2013) theoretical framework, to develop the optimal production frontier, this study constructs the PPS that includes both desirable and undesirable outputs. In this way, China's provinces are treated as decision-making units (DMU). Assume that there are K DMUs; x^k, y^k and b^k represent the N-dimensional input vector, the M-dimensional desirable output vector, and the L-dimensional undesirable output vector, respectively. For $DMU_k (k = 1, \ldots, K)$, during period $t (t = 1, 2, \ldots, T)$, the three vectors satisfy the following:

$$x^{t,k} = \left(x_1^{t,k}, x_2^{t,k}, \cdots, x_N^{t,k}\right) \in R_+^N \tag{1}$$

$$y^{t,k} = \left(y_1^{t,k}, y_2^{t,k}, \cdots, y_M^{t,k}\right) \in R_+^M \tag{2}$$

$$b^{t,k} = \left(b_1^{t,k}, b_2^{t,k}, \cdots, b_L^{t,k}\right) \in R_+^L \tag{3}$$

$$\begin{aligned} T^t = \Bigg\{ & (x^t, y^t, b^t) : \sum_{k=1}^{K} \lambda_k^t y_{km}^t \geq y_{km}^t, m = 1, \ldots, M; \\ & \sum_{k=1}^{K} \lambda_k^t x_{kn}^t \geq x_{kn}^t, n = 1, \cdots, N;\ \sum_{k=1}^{K} \lambda_k^t b_{kl}^t \geq x_{kl}^t, \\ & l = 1, \cdots, L, \lambda_k^t \geq 0 \Bigg\} \end{aligned} \tag{4}$$

Under the condition that input (x) and desirable output (y) are strongly disposable and undesirable output (b) is weakly disposable, the DEA production technology during period t is given in Eq. 1, where $\lambda = (\lambda_1^t, \lambda_2^t, \ldots, \lambda_K^t)$ is a K-dimension weighting vector. Building on Tone's (2001) approach, the SBM model for the undesirable output is developed as:

$$\theta=\min_{s^x,s^y,s^b,\lambda}\frac{1-\frac{1}{N}\sum_{n=1}^{N}\frac{s_n^x}{x_{k'n}^t}}{1+\frac{1}{M+L}\left(\sum_{m=1}^{M}\frac{s_m^y}{y_{k'm}^t}+\sum_{l=1}^{L}\frac{s_l^b}{b_{k'l}^t}\right)}$$
$$s.t.\sum_{k=1}^{K}\lambda_k^t x_{kn}^t+s_n^x=x_{k'n}^t,n=1,\cdots,N;\sum_{k=1}^{K}\lambda_k^t y_{km}^t-s_m^y=y_{k'm}^t,m=1,\cdots,M;$$
$$\sum_{k=1}^{K}\lambda_k^t b_{kl}^t+s_l^b=b_{k'l}^t,l=1,\cdots,L;\lambda_k^t\ge 0,k=1,\cdots,K;s_n^x\ge 0,s_m^y\ge 0;s_l^b\ge 0 \tag{5}$$

Eq. 5 is the SBM-DEA model under a constant return to scale. If the constraint $\sum\lambda=1$ is added to the model, then it becomes the SBM model under changing returns to scale. In the equation, θ is the efficiency, and $(x_{k'n}^t, y_{k'm}^t, b_{k'l}^t)$ are the input vector, desirable output vector, and undesirable output vector, respectively, of the kth *DMU*; (s_n^x, s_m^y, s_l^b) are the slack variables of the input, desirable output, and undesirable output, respectively, indicating excessive input or insufficient output. If $\theta=1$, then all slack variables have a value of zero, implying that there is excessive input or insufficient output. Under this circumstance, the *DMU* is completely effective in terms of technology.

2.2. Green productivity and its decomposition

The definition of the *GP* is based on the distance function; therefore, it can be directly expressed using the measurement of SBM-DEA efficiency (Zhou et al., 2008). Assume $\theta^t(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})$ and $\theta^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})$ are the kth *DMU*'s efficiencies in period t and $t+1$ as a function of input vector, desirable output vector, and undesirable output vector of period t; and $\theta^t(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})$ and $\theta^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})$ are the kth *DMU*'s efficiencies in period t and $t+1$ as a function of input vector, desirable output vector, and undesirable output vector of period $t+1$. So the *GP* of the kth *DMU* from period t to $t+1$ can be calculated as:

$$GP_k^{t,t+1}=\left[\frac{\theta^t\left(x_k^{t+1},y_k^{t+1},b_k^{t+1}\right)}{\theta^t\left(x_k^t,y_k^t,b_k^t\right)}\bullet\frac{\theta^{t+1}\left(x_k^{t+1},y_k^{t+1},b_k^{t+1}\right)}{\theta^t\left(x_k^t,y_k^t,b_k^t\right)}\right]^{1/2} \tag{6}$$

where $GP_k^{t,t+1}$ measures the change in the *GP* of the k^{th} *DMU* from period t to period $t+1$. If $GP_k^{t,t+1}>1$, then the *GP* has increased; if $GP_k^{t,t+1}<1$, it has decreased; if $GP_k^{t,t+1}=1$, then no change has occurred. In accordance with Färe et al. (1994), $GP_k^{t,t+1}$ is decomposed into two components: green technology efficiency change (*GEC*) and green technical progress change (*GTC*), as shown in Eq. 7. *GEC* reflects the intertemporal relative change in efficiency, and *GTC* measures the change in the optimal production frontier from period t to period $t+1$. A value of *GP, GEC, and GTC* that is greater than (less than) 1 denotes a *GP* increase (decrease), an improvement (deterioration) of green efficiency, and frontier technical progress (retrogression), respectively. The calculation in Eq. 7 involves four SBM-DDFs, which require solving through the corresponding linear programming.

2.3. GP convergence test and spatial panel data model

The preferential policies of the Chinese government could drive factors of production and innovation input to relatively underdeveloped regions and enhance their endogenous development; therefore, these policies advance the convergence of regional *GP*. Therefore, in reality, the spatial convergence of regional *GP* depends on a variety of factors, including the cross-regional learning effect, knowledge diffusion, and government policies. This study employs the β-convergence approach to examine the convergence of China's regional *GP*. The β-convergence can be manifested in the form of absolute convergence or conditional convergence. This conditional convergence assumption better reflects the

$$GP_k^{t,t+1}=\underbrace{\frac{\theta^{t+1}\left(x_k^{t+1},y_k^{t+1},b_k^{t+1}\right)}{\theta^t\left(x_k^t,y_k^t,b_k^t\right)}}_{GEC}\underbrace{\left[\frac{\theta^t\left(x_k^t,y_k^t,b_k^t\right)}{\theta^{t+1}\left(x_k^t,y_k^t,b_k^t\right)}\bullet\frac{\theta^t\left(x_k^{t+1},y_k^{t+1},b_k^{t+1}\right)}{\theta^{t+1}\left(x_k^{t+1},y_k^{t+1},b_k^{t+1}\right)}\right]^{1/2}}_{GTC} \tag{7}$$

economic development reality than the assumptions under the absolute convergence approach. Therefore, we focused on conditional β-convergence. When analyzing the convergence of regional *GP*, the model's effectiveness could be significantly undermined if the spatial correlation between variables is not considered. This impact is because when constructing the model using regional data, due to the widespread spatial spillovers between geographic units, the variables have a strong autocorrelation and spatial heterogeneity. In spatial models, this relationship between the variables is an important source of endogeny, which, in turn, has a severe impact on statistical inference.

The commonly-used spatial data model includes spatial autoregression models and spatial error models, which can help to control the impact of the autocorrelation between variables (Kelejian and Piras, 2017). We considered the spatial effects among Chinese provinces and sets the spatial model of the conditional convergence of regional *GP* as follows:

$$GP_{it}/GP_{it-1} = \alpha_i + \rho_1 W \times GP_{it}/GP_{it-1} + \beta GP_{it-1} + \gamma^T X_{it} + \mu_{it} \\ \mu_{it} = \rho_2 W \times \mu_{it-1} + \varepsilon_{it} \tag{8}$$

where GP_{it} denotes the *GP* of region i during period t, α_i is the random effect, and W denotes the spatial weighting matrix. ρ is the spatial error autoregression coefficient, and X_{it} denotes a set of control variables that represent the characteristics of the economic structure of region i in period t. The value of β can be used to determine whether the GP demonstrates conditional convergence. If β is a negative value, then the *GP* demonstrates conditional convergence; otherwise, no conditional convergence exists for the *GP*. If conditional convergence exists, the following equations can be used to further calculate the convergence rate (r) and the convergence time (T) required to reduce the gap by half:

$$r = -\frac{\ln(1+\beta)}{t} \tag{9}$$

$$T = \frac{\ln 2}{r} \tag{10}$$

2.4. Data

We collected the panel data of 30 provinces (due to the lack of data, Tibet was excluded) in mainland China from 2001 to 2018 and applies the SBM-DDF approach to calculate the *GP*. Although China's National Bureau of Statistics began to publish environmental statistics in 1997, the data from 1997 to 2000 are not comparable with those after 2000 due to the change of statistical caliber in 2000. Therefore, we took 2001 as the starting point of the research sample. In the SBM-DDF model, the input variables consist of the capital stock, labor input, and energy input. The capital stock is measured by the physical capital stock and is calculated by using the perpetual inventory system (with a depreciation rate of 9.6%). The labor input is measured by the number of workers, which is the year-end number of employees in each of the three primary sectors. The energy input is measured by each province's total annual energy consumption. The output variables include both desirable and undesirable outputs. The desirable outputs are measured by each region's total annual production, which is converted to real GDP by using the year 2000 as the base year. The undesirable outputs are measured by each province's annual discharges of three types of waste: sulfur dioxide, solid industrial waste, and wastewater. The data are collected from *China Statistical Yearbook (2002−2019)*, *China Environment Yearbook (2002−2019)*, and *China Energy Statistical Yearbook (2002−2019)*. Based on China's Five-Year Plans, we divided the sample period (2001−2018) into four stages (2001−2005, 2006−2010, 2011−2015, and 2016−2018) to analyze the changing characteristics of China's green productivity in different stages.

3. Results

3.1. Patterns of China's regional GP

3.1.1. China's regional GP and its components

The results indicate that China's *GP*, *GTC*, and *GEC* have shown a continuous growing trend since 2001 (see Table 1). The *GP* increased from 0.9738 in 2001 to 1.0288 in 2018, although the overall upward trend also contains some short-term ‘up-down-up’ fluctuations. The *GTC* increased from 0.9623 in 2001 to 1.0278 in 2018, demonstrating a continuously growing trend. The *GEC* increased from 1.0120 to 1.0010 during the sample period. The changes in the *GTC* and *GEC* show that *GTC* plays an increasingly critical role in the sustainable economic development in China and has become the main driver in improving the nation's green total factor productivity (*GTFP*).

3.1.2. GP changes in each development phase

During 2001−2005, the main approach to economic growth in China was “to treat development as the main theme, take

Table 1
China's *GP* and its components.

Year	*GP*	*GTC*	*GEC*
2001−2002	0.9738	0.9623	1.0120
2002−2003	0.9881	0.9921	0.9960
2003−2004	0.9804	0.9943	0.9860
2004−2005	0.9913	1.0054	0.9860
2005−2006	1.0004	0.9732	1.0280
2006−2007	1.0004	0.9895	1.0110
2007−2008	1.0201	1.0232	0.9970
2008−2009	1.0053	1.0083	0.9970
2009−2010	1.0190	1.0160	1.0030
2011−2012	1.0023	1.0196	0.9830
2012−2013	1.0060	1.0000	1.0060
2013−2014	1.0133	1.0083	1.0050
2014−2015	1.0136	1.0036	1.0100
2015−2016	1.0454	1.0444	1.0010
2016−2017	1.0305	1.0213	1.0090
2017−2018	1.0288	1.0278	1.0010

structural adjustment as the main thread, and capitalize on reform and opening up as well as technological progress as the driving force" (Yueh, 2013). As a result, the economy experienced high growth, but the environment did not receive as much attention as it should have. Table 2 shows that the *GP* was only 0.9837 and experienced a decline during 2001–2005; the *GTC* and *GEC* were 0.9882 and 0.9954, respectively, during this period and demonstrated a continuous declining trend.

During 2006–2010, the Chinese government declared resource conservation as a fundamental national policy and proposed to develop the circular economy and preserve the ecological environment (Yueh, 2013). Specifically, the government required energy consumption per unit GDP to be reduced by 20% and major pollutant discharges (COD and SO_2) to be reduced by 10%; these requirements were integrated into China's 11th Five-Year Plan Outline as mandatory measures, which enhanced the protection of the environment. During this period, the *GP*, *GTC*, and *GEC* all experienced continuous growth, substantiating the effectiveness of the policies. As a result of the policy incentives, many firms started using environmentally friendly raw materials and energy to conduct research and development (R&D) in order to upgrade existing products, which led to high levels of technological innovation (Wang et al., 2021a).

During 2011–2015, the Chinese government set the major economic development goal as maintaining stable yet relatively high growth but still emphasized speeding up the development of a resource-conserving and environment-friendly society and continued pursue of the circular economy initiated in 2006–2010 (Yueh, 2013). During the is period, the decrease rate of energy consumption per 10 thousand CNY GDP increased from 2% in 2011 to 5.6% in 2015. The values of *GP*, *GTC*, and *GEC* indicates that China's *GP* experienced a continuous upward trend.

During 2016–2018, the Chinese government defined the 'development philosophy' as "being green, innovation, coordination, openness, and sharing". These five concepts constituted the major development mode and guided the key social-economic development areas during 2016–2018 and beyond.

3.1.3. Spatial distribution of China's GP

We further analyzed China's regional *GP* by classifying sample provinces into three regions based on classification standard from National Bureau of Statistics of China, including eastern, central, and western regions (see Table A1 in Appendix A). Results show that overall, the changes in each regions' *GP* and their components vary significantly.

Table 2
China's *GPI* and its components during different phases.

Phase	*GPI*	*GTC*	*GEC*
2001–2005	0.9837	0.9882	0.9954
2006–2010	1.0101	1.0025	1.0076
2011–2015	1.0170	1.0156	1.0014
2016–2018	1.0252	1.0205	1.0046

Specifically, the results in Table A1 show that the national average of the *GP* between 2001 and 2018 is 1.1442, indicating that China's green total factor productivity experienced significant improvement in recent two decades, with an annual growth rate of 6.74%. The two components of the *GP*, namely, the *GTC* and the *GEC*, have an average value of 1.1095 and 1.0313, respectively.

In terms of the *GEC*, it takes on higher values in the central and western regions, at 1.1132 and 1.0374, respectively, while the eastern region has a relatively lower value of 1.0069. This indicates that for over more than a decade, some development strategies implemented by the central and western regions have had effects.

In terms of the *GTC*, the eastern region scores the highest value, 1.1299, followed by the central and western regions, with scores of 1.1173 and 1.0906, respectively. Although a consensus has been reached on the ability of technological progress to enhance productivity, disparities in the development environment, human resources, and the existing technical foundation among different regions has led to major differences in the effect of technical progress. The eastern region has the most solid foundation for promoting economic development through technical progress and thereby has the highest *GTC*; in contrast, the western region has the weakest foundation and therefore the lowest *GTC*. Almost all of the 30 provinces have experienced certain technical progress[1] and have a *GTC* greater than 1; however, the progressions vary across regions. The five provinces that have seen the most significant technical progress are Guangdong, Hebei, Zhejiang, Xinjiang, and Guangxi. Ranked in the first place, Guangdong has seen an average annual growth rate of 19.48% in its *GTC*. Moreover, in terms of the regional *GP*, the central region has the highest score (1.1811), followed by the eastern and western regions, with scores of 1.1307 and 1.1193, respectively. During the study period, all regions have seen significant improvements in their *GP*, which indicates that they have all made progress in upgrading their industry structure and transforming the development pattern. An increase in the *GP* occurred in all 30 provinces except for Hainan Province. The top five provinces in the *GP* ranking are: Hubei, Jiangxi, Hunan, Liaoning, and Guangdong.

3.2. Spatial correlation test of China's green productivity

The global spatial autocorrelation analysis was performed to test the spatial autocorrelation of China's *GP*. We used the Moran I test to examine whether China's *GP* has a significant spatial correlation (Table A2).

Most Moran I test results are positive and significant under different spatial weighting matrices during the period 2001–2018. The reason for choosing three different spatial weight matrices is that the relevant conclusions of spatial econometric analyses are related to the specific form of spatial

[1] Only Hainan and Inner Mongolia experienced technical retrogression, with a *GTC* value less than 1.

weight setting. In order to obtain more robust empirical conclusions, we thus used three different spatial weight matrices for relevant calculations. The significantly positive results mean that the spatial distribution of China's green productivity has significant spatial autocorrelation during the study period and that this autocorrelation has been continuously strengthened. Therefore, the positive correlation indicates that the spatial correlation of China's green productivity exists demonstrates a characteristic of spatial clustering (Huang et al., 2021).

3.3. Conditional convergence of China's GP

Existing studies (Su et al., 2020; Wang et al., 2021b; Xie et al., 2021) indicate that the degree of population urbanization (*URB*), industry upgrade (*IND*), openness (*OPE*), and marketization (*MAR*) affect productivity and the efficiency of green development. The migration into urban areas enables a more intensive use of resources and energy; the internal learning effect and advantages of diversification also help to increase the output from each input unit. A high degree of openness enables a region to attract and integrate resources at a large scope and to acquire more advanced technologies through trade expansion to improve productivity. Besides, a high degree of marketization creates reasonable competition in the marketplace and a favorable business environment that drives firms to adopt more resource-conserving and environmentally friendly production methods. Therefore, we selected the four factors discussed above as the control variables in the analysis of conditional convergence of China's *GP*.

Specifically, the four control variables are defined as follows: urbanization is measured by the proportion of the non-agricultural population in the total regional population; industry structure upgrading is measured by the proportion of value added from the second and tertiary sectors in the total regional GDP; openness is measured by the proportion of total foreign investment (adjusted by average annual exchange rate) in the regional GDP; and marketization is measured by the proportion of workers in privately or individually owned businesses in the total regional population.

The following static spatial panel model is developed to test the β-convergence of China's regional *GP*:

$$\begin{aligned} &GP_{it}/GP_{it-1} = \alpha_i + \rho_1 W \times GP_{it}/GP_{it-1} + \beta GP_{it-1} + \gamma_1 URB_{it} \\ &+\gamma_2 IND_{it} + \gamma_3 OPE_{it} + \gamma_4 MAR_{it} + \mu_{it} \\ &\mu_{it} = \rho_2 W \times \mu_{it-1} + \varepsilon_{it} \end{aligned} \tag{11}$$

Before running the spatial panel model, a Lagrange Multiplier (LM) test and a spatial Hausman test are performed for testing the model settings. As aforementioned, to avoid test failures due to inappropriate settings of the spatial weighting matrices, this stully applies the KNN spatial weight matrix ($K = 3$), the exponential distance spatial weighting matrix ($\alpha = 2$) and the spatial weighting matrix based on socio-economic relationships to implement the spatial econometric model. The results are shown in Table 3.

Table 3
Test for spatial panel model settings.

Test statistic	KNN spatial weight matrix	Exponential distance spatial weighting matrix	Spatial weighting matrix based on economic relationships
LM (lag)	7.9234***	8.6477***	8.9208***
Robust LM (lag)	10.6604***	9.3086***	10.8184***
LM (error)	0.1775	0.1782	0.1396
Robust LM (error)	0.1547	0.1374	0.1260
Wald (lag)	13.5258***	13.6067***	14.6190***
Wald (error)	0.1951	0.1979	0.1396
LR (lag)	10.5153***	10.3186***	11.1185***
LR (error)	0.1756	0.1295	0.1996
Spatial Hausman	22.3224***	24.5936***	22.6947***

Note: *, **, and *** denote results statistically significant at the 10%, 5%, and 1% confidence level, respectively.

The results in Table 3 indicate that the Lagrange Multiplier (lag), Robust LM (lag), Wald (lag), LR (lag) are significant at the 1% level, while the Lagrange Multiplier (error), Robust LM (error), Wald (error), LR (error) are not significant. Therefore, the spatial autoregression model shall be applied (Anselin, 2002, 2003). Further, the spatial Hausman test indicates that the fixed-effects spatial panel model should be used.

Considering the complexity in the spatial correlation of the regional *GP*, to test the conditional β-convergence of China's 30 provinces over the period 2001−2018, three types of spatial weighting matrices are employed. The results are displayed in Table 4.

Table 3 indicates that the spatial lag coefficient ρ is significant for all three spatial weighting matrices. Under the three spatial weighting matrices that consider the spatial impact, the *GP* demonstrates a trend of convergence at the 5%−10% level.[2] Whereas the results from the model in which the spatial impact is not considered, China's *GP* does not demonstrate a trend of convergence. Accordingly, biased results are likely when spatial factors are not included when analyzing China's green total factor productivity. Therefore, our analysis will be based on the results from models using the three spatial weighting matrices.

Specifically, under the KNN spatial weight matrix ($K = 3$), the exponential distance spatial weighting matrix ($\alpha = 2$) and the spatial weighting matrix based on socio-economic relationships, the convergence rate of China's *GP* is 3.21%, 2.49%, and 1.35%, respectively, suggesting the respective convergence time required to close the gap by half is 22.10, 28.53, and 52.97 years. Among the control variables, *URB* and *IND* have a positive impact on *GP* growth and are significant at the 5% level. This is an indication that population urbanization and industry upgrading help to enhance China's *GP* growth. The regions with low *GP* can accelerate population

[2] Whether the convergence trend of green productivity exists can be judged by the sign and significance of the coefficient of GP_{it-1}. If the coefficient is significant and negative, it indicates that the convergence trend of green productivity exists.

Table 4
Results of spatial convergence of China's *GP*.

Variable	No spatial weighting matrix	KNN spatial weight matrix	Exponential distance spatial weighting matrix	Spatial weighting matrix based on economic relationships
ρ		0.0244*** (0.0073)	0.0991* (0.0716)	0.0807** (0.0494)
GPI_{it-1}	0.0113 (0.1599)	−0.0316** (0.0180)	−0.0246* (0.0165)	−0.0134** (0.0086)
URB	0.2212** (0.1034)	0.8886** (0.4770)	0.6467*** (0.1843)	0.6851*** (0.2801)
IND	0.5843*** (0.3150)	0.2807*** (0.1083)	0.6422** (0.2099)	0.6364** (0.1973)
OPE	0.5543 (0.8980)	0.5562 (1.2818)	0.1246 (0.3261)	0.3421 (0.3969)
MAR	−0.7566*** (0.2040)	−0.6210* (0.3903)	−0.8303** (0.4047)	−0.9164** (0.4812)
Province effect	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes
Convergence rate		0.0321	0.0249	0.0135
Adjust R^2	0.4593	0.3792	0.4015	0.3983

Note: Values in parentheses are robust standard error. *, **, and *** denote results statistically significant at the 10%, 5%, and 1% level, respectively.

urbanization and encourage industry upgrading to improve their *GP*. *OPE* does not have a significant impact on the *GP*, and *MAR* has a significant negative impact on the *GP*, partially because certain heavy industries create an overuse of energy and environmental pollution, thereby reducing *GP*.

3.4. Further discussion

To further analyze the regional effects of China's *GP* convergence and its two components, we implemented the spatial econometric model with the three spatial weighting matrices again to each of the three China's regions (Section 3.4.1) and to *GEC* and *GTC* (Section 3.4.2), respectively.

3.4.1. Green productivity convergence in different regions

Table 5 shows the spatial convergence of GP in different regions. The *GP* of the eastern region demonstrates significant conditional convergence trend; when the spatial effect is considered, the convergence rate is even higher. Under the KNN spatial weight matrix ($K = 3$), the exponential distance spatial weighting matrix ($\alpha = 2$) and the spatial weighting matrix based on socio-economic relationships, the convergence rate of the eastern region's *GP* is 6.36%, 6.58%, and 6.24%, respectively; and the respective corresponding convergence time required to close the gap by half is 10.90, 10.53, and 11.11 years. The *GP* of the central region does not demonstrate any convergence trend. The *GP* of the western region demonstrates significant convergence trend; when the spatial effect is considered, the convergence rate is even higher. In comparison with the convergence rate of the eastern region, however, the convergence rate in the western region is considerably lower. Under the three types of spatial weighting matrices, the convergence rate of the western region's *GP* is 2.28%, 2.48%, and 2.35%, respectively; the respective convergence time required to close the gap by half is 30.46, 28.18, and 29.53 years. The geographic location of the central region is an important reason why the *GP* does not demonstrate a convergence trend. To promote economic development, the aim of some provinces in the central region is to catch up with the eastern region, while some others try to align with their counterparts in the western region. These differences in development strategies lead to greater disparities in central China's Green Productivity.

Among the control variables, the coefficients of *URB* and *MAR* of the eastern region are negative and significant. The eastern region mainly consists of provinces that are more economically developed and located on the coast. Urbanization in this region is close to saturation, and further growth in the urban population may have a negative impact on the *GP*; the eastern region's results are contrary to the overall results at the national level. As for the marketization process, in the eastern region, some firms with heavy pollution have been established, which also contributes to the negative coefficient. *OPE* does not have a significant impact on the *GP* of the eastern region, while *IND* has a significant positive impact. In the developed eastern region, to improve the *TFP* that contains environmental efficiency, the industry structure needs to be upgraded to improve the efficiency of resource and energy consumption. *URB* has a significant positive impact on the central region's *GP*, while *OPE* and *MAR* have a significant negative impact. The possible reason for this is that in comparison with the eastern region, the central region has neither a superior geographic location nor a strong ability to attract a large amount of foreign investment into the tertiary industries, such as the service sector; rather, most investment in this region is in the industries with high energy consumption and heavy pollution. Marketization attracts a large number of factors of production into the region; however, the market mechanism cannot effectively phase out firms with high energy consumption and heavy pollution, which leads to the *GP* decline. Therefore, the most effective approach to improving the central region's *GP* is still industry structure upgrading; that is, making every effort to grow the tertiary sector. Economic development in the western region lags behind that of other regions. Except for *OPE*, which does not have a significant impact on the region's *GP*, all other three indicators have a significant positive impact. In the western region, advancing urbanization could help develop the urban labor force, improve productivity, and promote the economy.

Table 5
Spatial convergence of *GP* in different regions.

Variable		No spatial weighting matrix	KNN spatial weight matrix	Exponential distance spatial weighting matrix	Spatial weighting matrix based on economic relationships
Eastern region	ρ		0.1720** (0.0989)	0.1759*** (0.0467)	0.1468*** (0.0585)
	$GP_{it\text{-}1}$	−0.0539* (0.0382)	−0.0616** (0.0335)	−0.0637*** (0.0243)	−0.0605*** (0.01933)
	URB	−0.5520** (0.3110)	−0.8066** (0.4586)	−0.6323* (0.4399)	−0.5230** (0.2674)
	IND	0.8252** (0.3896)	0.8037** (0.3893)	0.2354*** (0.0894)	0.3011*** (0.0962)
	OPE	0.1430 (0.5881)	0.2522 (0.4993)	0.1267 (0.2305)	0.1343 (0.1485)
	MAR	−0.2513** (0.1374)	−0.6722** (0.3466)	−0.6043*** (0.1931)	−0.3723*** (0.1466)
	Province effect	Yes	Yes	Yes	Yes
	Year effect	Yes	Yes	Yes	Yes
	Convergence rate	0.0554	0.0636	0.0658	0.0624
	Adjust R^2	0.4080	0.5158	0.6593	0.4342
Central region	ρ		0.1022*** (0.0277)	0.1990*** (0.0921)	0.1232*** (0.0473)
	$GP_{it\text{-}1}$	0.0135 (0.04773)	0.0182 (0.0483)	0.0091 (0.0624)	0.0065 (0.0093)
	URB	0.6943*** (0.2042)	0.3911** (0.2142)	0.2077*** (0.0664)	0.2835** (0.1199)
	IND	0.4942** (0.2560)	0.9467*** (0.2453)	0.1268** (0.0589)	0.3651*** (0.0976)
	OPE	−0.6882* (0.4774)	−0.7534** (0.3874)	−0.6436* (0.4908)	−0.8387** (0.4280)
	MAR	−0.5451*** (0.2196)	−0.5793*** (0.2191)	−0.5195*** (0.1472)	−0.7664*** (0.2012)
	Province effect	Yes	Yes	Yes	Yes
	Year effect	Yes	Yes	Yes	Yes
	Convergence rate				
	Adjust R^2	0.5352	0.5496	0.5660	0.6881
Western region	ρ		0.1602** (0.08804)	0.1528** (0.0821)	0.1891*** (0.0782)
	$GP_{it\text{-}1}$	−0.0170** (0.0098)	−0.0225*** (0.0073)	−0.0243** (0.0146)	−0.0232*** (0.0082)
	URB	0.2237*** (0.0590)	0.9440* (0.6596)	0.9136** (0.4688)	0.1697** (0.0983)
	IND	0.1854** (0.1083)	0.1366** (0.0821)	0.5672** (0.3047)	0.4477*** (0.1286)
	OPE	0.0744 (0.3765)	−0.0210 (0.0305)	0.0340 (0.2745)	0.0561 (0.1571)
	MAR	0.7287** (0.3723)	0.3563** (0.1704)	0.3441* (0.2362)	0.5615*** (0.1586)
	Province effect	Yes	Yes	Yes	Yes
	Year effect	Yes	Yes	Yes	Yes
	Convergence rate	0.0172	0.0228	0.0248	0.0235
	Adjust R^2	0.4677	0.4292	0.3798	0.4164

Notes: Values in parentheses are robust standard error.*, **, and *** denote results statistically significant at a 10%, 5%, and 1% confidence level, respectively.

3.4.2. Spatial convergence of GP components

The spatial convergence tests for the components of the *GTC* and *GEC* are performed, and the results are shown in Table 6.

The results indicate that without considering the spatial impact, neither the *GTC* nor the *GEC* demonstrates a trend of convergence. After the spatial impact is considered, however, the *GTC* demonstrates a trend of convergence; under the three spatial weighting matrices, the convergence rate of the *GTC* is 3.47%, 3.87%, and 3.17%, respectively; the respective convergence time required to close the gap by half is 20.04, 17.89, and 22.01 years. Even after considering the spatial impact, the *GEC* still does not demonstrate a trend of convergence.

4. Environmental regulation and the spatial convergence of *GP*

The picture of the convergence of China's *GP* is incomplete if institutional factor is not considered. For example, Shen et al. (2020) uses panel data of 48 coastal cities in China from 2004 to 2017 to explore the impact of local government competition on water pollution by using a two-way fixed-effect panel regression model. Results show that local government competition has significantly increased water pollution. The government can improve the quality of economic growth through advantageous institutional arrangements (Dong et al., 2020; Tian et al., 2020). Environmental regulation constitutes the most important policy arrangement in China's environmental management system and is especially pertinent in the industrial sector where environmental measures are tasked with promoting industry growth while reducing energy consumption and waste discharge. Prior research has not reached a consensus on the relationship between environmental regulation and green economic growth. Some researchers argue that strict regulations imposed on firms may bring about social benefits but are not conducive to fostering innovation capacity and environmental stewardship among firms (Gray, 1987; Jaffe and Palmer, 1997). Some other researchers state that strict yet appropriate environmental regulations not only generate beneficial externalities that contribute to public benefits but also create the 'offset effects of innovation' among firms in the

Table 6
Spatial convergence of *GTC* and *GEC*.

Variable		No spatial weighting matrix	KNN spatial weight matrix	Exponential distance spatial weighting matrix	Spatial weighting matrix based on economic relationships
GTC	ρ		0.1631*** (0.0399)	0.1579*** (0.0266)	0.1553*** (0.0388)
	$GTC_{it\text{-}1}$	−0.0182 (0.0503)	−0.0341** (0.0184)	−0.0380** (0.0253)	−0.0312*** (0.0083)
	URB	0.2891** (0.1280)	0.3533** (0.1854)	0.8132*** (0.2170)	0.4346*** (0.1041)
	IND	0.7088*** (0.1532)	0.4510** (0.2406)	0.8813*** (0.2810)	0.1339*** (0.0341)
	OPE	0.6343 (1.1441)	0.4991 (2.2332)	0.1876 (0.3254)	0.9555 (2.3737)
	MAR	−0.3240*** (0.0893)	−0.4403** (0.2375)	−0.6455** (0.3644)	−0.2052*** (0.0492)
	Province effect	Yes	Yes	Yes	Yes
	Year effect	Yes	Yes	Yes	Yes
	Convergence rate		0.0347	0.0387	0.0317
	Adjust R^2	0.4502	0.5243	0.4051	0.5796
GEC	ρ		0.1326 (1.6568)	0.1373 (0.4333)	0.1245 (0.1766)
	$GEC_{it\text{-}1}$	0.0033 (0.0142)	−0.0121 (0.0150)	0.00245 (0.0068)	0.0127 (0.0203)
	URB	0.3897*** (0.0667)	0.7213*** (0.1047)	0.7733* (0.5170)	0.8604*** (0.3071)
	IND	0.6682*** (0.2143)	0.8388** (0.4783)	0.2195** (0.1284)	0.7493*** (0.1772)
	OPE	0.4352 (1.1640)	0.2680 (0.4932)	0.7702 (1.4525)	0.1341 (0.4426)
	MAR	−0.5054*** (0.1393)	−0.6256** (0.1346)	−0.9382** (0.5446)	−0.4920*** (0.1038)
	Province effect	Yes	Yes	Yes	Yes
	Year effect	Yes	Yes	Yes	Yes
	Adjust R^2	0.4335	0.5312	0.5630	0.5734

Notes: Values in parentheses are robust standard error. *, **, and *** denote results statistically significant at the 10%, 5%, and 1% confidence level, respectively.

long run. Under this proposition, firms subjected to these regulations are induced to optimize resource allocation, improve production processes and techniques, and enhance their innovation capacity. Therefore, the firms' economic performance and environmental performance are both improved (Porter and van der Linde, 1995; Brunnermeier and Cohen, 2003).

To test the impact of environmental regulations on the convergence of China's GP, we develop a spatial autoregression model as follows:

$$GPI_{it}/GPI_{it-1} = \alpha_i + \rho W \times GPI_{it}/GPI_{it-1} + \theta ER_{it} + \beta GPI_{it-1} + \gamma_1 URB_{it} + \gamma_2 IND_{it} + \gamma_3 OPE_{it} + \gamma_4 MAR_{it} + \mu_{it} \tag{12}$$

ER_{it} denotes the environmental regulations, and the other variables are the same as those in Eq. (12). In the reality of environmental regulation, the intervention modes of the governments are not fixed, and the types of policy instruments are also diverse. We divided the environmental regulations into administrative controls (*DEM*), fee-based regulatory measures (*COST*), and investment-based regulatory measures (*INV*). *DEM* is measured by the number of cases that involve administrative fines in response to the firms' environmental breach. *COST* is measured by the annual waste discharge fees collected by each region, with larger amount of discharge fee indicates a more stringent regulation. We apply the GDP deflator by using 2000 as the base year to adjust the effect of inflation. *INV* is measured by each region's total annual investment in reducing pollution and remediating the environment: a large amount indicates a more vigorous regulation. Similarly, the GDP deflator is applied to adjust the nominal investment amount to account for inflation. The data source is the *China Statistical Yearbook*.

The results in Table 7 indicate that environmental regulation has a significant impact on the spatial convergence of China's regional GP. Specifically, all three types of regulatory measures, *DEM*, *COST*, and *INV*, have a significant positive impact on the spatial convergence of China's regional GP. It is evident that after the environmental regulation is added to the model as a variable, the convergence rate of the GP increases, and the convergence time required to reduce the gap by 50% decreases. For instance, under the KNN spatial weight matrix, after the variables of *DEM*, *COST*, and *INV* are introduced, the GP convergence rate is 6.56%, 5.47%, and 5.26%, respectively, and the convergence time required to reduce the gap by 50% is 10.60, 12.73, and 13.24 years, respectively. The convergence rate is significantly higher than that when the environmental regulation is not introduced into the model. Therefore, the environmental regulation effectively reduces the disparity between the regional GP and could help to improve the convergence of GP.

5. Conclusion and policy recommendations

This study uses the panel data of China's 30 provinces from 2001 to 2018 to calculate each province's *GP* and further employs the spatial econometric model to analyze the convergence of the regional *GP*. The findings indicate that the *GP* and its components (*GTC* and *GEC*) have demonstrated a continuous upward trend since 2001. The *GP* increased from 0.9738 in 2001 to 1.0288 in 2018, although short-term ‘up-down-up’ fluctuations occurred during the overall upward

Table 7
Environmental regulation and spatial convergence of GP.

Variable	KNN spatial weight matrix			Exponential distance spatial weighting matrix			Spatial weighting matrix based on economic relationships		
ρ	0.1451*** (0.0386)	0.1813*** (0.0344)	0.1185*** (0.0310)	0.1769*** (0.0402)	0.1965*** (0.0274)	0.1739*** (0.0361)	0.1379*** (0.0260)	0.1933*** (0.0643)	0.1327*** (0.0183)
DEM	0.819** (0.4144)			0.680* (0.5279)			0.676** (0.3294)		
COST		0.6160** (0.3052)			0.4312** (0.2189)			0.4451** (0.0264)	
INV			0.2768** (0.1432)			0.4033** (0.1995)			0.3321** (0.1944)
GPI_{it-1}	−0.0635*** (0.0147)	−0.0532*** (0.0193)	−0.0512*** (0.0103)	−0.0692*** (0.0142)	−0.0567*** (0.0194)	−0.0522*** (0.0144)	−0.0571*** (0.0121)	−0.0522*** (0.0152)	−0.0500*** (0.0085)
URB	0.3781** (0.1986)	0.4696** (0.2438)	0.8403** (0.4842)	0.2844*** (0.0591)	0.8781** (0.4594)	0.6266** (0.3184)	0.4773** (0.2236)	0.9006*** (0.2320)	0.4053*** (0.0742)
IND	0.3959** (0.1892)	0.6690* (0.4744)	0.6652*** (0.1955)	0.4111** (0.2077)	0.6183** (0.3210)	0.2077** (0.1038)	0.2542*** (0.0542)	0.7005*** (0.2066)	0.8310** (0.4863)
OPE	0.7554 (0.8791)	0.9311 (1.0547)	0.2409 (2.1284)	0.5954 (1.0942)	0.9534 (3.1583)	0.1552 (0.2232)	0.9213 (1.8568)	0.6931 (0.7948)	0.3988 (0.5044)
MAR	−0.2343*** (0.0493)	−0.5566*** (0.1811)	−0.2397*** (0.0581)	−0.4201*** (0.0653)	−0.7996*** (0.1193)	−0.6572*** (0.1362)	−0.7215*** (0.1982)	−0.3348*** (0.0579)	−0.1942*** (0.0365)
Province effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Convergence rate	0.0656	0.0547	0.0526	0.0717	0.0584	0.0536	0.0588	0.0536	0.0513
Adjust R^2	0.5123	0.5881	0.5038	0.6504	0.6675	0.6812	0.6891	0.6188	0.6320

Notes: Values in parentheses robust standard error. *, **, and *** denote results statistically significant at the 10%, 5%, and 1% confidence level, respectively.

trend. The *GTC* increased from 0.9623 in 2001 to 1.0278 in 2018, demonstrating a trend of continuous growth. The *GEC* increased from 1.0120 in 2001 to 1.0010 in 2018, demonstrating more fluctuations than did the *GTC*. After considering the spatial impact, China' *GP* demonstrates a trend of convergence. Moreover, when environmental regulation is introduced to the model, the convergence rate increases, and the convergence time required to close the gap by half decreases. Therefore, environmental regulation effectively reduces the disparity between China's regional *GP* and is conducive to the *GP* convergence. Based on the results of the empirical findings, China's green economic development shall focus more on the following aspects.

First, integrate green productivity into regional economic development strategic plans. High-quality economic development requires stable economic growth while promoting the environmental quality, which highlights the important role of green production in the economic development. The fluctuation pattern of China's green productivity as indicated in our findings indicates the need to stabilize green production and so enhance the economic development quality. To achieve and promote the stabilization of green production, we find that urbanization and industrial structure upgrade exert a positive impact on China's green productivity. Therefore, appropriate measures should be taken to enhance the quality of urbanization and the industrial structure upgrade. The urbanization process should focus more on the intensive use of resources, be mindful of the green economy; and should promote consumer products that are more energy-conserving to develop green cities. For the eastern and central regions, a reasonable spatial layout should be developed between cities and smaller urban centers; the integration of urban and rural areas should be accelerated, and cities should play a leading role in driving rural development. An early warning mechanism for the ecosystem should be developed in cities; and an over-concentration of production factors should be avoided in order to improve development efficiency and prevent unnecessary generation of environment pollution. For the western region, urban centers should be developed based on sound urban planning and in an orderly manner; industry development should become the driving force for employment growth, population agglomeration, and urbanization. In addition, the industrial structure should be transformed and updated. To achieve a balanced development mode between productivity improvement and resource and energy conservation, the government should strictly control the extensive expansion and facility replication of the high-pollution industry (Grubb et al., 2021). Increasing the capacity of independent innovation should be at the heart of industrial structure adjustments. The government should encourage the use of more advanced factors of production, reduce the local economies' reliance on high energy consumption industries, and strive to develop a resource-conserving and environmentally friendly economy. Relatively underdeveloped regions should embrace the inter-regional transfer of industries (Jia et al., 2021), especially the import of knowledge and intelligence-intensive industries from developed areas, in order to reduce the gap in industrial development and knowledge accumulation. This could foster the capacity of endogenous development and reduce the large green productivity disparity caused by the gap in industrial development.

Second, the findings indicate that environmental regulation is conducive to the convergence of China's regional *GP*. Therefore, the Chinese central and local governments should further improve environmental regulations. In addition to strengthening the existing regulatory measures, the government should try to combine and utilize multiple policy instruments. China has piloted the national emissions trading scheme (ETS) recently and encouraged innovative green financing schemes to support green projects. Therefore, exploring novel environmental regulation possibilities from various instruments paves the basis for China to achieve a low-carbon development and ultimately accelerate the carbon neutrality process.

We have used province-level data to analyze China's regional green productivity and the convergence of the regional green productivity. The within-province heterogeneity might generate more interesting and important findings than the province-level findings. Therefore, future studies may collect sub-provincial data such as city-level or county-level data to further explore more specific spatial and time-varying characteristics of China's regional *GP*. Moreover, the policy effect on China's regional green productivity has not been explored in this study. Chinese government has made substantial efforts to improve environmental performance and achieved great improvements in recent years. The relevant environmental policies have generated positive impacts on China's green productivity. Future studies can investigate the impacts of important environmental policies on regional green productivity such as the recently launched national carbon emissions trading scheme (ETS).

Declaration of competing interest

The author declares no conflict of interest.

Acknowledgments

This work was supported by the Humanities and Social Science Fund of Ministry of Education of the People’s Republic of China (19YJC790044).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.accre.2022.01.004.

References

Anselin, L., 2002. Under the hood: issues in the specification and interpretation of spatial regression models. Agric. Econ. 17 (3), 247–267.

Anselin, L., 2003. Spatial externalities, spatial multipliers, and spatial econometrics. Int. Reg. Sci. Rev. 26 (2), 153–166.

Arabi, B., Munisamy, S., Emrouznejad, A., 2015. A new slacks-based measure of Malmquist-Luenberger index in the presence of undesirable outputs. Omega 51 (1), 29–37.

Barbier, E.B., 2020. Greening the post-pandemic recovery in the G20. Environ. Resour. Econ. 76, 685–703..

Barro, R.J., Sala-I-Martin, X., 1995. Economic Growth. McGraw-Hill, New York.

Baumol, W.J., 1986. Productivity growth, convergence, and welfare: what the long-run data show. Am. Econ. Rev. 76 (5), 1072–1085.

Brunnermeier, S.B., Cohen, M.A., 2003. Determinants of environmental innovation in US manufacturing industries. J. Environ. Econ. Manag. 45 (2), 278–293.

Dong, Z.Q., Wang, H., Wang, S.X., et al., 2020. The validity of carbon emission trading policies: evidence from a quasi-natural experiment in China. Adv. Clim. Chang. Res. 11, 102–109.

Easterly, W., Levine, R., 2001. It's not factor accumulation: stylized facts and growth models. World Bank Econ. Rev. 15 (2), 177–219.

Färe, R., Grosskopf, S., 2010. Directional distance functions and slacks-based of efficiency. Eur. J. Oper. Res. 200 (1), 320–322.

Färe, R., Grosskopf, S., Whittaker, G., 2013. Directional output distance functions: endogenous directions based on exogenous normalization constraints. J. Prod. Anal. 40 (3), 267–269.

Färe, R., Grosskopf, S., Norris, M., et al., 1994. Productivity growth, technical progress, and efficiency change in industrialized countries. Am. Econ. Rev. 87 (5), 1033–1039.

Gerschenkron, A., 1962. Economic Backwardness in Historical Perspective. The Belknap Press of Harvard University Press, Cambridge.

Giddings, B., Hopwood, B., O'Brien, G., 2002. Environment, economy and society: fitting them together into sustainable development. Sustain. Dev. 10 (4), 187–196.

Gray, W.B., 1987. The cost of regulation: OSHA, EPA and the productivity slowdown. Am. Econ. Rev. 77 (5), 998–1006.

Grossman, G.M., Helpman, E., 1991. Innovation and Growth in the Global Economy. MIT Press, Cambridge.

Grubb, M., Drummond, P., Poncia, A., et al., 2021. Induced innovation in energy technologies and systems: a review of evidence and potential implications for CO_2 mitigation. Environ. Res. Lett. 16, 043007.

Hailu, A., Veeman, T.S., 2000. Environmentally sensitive productivity analysis of the Canadian pulp and paper industry, 1959–1994: an input distance function approach. J. Environ. Econ. Manag. 40 (3), 251–274.

Hailu, A., Veeman, T.S., 2001. Non-parametric productivity analysis with undesirable outputs: an application to the Canadian pulp and paper industry. Eur. J. Oper. Res. 83 (3), 605–616.

Halická, M., Trnovská, M., 2021. A unified approach to non-radial graph models in data envelopment analysis: common features, geometry, and duality. Eur. J. Oper. Res. 289 (2), 611–627.

Huang, H.Y., Mo, R.B., Chen, X.Q., 2021. New patterns in China's regional green development: an interval Malmquist-Luenberger productivity analysis. Struct. Change Econ. Dynam. 58, 161–173.

Huang, J., Yu, Y., Ma, C., 2018. Energy efficiency convergence in China: catch-up, lock-in and regulatory uniformity. Environ. Resour. Econ. 70 (1), 107–130.

Huang, M.T., Zhai, P.M., 2021. Achieving Paris Agreement temperature goals requires carbon neutrality by middle century with far-reaching transitions in the whole society. Adv. Clim. Chang. Res. 12, 281–286.

Islam, N., 2003. Productivity dynamics in a large sample of countries a panel study. Rev. Income Wealth 49 (2), 247–272.

Jaffe, A.B., Palmer, K., 1997. Environmental regulation and innovation: a panel data study. Rev. Econ. Stat. 79 (4), 610–619.

Jia, R., Shao, S., Yang, L., 2021. High-speed rail and CO_2 emissions in urban China: a spatial difference-in-differences approach. Energy Econ. 99, 105271.

Jie, D., Xu, X., Guo, F., 2021. The future of coal supply in China based on non-fossil energy development and carbon price strategies. Energy 220, e119644.

Kelejian, H., Piras, G., 2017. Spatial Econometrics. Academic Press, Salt Lake City.

Lin, C., Qi, J., Liang, S., et al., 2020. Saving less in China facilitates global CO_2 mitigation. Nat. Commun. 11, 1358.

Liu, D., Zhu, X., Wang, Y., 2021a. China's agricultural green total factor productivity based on carbon emission: an analysis of evolution trend and influencing factors. J. Clean. Prod. 278, 123692.

Liu, H., Wang, Y., Xue, R., et al., 2021b. Green commitment and stock price crash risk. Financ. Res. Lett. 102646.

Liu, T.L., Song, Q.J., Lu, J.Q., et al., 2021c. An integrated approach to evaluating the coupling coordination degree between low-carbon development and air quality in Chinese cities. Adv. Clim. Chang. Res. 12 (5). https://doi.org/10.1016/j.accre.2021.08.001.

Long, X., Zhao, X., Cheng, F., 2015. The comparison analysis of total factor productivity and eco-efficiency in China's cement manufactures. Energy Pol. 81, 61−66.

Lovell, C.A.K., Pastor, J.T., Turner, J.A., 1995. Measuring macroeconomic performance in the OECD: a comparison of European and non-European countries. Eur. J. Oper. Res. 87 (3), 507−518.

Ma, G.X., Peng, F., Yi, F., 2019. Chinese Environmental and Economic Accounting Report 2013–2014. China Environmental Science Press, Beijing.

Miketa, A., Mulder, P., 2005. Energy productivity across developed and developing countries in 10 manufacturing sectors: patterns of growth and convergence. Energy Econ. 27 (3), 429−453.

Miller, S., Upadhyay, M., 2002. Total factor productivity and the convergence hypothesis. J. Macroecon. 24 (2), 267−286.

Mulder, P., De Groot, H.L.F., 2012. Structural change and convergence of energy intensity across OECD countries, 1970–2005. Energy Econ. 34 (6), 1910−1921.

Picazo-Tadeo, A.J., Castillo-Giménez, J., Beltrán-Esteve, M., 2014. An intertemporal approach to measuring environmental performance with directional distance functions: greenhouse gas emissions in the European Union. Ecol. Econ. 100, 173−182.

Porter, M.E., van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. J. Econ. Perspect. 9 (4), 97−118.

Sáez-Fernández, F.J., Picazo-Tadeo, A.J., Llorca-rodríguez, C.M., 2012. Do labour societies perform differently to cooperatives? Evidence from the Spanish building industry. Ann. Publ. Cooper. Econ. 83 (1), 61−81.

Scheel, H., 2001. Undesirable outputs in efficiency valuations. Eur. J. Oper. Res. 132 (2), 400−410.

Seiford, L.M., Zhu, J., 2002. Modeling undesirable factors in efficiency evaluation. Eur. J. Oper. Res. 142 (1), 16−20.

Shao, S., Li, B., Fan, M., et al., 2021. How does labor transfer affect environmental pollution in rural China? Evidence from a survey. Energy Econ. 102, 105515.

Shen, W.T., Hu, Q.G., Yu, X., et al., 2020. Does coastal local government competition increase coastal water pollution? Evidence from China. Int. J. Environ. Res. Public Health 17, 6862.

Su, H.P., Kporsu, A.K., Hessary, F.T., et al., 2020. Estimating environmental efficiency and convergence: 1980 to 2016. Energy 208, 118224.

Tian, J.F., Pan, C., Xue, R., et al., 2020. Corporate innovation and environmental investment: the moderating role of institutional environment. Adv. Clim. Chang. Res. 11, 85−91.

Tian, J.F., Yu, L., Xue, R., et al., 2022. Global low-carbon energy transition in the post-COVID-19 era. Appl. Energy 307, 118205.

Tone, K., 2001. A slacks-based measure of efficiency in data envelopment. Eur. J. Oper. Res. 130 (3), 498−509.

Wan, D., Xue, R., Linnenluecke, M., et al., 2021. The impact of investor attention during COVID-19 on investment in clean energy versus fossil fuel firms. Financ. Res. Lett. 43, 101955.

Wan, J., Baylis, K., Mulder, P., 2015. Trade facilitated technology spillovers in energy productivity convergence processes across EU countries. Energy Econ. 48, 253−264.

Wang, H.R., Cui, H.R., Zhao, Q.Z., 2021a. Effect of green technology innovation on green total factor productivity in China: evidence from spatial Durbin model analysis. J. Clean. Prod. 288, 125624.

Wang, M., Xu, M., Ma, S.J., 2021b. The effect of the spatial heterogeneity of human capital structure on regional green total factor productivity. Struct. Change Econ. Dynam. 59, 427−441.

Xie, F.M., Zhang, B., Wang, N., 2021. Non-linear relationship between energy consumption transition and green total factor productivity: a perspective on different technology paths. Sustain. Prod. Consum. 28, 91−104.

Xu, L., Fan, M., Yang, L., et al., 2021. Heterogeneous green innovations and carbon emission performance: evidence at China's city level. Energy Econ. 99, 105269.

Yueh, L., 2013. China's Growth: the Making of an Economic Superpower. Oxford University Press, Oxford.

Young, A., 1995. The tyranny of numbers: confronting the statistical realities of the east Asian growth experience. Q. J. Econ. 110 (3), 964−973.

Zhou, P., Ang, B.W., Poh, K.L., 2008. A survey of data envelopment analysis in energy and environmental studies. Eur. J. Oper. Res. 189 (1), 1−18.

Zhu, Y., Liang, D., Liu, T., 2020. Can China's underdeveloped regions catch up with green economy? A convergence analysis from the perspective of environmental total factor productivity. J. Clean. Prod. 255, 1202.