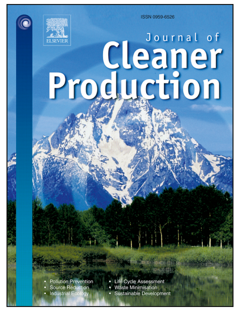
Journal Pre-proof



Measurement of green transition and its driving factors: Evidence from China

Xueqi Zhai, Yunfei An, Xunpeng Shi, Xiao Liu

PII: S0959-6526(21)04457-7

DOI: https://doi.org/10.1016/j.jclepro.2021.130292

Reference: JCLP 130292

To appear in: *Journal of Cleaner Production*

Received Date: 2 August 2021

Revised Date: 12 November 2021

Accepted Date: 26 December 2021

Credit Author Statement

Xueqi Zhai: Conceptualization, Methodology, Formal analysis, Writing-Original draft preparation.

Yunfei An: Methodology, Investigation, Supervision, Validation, Writing-Reviewing and Editing.

Xunpeng Shi: Visualization, Supervision, Writing-Reviewing and Editing.

Xiao Liu: Investigation, Data curation, Software.

Measurement of Green Transition and its driving factors: Evidence from China

Xueqi Zhai[a], Yunfei An[b*], Xunpeng Shi[c,d], Xiao Liu[e]

[a] *School of Business Administration, Henan University of Economics and Law, 180 Jinshui East Road, Zhengzhou 450001, China*
[b] *Business School, Henan University, Jinming Avenue, Kaifeng 475001, China*
[c] *Australia-China Relations Institute, University of Technology Sydney, Ultimo, NSW, 2007, Australia*
[d] *Center of Hubei Cooperative Innovation for Emissions Trading System, Wuhan 430205, China*
[e] *College of Economics and Management, Huaiyin Normal University, 71 Jiaotong Avenue, Huaian, 223001, China*

Abstract: Achieving a high-quality green transition has become an important way toward sustainable development in the world. In this study, we propose a measuring framework of green transition based on the entropy weight method. Then the driving factors of green transition are analyzed with a spatial Durbin model. Taking China as an empirical case study, the results showed that: (1) the overall level of green transition in China increased, but the green transition index (GTI) remained low. The GTIs' means and growths of the eastern region exceeded those of both the central region and the western region. Moreover, the GTIs in 30 provinces were significant gaps. (2) China's GTIs showed a significant positive spatial dependence. Furthermore, the driving factors of reform and openness, investing capacity, government intervention, and environmental regulation positively impacted the green transition development; however, the industrial structure had a negative impact. (3) Reform and openness, as well as environmental regulation, exerted positive spillover effects on other provinces, while investing capacity and government intervention exerted negative spillover effects. Moreover, the spillover effect of the industrial structure was not significant. Relevant recommendations for green transition development are proposed.

Keywords: green transition; energy transition; driving factors; spillover effect; entropy weight method; spatial Durbin model

1. Introduction

Green transition, including the energy transition, has become an important strategy for sustainable global development and global environmental governance. The "brown economy", with its high energy consumption and high pollution, has caused many social, economic, and environmental problems. At the Global Environment Ministers' Meeting in October 2008, the "Global Green New Deal" and "Developing a Green Economy" were proposed by the United Nations Environment Programme, thus calling for a global shift from a "brown economy" to a "green economy" (Mundaca and Markandya, 2016). Since then, under the connotation of the green economy (Pearce *et al.*, 1989), a green transition is considered as a mode transition from high energy consumption and high emission to low energy consumption and low emission (Ringel

* Corresponding author. Tel: +86 18624919275
E-mail address: ayf1990@163.com (Yunfei An)

et al., 2016; Kemp and Never, 2017), thereby realizing the goals of sustainable economic development and environmental protection (Springer *et al.*, 2019; Feng and Wang, 2019).

Accelerating the process of green transition has been a hot issue for governments around the world (Kemp and Never, 2017; Lamperti *et al.*, 2020). Green transition not only informs the development of global climate change policies and transition of the energy mix, but also suggest consumption side changes, such as low carbon lifestyle (Zhang *et al.*, 2020), and therefore can provide a comprehensive framework for achieving carbon neutrality (Samper *et al.*, 2021). The green transition can be affected by many factors and their effects are inconsistent (Kemp and Never, 2017; Shi *et al.*, 2020). To provide a basis for decision-making in formulating effective green transition policies, it is necessary to measure the green transition and its driving factors accurately.

Most existing studies focus on measuring green transition by calculating green total factor productivity or green efficiency with the environmental output. However, green transition emphasizes the changes of development patterns about the economy, technology, society, energy, and environment. Neither green total factor productivity nor green efficiency can reflect the characteristics of green transition comprehensively. Furthermore, many scholars use different methods to analyze the driving factors of green transition, which can be summarized as decomposition analysis methods (Su and Ang, 2016; Zhou and Ang, 2008) and econometric models (Zhang and Liu, 2015; Zhang *et al.*, 2018; Yuan and Xiang, 2018). However, due to the inaccuracy of measuring the green transition, the analysis of the driving factors would be further incomplete and even misleading. Therefore, how to measure the green transition accurately is worth studying.

Measuring the green transition is actually to calculate a comprehensive index from the multiple indicators of the economy, technology, society, energy, and environment. The entropy method can determine the weights of various indicators according to their values' variations, and then obtain an objective and comprehensive evaluation value (Zou *et al.*, 2006). This method considers the contribution of each indicator to the green transition, but also avoids subjectivity. Consequently, we propose a measuring framework of the green transition index (GTI) based on the entropy weight method. Furthermore, considering the spatial relevance of regional green transition, spatial Durbin model (SDM) is adopted to analyze the driving factors of the green transition. On this basis, taking China as the case study object, the policy implications of its green transition are come out.

The contributions of this study mainly reflect two aspects. First, we propose a general method to measure GTI using the entropy weight method. The existing measurements of green transition, such as green efficiency and green index, cannot capture the comprehensiveness of green transition. Second, we demonstrated the spatiotemporal variation and driving factors of GTIs in China's provinces from 2008 to 2017. The Moran index suggests a significant regional correlation of GTIs.

The remainder of the paper is arranged as follows: Section 2 provides a literature review. Section 3 explains a methodology framework of entropy weight method for GTI and SDM for analyzing the driving factors. Section 4 provides the case study of China and its empirical results. The discussion and the conclusion are presented in Section 5 and Section 6.

2. Literature review

With the problems caused by the increasingly severe global environmental pollution, the development of a green economy has become a trend of the new era (Pearce *et al.*, 1989). Many scholars have studied the concepts of green development, green economy, and green transition. Today, the main subjects of related research are "sustainable development", "green economy", "green growth", and "low-carbon cities".

Recently, the green transition development theory and practice are still at the exploratory stage, and no unified definition has been agreed upon. Since green transition is a new developmental approach proposed in recent years due to environmental pollution, it mainly addresses the constraints between resources and the environment in the process of sustainable development. Thomas (2015) argued that energy innovation would cause structural change and thus expand the green space to achieve sustainable development. This process was named green transition. Similarly, Ferguson (2015) pointed out green transition meant to improve resource productivity and achieve the transition of an unsustainable development to a sustainable development model. Bandyopadhyay (2017) evaluated sustainable development from three aspects: economic, social, and environmental development. Rodenburg *et al.* (2001) established urban economic indicators to evaluate green structure and green space and proposed a green development framework from four dimensions: environmental resource, urban welfare and quality, green financing, and government management. In addition, several scholars analyzed sustainable development from the perspective of green energy. Midilli *et al.* (2006) reported that public awareness, information, environmental education, financing, and evaluation tools were essential factors for green energy strategy, and proposed several green energy strategies for sustainable development.

To measure green transition, many scholars focused on green development performance, green development index, and green growth efficiency. Feng *et al.* (2017) estimated the green development performance index and its influencing factors, using the DEA method. They found that a U-shaped environmental Kuznets curve (EKC) existed between the green development performance index and the economic development level. Moreover, living standards, energy structure, and oil price positively influenced the green development performance index, while ecological carrying capacity negatively influenced it. Kushwaha and Sharma (2016) proposed a green initiative based on exploratory research to analyze the relationship between the sustainable development of the automotive industry and its performance. To measure the green performance, Rashidi and Saen (2015) used the DEA method to calculate eco-efficiency indicators, and the results showed that the more energy is input, the more undesired the outputs will be. Zhao and Yang (2017) evaluated the green development performance of 286 cities in China using metafrontier-data envelopment analysis. Their results showed that the green growth efficiency of cities with different sizes and in different regions differed, which required environmental governance and government regulation.

Related to the driving factors of green transition, Dincer and Rosen (2005) identified four factors that affect sustainable development: energy and resources, economy, environment, and society. Yuan and Xiang (2018) estimated the green total factor productivity (GTFP) indicator and used it as a measure of China's industrial green development profile. They furthermore used the extended CDM model to examine the impact of environmental regulation on both technological innovation and green development. Green environmental efficiency was identified to vary from region to region and also showed clear spatial dependence and spatial variation (Chen *et al.*, 2019;

Shao *et al.*, 2020). They found that regional green development was affected positively by openness degree, urbanization, industrial structure, and technological innovation. However, economic growth, corporate structure, fiscal policy, and foreign investment negatively affected regional green development.

Furthermore, Choi *et al.* (2016) analyzed the new paradigm of sustainable challenges in Northeast Asia under the context of green growth policy and green strategy. They emphasized the key role of the government to stimulate green development governance. Similarly, Hamdouch and Depret (2010) described the leading role of the government in the green transition process. The government should make well-designed environmental and innovation policies, and obtain the support of both stakeholders and relevant organizations. However, Jorgenson and Wilcoxen (1990) demonstrated that the environmental policy increased the additional environmental costs of enterprises, thus resulting in insufficient investment in R&D and innovation, and exerting a significant negative effect on the growth of green total factor productivity.

In summary, there are two gaps in the literature. First, there is not a direct measurement of green transition. The existing studies used either green index or green efficiency to quantify the green transition. However, neither green efficiency nor green index can capture the comprehensiveness of green transition. Further, the green transition is a comprehensive reflection of economic transition, technological transition, social transition, energy transition, and ecological transition. Calculating an index from these aspects could be useful to reflect the reality of regional green transition. Another gap is the spillover effect of green transition across regions. With regard to China, green transition in the local region usually affects the other neighboring regions for a number of reasons (Cabrer and Serrano, 2007; Zhang *et al.*, 2018). Therefore, to explore the questions, this paper firstly analyzed the green transition index of China using the entropy weight method. Then SDM was used to analyze the driving factors of green transition and their spatial spillover effects.

3. Measurement of green transition and its driving factors: a methodology framework

3.1. Measurement of the green transition index (GTI)

3.1.1 Entropy weight method

Entropy is widely used to measure the degree of disorder in a system (Shannon, 1948). Hence, entropy weight, as an objective weighting method, also evaluates the degree of disorder in a system by using useful information (Zou *et al.*, 2006). The larger the entropy weight, the more useful information of the index. By using the entropy weight method, the GTI was measured with the following steps.

Step 1: Construct evaluation matrix R.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}_{m\times n} \tag{1}$$

where r_{ik} represents the evaluation value of the k indictor for the i province, i = 1, 2, …, m, and k = 1,2, …, n;

Step 2: Normalizing the matrix R. If k is a benefit indictor, a larger k value indicates a greater positive effect on GTI; therefore, formula (2) was used to normalize k. If k is a cost indictor, the larger its value is, the greater the negative effect on GTI will be; therefore, formula (3) was used to normalize k.

$$R_{ik}=\frac{r_{ik}-\min\limits_{1\le i\le m}\left(r_{ik}\right)}{\max\limits_{1\le i\le m}\left(r_{ik}\right)-\min\limits_{1\le i\le m}\left(r_{ik}\right)} \tag{2}$$

$$R_{ik}=\frac{\max\limits_{1\le i\le m}\left(r_{ik}\right)-r_{ik}}{\max\limits_{1\le i\le m}\left(r_{ik}\right)-\min\limits_{1\le i\le m}\left(r_{ik}\right)} \tag{3}$$

Step 3: Assume that p_{ik} represents the converted value via R_{ik}, which can be defined as Eq. (4).

$$P_{ik}=\frac{R_{ik}}{\sum\limits_{i=1}^{m}R_{ik}} \tag{4}$$

Step 4: Calculate the entropy e_{ik} of the k indicator for i province using Eq. (5), where λ represents the Boltzman's constant, λ = 1 / ln(n).

$$e_k=-\lambda\sum_{i=1}^{m}P_{ik}\ln P_{ik},\ \lambda=\frac{1}{\ln n} \tag{5}$$

Step 5: Provide the degree of diversification e_{k} of the information by Eq. (6).

$$d_k=1-e_k \tag{6}$$

Step 6: The entropy weight w_{k} of the k indicator is calculated by Eq. (7).

$$W_k=\frac{d_k}{\sum\limits_{k=1}^{n}d_k} \tag{7}$$

Step 7: The green transition index GTI_i of the i_{th} province in China is calculated by Eq. (8).

$$GTI_i=\sum_{k=1}^{n}R_{ik}W_k \tag{8}$$

3.1.2 Evaluation indicators of GTI

To measure the GTI by the entropy weight method, the evaluation indicators first had to be chosen. In reference to literature by Guo and Zhou (2018), Rodenburg *et al.* (2001), and Hou *et al.* (2019), the following five dimensions of green transition are analyzed: economic transition, technological transition, energy transition, social transition, and environmental transition. Economic transition refers to the industrial structure, investment, and foreign trade development (Yu *et al.*, 2021). Especially, China's industrial structure has been significantly changed since implementing economic reform and open up, which the tertiary industry has gradually replaced the dominant position of the secondary industry (Karl and Chen, 2010; Yin *et al.*, 2019; Zhao and Lin, 2019). Therefore, economic transition can be measured from the per capita GDP, tertiary industry value added, total social investment in fixed assets, and total imports and exports indicators. Technological development is the crucial driving force for achieving green transition. Therefore, technological transition is measured by the expenditure for new product development and the number of patent applications (Feng *et al.*, 2021). Moreover, achieving low carbon growth needs reduce the share of raw coal in energy production and increase the share of electricity in the total final energy consumption (IEA, 2020; GEDICO, 2021). For the energy transition, it is necessary to change the coal-based energy consumption structure and build a low carbon electricity-based power system (Zhao and You, 2020). Therefore, the energy transition is measured by raw coal consumption and electricity consumption. Further, green transition is also influenced by the changes in social production activities and behaviors (Bell, 2016). Therefore, the social transition can be measured by the expenditure of residents per capita, public budget expenditure, and unemployment rate. Finally, environmental transition, as a goal of achieving green transition, is measured by the total investment in industrial pollution control and sulfur dioxide emissions (Zhu *et al.*, 2019). Consequently, 13 indicators were selected as evaluation indicators to calculate green transition, as shown in Table 1.

Table 1 Evaluation indicators of GTI

First-level indicator	Second-level indicator	Third-level indicator
Green transition	Economic transition	GDP per capita
		Tertiary industry added value
		Total social investment in fixed assets
		Total imports and exports
	Technological transition	Expenditure for new product development
		Number of invention patent applications
	Energy transition	Raw coal consumption
		Electricity consumption
	Social transition	Consumption expenditure of residents per capita
		Public budget expenditure
		Unemployment rate
	Environmental transition	Total investment in industrial pollution control
		Sulfur dioxide emissions

3.2. The model of driving factor analysis

3.2.1. Spatial correlation test

Because of the complexity of the spatial econometric model, it is necessary to test the spatial correlation of variables before their empirical analysis. To determine whether the variables are spatially correlated, the common methods are Moran index test, Gillie index test, and Cetis index (Cabrer and Serrano, 2007). Among these, the Moran I index is widely used to measure the spatial correlation of variables. Its calculation formula is as follows:

$$Moran's\ I=\frac{\sum_{i=1}^{m}\sum_{j=1}^{m}w_{ij}\left(GTI_i-\overline{GTI}\right)\left(GTI_j-\overline{GTI}\right)}{S^2\sum_{i=1}^{m}\sum_{j=1}^{m}w_{ij}} \tag{9}$$

where i and j represent the province i and j, $\overline{GTI}$ represents the mean of the GTI; $S^2=\frac{\sum_{i=1}^{m}\left(GTI_i-\overline{GTI}\right)}{m}$ represents the variance in the sample; w_{ij} represents the spatial weight of the element (i, j) for measuring the distance between provinces i and j, and w represents the spatial weight matrix.

The Moran I index ranges from -1 to 1. A value above 0 indicates that the GTI of the local province is positively related to its neighbors. The closer the value is to 1, the stronger the positive spatial correlation will be. However, values below 0 indicate that the GTI of the local province is negatively related to its neighbors. A value close to -1 indicates a stronger negative spatial correlation. When the value is 0, no spatial autocorrelation is present.

3.2.2. The set of the spatial weight matrix

The spatial weight matrix reflects the interdependence of variables in different regions, which constitutes the premise of spatial correlation analysis (Chen *et al.*, 2019). New economic geography believes that the spatial relationship between two elements will weaken when increasing their distance (Krugman, 1998). That is, as the distance between two provinces of mainland China increases, the spatial spillover effect of green transition will weaken. Therefore, the spatial weight matrix was established with the inverse distance between two provinces as Eq. (10).

$$w_{ij} = \begin{cases} 1/d_{ij}, & i \neq j \\ 0, & i = j \end{cases} \tag{10}$$

where d_{ij} is the straight-line distance between the province i and j.

3.2.3. The spatial Durbin model

The flow of resources among provinces can easily affect the local province's GTI, which causes it to be affected by the GTIs of its neighboring provinces. As to the potential spatial correlation of the GTI, a spatial panel model was constructed to analyze the driving factors of the GTI. According to existing research, the spatial panel models contain three types, namely spatial lag model (SLM), spatial error model (SEM), and SDM (Chen et al., 2019; Feng and Wang, 2019). The SLM is used to describe the existence of spatial autocorrelation. By adding the spatial lag term of GTI to the independent variables, the SLM can be expressed as Eq. (11).

$$GTI = \alpha I_n + \rho WGIT + \beta X + \varepsilon \tag{11}$$

where GTI is the dependent variable, representing the green transition index; X is the independent variables, representing the driving factors of the green transition; ρ represents the spatial autocorrelation parameter; W is the spatial weight matrix; $WGTI$ represents the spatial lag term of GTI. β represents the spatial regressive parameter. I_n is a $n \times 1$ vector associated with the intercept parameter α; ε is the normal error term.

The SEM believes that the error item affected by GTI's factors becomes strong relevant as the existing spatial relationship, therefore the SEM can be expressed as Eq. (12).

$$\begin{aligned} GTI &= \alpha I_n + \beta X + \phi \\ \phi &= \lambda W \phi + \varepsilon \end{aligned} \tag{12}$$

where ϕ is the error item with strong relevance; λ represents the spatial regressive parameter.

When the spatial lag items of the GTI and its influencing factors are all considered, the SDM is expressed as Eq. (13).

$$GTI = \alpha I_n + \rho WGIT + \beta X + \theta WX + \varepsilon \tag{13}$$

where WX represents the spatial lag terms of independent variables; θ represents the spatial regressive parameters.

Before choosing the SDM, it is necessary to use the Lagrange Multiplier Method to test whether the null hypothesis of SLM or SEM is true. If the null hypothesis of SLM or SEM is not rejected, then SLM or SEM is selected. If the null hypotheses of both SLM and SEM are rejected, then the SDM is chosen.

4. A case study of China

With the rapid economic growth, China has become the world's second-largest economy. However, relying on administrative and planning policies of the Chinese government, this growth mode had the characteristics of high input, high consumption, and high pollution (Wang *et al.*, 2019; Song *et al.*, 2020). This not only caused resource exhaustion, but also caused severe ecological and environmental problems. The latest data from the Global Carbon Project showed that China's carbon dioxide emission increased by 4.7% in 2018, accounting for 27% of the global emissions (*Ding et al., 2019*). Therefore, the green transition of China plays a key role in promoting global sustainable development.

In order to demonstrate our methodology, we use China as a case study. To properly promote green transition, the Chinese government has formulated the green development goal and direction in the 12th Five-Year Plan. More recently, China has pledged to peak emissions by 2030 and neutralize emissions by 2060. However, what about the status of China's green transition? Are there any links between the local province and neighboring provinces? What are the driving factors of green transition? Answer to these questions will help China to formulate the urgently needed transition roadmap that is appropriate to its level of economic development, energy mix, and regional heterogeneity (Shi *et al.*, 2021; Shi, 2021).

Therefore, this study comprehensively calculated the green transition index (GTI) of China from 2008 to 2017 from the following five aspects: economic transition, technological transition, energy transition, social transition, and environmental transition. Moreover, industry structure, reform and openness, investing capacity, government intervention, and environmental regulation were selected as driving factors. Furthermore, China's regional GTI and spatiotemporal variation were studied from a spatial econometric perspective, and the driving factors of green transition and their spillover effects were analyzed. Finally, several recommendations for green transition development were proposed.

4.1. Variable selection and data source

4.1.1. Driving factors

According to economic theory, technological progress, structural change, environmental regulation, resources, and population are the main factors affecting sustainable economic development (Yang *et al.*, 2021). Furthermore, the green economy is essentially a production path with high technology, low resource consumption, and low environmental pollution (Jin *et al.*, 2021). Therefore, the driving factors of the GTI were summarized as industrial structure, reform and openness, investing capacity, government intervention, and environmental regulation.

(1) Industrial structure (IS). Fan *et al.* (2003) pointed out that structural change was a further source of economic growth. Changes in industrial structure actually indicated the reallocation of resources from low-productivity sectors to high-productivity sectors, thus contributing to the overall economic development (Zagler, 2009; Adom *et al.*, 2012). At present, the advanced degree of the industrial structure is usually characterized by the level of regional green transition (Laitner, 2010). The development of the tertiary industry has become an important indicator to evaluate the development level for a country. Increasing the proportion of the tertiary industry is conducive to stimulating economic development and accelerating the process of green development (Zhu *et al.*, 2019). Therefore, this study selected IS as the driving factor, which was measured by the proportion of tertiary industry output in the gross domestic product (GDP).

(2) Reform and openness (RO). Since the reform and openness was proposed by the Chinese government, China's economic development has been greatly promoted (Kanbur and Zhang, 2001). Hye *et al.* (2016) developed a trade openness index for China and found that trade openness was positively related to economic growth in both the long run and the short run. Moreover, the deeper the

reform and openness, the more frequent the flow of funds, talents, and technology into a region, which contributed to regional green transition (Tisdell, 2009). Then, the actual amount of foreign investment utilized capital per capita (US$/Person) was used to express RO.

(3) Investing capacity (IC). Governments around the world always emphasize the importance of investing capacity. This is the main driving force for accelerated economic development, and also an important tool for urban industrialization. Since green development has been proposed, Hall *et al.* (2017) showed that both finance and investment play an enormous role in facilitating transformative change. Moreover, Kemp-Benedict (2018) argued that private investment should be mobilized for a transition. The fixed-asset investment in the China Statistical Yearbook is a comprehensive indicator, including investment types of state-owned enterprises, collectives, individuals, and foreigners. Consequently, this study adopted fixed asset investment per capita (Thousand US$/Person) to measure IC.

(4) Government intervention (GI). It is necessary to strengthen governmental intervention in the process of sustainable development (Kemp and Never, 2017). The focus of the local government on green transition presents a major influence on the overall quality of regional economic and social development (Droste *et al.*, 2016). Especially when the transition is not interesting for enterprises and individuals, the government must enhance policy interventions to change this status (Owen *et al.*, 2018; Xu *et al.*, 2021). The power of governmental intervention is mainly related to local fiscal expenditure. Therefore, this study selected local fiscal expenditures per capita (US$/Person) as the indicator to measure GI.

(5) Environmental regulation (ER). Strict environmental regulation is an important policy, which China will continue to implement for a long time to realize green development (Jaffe *et al.*, 1995; Liao and Shi, 2018). Environmental regulation is conducive to restraining high energy-consuming and high-polluting industries, which is one of the key driving factors for green transition (Wang *et al.*, 2019; Zhai and An, 2020). Therefore, the indicator of environmental governance investment per capita (US$/Person) was used to denote ER in this paper.

Explanations and symbols of the above variables are provided in Table 2.

Table 2 Descriptive statistics for all variables.

Variables	Definition	Unit	Mean	Min	Max	Obs
GTI	A comprehensive index from the multiple indicators of economy, technology, society, energy, and environment	-	0.2397	0.0663	0.8156	300
IS	the proportion of tertiary industry output in the GDP	%	43.1831	28.6	80.6	300
RO	Actual amount of foreign investment utilized capital per capita	US$/Person	266.6088	4.3646	1808.893	300
IC	Fixed asset investment per capita	Thousand US$/Person	259.3316	4.5806	3762.6621	300
GI	Local fiscal expenditures per capita	US$/Person	13.1558	0.2489	102.4267	300
ER	Environmental governance investment per capita	US$/Person	1614.5723	4.1748	31065.2392	300

Note: exchange rate used: 1US$=6.x RMB.

4.1.2. Data Source

To analyze the driving factors of green transition, the panel data of 30 provinces in mainland China from 2008 to 2017 was utilized, except Tibet, due to a lack of data. The original data of evaluation indicators for GTI and its driving factors were collected from the China Statistical Yearbooks (2009-2018), the China Energy Statistical Yearbooks (2009-2018), and the statistical yearbooks of the 30 provinces in mainland China.

Furthermore, the spatial weight matrix was generated with the GeoDa software, and the data of the provincial latitude and longitude were collected from the national catalog service for geographic information. Moreover, the SDM model was realized with MATLAB software. To solve the heteroscedasticity of panel data and reduce data instability, the logarithm of driving factors was utilized in this paper.

4.2. The overall trend of GTI

Fig. 1 shows the overall trend of the GTI for mainland China from 2008 to 2017, and the regional GTI trends of the eastern region, central region, and western region. The GTI was lowest in 2012, and since then, has improved significantly. The overall GTI was still low and its mean was 0.240, which indicated that the GTI of the 30 provinces of mainland China was not effective.

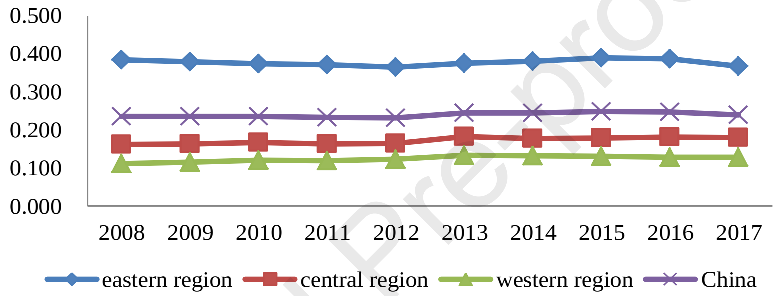


Fig. 1 GTI trends of China's regions

Table 3 describes the GTIs for selected years due to limited space. The GTIs in almost all provinces improved from 2008 to 2017, while there were significant gaps among them. In 2017, the GTIs in six provinces reached greater than 0.5, including Beijing, Shanghai, Jiangsu, Zhejiang, Guangdong, and Hainan. This means that the green development of these cities in China has reached a good level, however, it exists a great gap that the GTIs in other provinces are all below 0.5.

From the perspective of regional GTIs, the eastern region had a significantly higher GTI mean than both the central region and the western region. Fig. 2 shows the GTIs' means of China's 30 provinces from 2008 to 2017. The top five GTIs regions (according to their means) were Guangdong, Jiangsu, Beijing, Shanghai, and Zhejiang, which all belong to the eastern region. Particularly, the GTI means of Guangdong and Jiangsu reached 0.763 and 0.725, respectively. In the central region, the range of GTI means is between 0.125 and 0.238. Only the GTIs of Henan, Hubei, Anhui are greater than 0.2. However, in the western region, the GTIs in each province are lower than 0.2 except Sichuan.

Further, by analyzing the GTIs changes of China's 30 provinces from 2008 to 2017 as shown in Fig. 3, the GTI growth in the eastern region was higher than that in both the central region and the western region. The provinces with GTI growths greater than 0.1 were mainly concentrated in the eastern region, including Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, and Hainan. However, the growths of other provinces were less than 0.1. This result reflected the status of green transition in China. Compared with the central and western regions, the eastern region has the advantages of economic scale, industrial structure, and technological innovation. Furthermore, the agglomeration effect of the cities belonging to the eastern region has gradually been formed, thus shaping into a better decoupling between the economic development and the load of resources and environment. The results imply that regional gaps in GTIs are widening.

Table 3 The GTIs of the 30 provinces for selected years

Regions	No.	Provinces	2008	2011	2014	2017	Means	Growths
Eastern region	1	Beijing	0.489	0.519	0.659	0.763	0.606	0.274
	2	Tianjin	0.321	0.330	0.439	0.585	0.410	0.264
	3	Hebei	0.204	0.210	0.243	0.214	0.214	0.010
	6	Liaoning	0.267	0.264	0.263	0.272	0.267	0.005
	9	Shanghai	0.493	0.542	0.610	0.647	0.572	0.154
	10	Jiangsu	0.614	0.720	0.745	0.771	0.725	0.158
	11	Zhejiang	0.517	0.511	0.614	0.632	0.562	0.115
	13	Fujian	0.237	0.232	0.269	0.261	0.251	0.024
	15	Shandong	0.505	0.466	0.516	0.497	0.492	0.019
	19	Guangdong	0.816	0.728	0.735	0.806	0.763	0.011
	21	Hainan	0.380	0.524	0.600	0.637	0.545	0.257
	20	Guangxi	0.126	0.134	0.139	0.156	0.139	0.030
Central region	4	Shanxi	0.139	0.162	0.161	0.186	0.159	0.024
	5	Inner Mongolia	0.153	0.159	0.176	0.208	0.173	0.007
	7	Jilin	0.120	0.129	0.136	0.140	0.132	0.011
	8	Heilongjiang	0.100	0.125	0.131	0.132	0.125	0.031
	12	Anhui	0.164	0.181	0.205	0.234	0.202	0.070
	14	Jiangxi	0.121	0.144	0.138	0.158	0.139	0.037
	16	Henan	0.224	0.215	0.249	0.284	0.238	0.060
	17	Hubei	0.190	0.186	0.228	0.245	0.220	0.055
	18	Hunan	0.170	0.168	0.192	0.201	0.185	0.030
Western region	22	Chongqing	0.142	0.153	0.169	0.171	0.158	0.030
	23	Sichuan	0.198	0.190	0.215	0.223	0.204	0.025
	24	Guizhou	0.072	0.090	0.094	0.093	0.088	0.021
	25	Yunnan	0.110	0.104	0.116	0.119	0.113	0.008
	26	Shaanxi	0.139	0.164	0.175	0.172	0.170	0.033
	27	Gansu	0.098	0.089	0.103	0.103	0.103	0.014
	28	Qinghai	0.066	0.074	0.081	0.090	0.081	0.014
	29	Ningxia	0.078	0.070	0.075	0.090	0.079	0.020
	30	Xinjiang	0.104	0.120	0.133	0.125	0.120	0.022

Fig. 2 GTIs' means of China's 30 provinces from 2008 to 2017

Fig. 3 GTIs' growths of China's 30 provinces from 2008 to 2017

4.3. Model estimation of driving factors

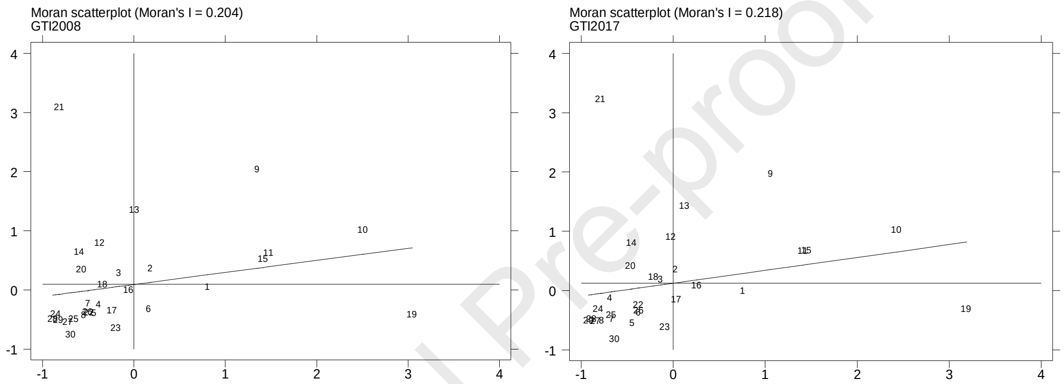
4.3.1. Spatial correlation test

Table 4 shows the Moran's I indices of GTIs for every year from 2008 to 2017. The Moran's I statistic values all exceeded 0, which demonstrated that the GTIs had a strong spatial correlation. Moreover, the statistic values of GTIs were significant at the 5% level. Therefore, a spatial econometric model was required to analyze the driving factors of the green transition of China.

Furthermore, the local Moran's I indices of 30 provinces were also calculated for mainland China from 2008 to 2017. Fig. 4 describes the Moran's I scatter plots in 2008 and 2017. Most of the investigated provinces are located in the second and third quadrants over the past ten years, indicating that they had the characteristics of high-value and low-value aggregation as well as low-value and low-value aggregation.

Table 4 Moran's I and its statistical test of GTIs from 2008 to 2017

Years	I	z	p-value
2008	0.192	2.132	0.033
2009	0.184	2.047	0.041
2010	0.201	2.220	0.026
2011	0.224	2.443	0.015
2012	0.215	2.365	0.018
2013	0.208	2.290	0.022
2014	0.205	2.244	0.025
2015	0.216	2.361	0.018
2016	0.217	2.342	0.019
2017	0.214	2.355	0.019



(a) The Moran scatter plot for GTIs in 2008 (b) The Moran scatter plot for GTIs in 2017

Fig. 4 The Moran'I scatter plots for GTIs in 2008 and 2017

(Note: The number denotes each province, and its meaning is shown in Table 3)

4.3.2. Estimation results

According to the comparison of non-spatial panel models, it could be further judged whether these models are suitable to build a spatial panel model, which is typically determined by Lagrange Multiplier (LM) test. Table 5 describes the estimation results of the Partial Least Squares (PLS) regression. It can be seen that reform and openness, investment capacity, government intervention, and environmental regulation affect GTI positively at 1% level. This shows that reform and openness, investment capacity, government intervention, and environmental regulation can promote green transition. However, the coefficient of industrial structure is negative, which exerts a significantly negative effect on green transition. Further, the results of the LM test and the Robust LM of the spatial lag panel were significant at 1% level, thus rejecting the null hypothesis of no spatial lag effect. Moreover, the statistics value of the LM test of spatial error panel rejected the null hypothesis of no spatial error effect at 1% level, while the statistics value of the Robust LM test could not reject the null hypothesis. Therefore, SDM is the better choice for analyzing GTI's driving factors.

By comparing the results of SLM, SEM, and SDM, the maximum likelihood method was adopted to estimate the three models. Since the panel model had two types, the random effect model and fixed effect model, it was necessary to choose whether the model contained random effects. This was done by the Hausman test. As shown in Table 6, the statistics of Hausman test significantly rejected the null hypothesis at 5% level. Hence, a spatial panel model with fixed effect was built.

Table 5 Estimation results of the PLS regression

Variables	PLS regression
_cons	-2.8759 (-16.92)
IS	-0.1964** (-3.12)
RO	0.0429*** (3.82)
IC	0.0821*** (6.73)
GM	0.1733*** (3.54)
ER	0.0506 ***(4.07)
R^2	0.6757
F	122.53
LM_spatial_lag	33.675***
Robust LM_spatial_lag	20.108***
LM_spatial_err	15.724***
Robust LM_spatial_err	0. 935

Note: The t-statistics are given in parentheses; *** and ** denote significance at 1% and 5% level, respectively.

Table 6 Estimation results for the spatial panel regression model

Spatial panel model with fixed effect	SDM	SLM	SEM
_cons	-	-2.8756 (-6.43)	-0.0951 (-1.46)
IS	-0.0068**(-3.09)	-0.0331** (-2.80)	-0.0367* (-2.13)
RO	0.0316*** (4.51)	0.0424*** (4.29)	0.0420***(7.26)
IC	0.1055*** (5.64)	0. 1022*** (3.39)	0.0834*** (3.59)
GM	0.0217*** (4.27)	0.0143** (2.82)	0.0416* (2.02)
ER	0.1128*** (5.38)	0. 1246 ***(5.99)	0.0755*** (7.08)
W*IS	0.0463*(1.98)	-	-
W*RO	0.1875**(3.16)	-	-
W*IC	-0.0485***(-4.56)	-	-
W*GM	-0.0521***(-3.98)	-	-
W*ER	-0.0187**(-3.11)	-	-
R^2	0. 7984	0.7283	0.7515
Log-likelihood	81.0866	62.6742	71.5401
Lambda/Rho	0.0523***(5.47)	0.0148**（3.04）	0.1237 (1.55)
sigma2_e	0.0025***(4.69)	0.0027***(11.60)	-
Wald spatial lag	22.3155***	-	-
LR spatial lag	11.4367**	-	-
Wald spatial error	28.8414***	-	-
LR spatial error	10.9983**	-	-
Hausman test	117.8827***	-	-

Notes: The t-statistics are given in parentheses; ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

It can be inferred that the coefficient of industrial structure is -0.0068, which is negatively correlated with green transition at 5% level. This may relate to the unreasonable development of the tertiary industry. The coefficients of reform and openness, investment capacity, government intervention, and environmental regulation are 0.0316, 0.1055, 0.0217, and 0.1128, respectively. That means they are all beneficial for green transition by decreasing carbon emissions and energy consumption. Subsequently, indicated by the estimation results of the three spatial models above, the *Lambda/Rho* shows that both SDM and SLM passed the significance test at the 5% level, while SEM is not significant. From the perspective of R-squared and Log-likelihood, SDM is better than SLM. Moreover, both the Wald test and the LR test reject the null hypothesis; therefore, the SDM could not be simplified to SLM or SEM. In summary, based on the above analysis, the

SDM may better express the spatial dependence of the driving factors of green transition.

4.3.3. Robustness test

The robustness of SDM is tested by two methods. The first method is to compare the estimation results of different models, which are shown in Tables 5 and 6. The coefficients of driving factors on GTI are consistent under the PSL regression and the spatial panel data models, only differ insignificance. Thereby, it can be inferred the results in this paper are robust.

The second method is to use different spatial matrices. The economic-geographical weight matrix was selected for comparison with the results of the geography distance matrix. With the convenience of transportation and the popularity of communication, economic distance should be studied when constructing a spatial weight matrix (Zhang *et al.*, 2018). Due to the economic and geographical factors, the economic-geographical weight matrix is built in this paper and is expressed as Eq. (14).

$$w_{ij} = \begin{cases} GDP_i * GDP_j / d_{ij}^2, & i \neq j \\ 0, & i = j \end{cases} \tag{14}$$

where GDP_i and GDP_j represent the GDPs of provinces *i* and *j*. d_{ij} represents the distance between provinces *i* and *j*.

Therefore, the estimation results with the economic-geographical weight matrix are shown in Table 7. Compared with the results in Table 6, the estimated coefficients of these five driving factors and their significance levels do not obviously change. This shows that the results in the paper are robust.

Table 7 Estimation results with the economic-geographical weight matrix

Spatial panel model with fixed effect	SDM	SLM	SEM
_cons	-	-1.6548 (-3.65)	-0.1264 (-1.64)
IS	-0.0058**(-2.83)	-0.0405** (-2.69)	-0.0259* (-2.27)
RO	0.0269*** (4.74)	0.0518*** (5.16)	0.0361***(6.42)
IC	0.1556*** (5.26)	0. 1086*** (4.27)	0.0863*** (3.66)
GM	0.0865*** (3.92)	0.0262* (2.28)	0.0435* (2.36)
ER	0. 1226*** (6.41)	0.0817 ***(3.86)	0. 1024*** (5.62)
W*IS	0.0461*(2.21)	-	-
W*RO	0.1746*** (3.25)	-	-
W*IC	-0.0722***(-6.13)	-	-
W*GM	-0.0381***(-3.86)	-	-
W*ER	-0.0167**(-2.88)	-	-
R^2	0. 8134	0.7168	0.7260
Log-likelihood	81.9342	66.3802	74.2283
Lambda/Rho	0.0529***(4.68)	0.01741**(3.07)	0.0424** (2.76)
sigma2_e	0.0024***(3.79)	0.0031***(6.52)	0.0029***(5.38)
Wald spatial lag	26.1724***	-	-
LR spatial lag	12.0431**	-	-
Wald spatial error	29.6634***	-	-
LR spatial error	10.7208**	-	-

Notes: The t-statistics are given in parentheses; ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

4.4. Spatial spillover effects of driving factors

The change of one or more driving factors not only affected the green transition of the local province directly, but also indirectly affected the green transition of the neighboring provinces.

Consequently, the estimation results of SDM could not accurately reflect the influence of driving factors on the green transition.

Therefore, the partial differential method was used to decompose the spatial spillover effect of the SDM into three parts: direct effect, indirect effect, and total effect (Lesage and Pace, 2009). The direct effects represented the influences of driving factors on the green transition of a local province. The indirect effects represented the influences of driving factors on the green transition of neighboring provinces. The total effects reflected the average influences of driving factors on both the local provinces and their neighboring provinces. Table 8 displays the results of direct, indirect, and total effects for the driving factors.

Table 8 Direct effects, indirect effects, and total effects of the SDM on GTI

variables	Direct effect	Indirect effect	Total effect
IS	-0.0125 (-3.13)**	0.0082 (2.11) *	-0.0043 (-1.98)*
RO	0.0317 (6.15) ***	0.0224 (3.20) **	0.0541 (6.13) ***
IC	0.0879 (4.28) ***	-0.1237 (-4.64) ***	0.0043 (3.88) ***
GM	0.0783 (3.99) ***	-0.1237 (-3.87) ***	-0.0454 (-2.95) **
ER	0.0175 (4.26) ***	-0.0092 (-2.03) *	0.0083 (2.14) *

Notes: The t-statistics are given in parentheses; ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

It can be found that the results of both direct and indirect effects were lined with the corresponding regression results in Table 6, illustrating that the results were steady and effective. Moreover, it demonstrated the rationality of using SDM to explore the spatial spillover of driving factors.

5. Discussion

With regard to direct effects, reform and openness, investing capacity, government intervention, and environmental regulation were significant at 1% level, and they positively impacted the green transition of China. The coefficients were (in descending order) investing capacity, government intervention, reform and openness, and environmental regulation. Fu and Balasubramanyam (2005) pointed out that reform and openness attracted advanced technology and promoted the development of both import and export trade. This also brought advantageous resources together to develop green transition (Holz, 2008). Moreover, similar to the work by DeLonge *et al.* (2016), investing could provide sufficient financing support for the green transition to optimize industrial structure. Moreover, the government, as a guide of China's green transition, plays an important role in promoting green transition. By formulating policies related to tax, innovation, and funding, the government can guide and encourage manufacturing enterprises to realize green transition (Kemp and Never, 2017). Furthermore, environmental regulation can strengthen the optimal allocation of various resources to explore green technology, green processes, and green development, which thus promotes green transition (Wang and Shao, 2019; Pan *et al.*, 2019).

However, the direct effect of industrial structure on green transition was significant at 5% level, and exerted a significant negative effect on green transition. These results were consistent with the research by Wang *et al.* (2019). Currently, the tertiary industry in China has grown fast and its proportion of GDP gradually increased. However, the tertiary industry is mainly dominated by traditional service industries, including commerce, catering, and transportation. Emerging industries, such as information, consulting, technology, and financing, have insufficient development momentum, which led to small industry outputs and unreasonable industry structure. Using the express delivery industry in China as an example, it has developed rapidly since e-commerce was booming, but it has brought a serious environmental burden due to consuming a large amount of express packaging materials (Fan *et al.*, 2017). This may be the reason why the industrial structure exerts a negative impact on green transition.

Furthermore, from the perspective of indirect effects, the driving factors of investing capacity and government intervention were both significant at 1% level. This indicates that they exerted spatial spillover effects on the GTIs of neighboring provinces through spatial transmission channel. However, they generated negative externalities, i.e., when the invested capacity in the local province increased, the investing capacity in the neighboring provinces would decrease and form a 'closure effect'. Moreover, when the local government issued policies to develop green transition, this would attract more resources into the local province (Huang *et al.*, 2019). Consequently, this caused the resources to flow out from neighboring provinces. Moreover, the driving factor of reform and openness was significant at 5% level, which exerted a positive impact on the green transition in the neighboring provinces. Because the local government intensified the reform and openness, this enhanced the reform and openness of neighboring provinces and thus attracted resources (Kanbur and Zhang, 2001). In addition, the driving factor of industrial structure was significant at 10% level, and exerted a positive impact on the green transition of neighboring provinces. Furthermore, the driving factor of environmental regulation was significant at 10% level, but exerted a negative impact on neighboring provinces.

In addition, according to the total effects of these five driving factors, the reform and openness was significant at 1% level and its coefficient value was largest. This implied that reform and openness promoted the green transition of 30 provinces in mainland China through spillover effects, and the driving force was stronger than that of other factors. The statistics value of governmental intervention was significant at 5% level and its coefficient value was negative, indicating that the negative diffusion effect of governmental intervention on green transition exceeded its direct effect. This is because when the local government formulates macroeconomic policies to promote green transition, it attracts the governments in neighboring provinces to learn and imitate, which can easily cause policy overlap to hinder green transition (Giri *et al.*, 2019). Moreover, both investing capacity and environmental regulation were significant at 10% level, and both their direct effects exceeded their indirect effects (An *et al.*, 2021). This demonstrated that their direct impact on green transition of China exceeded the negative effect on the neighboring provinces.

6. Conclusion and Policy Implications

To explore the status quo of China's green transition development, this paper used the entropy weight method to calculate the GTIs of 30 provinces of China. On the basis, SDM was used to analyze the driving factors and spillover effects of China's green transition. The main conclusions are as follows:

(1) The overall level of China's green transition increased, but there is still enormous potential for improvement. China's GTI was low from an overall perspective and the gaps among provinces are widening. From the perspective of geographical distribution, the GTIs in the eastern region of China were much higher than those in both the central and western regions.

(2) The regional GTI in China had significant positive spatial dependence. Consequently, the

green transition of local provinces positively affected the development of neighboring provinces, showing that the spatial linkage effect has steadily developed.

(3) The results of the SDM showed that reform and openness, investing capacity, government intervention, and environmental regulation significantly promoted the green transition development in China. Among these, reform and openness had the greatest influence on green transition. However, the industrial structure harmed the green transition.

All factors exerted both direct and indirect impacts on the green transition development of China. How to realize high-quality green transition and coordinate the development among different regions has become the key for China's current development. Based on the main conclusions above, the following lists several implications for China's policy formulation toward the realization of the green transition and regional coordinated development:

(1) The positive space spillover effect of the reform and openness and environmental regulation should be fully utilized when China’s government plans for the green transition development. It is centrally important to increase the depth and intensity of the reform and openness. The cooperation and trust between provincial governments should be strengthened. Instead of narrow regional thinking, provincial governments need to fully account for regional agglomeration effects. Moreover, appropriate national coordination is needed to narrow the GTI development gaps among provinces.

(2) When promoting the regional green transition, the provincial governments of China must further strengthen the rationalization of the industrial structure. Moreover, emerging industries such as information, consulting, technology, and finance need to be vigorously developed, to increase the total tertiary industry. Furthermore, the governments should broaden the idea of green transition, and use the enterprises as the main bodies to mobilize their enthusiasm for the green transition. In addition, public awareness of green consumption and green behavior should be raised.

(3) With regard to the negative spatial spillover effect of investing capacity and government intervention, positive measures should be formulated to attract investment from large and medium-sized enterprises. In this process, the advantages of location and resources should also be fully utilized. Simultaneously, to realize a high-quality green transition, governments should further optimize the investment environment and improve the hard environment such as infrastructure and geographical environment. Moreover, the soft environment, including finance, talent, and technological innovation, needs to be improved.

Although this study has obtained several valuable conclusions, some limitations could be improved in further work. First, the GTI is affected by many factors, including resource, environment, economy, policies, etc., some of these perspectives were not well captured due to the data limitation. Second, the driving factors of GTI and their spatial spillover effects are discussed using the SDM. However, the economic development and resource condition of each region differ greatly, thus their heterogeneities need to be further explored in future research.

Acknowledgments

This work was supported by the Soft Science Research Project of Henan Province (212400410056) and the National Natural Science Foundation of China (71904059, 72174056, 71828401).

References

Adom, P. K., Bekoe, W., Amuakwa-Mensah, F., Mensah, J. T., Botchway, E. (2012). Carbon dioxide emissions, economic growth, industrial structure, and technical efficiency: Empirical evidence from Ghana, Senegal, and Morocco on the causal dynamics. *Energy*, *47*(1), 314-325.

An, Y., Zhou, D., Yu, J., Shi, X., Wang, Q. (2021). Carbon emission reduction characteristics for China's manufacturing firms: Implications for formulating carbon policies. *Journal of Environmental Management*, 284, 112055.

Bandyopadhyay, S. (2017). Evaluating sustainable economic development. *Clean Technologies and Environmental Policy*, 19(7), 1815–1816

Bell, K. (2016). Green Economy or Living Well? Assessing divergent paradigms for equitable eco-social transition in South Korea and Bolivia. *Journal of Political Ecology*, *23*(1), 71-92.

Cabrer, B. B., Serrano, D. G. (2007). Innovation and R&D spillover effects in Spanish regions: A spatial approach. *Research Policy*, *36*(9), 1357-1371.

Chen, L., Zhang, X., He, F., Yuan, R. (2019). Regional green development level and its spatial relationship under the constraints of haze in China. *Journal of Cleaner Production*, *210*, 376-387.

Choi, Y., Bone, C., Zhang, N. (2016). Sustainable policies and strategies in Asia: Challenges for green growth. *Technological Forecasting & Social Change*, 112, 134-137.

DeLonge, M. S., Miles, A., Carlisle, L. (2016). Investing in the transition to sustainable agriculture. *Environmental Science & Policy*, *55*, 266-273.

Dincer, I., Rosen, M. A. (2005). Thermodynamic aspects of renewables and sustainable development. *Renewable and Sustainable Energy Reviews*, *9*(2), 169-189.

Ding, S., Zhang, M., Song, Y. (2019). Exploring China's carbon emissions peak for different carbon tax scenarios. *Energy Policy*, *129*, 1245-1252.

Droste, N., Hansjürgens, B., Kuikman, P., Otter, N., Antikainen, R., Leskinen, P., Thomsen, M. (2016). Steering innovations towards a green economy: Understanding government intervention. *Journal of Cleaner Production*, *135*, 426-434.

Fan, S., Zhang, X., Robinson, S. (2003). Structural change and economic growth in China. *Review of Development Economics*, *7*(3), 360-377.

Fan, W., Xu, M., Dong, X., Wei, H. (2017). Considerable environmental impact of the rapid development of China's express delivery industry. *Resources, Conservation and Recycling*, *126*, 174-176.

Feng, C., Wang, M. (2019). Journey for green development transformation of China's metal industry: A spatial econometric analysis. *Journal of Cleaner Production*, *225*, 1105-1117.

Feng, C., Wang, M., Liu, G. C., Huang, J. B. (2017). Green development performance and its influencing factors: A global perspective. *Journal of Cleaner Production*, *144*, 323-333.

Feng, Y., Wang, X., Liang, Z., Hu, S., Xie, Y., Wu, G. (2021). Effects of emission trading system on green total factor productivity in China: Empirical evidence from a quasi-natural experiment. *Journal of Cleaner Production*, *294*, 126262.

Ferguson, P. (2015). The green economy agenda: business as usual or transformational discourse? *Environmental Politics*, 24(1):17-37.

Fu, X., Balasubramanyam, V. N. (2005). Exports, foreign direct investment and employment: The case of China. *World Economy*, 28(4), 607-625.

Giri, R. N., Mondal, S. K., Maiti, M. (2019). Government intervention on a competing supply chain with two green manufacturers and a retailer. *Computers & Industrial Engineering*, *128*, 104-121.

Global Energy Interconnection Development and Cooperation Organization. (2021). *China's Carbon Neutrality Research Report by 2060 (In Chinese)*. https://iea.blob.core.windows.net/assets/a72d8abf-de08-4385-8711-b8a062d6124a/WEO2020.pdf

Guo, P. F., Zhou, Y. N. (2018). A Grounded-theory-based Study on the Evaluation Index Extraction and Construction of China's City Green Transition Policy. *Management reviews*, 30(8), 257-267

Hall, S., Foxon, T. J., Bolton, R. (2017). Investing in low-carbon transitions: energy finance as an adaptive market. *Climate policy*, *17*(3), 280-298.

Hamdouch, A., Depret, M. H. (2010). Policy integration strategy and the development of the 'green economy': foundations and implementation patterns. *Journal of environmental planning and management*, *53*(4), 473-490.

Holz, C. A. (2008). China's economic growth 1978–2025: what we know today about China's economic growth tomorrow. *World Development*, *36*(10), 1665-1691.

Hou, D., Li, G., Chen, D., Zhu, B., Hu, S. (2019). Evaluation and analysis on the green development of China's industrial parks using the long-tail effect model. *Journal of environmental management*, *248*, 109288. https://doi.org/10.1016/j.jenvman.2019.109288

Huang, Z., He, C., Li, H. (2019). Local government intervention, firm–government connection, and industrial land expansion in China. *Journal of Urban Affairs*, *41*(2), 206-222.

Hye, Q. M., Wizarat, S., Lau, W. Y. (2016). The impact of trade openness on economic growth in China: An empirical analysis. *The Journal of Asian Finance, Economics and Business*, *3*(3), 27-37.

International Energy Agency. (2020). *World energy outlook 2020*. OECD Publishing.

Jaffe, A.B., Peterson, S.R., Stavins, P. R. N. (1995). Environmental regulation and the competitiveness of U.S. manufacturing: what does the evidence tell us? *Journal of Economic Literature*, 33(1), 132-163.

Jin, W., Shi, X. Zhang, L. (2021). Energy Transition without Dirty Capital Stranding, *Energy Economics*, 102:105508.

Jorgenson, D. W., Wilcoxen, P. J. (1990). Intertemporal general equilibrium modeling of US environmental regulation. *Journal of Policy Modeling*, *12*(4), 715-744.

Kanbur, R., Zhang, X. (2001). Fifty years of regional inequality in China: a journey through revolution, reform and openness. *Review of development Economics*, *9*(1), 87-106.

Karl, Y., Chen, Z. (2010). Government expenditure and energy intensity in China. *Energy Policy*, *38*(2), 691-694.

Kemp, R., Never, B. (2017). Green transition, industrial policy, and economic development. *Oxford Review of Economic Policy*, *33*(1), 66-84.

Kemp-Benedict, E.. (2018). Investing in a green transition. *Ecological economics*, *153*, 218-236.

Krugman, P. (1998). What's new about the new economic geography?. *Oxford review of economic policy*, *14*(2), 7-17.

Kushwaha, G. S., Sharma, N. K. (2016). Green initiatives: a step towards sustainable development and firm's performance in the automobile industry. *Journal of Cleaner Production*, *121*, 116-129.

Laitner, J. (2000). Structural change and economic growth. *The Review of Economic Studies*, *67*(3), 545-561.

Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., Sapio, A. (2020). Climate change and green transitions in an agent-based integrated assessment model. *Technological Forecasting and Social Change*, *153*, 119806.

LeSage, J., Pace, R.K., (2009). *Introduction to spatial econometrics*. Chapman and Hall/CRC press.

Liao, X.C., Shi X.P.. (2018). Public appeal, environmental regulation and green investment: Evidence from China. *Energy policy*, *119*, 554-562.

Midilli, A., Dincer, I., Ay, M. (2006). Green energy strategies for sustainable development. *Energy Policy*, *34*(18), 3623-3633.

Mundaca, L., Markandya, A. (2016). Assessing regional progress towards a 'Green Energy Economy'. *Applied Energy*, *179*, 1372-1394.

Owen, R., Brennan, G., Lyon, F. (2018). Enabling investment for the transition to a low carbon economy: government policy to finance early stage green innovation. *Current Opinion in Environmental Sustainability*, *31*, 137-145.

Pan, X., Ai, B., Li, C., Pan, X., Yan, Y. (2019). Dynamic relationship among environmental regulation, technological innovation and energy efficiency based on large scale provincial panel data in China. *Technological Forecasting and Social Change*, *144*, 428-435.

Pearce, D. , Markandya, A. , Barbier, E. B. . (1989). Blueprint for a green economy. Earthscan Publications, London, UK.

Rashidi, K., Saen, R. F. (2015). Measuring eco-efficiency based on green indicators and potentials in energy saving and undesirable output abatement. *Energy Economics*, *50*, 18-26.

Ringel, M., Schlomann, B., Krail, M., Rohde, C. (2016). Towards a green economy in Germany? The role of energy efficiency policies. *Applied energy*, *179*, 1293-1303.

Rodenburg, C., Baycan-Levent, T., Van Leeuwen, E., Nijkamp, P. (2001). Urban Economic Indicators for Green Development in Cities. *Greener Management International*, 36: 105-119

Samper, J. A., Schockling, A., Islar, M. (2021). Climate politics in green deals: Exposing the political frontiers of the European Green Deal. *Politics and Governance*, *9*(2), 8-16.

Shannon, C. E. (1948). A note on the concept of entropy. *Bell System Tech. J*, *27*(3), 379-423.

Shao, S., Zhang. Y., Tian, Z., Li, D., Yang, L, (2020). The Regional Dutch Disease Effect within China: A Spatial Econometric Investigation. Energy Economics, 88: 104766.

Shi X, Ji Q, Zhang D, Taghizadeh-Hesary F and Han P, (2020). Editorial: Energy Market and Energy Transition: Dynamics and Prospects. *Front. Energy Res*. 8:603985.

Shi, X., Sun, Y., Shen, Y. (2021). China's ambitious energy transition plans, *Science*, 373 (6551): 170.

Shi, X. (2021). People-centred Just Energy Transitions for Social Justice, *Journal of Environmental Economics*, 2021(3):122-127.

Song, Y., Sun, J., Zhang, M., Su, B. (2020). Using the Tapio-Z decoupling model to evaluate the decoupling status of China's CO2 emissions at provincial level and its dynamic trend. *Structural Change and Economic Dynamics*, *52*, 120-129.

Springer, C., Evans, S., Lin, J., Roland-Holst, D. (2019). Low carbon growth in China: The role of emissions trading in a transitioning economy. *Applied Energy*, *235*, 1118-1125.

Su, B., Ang, B. W.. (2016). Multi-region comparisons of emission performance: The structural decomposition analysis approach. *Ecological indicators, 67,* 78-87.

Thomas, K.D. (2015). Handbook of Research on Sustainable Development and Economics, Pennsylvania: IGI Global.

Tisdell, C. (2009). Economic reform and openness in China: China's development policies in the last 30 years. *Economic Analysis and Policy*, *39*(2), 271-294.

Wang, P., Chen, L. Y., Ge, J. P., Cai, W., Chen, W. Q. (2019). Incorporating critical material cycles into metal-energy nexus of China's 2050 renewable transition. *Applied Energy*, *253*, 113612.

Wang, X. L., Shao, Q.L. (2019). Non-linear effects of heterogeneous environmental regulations on green growth in G20 countries: evidence from panel threshold regression. *Science of The Total Environment*, *660*, 1346-1354.

Wang, Y., Sun, X., Guo, X. (2019). Environmental regulation and green productivity growth: Empirical evidence on the Porter Hypothesis from OECD industrial sectors. *Energy Policy*, *132*, 611-619.

Xu, L., Fan, M., Yang, L., Shao, S. (2021). Heterogeneous Green Innovations and Carbon Emission Performance: Evidence at China's City Level. *Energy Economics*, 2021, 99: 105269.

Yang, Z., Shao, S., Fan, M., Yang, L. (2021). Wage Distortion and Green Technological Progress: A Directed Technological Progress Perspective. Ecological Economics, 2021, 181: 106912.

Yin, L., Bo, N., Jia, J. (2019). Location oriented induction: research on the industrial structure upgrade mode in China (in Chinese). *Finan. Trade Res.*, *2*, 38-45.

Yu, D., Li, X., Yu, J., Li, H. (2021). The impact of the spatial agglomeration of foreign direct investment on green total factor productivity of Chinese cities. *Journal of Environmental Management*, *290*, 112666.

Yuan, B., Xiang, Q. (2018). Environmental regulation, industrial innovation and green development of Chinese manufacturing: Based on an extended CDM model. *Journal of cleaner production*, *176*, 895-908.

Zagler, M. (2009). Economic growth, structural change, and search unemployment. *Journal of Economics*, *96*(1), 63-78.

Zhai, X., An, Y. (2020). Analyzing influencing factors of green transformation in China's manufacturing industry under environmental regulation: A structural equation model. *Journal of Cleaner Production*, 251, 119760.

Zhang, C., Liu, C. (2015). The impact of ICT industry on CO2 emissions: a regional analysis in China. *Renewable and Sustainable Energy Reviews*, *44*, 12-19.

Zhang, H, Shi, X., Wang, K, Xue, J., Song, L., Sun, Y. (2020). Intertemporal Lifestyle Changes and Carbon Emissions: Evidence from a China Household Survey. *Energy Economic*s, 86:104655.

Zhang, J., Chang, Y., Zhang, L., Li, D. (2018). Do technological innovations promote urban green development?—A spatial econometric analysis of 105 cities in China. *Journal of cleaner production*, *182*, 395-403.

Zhao, H., Lin, B. (2019). Will agglomeration improve the energy efficiency in China's textile industry: Evidence and policy implications. *Applied Energy*, *237*, 326-337.

Zhao, N., You, F. (2020). Can renewable generation, energy storage and energy efficient technologies enable carbon neutral energy transition?. *Applied Energy*, *279*, 115889.

Zhao, T., Yang, Z. (2017). Towards green growth and management: Relative efficiency and gaps of Chinese cities. *Renewable and Sustainable Energy Reviews, 80,* 481-494.

Zhou, P., Ang, B. W.. (2008). Decomposition of aggregate CO2 emissions: a production-theoretical approach. *Energy Economics, 3,* 1054-1067.

Zhu, B., Zhang, M., Zhou, Y., Wang, P., Sheng, J., He, K., Wei, Y., Xie, R. (2019). Exploring the effect of industrial structure adjustment on interprovincial green development efficiency in China: A novel integrated approach. *Energy Policy*, *134*, 110946.

Zou, Z. H., Yi, Y., Sun, J. N. (2006). Entropy method for determination of weight of evaluating indicators in fuzzy synthetic evaluation for water quality assessment. *Journal of Environmental sciences*, *18*(5), 1020-1023.

Measurement of Green Transition and its driving factors: Evidence from China

Xueqi Zhai[a], Yunfei An[b*], Xunpeng Shi[c,d], Xiao Liu[e]

[a] *School of Business Administration, Henan University of Economics and Law, 180 Jinshui East Road, Zhengzhou 450001, China*
[b] *Business School, Henan University, Jinming Avenue, Kaifeng 475001, China*
[c] *Australia-China Relations Institute, University of Technology Sydney, Ultimo, NSW, 2007, Australia*
[d] *Center of Hubei Cooperative Innovation for Emissions Trading System, Wuhan 430205, China*
[e] *College of Economics and Management, Huaiyin Normal University, 71 Jiaotong Avenue, Huaian, 223001, China*

Abstract: Achieving a high-quality green transition has become an important way toward sustainable development in the world. In this study, we propose a measuring framework of green transition based on the entropy weight method. Then the driving factors of green transition are analyzed with a spatial Durbin model. Taking China as an empirical case study, the results showed that: (1) the overall level of green transition in China increased, but the green transition index (GTI) remained low. The GTIs' means and growths of the eastern region exceeded those of both the central region and the western region. Moreover, the GTIs in 30 provinces were significant gaps. (2) China's GTIs showed a significant positive spatial dependence. Furthermore, the driving factors of reform and openness, investing capacity, government intervention, and environmental regulation positively impacted the green transition development; however, the industrial structure had a negative impact. (3) Reform and openness, as well as environmental regulation, exerted positive spillover effects on other provinces, while investing capacity and government intervention exerted negative spillover effects. Moreover, the spillover effect of the industrial structure was not significant. Relevant recommendations for green transition development are proposed.
Keywords: green transition; energy transition; driving factors; spillover effect; entropy weight method; spatial Durbin model

1. Introduction

Green transition, including the energy transition, has become an important strategy for sustainable global development and global environmental governance. The "brown economy", with its high energy consumption and high pollution, has caused many social, economic, and environmental problems. At the Global Environment Ministers' Meeting in October 2008, the "Global Green New Deal" and "Developing a Green Economy" were proposed by the United Nations Environment Programme, thus calling for a global shift from a "brown economy" to a "green economy" (Mundaca and Markandya, 2016). Since then, under the connotation of the green economy (Pearce *et al.*, 1989), a green transition is considered as a mode transition from high energy consumption and high emission to low energy consumption and low emission (Ringel

* Corresponding author. Tel: +86 18624919275
E-mail address: ayf1990@163.com (Yunfei An)

et al., 2016; Kemp and Never, 2017), thereby realizing the goals of sustainable economic development and environmental protection (Springer *et al.*, 2019; Feng and Wang, 2019).

Accelerating the process of green transition has been a hot issue for governments around the world (Kemp and Never, 2017; Lamperti *et al.*, 2020). Green transition not only informs the development of global climate change policies and transition of the energy mix, but also suggest consumption side changes, such as low carbon lifestyle (Zhang *et al.*, 2020), and therefore can provide a comprehensive framework for achieving carbon neutrality (Samper *et al.*, 2021). The green transition can be affected by many factors and their effects are inconsistent (Kemp and Never, 2017; Shi *et al.*, 2020). To provide a basis for decision-making in formulating effective green transition policies, it is necessary to measure the green transition and its driving factors accurately.

Most existing studies focus on measuring green transition by calculating green total factor productivity or green efficiency with the environmental output. However, green transition emphasizes the changes of development patterns about the economy, technology, society, energy, and environment. Neither green total factor productivity nor green efficiency can reflect the characteristics of green transition comprehensively. Furthermore, many scholars use different methods to analyze the driving factors of green transition, which can be summarized as decomposition analysis methods (Su and Ang, 2016; Zhou and Ang, 2008) and econometric models (Zhang and Liu, 2015; Zhang *et al.*, 2018; Yuan and Xiang, 2018). However, due to the inaccuracy of measuring the green transition, the analysis of the driving factors would be further incomplete and even misleading. Therefore, how to measure the green transition accurately is worth studying.

Measuring the green transition is actually to calculate a comprehensive index from the multiple indicators of the economy, technology, society, energy, and environment. The entropy method can determine the weights of various indicators according to their values' variations, and then obtain an objective and comprehensive evaluation value (Zou *et al.*, 2006). This method considers the contribution of each indicator to the green transition, but also avoids subjectivity. Consequently, we propose a measuring framework of the green transition index (GTI) based on the entropy weight method. Furthermore, considering the spatial relevance of regional green transition, spatial Durbin model (SDM) is adopted to analyze the driving factors of the green transition. On this basis, taking China as the case study object, the policy implications of its green transition are come out.

The contributions of this study mainly reflect two aspects. First, we propose a general method to measure GTI using the entropy weight method. The existing measurements of green transition, such as green efficiency and green index, cannot capture the comprehensiveness of green transition. Second, we demonstrated the spatiotemporal variation and driving factors of GTIs in China's provinces from 2008 to 2017. The Moran index suggests a significant regional correlation of GTIs.

The remainder of the paper is arranged as follows: Section 2 provides a literature review. Section 3 explains a methodology framework of entropy weight method for GTI and SDM for analyzing the driving factors. Section 4 provides the case study of China and its empirical results. The discussion and the conclusion are presented in Section 5 and Section 6.

2. Literature review

With the problems caused by the increasingly severe global environmental pollution, the development of a green economy has become a trend of the new era (Pearce *et al.*, 1989). Many scholars have studied the concepts of green development, green economy, and green transition. Today, the main subjects of related research are “sustainable development”, “green economy”, “green growth”, and “low-carbon cities”.

Recently, the green transition development theory and practice are still at the exploratory stage, and no unified definition has been agreed upon. Since green transition is a new developmental approach proposed in recent years due to environmental pollution, it mainly addresses the constraints between resources and the environment in the process of sustainable development. Thomas (2015) argued that energy innovation would cause structural change and thus expand the green space to achieve sustainable development. This process was named green transition. Similarly, Ferguson (2015) pointed out green transition meant to improve resource productivity and achieve the transition of an unsustainable development to a sustainable development model. Bandyopadhyay (2017) evaluated sustainable development from three aspects: economic, social, and environmental development. Rodenburg *et al.* (2001) established urban economic indicators to evaluate green structure and green space and proposed a green development framework from four dimensions: environmental resource, urban welfare and quality, green financing, and government management. In addition, several scholars analyzed sustainable development from the perspective of green energy. Midilli *et al.* (2006) reported that public awareness, information, environmental education, financing, and evaluation tools were essential factors for green energy strategy, and proposed several green energy strategies for sustainable development.

To measure green transition, many scholars focused on green development performance, green development index, and green growth efficiency. Feng *et al.* (2017) estimated the green development performance index and its influencing factors, using the DEA method. They found that a U-shaped environmental Kuznets curve (EKC) existed between the green development performance index and the economic development level. Moreover, living standards, energy structure, and oil price positively influenced the green development performance index, while ecological carrying capacity negatively influenced it. Kushwaha and Sharma (2016) proposed a green initiative based on exploratory research to analyze the relationship between the sustainable development of the automotive industry and its performance. To measure the green performance, Rashidi and Saen (2015) used the DEA method to calculate eco-efficiency indicators, and the results showed that the more energy is input, the more undesired the outputs will be. Zhao and Yang (2017) evaluated the green development performance of 286 cities in China using metafrontier-data envelopment analysis. Their results showed that the green growth efficiency of cities with different sizes and in different regions differed, which required environmental governance and government regulation.

Related to the driving factors of green transition, Dincer and Rosen (2005) identified four factors that affect sustainable development: energy and resources, economy, environment, and society. Yuan and Xiang (2018) estimated the green total factor productivity (GTFP) indicator and used it as a measure of China's industrial green development profile. They furthermore used the extended CDM model to examine the impact of environmental regulation on both technological innovation and green development. Green environmental efficiency was identified to vary from region to region and also showed clear spatial dependence and spatial variation (Chen *et al.*, 2019;

Shao *et al.*, 2020). They found that regional green development was affected positively by openness degree, urbanization, industrial structure, and technological innovation. However, economic growth, corporate structure, fiscal policy, and foreign investment negatively affected regional green development.

Furthermore, Choi *et al.* (2016) analyzed the new paradigm of sustainable challenges in Northeast Asia under the context of green growth policy and green strategy. They emphasized the key role of the government to stimulate green development governance. Similarly, Hamdouch and Depret (2010) described the leading role of the government in the green transition process. The government should make well-designed environmental and innovation policies, and obtain the support of both stakeholders and relevant organizations. However, Jorgenson and Wilcoxen (1990) demonstrated that the environmental policy increased the additional environmental costs of enterprises, thus resulting in insufficient investment in R&D and innovation, and exerting a significant negative effect on the growth of green total factor productivity.

In summary, there are two gaps in the literature. First, there is not a direct measurement of green transition. The existing studies used either green index or green efficiency to quantify the green transition. However, neither green efficiency nor green index can capture the comprehensiveness of green transition. Further, the green transition is a comprehensive reflection of economic transition, technological transition, social transition, energy transition, and ecological transition. Calculating an index from these aspects could be useful to reflect the reality of regional green transition. Another gap is the spillover effect of green transition across regions. With regard to China, green transition in the local region usually affects the other neighboring regions for a number of reasons (Cabrer and Serrano, 2007; Zhang *et al.*, 2018). Therefore, to explore the questions, this paper firstly analyzed the green transition index of China using the entropy weight method. Then SDM was used to analyze the driving factors of green transition and their spatial spillover effects.

3. Measurement of green transition and its driving factors: a methodology framework

3.1. Measurement of the green transition index (GTI)

3.1.1 Entropy weight method

Entropy is widely used to measure the degree of disorder in a system (Shannon, 1948). Hence, entropy weight, as an objective weighting method, also evaluates the degree of disorder in a system by using useful information (Zou *et al.*, 2006). The larger the entropy weight, the more useful information of the index. By using the entropy weight method, the GTI was measured with the following steps.

Step 1: Construct evaluation matrix R.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}_{m\times n} \tag{1}$$

where r_{ik} represents the evaluation value of the k indictor for the i province, i = 1, 2, …, m, and k = 1,2, …, n;

Step 2: Normalizing the matrix R. If k is a benefit indictor, a larger k value indicates a greater positive effect on GTI; therefore, formula (2) was used to normalize k. If k is a cost indictor, the larger its value is, the greater the negative effect on GTI will be; therefore, formula (3) was used to normalize k.

$$R_{ik} = \frac{r_{ik} - \min\limits_{1\le i\le m}\left(r_{ik}\right)}{\max\limits_{1\le i\le m}\left(r_{ik}\right) - \min\limits_{1\le i\le m}\left(r_{ik}\right)} \tag{2}$$

$$R_{ik} = \frac{\max\limits_{1\le i\le m}\left(r_{ik}\right) - r_{ik}}{\max\limits_{1\le i\le m}\left(r_{ik}\right) - \min\limits_{1\le i\le m}\left(r_{ik}\right)} \tag{3}$$

Step 3: Assume that p_{ik} represents the converted value via R_{ik}, which can be defined as Eq. (4).

$$P_{ik} = \frac{R_{ik}}{\sum_{i=1}^{m} R_{ik}} \tag{4}$$

Step 4: Calculate the entropy e_{ik} of the k indicator for i province using Eq. (5), where λ represents the Boltzman's constant, λ = 1 / ln(n).

$$e_k = -\lambda \sum_{i=1}^{m} P_{ik} \ln P_{ik}, \quad \lambda = \frac{1}{\ln n} \tag{5}$$

Step 5: Provide the degree of diversification e_k of the information by Eq. (6).

$$d_k = 1 - e_k \tag{6}$$

Step 6: The entropy weight w_k of the k indicator is calculated by Eq. (7).

$$W_k = \frac{d_k}{\sum_{k=1}^{n} d_k} \tag{7}$$

Step 7: The green transition index GTI_i of the i_{th} province in China is calculated by Eq. (8).

$$GTI_i = \sum_{k=1}^{n} R_{ik} W_k \tag{8}$$

3.1.2 Evaluation indicators of GTI

To measure the GTI by the entropy weight method, the evaluation indicators first had to be chosen. In reference to literature by Guo and Zhou (2018), Rodenburg *et al.* (2001), and Hou *et al.* (2019), the following five dimensions of green transition are analyzed: economic transition, technological transition, energy transition, social transition, and environmental transition. Economic transition refers to the industrial structure, investment, and foreign trade development (Yu *et al.*, 2021). Especially, China's industrial structure has been significantly changed since implementing economic reform and open up, which the tertiary industry has gradually replaced the dominant position of the secondary industry (Karl and Chen, 2010; Yin *et al.*, 2019; Zhao and Lin, 2019). Therefore, economic transition can be measured from the per capita GDP, tertiary industry value added, total social investment in fixed assets, and total imports and exports indicators. Technological development is the crucial driving force for achieving green transition. Therefore, technological transition is measured by the expenditure for new product development and the number of patent applications (Feng *et al.*, 2021). Moreover, achieving low carbon growth needs reduce the share of raw coal in energy production and increase the share of electricity in the total final energy consumption (IEA, 2020; GEDICO, 2021). For the energy transition, it is necessary to change the coal-based energy consumption structure and build a low carbon electricity-based power system (Zhao and You, 2020). Therefore, the energy transition is measured by raw coal consumption and electricity consumption. Further, green transition is also influenced by the changes in social production activities and behaviors (Bell, 2016). Therefore, the social transition can be measured by the expenditure of residents per capita, public budget expenditure, and unemployment rate. Finally, environmental transition, as a goal of achieving green transition, is measured by the total investment in industrial pollution control and sulfur dioxide emissions (Zhu *et al.*, 2019). Consequently, 13 indicators were selected as evaluation indicators to calculate green transition, as shown in Table 1.

Table 1 Evaluation indicators of GTI

First-level indicator	Second-level indicator	Third-level indicator
Green transition	Economic transition	GDP per capita
		Tertiary industry added value
		Total social investment in fixed assets
		Total imports and exports
	Technological transition	Expenditure for new product development
		Number of invention patent applications
	Energy transition	Raw coal consumption
		Electricity consumption
	Social transition	Consumption expenditure of residents per capita
		Public budget expenditure
		Unemployment rate
	Environmental transition	Total investment in industrial pollution control
		Sulfur dioxide emissions

3.2. The model of driving factor analysis

3.2.1. Spatial correlation test

Because of the complexity of the spatial econometric model, it is necessary to test the spatial correlation of variables before their empirical analysis. To determine whether the variables are spatially correlated, the common methods are Moran index test, Gillie index test, and Cetis index (Cabrer and Serrano, 2007). Among these, the Moran I index is widely used to measure the spatial correlation of variables. Its calculation formula is as follows:

$$Moran's\ I = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m} w_{ij}\left(GTI_i - \overline{GTI}\right)\left(GTI_j - \overline{GTI}\right)}{S^2 \sum_{i=1}^{m}\sum_{j=1}^{m} w_{ij}} \quad (9)$$

where i and j represent the province i and j, $\overline{GTI}$ represents the mean of the GTI; $S^2 = \frac{\sum_{i=1}^{m}\left(GTI_i - \overline{GTI}\right)}{m}$ represents the variance in the sample; w_{ij} represents the spatial weight of the element (i, j) for measuring the distance between provinces i and j, and w represents the spatial weight matrix.

The Moran I index ranges from -1 to 1. A value above 0 indicates that the GTI of the local province is positively related to its neighbors. The closer the value is to 1, the stronger the positive spatial correlation will be. However, values below 0 indicate that the GTI of the local province is negatively related to its neighbors. A value close to -1 indicates a stronger negative spatial correlation. When the value is 0, no spatial autocorrelation is present.

3.2.2. The set of the spatial weight matrix

The spatial weight matrix reflects the interdependence of variables in different regions, which constitutes the premise of spatial correlation analysis (Chen *et al.*, 2019). New economic geography believes that the spatial relationship between two elements will weaken when increasing their distance (Krugman, 1998). That is, as the distance between two provinces of mainland China increases, the spatial spillover effect of green transition will weaken. Therefore, the spatial weight matrix was established with the inverse distance between two provinces as Eq. (10).

$$w_{ij} = \begin{cases} 1/d_{ij}, & i \neq j \\ 0, & i = j \end{cases} \tag{10}$$

where d_{ij} is the straight-line distance between the province i and j.

3.2.3. The spatial Durbin model

The flow of resources among provinces can easily affect the local province's GTI, which causes it to be affected by the GTIs of its neighboring provinces. As to the potential spatial correlation of the GTI, a spatial panel model was constructed to analyze the driving factors of the GTI. According to existing research, the spatial panel models contain three types, namely spatial lag model (SLM), spatial error model (SEM), and SDM (Chen et al., 2019; Feng and Wang, 2019). The SLM is used to describe the existence of spatial autocorrelation. By adding the spatial lag term of GTI to the independent variables, the SLM can be expressed as Eq. (11).

$$GTI = \alpha I_n + \rho WGIT + \beta X + \varepsilon \tag{11}$$

where GTI is the dependent variable, representing the green transition index; X is the independent variables, representing the driving factors of the green transition; ρ represents the spatial autocorrelation parameter; W is the spatial weight matrix; $WGTI$ represents the spatial lag term of GTI. β represents the spatial regressive parameter. I_n is a $n \times 1$ vector associated with the intercept parameter α ; ε is the normal error term.

The SEM believes that the error item affected by GTI's factors becomes strong relevant as the existing spatial relationship, therefore the SEM can be expressed as Eq. (12).

$$\begin{aligned} GTI &= \alpha I_n + \beta X + \phi \\ \phi &= \lambda W \phi + \varepsilon \end{aligned} \tag{12}$$

where ϕ is the error item with strong relevance; λ represents the spatial regressive parameter.

When the spatial lag items of the GTI and its influencing factors are all considered, the SDM is expressed as Eq. (13).

$$GTI = \alpha I_n + \rho WGIT + \beta X + \theta WX + \varepsilon \tag{13}$$

where WX represents the spatial lag terms of independent variables; θ represents the spatial regressive parameters.

Before choosing the SDM, it is necessary to use the Lagrange Multiplier Method to test whether the null hypothesis of SLM or SEM is true. If the null hypothesis of SLM or SEM is not rejected, then SLM or SEM is selected. If the null hypotheses of both SLM and SEM are rejected, then the SDM is chosen.

4. A case study of China

With the rapid economic growth, China has become the world's second-largest economy. However, relying on administrative and planning policies of the Chinese government, this growth mode had the characteristics of high input, high consumption, and high pollution (Wang *et al.*, 2019; Song *et al.*, 2020). This not only caused resource exhaustion, but also caused severe ecological and environmental problems. The latest data from the Global Carbon Project showed that China's carbon dioxide emission increased by 4.7% in 2018, accounting for 27% of the global emissions (*Ding et al., 2019*). Therefore, the green transition of China plays a key role in promoting global sustainable development.

In order to demonstrate our methodology, we use China as a case study. To properly promote green transition, the Chinese government has formulated the green development goal and direction in the 12th Five-Year Plan. More recently, China has pledged to peak emissions by 2030 and neutralize emissions by 2060. However, what about the status of China's green transition? Are there any links between the local province and neighboring provinces? What are the driving factors of green transition? Answer to these questions will help China to formulate the urgently needed transition roadmap that is appropriate to its level of economic development, energy mix, and regional heterogeneity (Shi *et al.*, 2021; Shi, 2021).

Therefore, this study comprehensively calculated the green transition index (GTI) of China from 2008 to 2017 from the following five aspects: economic transition, technological transition, energy transition, social transition, and environmental transition. Moreover, industry structure, reform and openness, investing capacity, government intervention, and environmental regulation were selected as driving factors. Furthermore, China's regional GTI and spatiotemporal variation were studied from a spatial econometric perspective, and the driving factors of green transition and their spillover effects were analyzed. Finally, several recommendations for green transition development were proposed.

4.1. Variable selection and data source

4.1.1. Driving factors

According to economic theory, technological progress, structural change, environmental regulation, resources, and population are the main factors affecting sustainable economic development (Yang *et al.*, 2021). Furthermore, the green economy is essentially a production path with high technology, low resource consumption, and low environmental pollution (Jin *et al.*, 2021). Therefore, the driving factors of the GTI were summarized as industrial structure, reform and openness, investing capacity, government intervention, and environmental regulation.

(1) Industrial structure (IS). Fan *et al.* (2003) pointed out that structural change was a further source of economic growth. Changes in industrial structure actually indicated the reallocation of resources from low-productivity sectors to high-productivity sectors, thus contributing to the overall economic development (Zagler, 2009; Adom *et al.*, 2012). At present, the advanced degree of the industrial structure is usually characterized by the level of regional green transition (Laitner, 2010). The development of the tertiary industry has become an important indicator to evaluate the development level for a country. Increasing the proportion of the tertiary industry is conducive to stimulating economic development and accelerating the process of green development (Zhu *et al.*, 2019). Therefore, this study selected IS as the driving factor, which was measured by the proportion of tertiary industry output in the gross domestic product (GDP).

(2) Reform and openness (RO). Since the reform and openness was proposed by the Chinese government, China's economic development has been greatly promoted (Kanbur and Zhang, 2001). Hye *et al.* (2016) developed a trade openness index for China and found that trade openness was positively related to economic growth in both the long run and the short run. Moreover, the deeper the

reform and openness, the more frequent the flow of funds, talents, and technology into a region, which contributed to regional green transition (Tisdell, 2009). Then, the actual amount of foreign investment utilized capital per capita (US$/Person) was used to express RO.

(3) Investing capacity (IC). Governments around the world always emphasize the importance of investing capacity. This is the main driving force for accelerated economic development, and also an important tool for urban industrialization. Since green development has been proposed, Hall *et al.* (2017) showed that both finance and investment play an enormous role in facilitating transformative change. Moreover, Kemp-Benedict (2018) argued that private investment should be mobilized for a transition. The fixed-asset investment in the China Statistical Yearbook is a comprehensive indicator, including investment types of state-owned enterprises, collectives, individuals, and foreigners. Consequently, this study adopted fixed asset investment per capita (Thousand US$/Person) to measure IC.

(4) Government intervention (GI). It is necessary to strengthen governmental intervention in the process of sustainable development (Kemp and Never, 2017). The focus of the local government on green transition presents a major influence on the overall quality of regional economic and social development (Droste *et al.*, 2016). Especially when the transition is not interesting for enterprises and individuals, the government must enhance policy interventions to change this status (Owen *et al.*, 2018; Xu *et al.*, 2021). The power of governmental intervention is mainly related to local fiscal expenditure. Therefore, this study selected local fiscal expenditures per capita (US$/Person) as the indicator to measure GI.

(5) Environmental regulation (ER). Strict environmental regulation is an important policy, which China will continue to implement for a long time to realize green development (Jaffe *et al.*, 1995; Liao and Shi, 2018). Environmental regulation is conducive to restraining high energy-consuming and high-polluting industries, which is one of the key driving factors for green transition (Wang *et al.*, 2019; Zhai and An, 2020). Therefore, the indicator of environmental governance investment per capita (US$/Person) was used to denote ER in this paper.

Explanations and symbols of the above variables are provided in Table 2.

Table 2 Descriptive statistics for all variables.

Variables	Definition	Unit	Mean	Min	Max	Obs
GTI	A comprehensive index from the multiple indicators of economy, technology, society, energy, and environment	-	0.2397	0.0663	0.8156	300
IS	the proportion of tertiary industry output in the GDP	%	43.1831	28.6	80.6	300
RO	Actual amount of foreign investment utilized capital per capita	US$/Person	266.6088	4.3646	1808.893	300
IC	Fixed asset investment per capita	Thousand US$/Person	259.3316	4.5806	3762.6621	300
GI	Local fiscal expenditures per capita	US$/Person	13.1558	0.2489	102.4267	300
ER	Environmental governance investment per capita	US$/Person	1614.5723	4.1748	31065.2392	300

Note: exchange rate used: 1US$=6.x RMB.

4.1.2. Data Source

To analyze the driving factors of green transition, the panel data of 30 provinces in mainland China from 2008 to 2017 was utilized, except Tibet, due to a lack of data. The original data of evaluation indicators for GTI and its driving factors were collected from the China Statistical Yearbooks (2009-2018), the China Energy Statistical Yearbooks (2009-2018), and the statistical yearbooks of the 30 provinces in mainland China.

Furthermore, the spatial weight matrix was generated with the GeoDa software, and the data of the provincial latitude and longitude were collected from the national catalog service for geographic information. Moreover, the SDM model was realized with MATLAB software. To solve the heteroscedasticity of panel data and reduce data instability, the logarithm of driving factors was utilized in this paper.

4.2. The overall trend of GTI

Fig. 1 shows the overall trend of the GTI for mainland China from 2008 to 2017, and the regional GTI trends of the eastern region, central region, and western region. The GTI was lowest in 2012, and since then, has improved significantly. The overall GTI was still low and its mean was 0.240, which indicated that the GTI of the 30 provinces of mainland China was not effective.

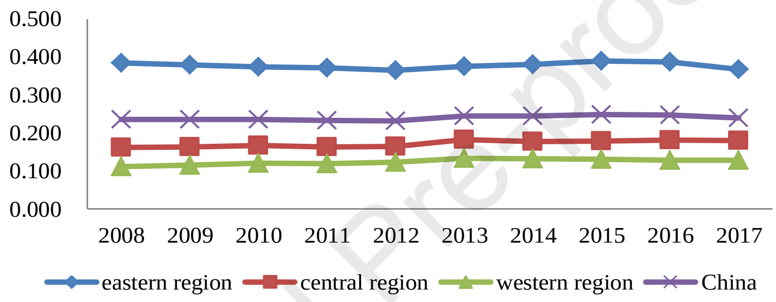


Fig. 1 GTI trends of China's regions

Table 3 describes the GTIs for selected years due to limited space. The GTIs in almost all provinces improved from 2008 to 2017, while there were significant gaps among them. In 2017, the GTIs in six provinces reached greater than 0.5, including Beijing, Shanghai, Jiangsu, Zhejiang, Guangdong, and Hainan. This means that the green development of these cities in China has reached a good level, however, it exists a great gap that the GTIs in other provinces are all below 0.5.

From the perspective of regional GTIs, the eastern region had a significantly higher GTI mean than both the central region and the western region. Fig. 2 shows the GTIs' means of China's 30 provinces from 2008 to 2017. The top five GTIs regions (according to their means) were Guangdong, Jiangsu, Beijing, Shanghai, and Zhejiang, which all belong to the eastern region. Particularly, the GTI means of Guangdong and Jiangsu reached 0.763 and 0.725, respectively. In the central region, the range of GTI means is between 0.125 and 0.238. Only the GTIs of Henan, Hubei, Anhui are greater than 0.2. However, in the western region, the GTIs in each province are lower than 0.2 except Sichuan.

Further, by analyzing the GTIs changes of China's 30 provinces from 2008 to 2017 as shown in Fig. 3, the GTI growth in the eastern region was higher than that in both the central region and the western region. The provinces with GTI growths greater than 0.1 were mainly concentrated in the eastern region, including Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, and Hainan. However, the growths of other provinces were less than 0.1. This result reflected the status of green transition in China. Compared with the central and western regions, the eastern region has the advantages of economic scale, industrial structure, and technological innovation. Furthermore, the agglomeration effect of the cities belonging to the eastern region has gradually been formed, thus shaping into a better decoupling between the economic development and the load of resources and environment. The results imply that regional gaps in GTIs are widening.

Table 3 The GTIs of the 30 provinces for selected years

Regions	No.	Provinces	2008	2011	2014	2017	Means	Growths
Eastern region	1	Beijing	0.489	0.519	0.659	0.763	0.606	0.274
	2	Tianjin	0.321	0.330	0.439	0.585	0.410	0.264
	3	Hebei	0.204	0.210	0.243	0.214	0.214	0.010
	6	Liaoning	0.267	0.264	0.263	0.272	0.267	0.005
	9	Shanghai	0.493	0.542	0.610	0.647	0.572	0.154
	10	Jiangsu	0.614	0.720	0.745	0.771	0.725	0.158
	11	Zhejiang	0.517	0.511	0.614	0.632	0.562	0.115
	13	Fujian	0.237	0.232	0.269	0.261	0.251	0.024
	15	Shandong	0.505	0.466	0.516	0.497	0.492	0.019
	19	Guangdong	0.816	0.728	0.735	0.806	0.763	0.011
	21	Hainan	0.380	0.524	0.600	0.637	0.545	0.257
	20	Guangxi	0.126	0.134	0.139	0.156	0.139	0.030
Central region	4	Shanxi	0.139	0.162	0.161	0.186	0.159	0.024
	5	Inner Mongolia	0.153	0.159	0.176	0.208	0.173	0.007
	7	Jilin	0.120	0.129	0.136	0.140	0.132	0.011
	8	Heilongjiang	0.100	0.125	0.131	0.132	0.125	0.031
	12	Anhui	0.164	0.181	0.205	0.234	0.202	0.070
	14	Jiangxi	0.121	0.144	0.138	0.158	0.139	0.037
	16	Henan	0.224	0.215	0.249	0.284	0.238	0.060
	17	Hubei	0.190	0.186	0.228	0.245	0.220	0.055
	18	Hunan	0.170	0.168	0.192	0.201	0.185	0.030
Western region	22	Chongqing	0.142	0.153	0.169	0.171	0.158	0.030
	23	Sichuan	0.198	0.190	0.215	0.223	0.204	0.025
	24	Guizhou	0.072	0.090	0.094	0.093	0.088	0.021
	25	Yunnan	0.110	0.104	0.116	0.119	0.113	0.008
	26	Shaanxi	0.139	0.164	0.175	0.172	0.170	0.033
	27	Gansu	0.098	0.089	0.103	0.103	0.103	0.014
	28	Qinghai	0.066	0.074	0.081	0.090	0.081	0.014
	29	Ningxia	0.078	0.070	0.075	0.090	0.079	0.020
	30	Xinjiang	0.104	0.120	0.133	0.125	0.120	0.022

Fig. 2 GTIs' means of China's 30 provinces from 2008 to 2017

Fig. 3 GTIs' growths of China's 30 provinces from 2008 to 2017

4.3. Model estimation of driving factors

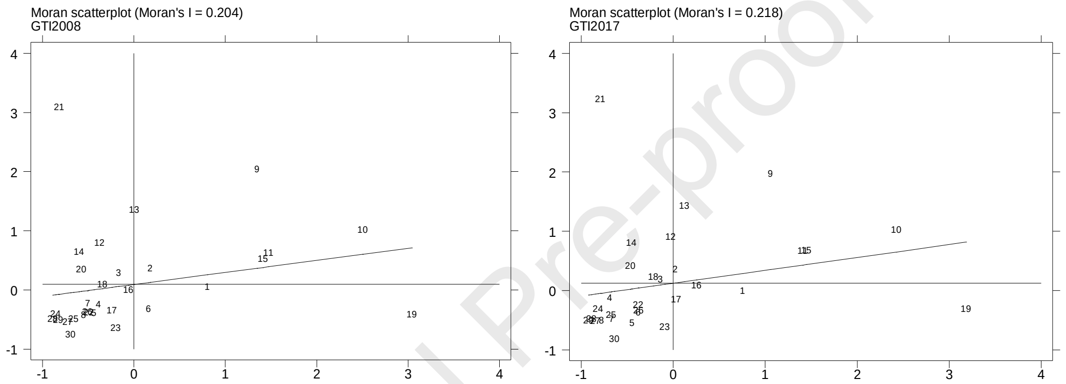
4.3.1. Spatial correlation test

Table 4 shows the Moran's I indices of GTIs for every year from 2008 to 2017. The Moran's I statistic values all exceeded 0, which demonstrated that the GTIs had a strong spatial correlation. Moreover, the statistic values of GTIs were significant at the 5% level. Therefore, a spatial econometric model was required to analyze the driving factors of the green transition of China.

Furthermore, the local Moran's I indices of 30 provinces were also calculated for mainland China from 2008 to 2017. Fig. 2 describes the Moran's I scatter plots in 2008 and 2017. Most of the investigated provinces are located in the second and third quadrants over the past ten years, indicating that they had the characteristics of high-value and low-value aggregation as well as low-value and low-value aggregation.

Table 4 Moran's I and its statistical test of GTIs from 2008 to 2017

Years	I	z	p-value
2008	0.192	2.132	0.033
2009	0.184	2.047	0.041
2010	0.201	2.220	0.026
2011	0.224	2.443	0.015
2012	0.215	2.365	0.018
2013	0.208	2.290	0.022
2014	0.205	2.244	0.025
2015	0.216	2.361	0.018
2016	0.217	2.342	0.019
2017	0.214	2.355	0.019



(a) The Moran scatter plot for GTIs in 2008 (b) The Moran scatter plot for GTIs in 2017

Fig. 2 The Moran'I scatter plots for GTIs in 2008 and 2017

(Note: The number denotes each province, and its meaning is shown in Table 3)

4.3.2. Estimation results

According to the comparison of non-spatial panel models, it could be further judged whether these models are suitable to build a spatial panel model, which is typically determined by Lagrange Multiplier (LM) test. Table 5 describes the estimation results of the Partial Least Squares (PLS) regression. It can be seen that reform and openness, investment capacity, government intervention, and environmental regulation affect GTI positively at 1% level. This shows that reform and openness, investment capacity, government intervention, and environmental regulation can promote green transition. However, the coefficient of industrial structure is negative, which exerts a significantly negative effect on green transition. Further, the results of the LM test and the Robust LM of the spatial lag panel were significant at 1% level, thus rejecting the null hypothesis of no spatial lag effect. Moreover, the statistics value of the LM test of spatial error panel rejected the null hypothesis of no spatial error effect at 1% level, while the statistics value of the Robust LM test could not reject the null hypothesis. Therefore, SDM is the better choice for analyzing GTI's driving factors.

By comparing the results of SLM, SEM, and SDM, the maximum likelihood method was adopted to estimate the three models. Since the panel model had two types, the random effect model and fixed effect model, it was necessary to choose whether the model contained random effects. This was done by the Hausman test. As shown in Table 6, the statistics of Hausman test significantly rejected the null hypothesis at 5% level. Hence, a spatial panel model with fixed effect was built.

Table 5 Estimation results of the PLS regression

Variables	PLS regression
_cons	-2.8759 (-16.92)
IS	-0.1964** (-3.12)
RO	0.0429*** (3.82)
IC	0.0821*** (6.73)
GM	0.1733*** (3.54)
ER	0.0506 ***(4.07)
R^2	0.6757
F	122.53
LM_spatial_lag	33.675***
Robust LM_spatial_lag	20.108***
LM_spatial_err	15.724***
Robust LM_spatial_err	0. 935

Note: The t-statistics are given in parentheses; *** and **denote significance at 1% and 5% level, respectively.

Table 6 Estimation results for the spatial panel regression model

Spatial panel model with fixed effect	SDM	SLM	SEM
_cons	-	-2.8756 (-6.43)	-0.0951 (-1.46)
IS	-0.0068**(-3.09)	-0.0331** (-2.80)	-0.0367* (-2.13)
RO	0.0316*** (4.51)	0.0424*** (4.29)	0.0420***(7.26)
IC	0.1055*** (5.64)	0. 1022*** (3.39)	0.0834*** (3.59)
GM	0.0217*** (4.27)	0.0143** (2.82)	0.0416* (2.02)
ER	0.1128*** (5.38)	0. 1246 ***(5.99)	0.0755*** (7.08)
W*IS	0.0463*(1.98)	-	-
W*RO	0.1875**(3.16)	-	-
W*IC	-0.0485***(-4.56)	-	-
W*GM	-0.0521***(-3.98)	-	-
W*ER	-0.0187**(-3.11)	-	-
R^2	0. 7984	0.7283	0.7515
Log-likelihood	81.0866	62.6742	71.5401
Lambda/Rho	0.0523***(5.47)	0.0148**（3.04）	0.1237 (1.55)
sigma2_e	0.0025***(4.69)	0.0027***(11.60)	-
Wald spatial lag	22.3155***	-	-
LR spatial lag	11.4367**	-	-
Wald spatial error	28.8414***	-	-
LR spatial error	10.9983**	-	-
Hausman test	117.8827***	-	-

Notes: The t-statistics are given in parentheses; ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

It can be inferred that the coefficient of industrial structure is -0.0068, which is negatively correlated with green transition at 5% level. This may relate to the unreasonable development of the tertiary industry. The coefficients of reform and openness, investment capacity, government intervention, and environmental regulation are 0.0316, 0.1055, 0.0217, and 0.1128, respectively. That means they are all beneficial for green transition by decreasing carbon emissions and energy consumption. Subsequently, indicated by the estimation results of the three spatial models above, the *Lambda/Rho* shows that both SDM and SLM passed the significance test at the 5% level, while SEM is not significant. From the perspective of R-squared and Log-likelihood, SDM is better than SLM. Moreover, both the Wald test and the LR test reject the null hypothesis; therefore, the SDM could not be simplified to SLM or SEM. In summary, based on the above analysis, the

SDM may better express the spatial dependence of the driving factors of green transition.

4.3.3. Robustness test

The robustness of SDM is tested by two methods. The first method is to compare the estimation results of different models, which are shown in Tables 5 and 6. The coefficients of driving factors on GTI are consistent under the PSL regression and the spatial panel data models, only differ insignificance. Thereby, it can be inferred the results in this paper are robust.

The second method is to use different spatial matrices. The economic-geographical weight matrix was selected for comparison with the results of the geography distance matrix. With the convenience of transportation and the popularity of communication, economic distance should be studied when constructing a spatial weight matrix (Zhang *et al.*, 2018). Due to the economic and geographical factors, the economic-geographical weight matrix is built in this paper and is expressed as Eq. (14).

$$w_{ij} = \begin{cases} GDP_i * GDP_j / d_{ij}^2, & i \neq j \\ 0, & i = j \end{cases} \tag{14}$$

where GDP_i and GDP_j represent the GDPs of provinces *i* and *j*. d_{ij} represents the distance between provinces *i* and *j*.

Therefore, the estimation results with the economic-geographical weight matrix are shown in Table 7. Compared with the results in Table 6, the estimated coefficients of these five driving factors and their significance levels do not obviously change. This shows that the results in the paper are robust.

Table 7 Estimation results with the economic-geographical weight matrix

Spatial panel model with fixed effect	SDM	SLM	SEM
_cons	-	-1.6548 (-3.65)	-0.1264 (-1.64)
IS	-0.0058**(-2.83)	-0.0405** (-2.69)	-0.0259* (-2.27)
RO	0.0269*** (4.74)	0.0518*** (5.16)	0.0361***(6.42)
IC	0.1556*** (5.26)	0. 1086*** (4.27)	0.0863*** (3.66)
GM	0.0865*** (3.92)	0.0262* (2.28)	0.0435* (2.36)
ER	0. 1226*** (6.41)	0.0817 ***(3.86)	0. 1024*** (5.62)
W*IS	0.0461*(2.21)	-	-
W*RO	0.1746*** (3.25)	-	-
W*IC	-0.0722***(-6.13)	-	-
W*GM	-0.0381***(-3.86)	-	-
W*ER	-0.0167**(-2.88)	-	-
R^2	0. 8134	0.7168	0.7260
Log-likelihood	81.9342	66.3802	74.2283
Lambda/Rho	0.0529***(4.68)	0.01741**(3.07)	0.0424** (2.76)
sigma2_e	0.0024***(3.79)	0.0031***(6.52)	0.0029***(5.38)
Wald spatial lag	26.1724***	-	-
LR spatial lag	12.0431**	-	-
Wald spatial error	29.6634***	-	-
LR spatial error	10.7208**	-	-

Notes: The t-statistics are given in parentheses; ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

4.4. Spatial spillover effects of driving factors

The change of one or more driving factors not only affected the green transition of the local province directly, but also indirectly affected the green transition of the neighboring provinces.

Consequently, the estimation results of SDM could not accurately reflect the influence of driving factors on the green transition.

Therefore, the partial differential method was used to decompose the spatial spillover effect of the SDM into three parts: direct effect, indirect effect, and total effect (Lesage and Pace, 2009). The direct effects represented the influences of driving factors on the green transition of a local province. The indirect effects represented the influences of driving factors on the green transition of neighboring provinces. The total effects reflected the average influences of driving factors on both the local provinces and their neighboring provinces. Table 8 displays the results of direct, indirect, and total effects for the driving factors.

Table 8 Direct effects, indirect effects, and total effects of the SDM on GTI

variables	Direct effect	Indirect effect	Total effect
IS	-0.0125 (-3.13)**	0.0082 (2.11) *	-0.0043 (-1.98)*
RO	0.0317 (6.15) ***	0.0224 (3.20) **	0.0541 (6.13) ***
IC	0.0879 (4.28) ***	-0.1237 (-4.64) ***	0.0043 (3.88) ***
GM	0.0783 (3.99) ***	-0.1237 (-3.87) ***	-0.0454 (-2.95) **
ER	0.0175 (4.26) ***	-0.0092 (-2.03) *	0.0083 (2.14) *

Notes: The t-statistics are given in parentheses; ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

It can be found that the results of both direct and indirect effects were lined with the corresponding regression results in Table 6, illustrating that the results were steady and effective. Moreover, it demonstrated the rationality of using SDM to explore the spatial spillover of driving factors.

5. Discussion

With regard to direct effects, reform and openness, investing capacity, government intervention, and environmental regulation were significant at 1% level, and they positively impacted the green transition of China. The coefficients were (in descending order) investing capacity, government intervention, reform and openness, and environmental regulation. Fu and Balasubramanyam (2005) pointed out that reform and openness attracted advanced technology and promoted the development of both import and export trade. This also brought advantageous resources together to develop green transition (Holz, 2008). Moreover, similar to the work by DeLonge *et al.* (2016), investing could provide sufficient financing support for the green transition to optimize industrial structure. Moreover, the government, as a guide of China’s green transition, plays an important role in promoting green transition. By formulating policies related to tax, innovation, and funding, the government can guide and encourage manufacturing enterprises to realize green transition (Kemp and Never, 2017). Furthermore, environmental regulation can strengthen the optimal allocation of various resources to explore green technology, green processes, and green development, which thus promotes green transition (Wang and Shao, 2019; Pan *et al.*, 2019).

However, the direct effect of industrial structure on green transition was significant at 5% level, and exerted a significant negative effect on green transition. These results were consistent with the research by Wang *et al.* (2019). Currently, the tertiary industry in China has grown fast and its proportion of GDP gradually increased. However, the tertiary industry is mainly dominated by traditional service industries, including commerce, catering, and transportation. Emerging industries, such as information, consulting, technology, and financing, have insufficient development momentum, which led to small industry outputs and unreasonable industry structure. Using the express delivery industry in China as an example, it has developed rapidly since e-commerce was booming, but it has brought a serious environmental burden due to consuming a large amount of express packaging materials (Fan *et al.*, 2017). This may be the reason why the industrial structure exerts a negative impact on green transition.

Furthermore, from the perspective of indirect effects, the driving factors of investing capacity and government intervention were both significant at 1% level. This indicates that they exerted spatial spillover effects on the GTIs of neighboring provinces through spatial transmission channel. However, they generated negative externalities, i.e., when the invested capacity in the local province increased, the investing capacity in the neighboring provinces would decrease and form a 'closure effect'. Moreover, when the local government issued policies to develop green transition, this would attract more resources into the local province (Huang *et al.*, 2019). Consequently, this caused the resources to flow out from neighboring provinces. Moreover, the driving factor of reform and openness was significant at 5% level, which exerted a positive impact on the green transition in the neighboring provinces. Because the local government intensified the reform and openness, this enhanced the reform and openness of neighboring provinces and thus attracted resources (Kanbur and Zhang, 2001). In addition, the driving factor of industrial structure was significant at 10% level, and exerted a positive impact on the green transition of neighboring provinces. Furthermore, the driving factor of environmental regulation was significant at 10% level, but exerted a negative impact on neighboring provinces.

In addition, according to the total effects of these five driving factors, the reform and openness was significant at 1% level and its coefficient value was largest. This implied that reform and openness promoted the green transition of 30 provinces in mainland China through spillover effects, and the driving force was stronger than that of other factors. The statistics value of governmental intervention was significant at 5% level and its coefficient value was negative, indicating that the negative diffusion effect of governmental intervention on green transition exceeded its direct effect. This is because when the local government formulates macroeconomic policies to promote green transition, it attracts the governments in neighboring provinces to learn and imitate, which can easily cause policy overlap to hinder green transition (Giri *et al.*, 2019). Moreover, both investing capacity and environmental regulation were significant at 10% level, and both their direct effects exceeded their indirect effects (An *et al.*, 2021). This demonstrated that their direct impact on green transition of China exceeded the negative effect on the neighboring provinces.

6. Conclusion and Policy Implications

To explore the status quo of China's green transition development, this paper used the entropy weight method to calculate the GTIs of 30 provinces of China. On the basis, SDM was used to analyze the driving factors and spillover effects of China's green transition. The main conclusions are as follows:

(1) The overall level of China's green transition increased, but there is still enormous potential for improvement. China's GTI was low from an overall perspective and the gaps among provinces are widening. From the perspective of geographical distribution, the GTIs in the eastern region of China were much higher than those in both the central and western regions.

(2) The regional GTI in China had significant positive spatial dependence. Consequently, the

green transition of local provinces positively affected the development of neighboring provinces, showing that the spatial linkage effect has steadily developed.

(3) The results of the SDM showed that reform and openness, investing capacity, government intervention, and environmental regulation significantly promoted the green transition development in China. Among these, reform and openness had the greatest influence on green transition. However, the industrial structure harmed the green transition.

All factors exerted both direct and indirect impacts on the green transition development of China. How to realize high-quality green transition and coordinate the development among different regions has become the key for China's current development. Based on the main conclusions above, the following lists several implications for China's policy formulation toward the realization of the green transition and regional coordinated development:

(1) The positive space spillover effect of the reform and openness and environmental regulation should be fully utilized when China’s government plans for the green transition development. It is centrally important to increase the depth and intensity of the reform and openness. The cooperation and trust between provincial governments should be strengthened. Instead of narrow regional thinking, provincial governments need to fully account for regional agglomeration effects. Moreover, appropriate national coordination is needed to narrow the GTI development gaps among provinces.

(2) When promoting the regional green transition, the provincial governments of China must further strengthen the rationalization of the industrial structure. Moreover, emerging industries such as information, consulting, technology, and finance need to be vigorously developed, to increase the total tertiary industry. Furthermore, the governments should broaden the idea of green transition, and use the enterprises as the main bodies to mobilize their enthusiasm for the green transition. In addition, public awareness of green consumption and green behavior should be raised.

(3) With regard to the negative spatial spillover effect of investing capacity and government intervention, positive measures should be formulated to attract investment from large and medium-sized enterprises. In this process, the advantages of location and resources should also be fully utilized. Simultaneously, to realize a high-quality green transition, governments should further optimize the investment environment and improve the hard environment such as infrastructure and geographical environment. Moreover, the soft environment, including finance, talent, and technological innovation, needs to be improved.

Although this study has obtained several valuable conclusions, some limitations could be improved in further work. First, the GTI is affected by many factors, including resource, environment, economy, policies, etc., some of these perspectives were not well captured due to the data limitation. Second, the driving factors of GTI and their spatial spillover effects are discussed using the SDM. However, the economic development and resource condition of each region differ greatly, thus their heterogeneities need to be further explored in future research.

Acknowledgments

This work was supported by the Soft Science Research Project of Henan Province (212400410056) and the National Natural Science Foundation of China (71904059, 72174056, 71828401).

References

Adom, P. K., Bekoe, W., Amuakwa-Mensah, F., Mensah, J. T., Botchway, E. (2012). Carbon dioxide emissions, economic growth, industrial structure, and technical efficiency: Empirical evidence from Ghana, Senegal, and Morocco on the causal dynamics. *Energy*, *47*(1), 314-325.

An, Y., Zhou, D., Yu, J., Shi, X., Wang, Q. (2021). Carbon emission reduction characteristics for China's manufacturing firms: Implications for formulating carbon policies. *Journal of Environmental Management*, 284, 112055.

Bandyopadhyay, S. (2017). Evaluating sustainable economic development. *Clean Technologies and Environmental Policy*, 19(7), 1815–1816

Bell, K. (2016). Green Economy or Living Well? Assessing divergent paradigms for equitable eco-social transition in South Korea and Bolivia. *Journal of Political Ecology*, *23*(1), 71-92.

Cabrer, B. B., Serrano, D. G. (2007). Innovation and R&D spillover effects in Spanish regions: A spatial approach. *Research Policy*, *36*(9), 1357-1371.

Chen, L., Zhang, X., He, F., Yuan, R. (2019). Regional green development level and its spatial relationship under the constraints of haze in China. *Journal of Cleaner Production*, *210*, 376-387.

Choi, Y., Bone, C., Zhang, N. (2016). Sustainable policies and strategies in Asia: Challenges for green growth. *Technological Forecasting & Social Change*, 112, 134-137.

DeLonge, M. S., Miles, A., Carlisle, L. (2016). Investing in the transition to sustainable agriculture. *Environmental Science & Policy*, *55*, 266-273.

Dincer, I., Rosen, M. A. (2005). Thermodynamic aspects of renewables and sustainable development. *Renewable and Sustainable Energy Reviews*, *9*(2), 169-189.

Ding, S., Zhang, M., Song, Y. (2019). Exploring China's carbon emissions peak for different carbon tax scenarios. *Energy Policy*, *129*, 1245-1252.

Droste, N., Hansjürgens, B., Kuikman, P., Otter, N., Antikainen, R., Leskinen, P., Thomsen, M. (2016). Steering innovations towards a green economy: Understanding government intervention. *Journal of Cleaner Production*, *135*, 426-434.

Fan, S., Zhang, X., Robinson, S. (2003). Structural change and economic growth in China. *Review of Development Economics*, *7*(3), 360-377.

Fan, W., Xu, M., Dong, X., Wei, H. (2017). Considerable environmental impact of the rapid development of China's express delivery industry. *Resources, Conservation and Recycling*, *126*, 174-176.

Feng, C., Wang, M. (2019). Journey for green development transformation of China’s metal industry: A spatial econometric analysis. *Journal of Cleaner Production*, *225*, 1105-1117.

Feng, C., Wang, M., Liu, G. C., Huang, J. B. (2017). Green development performance and its influencing factors: A global perspective. *Journal of Cleaner Production*, *144*, 323-333.

Feng, Y., Wang, X., Liang, Z., Hu, S., Xie, Y., Wu, G. (2021). Effects of emission trading system on green total factor productivity in China: Empirical evidence from a quasi-natural experiment. *Journal of Cleaner Production*, *294*, 126262.

Ferguson, P. (2015). The green economy agenda: business as usual or transformational discourse? *Environmental Politics*, 24(1):17-37.

Fu, X., Balasubramanyam, V. N. (2005). Exports, foreign direct investment and employment: The case of China. *World Economy*, 28(4), 607-625.

Giri, R. N., Mondal, S. K., Maiti, M. (2019). Government intervention on a competing supply chain with two green manufacturers and a retailer. *Computers & Industrial Engineering*, *128*, 104-121.

Global Energy Interconnection Development and Cooperation Organization. (2021). *China's Carbon Neutrality Research Report by 2060 (In Chinese)*. https://iea.blob.core.windows.net/assets/a72d8abf-de08-4385-8711-b8a062d6124a/WEO2020.pdf

Guo, P. F., Zhou, Y. N. (2018). A Grounded-theory-based Study on the Evaluation Index Extraction and Construction of China's City Green Transition Policy. *Management reviews*, 30(8), 257-267

Hall, S., Foxon, T. J., Bolton, R. (2017). Investing in low-carbon transitions: energy finance as an adaptive market. *Climate policy*, *17*(3), 280-298.

Hamdouch, A., Depret, M. H. (2010). Policy integration strategy and the development of the 'green economy': foundations and implementation patterns. *Journal of environmental planning and management*, *53*(4), 473-490.

Holz, C. A. (2008). China's economic growth 1978–2025: what we know today about China's economic growth tomorrow. *World Development*, *36*(10), 1665-1691.

Hou, D., Li, G., Chen, D., Zhu, B., Hu, S. (2019). Evaluation and analysis on the green development of China's industrial parks using the long-tail effect model. *Journal of environmental management*, *248*, 109288. https://doi.org/10.1016/j.jenvman.2019.109288

Huang, Z., He, C., Li, H. (2019). Local government intervention, firm–government connection, and industrial land expansion in China. *Journal of Urban Affairs*, *41*(2), 206-222.

Hye, Q. M., Wizarat, S., Lau, W. Y. (2016). The impact of trade openness on economic growth in China: An empirical analysis. *The Journal of Asian Finance, Economics and Business*, *3*(3), 27-37.

International Energy Agency. (2020). *World energy outlook 2020*. OECD Publishing.

Jaffe, A.B., Peterson, S.R., Stavins, P. R. N. (1995). Environmental regulation and the competitiveness of U.S. manufacturing: what does the evidence tell us? *Journal of Economic Literature*, 33(1), 132-163.

Jin, W., Shi, X. Zhang, L. (2021). Energy Transition without Dirty Capital Stranding, *Energy Economics*, 102:105508.

Jorgenson, D. W., Wilcoxen, P. J. (1990). Intertemporal general equilibrium modeling of US environmental regulation. *Journal of Policy Modeling*, *12*(4), 715-744.

Kanbur, R., Zhang, X. (2001). Fifty years of regional inequality in China: a journey through revolution, reform and openness. *Review of development Economics*, *9*(1), 87-106.

Karl, Y., Chen, Z. (2010). Government expenditure and energy intensity in China. *Energy Policy*, *38*(2), 691-694.

Kemp, R., Never, B. (2017). Green transition, industrial policy, and economic development. *Oxford Review of Economic Policy*, *33*(1), 66-84.

Kemp-Benedict, E.. (2018). Investing in a green transition. *Ecological economics*, *153*, 218-236.

Krugman, P. (1998). What's new about the new economic geography?. *Oxford review of economic policy*, *14*(2), 7-17.

Kushwaha, G. S., Sharma, N. K. (2016). Green initiatives: a step towards sustainable development and firm's performance in the automobile industry. *Journal of Cleaner Production*, *121*, 116-129.

Laitner, J. (2000). Structural change and economic growth. *The Review of Economic Studies*, *67*(3), 545-561.

Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., Sapio, A. (2020). Climate change and green transitions in an agent-based integrated assessment model. *Technological Forecasting and Social Change*, *153*, 119806.

LeSage, J., Pace, R.K., (2009). *Introduction to spatial econometrics*. Chapman and Hall/CRC press.

Liao, X.C., Shi X.P.. (2018). Public appeal, environmental regulation and green investment: Evidence from China. *Energy policy*, *119*, 554-562.

Midilli, A., Dincer, I., Ay, M. (2006). Green energy strategies for sustainable development. *Energy Policy*, *34*(18), 3623-3633.

Mundaca, L., Markandya, A. (2016). Assessing regional progress towards a 'Green Energy Economy'. *Applied Energy*, *179*, 1372-1394.

Owen, R., Brennan, G., Lyon, F. (2018). Enabling investment for the transition to a low carbon economy: government policy to finance early stage green innovation. *Current Opinion in Environmental Sustainability*, *31*, 137-145.

Pan, X., Ai, B., Li, C., Pan, X., Yan, Y. (2019). Dynamic relationship among environmental regulation, technological innovation and energy efficiency based on large scale provincial panel data in China. *Technological Forecasting and Social Change*, *144*, 428-435.

Pearce, D. , Markandya, A. , Barbier, E. B. . (1989). Blueprint for a green economy. Earthscan Publications, London, UK.

Rashidi, K., Saen, R. F. (2015). Measuring eco-efficiency based on green indicators and potentials in energy saving and undesirable output abatement. *Energy Economics*, *50*, 18-26.

Ringel, M., Schlomann, B., Krail, M., Rohde, C. (2016). Towards a green economy in Germany? The role of energy efficiency policies. *Applied energy*, *179*, 1293-1303.

Rodenburg, C., Baycan-Levent, T., Van Leeuwen, E., Nijkamp, P. (2001). Urban Economic Indicators for Green Development in Cities. *Greener Management International*, 36: 105-119

Samper, J. A., Schockling, A., Islar, M. (2021). Climate politics in green deals: Exposing the political frontiers of the European Green Deal. *Politics and Governance*, *9*(2), 8-16.

Shannon, C. E. (1948). A note on the concept of entropy. *Bell System Tech. J*, *27*(3), 379-423.

Shao, S., Zhang. Y., Tian, Z., Li, D., Yang, L, (2020). The Regional Dutch Disease Effect within China: A Spatial Econometric Investigation. Energy Economics, 88: 104766.

Shi X, Ji Q, Zhang D, Taghizadeh-Hesary F and Han P, (2020). Editorial: Energy Market and Energy Transition: Dynamics and Prospects. *Front. Energy Res*. 8:603985.

Shi, X., Sun, Y., Shen, Y. (2021). China's ambitious energy transition plans, *Science*, 373 (6551): 170.

Shi, X. (2021). People-centred Just Energy Transitions for Social Justice, *Journal of Environmental Economics*, 2021(3):122-127.

Song, Y., Sun, J., Zhang, M., Su, B. (2020). Using the Tapio-Z decoupling model to evaluate the decoupling status of China's CO2 emissions at provincial level and its dynamic trend. *Structural Change and Economic Dynamics*, *52*, 120-129.

Springer, C., Evans, S., Lin, J., Roland-Holst, D. (2019). Low carbon growth in China: The role of emissions trading in a transitioning economy. *Applied Energy*, *235*, 1118-1125.

Su, B., Ang, B. W.. (2016). Multi-region comparisons of emission performance: The structural decomposition analysis approach. *Ecological indicators, 67*, 78-87.

Thomas, K.D. (2015). Handbook of Research on Sustainable Development and Economics, Pennsylvania: IGI Global.

Tisdell, C. (2009). Economic reform and openness in China: China's development policies in the last 30 years. *Economic Analysis and Policy*, *39*(2), 271-294.

Wang, P., Chen, L. Y., Ge, J. P., Cai, W., Chen, W. Q. (2019). Incorporating critical material cycles into metal-energy nexus of China's 2050 renewable transition. *Applied Energy*, *253*, 113612.

Wang, X. L., Shao, Q.L. (2019). Non-linear effects of heterogeneous environmental regulations on green growth in G20 countries: evidence from panel threshold regression. *Science of The Total Environment*, *660*, 1346-1354.

Wang, Y., Sun, X., Guo, X. (2019). Environmental regulation and green productivity growth: Empirical evidence on the Porter Hypothesis from OECD industrial sectors. *Energy Policy*, *132*, 611-619.

Xu, L., Fan, M., Yang, L., Shao, S. (2021). Heterogeneous Green Innovations and Carbon Emission Performance: Evidence at China's City Level. *Energy Economics*, 2021, 99: 105269.

Yang, Z., Shao, S., Fan, M., Yang, L. (2021). Wage Distortion and Green Technological Progress: A Directed Technological Progress Perspective. Ecological Economics, 2021, 181: 106912.

Yin, L., Bo, N., Jia, J. (2019). Location oriented induction: research on the industrial structure upgrade mode in China (in Chinese). *Finan. Trade Res.*, *2*, 38-45.

Yu, D., Li, X., Yu, J., Li, H. (2021). The impact of the spatial agglomeration of foreign direct investment on green total factor productivity of Chinese cities. *Journal of Environmental Management*, *290*, 112666.

Yuan, B., Xiang, Q. (2018). Environmental regulation, industrial innovation and green development of Chinese manufacturing: Based on an extended CDM model. *Journal of cleaner production*, *176*, 895-908.

Zagler, M. (2009). Economic growth, structural change, and search unemployment. *Journal of Economics*, *96*(1), 63-78.

Zhai, X., An, Y. (2020). Analyzing influencing factors of green transformation in China's manufacturing industry under environmental regulation: A structural equation model. *Journal of Cleaner Production*, 251, 119760.

Zhang, C., Liu, C. (2015). The impact of ICT industry on CO2 emissions: a regional analysis in China. *Renewable and Sustainable Energy Reviews*, *44*, 12-19.

Zhang, H, Shi, X., Wang, K, Xue, J., Song, L., Sun, Y. (2020). Intertemporal Lifestyle Changes and Carbon Emissions: Evidence from a China Household Survey. *Energy Economic*s, 86:104655.

Zhang, J., Chang, Y., Zhang, L., Li, D. (2018). Do technological innovations promote urban green development?—A spatial econometric analysis of 105 cities in China. *Journal of cleaner production*, *182*, 395-403.

Zhao, H., Lin, B. (2019). Will agglomeration improve the energy efficiency in China's textile industry: Evidence and policy implications. *Applied Energy*, *237*, 326-337.

Zhao, N., You, F. (2020). Can renewable generation, energy storage and energy efficient technologies enable carbon neutral energy transition?. *Applied Energy*, *279*, 115889.

Zhao, T., Yang, Z. (2017). Towards green growth and management: Relative efficiency and gaps of Chinese cities. *Renewable and Sustainable Energy Reviews, 80*, 481-494.

Zhou, P., Ang, B. W.. (2008). Decomposition of aggregate CO2 emissions: a production-theoretical approach. *Energy Economics, 3,* 1054-1067.

Zhu, B., Zhang, M., Zhou, Y., Wang, P., Sheng, J., He, K., Wei, Y., Xie, R. (2019). Exploring the effect of industrial structure adjustment on interprovincial green development efficiency in China: A novel integrated approach. *Energy Policy*, *134*, 110946.

Zou, Z. H., Yi, Y., Sun, J. N. (2006). Entropy method for determination of weight of evaluating indicators in fuzzy synthetic evaluation for water quality assessment. *Journal of Environmental sciences*, *18*(5), 1020-1023.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: