Int. Journal of Economics and Management 16 (1): 21-43 (2022)

IJEM
International Journal of Economics and Management
Journal homepage: http://www.ijem.upm.edu.my

The Role of Industrial Structure Adjustment in China's Low-Carbon Eco-Efficiency: A Super-Slack-Based Measure (Super-SBM) Approach

TAO MIAOMIAO[a], GOH LIM THYE[a*] AND GOVINDARAJU V.G. R CHANDRAN[b]

[a]*Department of Economics and Applied Statistics, Faculty of Business and Economics, Universiti Malaya, Malaysia*
[b]*Department of Development Studies, Faculty of Business and Economics, Universiti Malaya, Malaysia*

ABSTRACT

Drawing on panel data of China's 30 selected provinces from 2005 to 2017, this paper examined the effects of industrial structure adjustment (IA) effects on low-carbon eco-efficiency (LCE). We utilised the Super-slack-based Measure (Super-SBM) to evaluate China's LCE and the Industrial structure advancement (ISA) and rationalisation (ISR), as an integrated part of IA, were selected to conduct the effect's examination adopting the Spatial Durbin Model (SDM). Our results indicate that the proposed Super-SBM model could effectively rank the SBM-efficiency provinces. However, the regional economic development did not follow a low-carbon pattern and LCE performance among regions and provinces was extremely uncoordinated, thus, forming a significant spatial distribution pattern. In addition, the SDM results proved that IA was a crucial channel for China to develop a low-carbon economy. In contrast, the comparative analysis showed that ISR could be regarded as an essential pathway for most provinces to sustain LCE growth compared with ISA.

JEL Classification: F64; O13; Q4

Keywords: Low-carbon eco-efficiency; undesirable outputs Super-SBM model; industrial structure adjustment; Spatial Durbin Model

Article history:
Received: 29 September 2021
Accepted: 11 Febuary 2022

[*] Corresponding author: Email: ltgoh@um.edu.my

INTRODUCTION

According to the National Bureau of Statistics of China (NBSC, 2020), China's GDP has multiplied by more than 170 times since the founding of the People's Republic of China. In 2010, China surpassed Japan to become the second-largest economy globally, known as the "China miracle". However, China's past extensive economic development pattern, characterised by a massive labour, resources and capital investment, brought with it an oversupply of primary products but a shortage of high-end products. However, the relationship between low-quality supply and high-quality demands continues to escalate, resulting in increasing strains on China's sustainable economic development (Liu et al., 2020). Moreover, China has become the world's largest energy consumer (Du et al., 2011) and the most significant carbon dioxide (CO_2) emitter (Gregg et al., 2008). Specifically, China accounted for one-quarter of the world's total CO_2 emissions in 2011 (Choi et al., 2012) and devoured almost half of all coal produced in 2012 (Wang et al., 2013). It made up 24% of the world's energy consumption, accounting for approximately 34% of global energy consumption growth (BP, 2019). Greenhouse gas emissions (GGE), especially CO_2 emissions, are generally accepted as one of the leading causes of climate change (Li et al., 2019).

Given that climate change will cause a series of profound influences on social and economic development, the associated risk will be equivalent to 5-20% of global GDP each year (Stern Report, 2006). China has introduced some initiatives which are targeted to prompt energy conservation and mitigate CO_2 emissions. For instance, in the National 12th Five-Year Plan (2011-2015) introduced many carbon and energy reduction targets by 2015, with 2010 as the base year, such as decreasing the carbon intensity by 17% and reducing energy intensity by 16% (SCPRC, 2011). Moreover, the "green development" proposed by the central government in the National 13th Five-Year Plan (2016-2020) became a principal guiding ideology in the crucial area of economic construction and social development. In the 75th United Nations General Assembly held in September 2020, China's President, Xi Jinping, announced that "China will struggle to reach a CO_2 emissions peak before 2030 and achieve carbon neutrality before 2060". Transforming its economic development model and cultivating a low-carbon economy (LE) (Wang and Chang, 2014; Liu et al., 2013) is vital for China to fulfill these goals.

The concept of a LE was first proposed in a British Government White Paper (DTI, 2003), which addressed that a LE would maximise economic output through lower resource consumption, thus, leading to lower GGE. At the same time, the policies related to a LE have also been introduced in many countries, such as; Japan, the United States and Germany (Cherry et al., 2014; Shimada et al., 2007). The international community has begun to arrive at a consensus on combating climate change and developing the LE. Special attention has been attached to the mitigation of CO_2 emissions and energy conservation. For example, Jiang et al. (2010) analysed China's energy development under the LE and its introduction of a set of energy development strategies. Liu and Gallagher (2010) developed a CCS (Carbon Capture and Storage) roadmap for China. Their results showed that coal gasification or polygeneration could be nearly unbeatable when combined with CCS for China's low-carbon future. Liu et al. (2013) put forward a five-pronged strategy to set China onto a low-carbon path after systematically analysing the significant bottlenecks of China's transition to a LE. To promote a LE, it is also essential for management to fully understand China's past low-carbon eco-efficiency (LCE).

An LCE could significantly reduce ecological deterioration to a minimum while maximizing total factor productivity (TFP). Generally, the industrial structure of developed economies is well advanced. Thus, the developed eco-efficient countries are more efficient than emerging markets at the lower end of the global industrial value chain. An economy can enhance its efficiency and capability in energy utilisation and reduce pollutant emissions by industrial adjustment (IA). Environmentally cleaner production methods by industries, especially heavy industries would foster economic growth, create a better environment, and increase economic gains in social welfare. Thus, pushing forward IA is an essential way for China to achieve a higher LCE. However, the dilemma of choosing economic growth or environmental protection remains a pressing issue faced by emerging markets. Countries worldwide constantly rearticulate their economies, especially their industrial structure, to achieve sustainable development (Buzdugan and Tuselmann, 2018; Fessehaie and Morris, 2018; Yashodha et al., 2018). China has also significantly restructured its industrial structure. Specifically, the contributions of three sectors, namely, the agriculture, industrial and tertiary sectors, have transformed from 27.7%, 47.7%, and 24.6% in 1978 to 7.1%, 39.0%, and 53.9% in 2019, respectively. The tertiary industry's contribution has increased monotonically since 1978 and exceeded 50% for the first time in 2015 (NBSC, 2020). China's industrial structure adjustment (IA) is consistent with the country's general industrial structure pattern, evolving from "primary, secondary, tertiary"; "secondary, tertiary, primary" to "tertiary, secondary, primary" industries.

China's rapid industrialisation has brought about sizable economic gains. At the same time, environmental problems, such as ecological deterioration and haze pollution, have arisen, which have harmed people's health and exacerbated ecological degradation, thereby curbing long-term inclusive economic development (Shi et al., 2017; Chen et al., 2018). Gryshova et al. (2020) highlighted that a progressive industrial structure promoted sustainable economic development and improved the population's quality of life. Nevertheless, the current research has not yet made an in-depth exploration of the effects of IA on LCE. Moreover, the pioneering research only used the percentage of capital to labour (He and Wang, 2012; Cole and Elliott, 2003) or the ratio of manufacturing industry to the GDP (Cole, 2000) to measure IA. Unfortunately, these methods do not truly reflect the real essence of IA, resulting in biased estimation. This situation is because capital might not be utilised in polluting industrial sectors, the manufacturing industry might not necessarily be clean. In contrast, the clean manufacturing industry might not be eco-efficient. Therefore, it is of great importance to probe into the underlying impacts of IA on LCE.

Data Envelopment Analysis (DEA), which is a nonparametric analysis approach, was developed by Mardani et al. (1978) to estimate the relative efficiencies of decision- making units (DMUs). The model has been widely adopted to assess eco-efficiency and the efficiency of CO_2 emissions because it incorporates both environmental and economic indicators into multiple inputs and outputs analyses simultaneously (Guo et al., 2011). For example, using the DEA model, Lee and Lee (2009) analysed the building energy performance in Taiwan Province by selecting 47 government office buildings. Lu et al. (2013) studied CO_2 emissions efficiency (where CO_2 emissions acted as an undesirable output) in OECD countries from 2005 to 2007 by performing a hybrid DEA model. The results demonstrated that the countries' efficiency from 2005 to 2007 presented volatility after controlling for CO_2 emissions, suggesting that CO_2 emissions were essential in evaluating regional LCE performance.

What is more, the DEA model does not require additional assumptions (i.e., functional form postulations), and it can avoid man-made weighting errors (Song et al., 2012). It should be noted that undesirable outputs (where CO_2 emissions are a typical example) as a by-product in the actual production process (i.e., coal-based production activities) are inevitable. Therefore, the core of the DEA model lies in maximising desirable outputs and lowering energy inputs (i.e., coal) while reducing undesirable outputs. However, the traditional DEA model (i.e., the CCR-DEA model) is not feasible and accurate to measure LCE when incorporating CO_2 emissions.

Subsequently, the slack-based measure (SBM) model, which was extended by Tone (2001) could be used to treat undesirable outputs, where the model takes the slackness problems of inputs and outputs caused by the radical and angular choices into consideration (Song et al., 2012). Moreover, this model can effectively address the potential issues of input excess and output shortfall in eco-efficiency measurement. As for studies concerning China, employing the non-radical DEA model, Choi et al. (2012) estimated the potential reductions and efficiency of CO_2 emission and estimated the marginal decrease in CO_2 emissions. Adopting 28 provinces in China, Song et al. (2013a) calculated the environmental efficiency from 1998 to 2009. They then compared the results estimated by the SBM model with the classic CCR-DEA model. The authors also proved that the results of the undesirable outputs of the SBM model were more reliable. Scholars have also included other undesirable variables (see Liang et al., 2021; Zhou et al., 2018; Liu and Dong, 2021; Meng and Qu, 2022) when implementing the undesirable outputs SBM model. However, it is not convenient to effectively rank the SBM-efficient DMUs, since the efficiency values of DMUs estimated by the undesirable outputs SBM model may be simultaneously equal to 1.

Therefore, the Super-SBM model with undesirable outputs (incorporating CO_2 emissions) was adopted to analyse China's regional and provincial LCE performance across its 30 provinces from the temporal and spatial perspectives. Further, we believed that IA played a crucial role in stimulating LCE. Hence, the Spatial Durbin Model was performed to conduct the regression analysis. The relevant measures for improving LCE in China were derived. The remainder of this paper is structured as follows: Section 2 introduces the methodology to be used. Section 3 discusses the variable's selection, data sources, descriptive statistics, and the necessary testing undertaken. The empirical results and related analysis are presented in Section 4, while Section 5 outlines the research conclusions.

RESEARCH METHODOLOGY

Super-SBM model with undesirable output

This research implemented a Super-SBM model incorporating undesirable output based on the SBM-DEA framework (Tone, 2001, 2002, 2004). Following Chang et al. (2013), it is asumed that technologies with less undesirable and more desirable outputs should be considered efficient. Suppose that the LCE production system has N MDUs with three dimensions: inputs, desirable and undesirable outputs. Each province invests m input factors to produce s1 and s2 desirable and undesirable outputs, respectively. X, Y^d and Y^{ud} were used to denote the inputs, desirable outputs and CO_2 emissions. The matrices X, Y^d and Y^{ud} as $X = [x_{ij}] = [x_1, \ldots, x_n] \in R^{m\times n}$, $Y^d = [y_{ij}] = [y_1, \ldots, y_n] \in R^{s_1\times n}$, and $Y^{ud} = [y_1^{ud}, \ldots, y_1^{ud}] \in R^{s_2\times n}$. were specified. The production possibility set (PPS) can be expressed as follows:

$$p(x) = \{(x, y^d, y^{ud}) | x \text{ produce } (x, y^d, y^{ud}), x \geq X\theta, y^d \geq y^d\theta, y^{ud} \geq y^{ud}\theta, \theta \geq 0\} \tag{1}$$

where λ expresses the non-negative intensity vector, meaning that the definition above corresponds to the constant returns-to-scale (CRS) condition.

Based on this PPS, and referring to Tone (2004), the SBM model treating undesirable outputs is specified as follows:

$$\rho = \min\left(\frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{y_r^d}{y_{r0}^d} + \sum_{t=1}^{s_2}\frac{y_t^{ud}}{y_{t0}^{ud}}\right)}\right)$$
$$\text{subject to}\begin{cases} x_0 = X\theta + s^- \\ y_0^d = Y^d\theta - s^d \\ y_0^{ud} = Y^{ud}\theta + s^{ud} \\ s^- \geq 0, s^d \geq 0, s^{ud} \geq 0, \theta \geq 0 \end{cases} \tag{2}$$

where the vector s^d is the slack in inputs, whereas s^- and s^{ud} denotes the excesses of inputs and undesirable outputs, respectively. The subscript o denotes a DMU whose efficiency is being estimated. The interval of the objective function value of ρ is $[0,1]$, which is the efficiency level of the DMUs. Precisely, the DMUs are regarded as SDM-efficiency when meeting the conditions of $\rho = 1$ and $s^- = s^d = s^{ud} = 0$. If $\rho < 1$, indicating that the DMUs are inefficient, thus, both inputs and outputs need to be improved. Adopting the Charnes-Cooper transformation, as suggested by Tone (2001), Eq. (2) was transformed into a linear form with the following equivalent form:

$$\kappa = \min\left(t - \frac{1}{m}\sum_{i=1}^{m}\frac{s_{i0}^-}{x_{i0}}\right)$$
$$\text{subject to}\begin{cases} 1 = t + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^d}{y_{r0}^d} + \sum_{r=1}^{s_2}\frac{s_r^{ud}}{y_{r0}^{ud}}\right) \\ x_0 t = X\mu + S^- \\ y_0^d t = Y^d\mu - S^d \\ y_0^{ud} = Y^{ud}\mu + S^{ud} \\ S^- \geq 0, S^d \geq 0, S^{ud} \geq 0, \mu \geq 0, t \geq 0 \end{cases} \tag{3}$$

The Super-SBM model incorporating CO_2 emissions was adopted as an undesirable variable based on the previous studies (Li et al., 2013; Zhang et al., 2018) to construct a reasonable efficiency assessment system, because some DMUs are simultaneously efficient. The formula is as follows:

$$\rho^{*} = \left[\frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}_i}{x_{i0}}}{\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{\bar{y}_r^{d}}{y_{r0}^{d}}+\sum_{r=1}^{s_2}\frac{\bar{y}_r^{ud}}{y_{r0}^{ud}}\right)}\right]$$

$$\text{subject to}\begin{cases}\bar{x} \geq \sum_{j=1,\neq 0}^{N}\theta_j x_j \\ \bar{y}^{d} \leq \sum_{j=1,\neq 0}^{N}\theta_j y_j^{d} \\ \bar{y}^{ud} \geq \sum_{j=1,\neq 0}^{N}\theta_j y_j{}^{ud} \\ \bar{x} \geq x, \bar{y}^{d} \leq y_0^{d}, \bar{y}^{ud} \geq y_0^{ud}, \bar{y}^{d} \geq 0, \theta \geq 0\end{cases} \tag{4}$$

where ρ^{*} represents the super efficiency of the DMUs, and its value can be >1, while other information is consistent with Eq. (2). Set $\sum_{i=1}^{n}\theta_i = 1$ in Eq. (2) and $\sum_{i=1,\neq 0}^{n}\theta_i = 1$ in Eq. (4), respectively, to meet the condition of CRS.

The above DEA models were mainly used to measure cross-sectional LCE comparisons between different DMUs. For a specific DMUs, it is necessary to track the changes in LCE performance over time (Wu et al., 2012). MPI (Malmquist productivity index) proposed by Färe et al. (1994) was used to estimate the dynamic changes in the TFP of China's LE. From period t to $t+1$, the MPI of the growth in TFP can be specified as follows:

$$MPI_j(t, t+1) = \left[\frac{\gamma^{t}\left(x_j^{(t+1)}, y_j^{(t+1)d}, y_j^{(t+1)ud}\right) \times \gamma^{(t+1)}\left(x_j^{(t+1)}, y_j^{(t+1)d}, y_j^{(t+1)ud}\right)}{\gamma^{t}\left(x_j^{(t)}, y_j^{(t)d}, y_j^{(t)ud}\right) \times \gamma^{(t+1)}\left(x_j^{(t)}, y_j^{(t)d}, y_j^{(t)ud}\right)}\right]^{1/2} \tag{5}$$

where $MPI_j(t, t+1)$ captures the dynamic low-carbon eco-efficiency (DLCE) of $DMUs_j$ from period t to $t+1$; $\gamma_t\left(x_j^{(t)}, y_j^{(t)d}, y_j^{(t)ud}\right)$ and $\gamma_{t+1}\left(x_j^{(t)}, y_j^{(t)d}, y_j^{(t)ud}\right)$ represent the efficiency values of $DMUs_j$ based on its inputs, desirable outputs and undesirable outputs at period t for the reference technology at t and $t+1$, while $\gamma_t\left(x_j^{(t+1)}, y_j^{(t+1)d}, y_j^{(t+1)ud}\right)$ and $\gamma_{t+1}\left(x_j^{(t+1)}, y_j^{(t+1)d}, y_j^{(t+1)ud}\right)$ are the efficiency values of $DMUs_j$ based on its inputs, desirable outputs and undesirable outputs at period $t+1$ for the reference technology at t and $t+1$. Specifically, $MPI_j(t, t+1) > 1$, $MPI_j(t, t+1) = 1$ and $MPI_j(t, t+1) < 1$ designate that the LCE of $DMUs_j$ has improved, remained unchanged and degraded from period t to $t+1$, respectively.

Spatial Econometric Model

Because flows of the production factors result in spatial autocorrelations, IA in one region exerts a spatial spillover effect on adjacent provinces (Wang et al., 2019; Damayanti and Walandoum, 2018). Therefore, a method based on spatial econometric modelling was introduced in this study. The first step for performing the spatial econometric model lay in the spatial weight matrix design. Unfortunately, a symmetric spatial weight matrix is usually not suitable for modelling interprovincial correlations. The correlations between different regions are also affected by the scale of investment and their economic development level (Lin et al., 2006). Amore economically developed province usually has a more significant spillover effect on its adjacent areas. For example, the effect of Guangdong province on Yunnan would be significantly higher than the effect of Yunnan province on Guangdong. Thus, an asymmetric spatial weight matrix needed to be constructed to reflect the heterogeneity in the mutual relationships between various provinces. Following the first law of geography (Tobler, 1970), everything is related to everything else, while near things are closer than those between things far away from each other. Therefore, we constructed an econometric-geographical weight matrix, which was expressed as the product of the geographical distance weight matrix and the diagonal elements of the matrix were the proportion of the per capita RGDP:

$$W_2 = W_1 * \mathrm{diag}\left(\frac{PRGDP_1}{\overline{\overline{PRGDP}}}, \frac{PRGDP_2}{\overline{\overline{PRGDP}}}, \ldots, \frac{PRGDP_n}{\overline{\overline{PRGDP}}}\right) \tag{6}$$

where $\mathrm{diag}(\cdot)$ expresses a diagonal matrix, while $\overline{\mathrm{PRGDP}}$ represents the average PRGDP of all provinces; W_1 represents the geographical spatial weight matrix, which was constructed based on the longitude and latitude between the two provinces.

The global Moran's index, first proposed by Moran (1948) to examine the spatial autocorrelation of the economic variables based on a spatial random distribution, can be used to detect whether the LCE exhibited spatial autocorrelation. The formula is as follows:

$$\text{Moran's I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(LCE_i - \overline{LCE}\right)\left(LCE_j - \overline{LCE}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(LCE_i - \overline{LCE}\right)^2} \tag{7}$$

where LCE_i represents the LCE index in province $i(j)$, while $\overline{LCE}$ expresses the average LCE; n is the number of provinces; w_{ij} is the spatial weight matrix constructed by Eq. (6). Specifically, the interval for Moran's I is $[-1,1]$, where$[-1,0]$ indicates the negative spatial autocorrelation among spatial entities, $[0,1]$ indicates the positive autocorrelation among spatial entities, while 0 means no spatial autocorrelation.

The Spatial Durbin Model (SDM) was adopted to verify the effects of IA on LCE. Referring to (Elhorst, 2013), the SDM with a general form is as follows:

$$Y = \alpha I_N + \rho WY + \beta X + \theta WX + \varepsilon \tag{8}$$

where Y denotes the dependent variable; X is the independent variables (including the core independent and control variables); α, β and θ are the vectors of the regression coefficients; I_N is an N −order identity matrix, while ε denotes the error term. Both the spatial lag term of the dependent variable (Wy) and the independent variables (Wx) are included in the SDM model (Yu et al., 2013). Notably, the criteria for selecting the Spatial Lag Model (SLM) or Spatial Error Model (SEM) depend on the significance of the Lagrange Multiplier (LM) test and its robustness test, and the model with a better R^2 will be selected. If $\theta = 0$, the SDM will be degraded to the SLM, while if $\theta + \rho\beta = 0$, the SDM model will be degraded to the SEM model (Lv et al., 2019). Therefore, the Wald and LR tests were adopted to examine whether the SDM model would be simplified to the SLM or SEM models.

Data sources and indicators

Adopting panel data from 30 selected provinces in China (excluding Tibet) from 2005 to 2017, we first explored the temporal and spatial characteristics of the LCE. Then the SDM model was employed to examine whether IA contributed to LCE in China. The data was mainly collected from; the China Environmental Statistical Yearbook, China Energy Statistical Yearbook, China Statistical Yearbook and Statistical Yearbook in each province.

Indicators used for calculating provincial low-carbon eco-efficiency

The LCE assessment system included three dimensions: the inputs, desirable outputs and undesirable outputs. The underlying principle was to reduce the inputs of production factors and the output of CO_2 emissions in regional economic development. First, capital and labour were two crucial production inputs factors at the macro-regional level (Chang et al., 2013). Meanwhile, energy consumption was also related to regional development[1] (Dhingra and Das, 2014), while water and land, as natural resources, are essential for improving LCE. Third, the real gross domestic product acted as the desired output. Finally, CO_2 emissions (CE), as a key indicator characterising LCE, was defined as an undesirable output (Wang and Chang, 2014). The relevant information concerning the LCE assessment system is shown in Table 1.

The paper adopted the perpetual inventory method to calculate provincial capital stocks (Zhang et al., 2019), taking into account with data availability, which was defined as follows:

$$\begin{aligned} K_{it} &= (1-\delta)K_{it-1} + I_{it} \\ K_{i2005} &= I_{i2005}/(g_i + \delta) \end{aligned} \tag{9}$$

[1] According to the NBSC, TE includes all types of energy, i.e., natural gas, petroleum and coal, all of which are transformed into tons of standard coal of equivalent. (The query link: http://www.stats.gov.cn/tjsj/ndsj/2020/indexch.htm).

where K_{it} denotes the provincial capital stocks in period i for year t; δ represents the depreciation rate of capital, which was 10.96% (Shan, 2008); I_{it} expresses the amount of investment in provincial fixed assets; g_i represents the annual average growth rate of the domestic fixed investment. The related monetary indicators in this paper were adjusted to 2005 constant prices. The GDP was deflated with GDP deflators, while the provincial capital stock was deflated by the price index for investment in fixed assets.

Following Shan et al. (2016), the provincial CE was calculated as follows:

$$\mathrm{CE_i} = \mathrm{AD_i} \times \mathrm{EF_i} \tag{10}$$

where $\mathrm{CE_i}$ denotes the CO_2 emissions from different energy types; $\mathrm{AD_i}$ denotes the (activity data) fossil fuels combusted within the provincial boundary measured in physical units (metric tons of fuel expressed as t fuel), while $\mathrm{EF_i}$ expresses the emissions factors for the relevant fossil fuels.

Table 1 shows the descriptive statistics of the LCE assessment system. The mean provincial capital stock was $40{,}120.398\times10^8$ Yuan (2005 constant prices). The desirable output of the GDP was $13{,}282.109\times10^8$ Yuan (2005 constant prices), whereas the undesirable output of CO_2 emissions was $2{,}043.369\times10^4$ tons.

Table 1 Indicator's selection for assessing the provincial LCE index

Dimension	Primary index	Sub-Index	Symbol	Unit	References
Inputs	Resource inputs	Land for urban construction	LU	sq.km	Ren et al. (2018)
		Total water consumption	TW	10^4 tons	Hubacek et al. (2009)
		Total energy consumption	TE	10^4 TCS	Yan Zhou et al. (2013)
	Social resource inputs	Capital stock	CS	10^8 yuan	Meng & Qu (2022)
		Labour employment	LE	10^4 persons	Shang et al. (2020)
Outputs	Desirable output	Gross domestic product	GDP	10^8 yuan	Cheng et al. (2018)
	Undesirable output	CO_2 emissions	CE	10^4 tons	Teng et al. (2021); Lin et al. (2020)

Table 2 displays the Pearson correlation matrices. It can be seen that the correlation coefficients between the input and output factors were all positive, implying the "isotonicity" of the inputs and outputs in the DEA model (Mostafa, 2009), which, in turn, highlights the reliability of the selected indexes capturing China's LCE.

Table 2 Pairwise correlation matrices for the LCE assessment system

Variables	LU	TW	TE	CS	LE	GDP	CE
LU	1.000						
TW	0.619*	1.000					
TE	0.780*	0.433*	1.000				
CS	0.565*	0.328*	0.643*	1.000			
LE	0.849*	0.515*	0.742*	0.546*	1.000		
GDP	0.622*	0.501*	0.766*	0.806*	0.729*	1.000	
CE	0.750*	0.328*	0.915*	0.597*	0.618*	0.659*	1.000

Note: *p<0.01 (two-tailed)

Selection of variables for industrial structure adjustment

As a dynamic process, IA usually refers to the proportion of changes of three industries, which is one of the determinants of economic growth. Referring to Zhang (2015), IA incorporates two crucial components: one regulates the speed of economic resources transfers between the industries, namely industrial structure advancement (ISA); the other regulates the proportion of changes of the three industries, namely industrial structure rationalisation (ISR). According to UNCTAD (2019), structural transformation is a crucial process; without improving a country's productive capacity and shifting resources to higher productivity sectors, countries will fail to deliver on the 2030 Agenda for Sustainable Development. Specifically, we used the following equations to measure provincial ISA and ISR levels:

ISA (Zheng et al., 2021). ISA mainly reflects the changes in industrial proportion and the improvement of the labour productivity (Lu et al., 2020). The output value of the tertiary industry to secondary industry was used to measure the provincial ISA level.

ISR (Liang et al., 2021). The formula for measuring the ISR level is as follows:

$$\mathrm{ISR} = \frac{\sum_{i=1}^{n}\left(\frac{Y_i}{Y}\right)\left(\frac{L_i}{L}\right)}{\sqrt{\sum_{i=1}^{n}\left(\frac{Y_i}{Y}\right)^2}\sqrt{\sum_{i=1}^{n}\left(\frac{L_i}{L}\right)^2}} \tag{11}$$

where Y_i represents the output values of industry i; L_i represents the employed people in industry i; Y and L denote the gross production and total employment. ISR $\in [0,1]$, the higher the value, the better the synergy between the input and output structures of factors; thus, the allocating of economic factors in three key industries is more reasonable (Liu et al., 2021).

Selection of control variables

Based on the existing literature and relevant theories, we chose four indicators as control variables.

(1) Technological innovation (TI). Schumpeter (1934) first integrated TI into the economic analysis and asserted that economic development was an evolutionary process with TI at its core. Subsequently, Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1922) and Goh et al. (2020) viewed R&D activities as a form of decision-making in firms and endogenised the impacts of TI on economic growth. Specifically, adopting environmentally-friendly technologies can aid firms to improve production capacity, lower energy consumption and reduce pollutant emissions to effectively enable cleaner production, thus, improving resource efficiency and promoting sustainable economic development. The proportion of three kinds of domestic patents granted to three kinds of domestic patent applications was adopted to denote the provincial TI level.

(2) Economic policy uncertainty[2] (EPU). According to Gulen & Ion (2016), EPU refers to any potential risks associated with economic policies. Market players cannot accurately foresee whether, when, and how the government may change economic policies. However, as one of the most crucial risks of firms, EPU plays a pivotal role in the decision-making processes of firms (Tran, 2019). Further, firms tend to use relatively cheap fossil fuels when they face the increased EPU, which, in turn, increases CO_2 emissions (Yu et al., 2021) and degrades the environment, thus negatively affecting the LCE.

(3) Foreign direct investment (FDI). According to the pollution haven hypothesis, multinational enterprises (MNEs) transfer energy-intensive and highly polluting industries to countries with lower environmental regulations to circumvent costly regulatory compliance in home countries. Thus, developing countries suffer more significant environmental issues limiting their eco-efficiency improvement. Conversely, the pollution halo hypothesis shows that MNEs diffuse their modern technologies in developing countries and further enhance the eco-efficiency caused by the technological spillover effect (Zhang and Zhou, 2016). Therefore, the paper selected the proportion of actual use of FDI to RGDP as an indicator.

(4) Financial development (FD). On the one hand, a sound financial system promotes economic activities by stimulating the stock market and encouraging investors to buy energy-saving production equipment, ultimately improving energy utilisation (Shah et al., 2019). On the other hand, a sound financial mechanism can also help reduce information asymmetries, especially in environmental projects and enrich investment returns by guiding capital flows, thus, enhancing environmental efficiency (Sadorsky, 2010). This paper selected the ratio of loans balance from banks and financial institutions to RGDP as an indicator.

RESULTS AND DISCUSSIONS

Low-carbon eco-efficiency

The temporal variations and spatial distribution of LCE for China from 2005 to 2017 are shown in Figure 1. Overall, it was observed that the temporal variations of LCE displayed a "U-shaped" trend. In the national 11th Five-Year Plan, China's central government announced that "China will establish and refine the GGE accounting system, establish a national carbon emissions trading market, reduce CO_2 emissions dramatically

[2] The link to EPU data provided by Yu et al. (2021) is as follows: https://doi.org/10.1016/j.eneco.2020.10507.

by adjusting industrial structure and energy structure, and increase forest carbon sinks". Therefore, the LCE exhibited a downward trend and went up since 2009. Further, the National 12th Five-Year Plan clarified the carbon and energy reduction goals (See, Introduction).

Moreover, to reduce CO_2 emissions and develop the LE, in October 2011, China's National Development and Reform Commission issued a Notice on Pilots for Carbon Emissions Trading, which formally approved carbon trading in seven of China's provinces and cities: Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong and Shenzhen. Shenzhen took the lead in this group in June 2013 to launch carbon emissions trading, with the other pilot areas following subsequently. Adopting the DID approach, Qi et al. (2021) proved that there was evidence to demonstrate that the effects of the carbon trading pilot policy on the low-carbon international competitiveness of industries were positive, highlighting that the policy was effective in reducing CO_2 emissions and improving LCE. Moreover, the results also demonstrated that the central government's efforts in combating GGE and improving LCE were productive because the LEC index had exhibited a significantly increasing trend since 2011. We also geo-visualised the spatial distribution of LCE in China for seven typical years, namely, 2005, 2007, 2009, 2011, 2013, 2015 and 2017. It was found that the LCE in China's eastern region was better than the central and western regions. The LCE levels of eastern coastal provinces, such as Guangdong, Zhejiang, Jiangsu were higher than the other eastern provinces (i.e., Shandong, Tianjin).

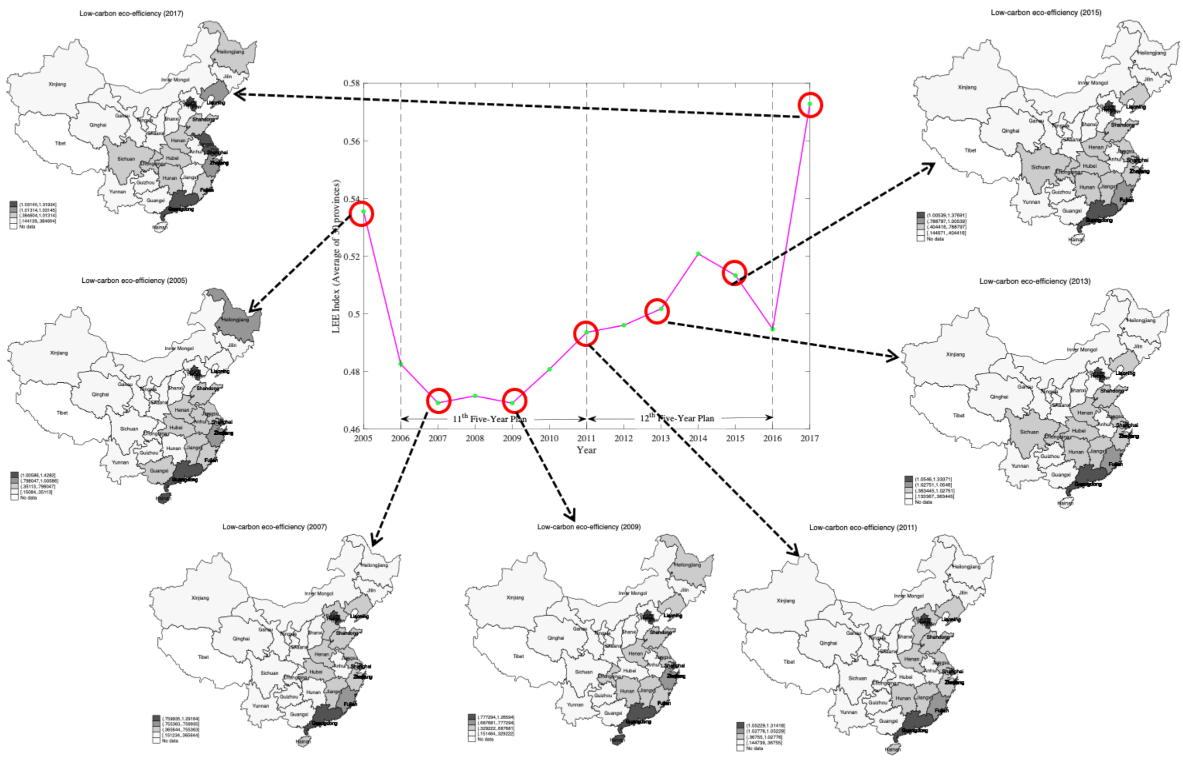

Figure 1 Spatial-temporal variation of LCE over China from 2005 to 2017

The LCE values of China's 30 provinces from 2005 to 2017 were expressed using a colour chart in Table 3. Firstly, on the whole, the LCE performance of Beijing, Tianjin, Shanghai and Guangdong was significantly higher than that of other provinces over the 13 years. Among them, Beijing played a leading role in the process of LCE, with Tianjin and Guangdong following subsequently. Concerning the temporal trend, all provinces exhibited an upward trend excluding small fluctuations in some provinces such as Fujian ("U-shaped" trend), Hainan (inverted "N-shaped" trend). However, the LCE levels of Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang were relatively low, among which Qinghai ranked at the bottom, with an average value of 0.147. Up until 2017, the top ten provinces in China for LCE levels were; Beijing, Tianjin, Shanghai, Guangdong, Jiangsu, Liaoning, Chongqing, Fujian, Sichuan and Shandong, comprising eight eastern provinces and two western provinces. Guangxi, Shaanxi, Inner Mongolia, Xinjiang, Jilin, Guizhou, Gansu, Shanxi, Ningxia and Qinghai ranked in the bottom ten comprising one eastern province, one central province and eight western provinces. The results demonstrated that the LCE performance of the central and western provinces was backward, as compared with the eastern provinces, and there was significant room for improvement. It is worth mentioning that the LCE in the northeastern provinces was not good, Jilin had the lowest value, and Heilongjiang exhibited a significant downward trend during the research period, while the growth of the LCE in Jilin was evident, especially in the year of 2016. Hence, the northeastern provinces must overcome backward production capacity and promote old and new economic kinetic energy transformation, thus gradually developing their LE and improving LCE.

Table 3 Color chart of LCE levels of China's 30 provinces from 2005 to 2017

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average
Beijing	1.276	1.286	1.275	1.240	1.240	1.288	1.314	1.297	1.334	1.301	1.291	1.304	1.319	1.290
Tianjin	1.428	1.305	1.292	1.158	1.266	1.103	1.223	1.258	1.268	1.375	1.377	1.390	1.285	1.287
Hebei	0.337	0.367	0.376	0.329	0.328	0.324	0.390	0.380	0.363	0.355	0.338	0.321	0.341	0.350
Shanxi	0.277	0.264	0.262	0.248	0.246	0.232	0.249	0.252	0.247	0.242	0.236	0.210	0.213	0.244
Inner Mogolia	0.249	0.193	0.205	0.207	0.217	0.219	0.238	0.243	0.256	0.257	0.259	0.248	0.277	0.236
Liaoning	0.351	0.401	0.411	0.369	0.408	0.382	0.453	0.431	0.435	0.438	0.442	1.002	1.016	0.503
Jilin	0.215	0.205	0.216	0.188	0.196	0.177	0.179	0.184	0.189	0.206	0.222	0.208	0.244	0.202
Heilongjiang	1.003	0.387	0.362	0.353	0.358	0.325	0.357	0.358	0.362	0.408	0.404	0.396	0.415	0.422
Shanghai	1.186	1.201	1.204	1.176	1.172	1.177	1.187	1.198	1.207	1.168	1.176	1.183	1.189	1.186
Jiangsu	0.642	0.695	0.646	0.547	0.546	0.678	0.704	0.702	0.688	0.708	0.684	0.627	1.042	0.685
Zhejiang	1.006	0.785	0.755	0.716	0.777	1.005	1.028	1.050	1.028	1.015	0.789	0.646	1.031	0.895
Anhui	0.482	0.390	0.366	0.298	0.318	0.321	0.353	0.362	0.362	0.387	0.385	0.352	0.371	0.365
Fujian	0.798	0.779	0.760	1.001	0.688	1.021	1.052	1.029	1.055	1.043	1.005	0.605	1.004	0.911
Jiangxi	0.355	0.389	0.379	0.339	0.346	0.337	0.441	0.383	0.384	0.424	0.406	0.349	0.385	0.378
Shandong	0.422	0.471	0.454	0.434	0.429	0.443	0.446	0.430	0.439	0.431	0.430	0.388	0.518	0.441
Henan	0.453	0.458	0.391	0.342	0.358	0.363	0.453	0.461	0.485	0.481	0.463	0.419	0.503	0.433
Hubei	0.497	0.398	0.369	0.352	0.329	0.314	0.358	0.408	0.429	0.453	0.438	0.403	0.493	0.403
Hubnan	0.340	0.364	0.365	0.363	0.347	0.336	0.411	0.399	0.408	0.467	0.473	0.414	0.478	0.397
Guangdong	1.059	1.102	1.112	1.101	1.096	1.030	1.058	1.082	1.074	1.152	1.150	1.118	1.122	1.097
Guangxi	0.357	0.358	0.332	0.307	0.279	0.249	0.289	0.295	0.312	0.295	0.297	0.274	0.325	0.305
Hainan	1.091	0.463	0.399	1.006	1.014	1.006	0.405	0.358	0.352	0.388	0.355	0.316	0.336	0.576
Chongqing	0.342	0.331	0.331	0.327	0.361	0.352	0.359	0.393	0.426	0.550	0.636	0.676	1.013	0.469
Sichuan	0.323	0.335	0.312	0.305	0.298	0.314	0.368	0.387	0.392	0.442	0.504	0.455	0.584	0.386
Guizhou	0.198	0.213	0.203	0.192	0.191	0.194	0.212	0.214	0.228	0.227	0.228	0.204	0.230	0.210
Yunnan	0.271	0.253	0.242	0.233	0.231	0.231	0.253	0.265	0.282	0.336	0.353	0.322	0.341	0.278
Shaanxi	0.324	0.287	0.272	0.265	0.264	0.264	0.282	0.300	0.302	0.312	0.302	0.293	0.312	0.291
Gansu	0.219	0.218	0.211	0.194	0.194	0.181	0.183	0.200	0.209	0.224	0.219	0.207	0.217	0.206
Qinghai	0.151	0.152	0.151	0.152	0.151	0.147	0.145	0.144	0.133	0.149	0.144	0.143	0.144	0.147
Ningxia	0.155	0.162	0.163	0.161	0.166	0.164	0.176	0.181	0.177	0.168	0.168	0.156	0.168	0.166
Xinjiang	0.256	0.267	0.255	0.242	0.256	0.244	0.240	0.234	0.225	0.222	0.226	0.212	0.269	0.242
Average	0.535	0.483	0.469	0.471	0.469	0.481	0.494	0.496	0.502	0.521	0.513	0.495	0.573	

To effectively capture the regional heterogeneity, Figure 2 displays the LCE during the research period. It can be seen that the LCE exhibited an upward trend among the four economic zones, indicating that provincial LCE increased volatility. The results also showed that the LCE of the northeast area gradually caught up with the level of the central area and successfully surpassed it in 2005, while the western area had the lowest efficiency level with an average LCE of 0.267. Moreover, the regional heterogeneity was indicated to be statistically significant by adopting the Kruskal-Wallis ranks test with a value of 41.239 (p-value=0.0001), which again emphasised that the LCE performance of eastern China was more evident than the other economic zones. It is widely acknowledged that the eastern region is economically more advanced. Therefore, the local government can allocate more funds and capital to develop high-tech industries characterised by the "two-low" group. Therefore, the re-articulation and optimisation of the industrial structure can improve energy utilisation efficiency and reduce CO_2 emissions. The tertiary industry mainly refers to the capital- and technologically-intensive industrial sectors (i.e., high-tech manufacturing). With the policy support from the Rise of Central China plan, the central region has developed rapidly based on its abundant natural resources. However, its industrial structure remains poorly managed; its economic activities have resulted in high energy consumption, thereby increasing CO_2 emissions. Compared with other economic zones, the western region has lagged economically concerning economic strength and technology levels. The results showed that the LCE performance of the western region was still hindered, even though the fact that the central government has made great efforts in the construction of local areas, such as the Development of the Western Region in China. Zhang and Choi (2013) suggested that the government provide adequate funds and technical support to the western region, thus gradually overcoming the regional discrepancy.

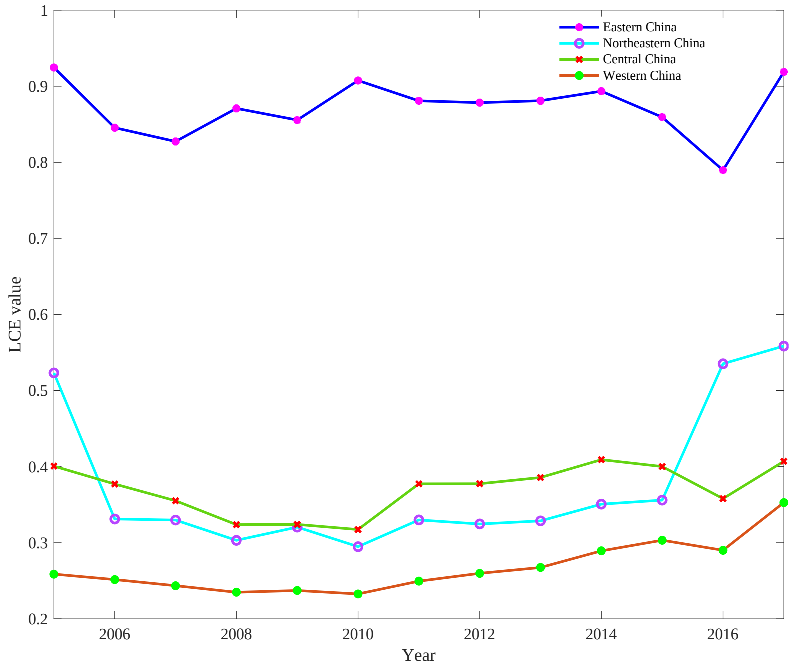

Figure 2 The average LCE of China's four economic zones

Adopting Eq. (5), we calculated the DLCE values of China's 30 provinces over time, as shown in Table 4. It can be seen that China's 30 provinces experienced an overall positive change $(= 1.028)$ during the research period, suggesting that the LCE improved by 2.8% annually since 2005. The provincial average DLCE values exhibited a positive shift, excluding Shaanxi Province $(= 0.996)$, designating that almost all of provinces made a great achievement in their LCE. Moreover, the annual average DLCE values showed a positive shift, indicating that China's economy is gradually following a low-carbon economic development pattern. Among them, Hainan, Beijing in the eastern region were found to have the highest annual growth rate. Figure 3 displays the average DLCE values of four economic zones over time.

Table 4 The DLCE values of China's 30 provinces from 2005/2006 to 2016/2017

Province	2005/2006	2006/2007	2007/2008	2008/2009	2009/2010	2010/2011	2011/2012	2012/2013
Beijing	1.042	1.047	1.028	1.081	1.035	1.064	1.042	1.052
Tianjin	1.024	1.013	1.020	1.028	1.020	1.002	1.007	1.008
Hebei	1.012	1.014	1.029	0.950	0.977	1.023	1.026	1.024
Shanxi	0.997	0.993	0.976	0.995	0.988	1.008	1.010	1.009
Inner Mongolia	1.018	1.073	1.040	1.040	1.023	1.011	1.012	1.043
Liaoning	1.072	1.026	1.079	1.034	0.975	1.076	0.996	1.030
Jilin	1.096	1.091	1.019	1.018	0.946	0.978	1.037	1.053
Heilongjiang	1.041	1.044	1.068	1.051	0.945	1.019	1.078	0.999
Shanghai	1.029	1.036	1.032	1.070	1.054	1.072	1.093	1.026
Jiangsu	1.064	1.089	1.010	1.028	1.015	0.975	0.988	1.093
Zhejiang	1.049	1.034	1.044	1.049	0.953	1.022	1.098	1.009
Anhui	1.029	1.045	1.018	1.023	1.056	1.097	1.079	1.070
Fujian	0.991	1.007	0.997	1.066	1.049	1.035	1.023	1.032
Jiangxi	0.988	1.017	1.029	0.947	0.970	1.017	1.029	1.040
Shandong	1.017	1.070	1.030	0.958	1.002	1.006	1.003	1.034
Henan	1.029	1.024	1.022	1.025	1.037	1.010	0.996	0.981
Hubei	1.024	1.040	1.027	1.029	1.039	1.020	1.008	1.004
Hunan	1.038	1.013	1.014	1.029	1.024	1.009	1.097	0.979
Guangdong	1.023	1.019	0.981	0.991	0.997	1.002	1.004	1.002
Guangxi	1.002	1.007	1.021	1.029	1.022	1.010	1.010	1.030
Hainan	1.077	1.061	1.000	1.072	1.065	1.091	1.080	1.065
Chongqing	0.993	1.007	1.017	1.048	0.984	0.992	1.046	1.090
Sichuan	1.014	0.945	1.003	0.946	1.033	1.026	0.999	0.994
Guizhou	1.025	1.040	1.057	1.067	1.076	1.030	1.060	1.074
Yunnan	0.958	1.030	1.030	0.979	0.988	1.011	1.015	1.023
Shaanxi	1.049	1.060	1.040	1.055	1.065	1.063	1.013	1.004
Gansu	1.030	1.043	1.007	1.040	1.029	1.040	1.007	1.040
Qinghai	1.059	1.064	1.007	1.040	1.057	1.070	1.049	1.037
Ningxia	1.033	1.010	1.015	1.006	1.025	1.007	1.040	1.050
Xinjiang	1.030	1.057	1.070	1.024	1.028	1.033	1.049	1.039
Average	1.028	1.034	1.024	1.024	1.016	1.027	1.033	1.031

Table 4 Cont.

Province	2013/2014	2014/2015	2015/2016	2016/2017	Average
Beijing	1.090	1.000	1.098	1.084	1.055
Tianjin	1.090	1.093	1.079	1.047	1.036
Hebei	0.992	0.971	1.040	0.977	1.003
Shanxi	0.997	0.980	0.995	1.004	0.996
Inner Mongolia	1.000	1.007	1.042	1.005	1.026
Liaoning	1.021	1.010	1.052	0.965	1.028
Jilin	1.021	1.094	1.042	1.068	1.039
Heilongjiang	0.998	1.000	1.025	1.003	1.023
Shanghai	1.087	1.051	1.024	1.005	1.048
Jiangsu	1.092	1.097	1.058	1.068	1.048
Zhejiang	1.019	1.003	1.078	1.004	1.030
Anhui	1.030	1.009	1.033	1.018	1.042
Fujian	1.069	1.044	1.022	1.052	1.032
Jiangxi	1.027	0.982	0.990	1.019	1.005
Shandong	1.001	0.984	1.013	0.990	1.009
Henan	1.017	0.989	1.041	1.064	1.019
Hubei	1.007	1.030	1.030	1.056	1.026
Hunan	0.952	1.027	1.021	1.047	1.021
Guangdong	1.003	1.021	1.028	1.003	1.006
Guangxi	0.949	1.014	1.039	1.031	1.014
Hainan	1.069	1.079	1.040	1.056	1.063
Chongqing	1.049	1.116	1.082	1.069	1.041
Sichuan	1.008	1.031	1.072	1.031	1.009
Guizhou	1.074	1.060	1.070	1.064	1.058
Yunnan	1.030	1.047	1.034	1.080	1.019
Shaanxi	1.002	1.024	1.043	1.088	1.042
Gansu	1.046	1.040	1.018	1.040	1.032
Qinghai	1.080	1.002	1.004	1.050	1.043
Ningxia	0.942	0.980	1.005	0.962	1.006
Xinjiang	1.010	1.007	1.013	1.028	1.032
Average	1.026	1.026	1.038	1.033	1.028

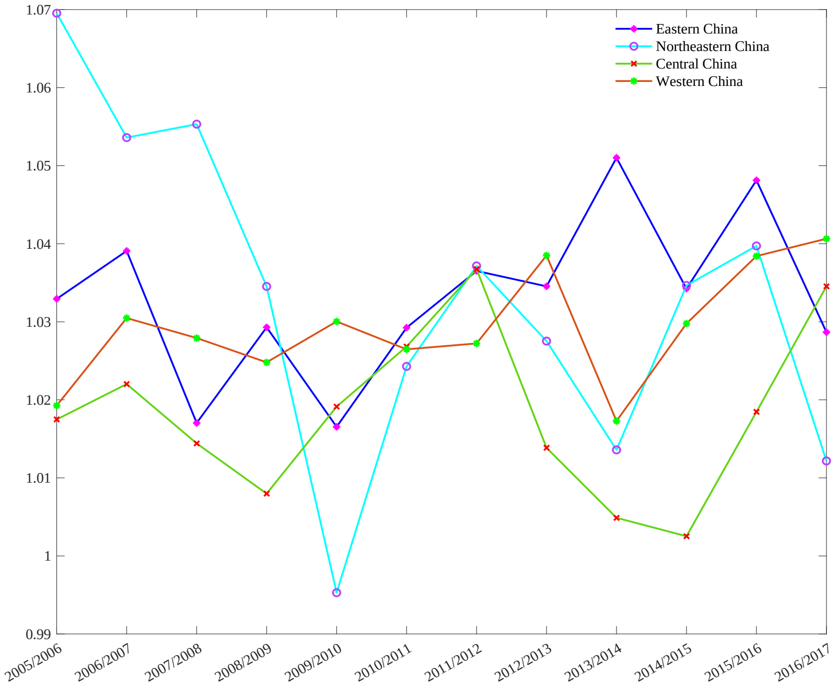

Figure 3 The average DLCE values of four economic zones over time

Stationary and cointegration testing

This paper adopted the Levin-Lin-Chu (LLC), Fisher PP and Fisher ADF tests to carry out the unit root testing to avoid spurious regression caused by the nonstationary data, as shown in Table 5. The results rejected the null hypothesis that all series contained unit-roots favouring the alternative hypothesis that at least some were stationary. The panel Pedroni cointegration test was used to conduct panel cointegration test. It was found that the model underlying the reported statistics in Table 6 rejected the null hypothesis of no cointegration, favouring the alternative hypothesis that the variables were cointegrated in all panels. Hence, the regression analysis could be performed.

Table 5 Unit root test results

Variable	LLC	Fisher PP	Fisher ADF
LEE	-1.3850*	10.1125***	4.7181***
ISA	-4.1358***	2.3938***	3.6601***
ISR	-1.5416*	10.7767***	3.2967***
FDI	-5.8490***	3.3244***	7.5712***
TI	-5.3170***	12.6997***	10.0728***
EPU	-6.5462***	15.8108***	9.3757***
FD	-14.3558***	2.9547***	5.4932***

Note: *p<0.1, ***p<0.001

Table 6 Pedroni cointegration test results

	AIS model		RIS model	
	Statistic	p-value	Statistic	p-value
Modified Phillips-Perron t	6.6133***	0.000	8.6013***	0.000
Phillips-Perron t	-11.2931***	0.000	-5.8861***	0.000
Augmented Dickey-Fuller t	-6.9437***	0.000	-3.6867***	0.000

Note: ***p<0.01

Spatial autocorrelation analysis

Table 7 lists the Moran's I test results for the whole sample. The results implied that Moran's I value passed at least the 1% significance test. At the same time, the results further confirmed a positive spatial correlation between the LCE in China's provinces. Provinces with a higher LCE were spatially adjacent to each other, while provinces with a lower LCE tended to be concentrated. The results showed that geographical factors played a vital role in studying China's LCE and that spatial influence elements should be included in the regression.

Table 7 Moran's I test results

Year	2005	2006	2006	2008	2009	2010	2011
Moran's I	0.327***	0.404***	0.397***	0.334***	0.362***	0.365***	0.411***
Year	2012	2013	2014	2015	2016	2017	
Moran's I	0.406***	0.402***	0.384***	0.350***	0.298***	0.281***	

Note: ***p<0.01

Effects of industrial structure adjustment on low-carbon eco-efficiency

The selection of the spatial model should be identified and tested to avoid the influence of setting errors on the effectiveness of the model estimation. Firstly, the MATLAB software was used to carry out the LM test and robust LM tests, as shown in Table 8. The results showed that the SDM model was accessible in this paper. Secondly, the Wald test and LR test results further revealed that the selected SDM model could not be simplified to the SLM or SEM models. Thirdly, the results of the Hausman test indicated that it was more appropriate to adopt a fixed-effects model.

Table 8 Model diagnostics

	ISA model	p-value	ISR model	p-value
LM Lag	290.799***	0.000	261.713***	0.000
LM Lag (Robust)	5.462***	0.000	24.374***	0.000
LM Error	333.745***	0.000	265.871***	0.000
LM Error (Robust)	48.408***	0.000	28.532***	0.000
LR Lag	20.34***	0.001	21.51***	0.000
LR Error	25.72***	0.000	26.77***	0.000
Wald Lag	30.83***	0.000	41.79**	0.023
Wald Error	71.24***	0.000	61.29***	0.000
Hausman	55.55***	0.000	63.87***	0.000

Note: ** p<0.05, *** p<0.01

Finally, the SDM model with fixed effects was adopted to verify the effects of ISA and ISR on China's LCE, respectively. According to Table 9, first, the coefficients of spatial ρ in two models were significantly positive, consistent with the Moran's I reported in Table 7. After incorporating spatial elements, the estimated coefficients of ISA and ISR were statistically positive at the 1% significance level, suggesting that vigorously adjusting and optimising industrial structure was conducive to reducing CO_2 emissions and further promoting China's LCE. Second, the coefficient of FDI was statistically positive in the two models. Thus, the pollution halo hypothesis was identified. FDI brought advanced technologies, and the resulting knowledge spillover and industrial driving effects have positively contributed to the LCE enhancement. Third, TI, as a crucial engine, was essential for promoting LCE. Fourth, referring to the real options theory, EPU increased the option value so that firms postponed their acquisition and investment until the potential uncertainty was eliminated (Wang et al., 2014). From a micro level, the increasing EPU also lowered the resource allocation efficiency of firms (Kim and Kung, 2017), thus, causing the insufficient allocation of economic resources and degrading the LCE growth of firms. Finally, financial sectors actively allocated financial resources to productive investment ventures that adopted energy-efficient and modern technologies for production (Shahbaz et al., 2018), which boomed domestic production and improved environmental quality by reducing energy consumption. Thus, the positive role of FD was determined.

Table 9 Spatial Durbin Model test results

Variable	LCE	W_x	LCE	W_x
ISA	0.093^{***}	0.213^{***}		
	(3.47)	(4.29)		
FDI	0.365^{***}	1.051^{***}	0.126^{*}	0.517^{***}
	(5.63)	(7.20)	(1.89)	(3.36)
TI	0.442^{***}	1.123^{***}	0.234^{**}	1.002^{***}
	(3.58)	(3.34)	(1.99)	(3.21)
EPU	-0.006	-0.193^{***}	-0.006	-0.209^{***}
	(-0.40)	(-4.19)	(-0.38)	(-4.93)
FD	0.124^{***}	0.022	0.195^{***}	0.270^{***}
	(3.40)	(0.27)	(7.05)	(4.78)
ISR			0.114^{***}	0.118^{***}
			(7.51)	(3.19)
Spatial ρ	0.493^{***}		0.371^{***}	
	(7.03)		(4.70)	
$Sigma^2$_e	0.049^{***}		0.043^{***}	
	(13.56)		(13.78)	
L-ratio test	27.152		56.678	
Adj R-squared	0.631		0.7752	
Observation	390		390	

Note: * p<0.1, ** p<0.05, *** p<0.01; t statistics in parentheses

As the spatial econometric model analysed the sophisticated spatial dependence among the spatial entities, the estimated coefficients contained a large amount of information about the relationships among the spatial entities. Changes in the independent variables associated with a spatial unit will directly affect the spatial it, generating a direct effect. At the same time, it also indirectly affects other spatial units, producing the so-called indirect effect. LeSage and Pace (2009) proposed the partial differential approach to decompose the spatial spillover effects into direct and indirect effects through spatial cross-sectional data. Elhorst (2013) further extended this method to spatial panel data. Therefore, the partial derivatives method was adopted to decompose the total effects of ISA and ISR on LCE into direct and indirect effects, as shown in Table 10. The resulted show that IA could be regarded as an excellent instrument to stimulate China's LCE growth because the direct, indirect and total effects of ISA and ISR on LCE were statistically positive at the 1% significance level. Specifically, for every 1 unit increase in local ISA, the LCE in the local province increased by 0.122.

In contrast, in adjacent areas, it increased by 0.491. At the same time, a 1 unit local area increase in ISA resulted in a net increase in the LCE of the country as a whole by 0.612. Similarly, an increase of 1 unit in local ISR increased LCE by 0.126, increasing by 0.245 in adjacent areas. A 1 unit local area increase in ISR resulted in a net increase in the LCE of the country as a whole by 0.371.

Table 10 Spatial spillover effect decomposition

	Direct effect	Indirect effect	Total effect
ISA	0.122^{***}	0.491^{***}	0.612^{***}
	(4.17)	(4.69)	(5.07)
Covariables	Yes	Yes	Yes
	Direct effect	Indirect effect	Total effect
ISR	0.126^{***}	0.245^{***}	0.371^{***}
	(8.36)	(5.08)	(7.46)
Covariables	Yes	Yes	Yes

Note: ***p<0.01; t statistics in parentheses

DISCUSSIONS AND ROBUSTNESS TEST

Discussions

Why IA plays a crucial role in promoting LCE in China? China has experienced long-term traditional industrialisation and industrial structure transformations, from the heavy industries to the technological and capital intensive sectors (Wang et al., 2013). The secondary industry was an essential pillar industry for stimulating China's economic growth (Fan et al., 2007). However, the secondary industry uses more energy and produces more CO_2 emissions than the primary and tertiary industries. The share of secondary output in the GDP in 2005 was 47.0%, while the industrial sector accounted for 41.6% of the GDP. Moreover, the consumption of TE in 2005 was 18.8×10^4 TCE, accounting for 71.9% of China's TE (NBS, 2019). Zhang (2015) and Guan et al. (2008) emphasized that a reasonable industrial structure accelerated economic resources distribution and promoted economic growth. Therefore, an advanced and appropriate industrial structure is pivotal for China's shift to the LE.

Figure 4 shows the scatter distribution characteristics of the average ISA and LCE values of each of China's provinces. The whole panel divided China's 30 provinces into four sub-regions. Sub-region II contained five provinces (including Tianjin, Guangdong, Shanghai, Fujian, Zhejiang), which belonged to eastern China and were the most developed provinces in China. Interestingly, China's central and western provinces were distributed in Sub-region III, while only Beijing was distributed in the Sub-region I.

Firstly, the average of ISA and LCE in Sub-region IV were 1.075 and 1.063, respectively. In comparison, the average of ISA and LCE in Sub-region I were higher than those of Sub-region IV, with the values of 1.2896 and 3.8391, respectively. Most of the Sub-region II provinces are coastal provinces (i.e., Guangdong, Tianjin, Shanghai) with high openness levels and abundant natural resources. Traditional industrial sectors in these provinces have been thoroughly rearticulated. The technological sectors were not energy-intensive industries (Lee and Hashim, 2014), but they were characterised by low energy consumption and low environmental pollutions ("two-low"). These provinces still need to commit to vigorously implementing national policies and converting industries with high energy consumption to capital- and technologically-oriented industries to promote LCE further. A "mismatching phenomenon" was identified (i.e., provinces in Sub-region IV with high ISA levels but low LCE levels).

Secondly, the average values of ISA and LCE in Sub-region III were 0.9473 and 0.3474, respectively. Sub-region III accounted for 65.77% of the total CO_2 emissions and 78.16% of the total RGDP of China in 2005 and 81.13% of total CO_2 emissions, and 41.87% of the total RGDP in 2007. There was a noticeable increase in CO_2 emissions and a significant decrease in the RGDP. Many heavy industries were located in Sub-region III, where the traditional northeast industrial zone was representative. The heavy industries, represented by steel and iron industries and cement industries could be regarded as the largest emitters of CO_2 emissions (Du et al., 2011). Most of them are characterised by high energy consumption and high pollutant emissions ("two-high"). Therefore, to effectively improve LCE, the local authorities should provide enough funds to gradually encourage these traditional industrial sectors to conduct R&D activities and overcome backward production capacity. Sequentially, two implicit influences can be derived. On the one hand, traditional industries can not only realise self-adjustment but also improve the quality of their products, thereby sizing the market share and improving competitiveness in the international market. On the other hand, heavy industries can mitigate CO_2 emissions and sustain LCE growth (Liu and Gallagher, 2010).

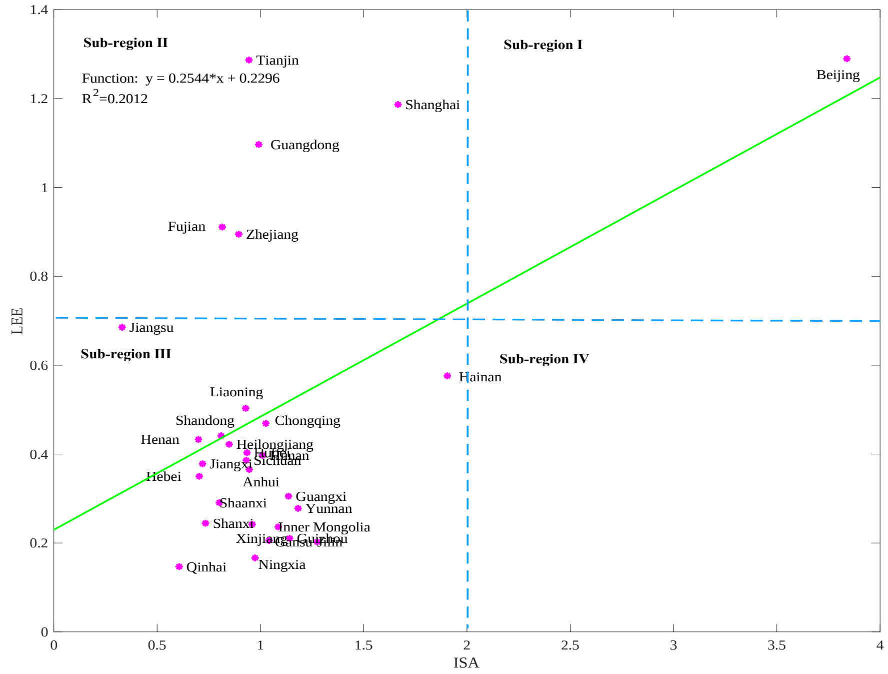

Figure 4 Scatter distribution of the average ISA and LEE of each province

Figure 5 shows the scatter distribution characteristics of the average ISA and LCE values for each province. Sub-region III included eight provinces from western China, excluding Shanxi, accounting for 63.64% of China's western provinces. Beijing was located in Sub-region I, while the other provinces were distributed in Sub-region IV. Table 11 further summarises the crucial information of Figure 5. Compared with ISA, the role of ISR was more crucial in stimulating provincial LCE growth. On the one hand, the goodness-of-fit in Figure 5 was higher than that of Figure 4, indicating that the average change trend of ISR in most provinces was consistent with that of LCE during 2005-2017. On the other hand, region IV was adjacent to Sub-region I. The path from IV → I could be regarded as a successful trajectory because different features characterised each Sub-region. For example, Hainan could step up to a new development stage by constantly rearticulating and its adjusting the industrial structure (Figure 5) to further improve its LCE further.

Table 11 Summary table of Figure 5

Sub-region	Numbers	$\overline{LEE}$	$\overline{ISR}$	$\overline{CO_2}$ emissions		$\overline{RGDP}$	
				2005	2017	2005	2017
I	7	1.0500	0.9528	0.2578	0.2275	0.4143	0.4077
III	10	0.2326	0.7253	0.2402	0.2925	0.1359	0.1375
IV	13	0.4097	0.8494	0.5020	0.4799	0.4305	0.4343

Note: $\overline{CO_2}$ emissions ($\overline{RGDP}$) denote the ratio of Sub-region average CO_2 emissions (RGDP) to the total CO_2 emissions (RGDP) of China

Finally, provinces such as Shanxi, Inner Mongolia and Xinjiang were the major coal- producing provinces in China, and their economic activities were excessively dependent on the coal-based industry. These provinces should improve the coal industry and promote economic diversification on the way to the LCE. Following Liu et al. (2013), provinces can achieve energy- and emissions-intensity targets by upgrading equipment and industrial processes to use less energy and then to drive down CO_2 emissions. What is more, expanding production scale, especially scale expansion, could contribute to China's improved energy intensity. Given the weak economic strength in Sub-region III (Figure 4 and Figure 5), those provinces should concentrate more on improving their socio-economic levels. A regional balanced development mechanism should be constructed to sustain LCE development. The central government should offer sufficient financial and technical support to encourage these provinces to conduct R&D activities. Besides, Appendix A reports the correspoding effects verification.

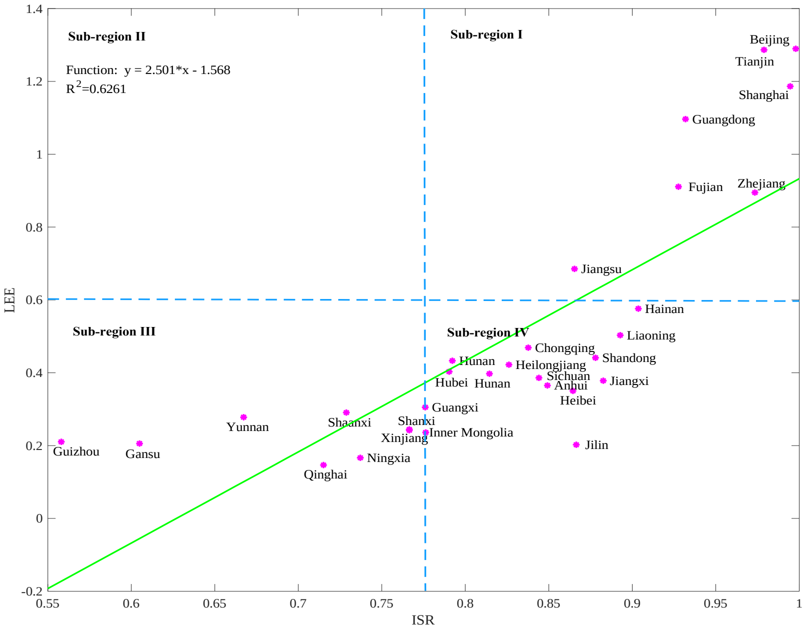

Figure 5 Scatter distribution of the average ISR and LCE of each province

Robustness test

The spatial weight matrix with the squared inverse distance was changed to verify the reliability of the derived results, which is expressed as follows:

$$w_{ij} = \begin{cases} 0, i = j \\ \dfrac{1}{{d_{ij}}^2}, i \neq j \end{cases} \tag{12}$$

where d_{ij} represents the greater-circle distance, determined based on the longitude and latitude between provinces i and j. w_{ij} needs to be normalised to ensure that sum of each row is 1.

According to Table 12, the effects of ISA and ISR on the LCE were statistically positive at the 1% significance level, highlighting that accelerating IA was conducive to promoting China's LCE. The coefficients of spatial ρ were significantly positive. Thus, it was feasible to nest the spatial elements into the regression. Furthermore, the spatial effect decomposition results showed that ISA and ISR positively contributed to the LCE in both local and adjacent areas. Therefore, our main conclusions were consistent with the former analyses, and the results were robust.

Table 12 Results for robustness testing and effect decomposition

ISA	0.118^{***} (4.85)	0.368^{***} (6.24)				
ISR				0.113^{***} (7.54)	0.170^{***} (4.25)	
Effect Dec.	DE	IE	TE	DE	IE	TE
ISA	0.171^{***} (6.08)	0.937^{***} (5.11)	1.108^{***} (5.56)			
ISR				0.129^{***} (8.79)	0.348^{***} (5.51)	0.477^{***} (7.42)
Covariables	Yes			Yes		
Spatial ρ	0.552^{***} (8.02)			0.401^{***} (4.95)		
$Sigma^2$_e	0.046^{***} (13.60)			0.042^{***} (13.76)		
L-ratio test	37.385			61.158		
Adj R-squared	0.6196			0.7915		
Obs.	390			390		

Notes: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$, t statistics in paratheses. Symbols "DE", "IE" and "TE" represent the direct, indirect and total effects, respectively.

CONCLUSIONS AND POLICY IMPLICATIONS

This paper examined the effects of ISA on China's LCE. Correspondingly, a Super-SBM model with undesirable output was constructed to estimate the LCE of 30 selected provinces in China from 2005 to 2017. Sequentially, two indicators (ISA and ISR) used to measure IA were adopted to verify the "promoting effect" on China's LCE. Firstly, nationally, China's LCE index exhibited an "U-shaped" trend during the research period. The central government's policy (i.e., carbon pilot trading policy) exerted a specific impact on the national LCE improvement. However, the LCE levels among China's various provinces and four economic zones were highly unbalanced. In general, the LCE level of the eastern area was better than the other areas.

Secondly, ISA and ISR positively affected the LCE in local and adjacent areas, indicating that rearticulating and upgrading industrial structure was crucial for China to develop the LE and improve the LCE further. Finally, for the comparative analysis of the LCE and IA (ISA and ISR) values, the whole panel divided China's 30 provinces into four Sub-regions. Beijing had the highest ISA, ISR and LCE values, which played a leading role in the process of LCE and IA. However, the central and western provinces were mainly distributed in Sub-region III and Sub-region IV. The development performance of the traditional northeast industrial zones concerning LCE and IA was not high quality because they were mainly located in Sub-region III. Fortunately, it was found that the ISR and LCE were better fitted, meaning that ISR was a pathway for most of China's provinces to achieve LCE.

The following policy implications aim to aid provinces with low LCE pursue LE, thus improving high-quality development.

1. Policies that are beneficial to IA should be implemented decisively. By ISR, the government is suggested to adjust the ratio between various industrial sectors, prohibiting over-dependence on one or more industrial sectors. In addition, ISR should be considered as an effective path to reduce CO_2 emissions and improve LCE. The local governments in different regions should expedite regional industrial structure transformation and re-articulation, gradually eliminating outdated production capacity to reduce pollutant emissions and stimulate regional LCE growth. By ISA, government subsidies and policies should be in place to encourage and support technological innovation, thereby stimulating the growth of modern service industries and smart manufacturing. As for technological innovation, local authorities should support and encourage technological renovations in traditional heavy industrial sectors and replace backward equipment and techniques to reduce CO_2 emissions.
2. Accordingly, a regional balanced development mechanism should be constructed to provide external technical and financial support to Sub-region III provinces. This situation is because the spatial spillover effects of IA on LCE ask for more critical collaboration among regional governments. The Chinese central government should act as a coordinator to help them build and design suitable policies to accelerate LE development and facilitate IA, avoiding the potential risks of unbalanced and uncoordinated development among regional policies.
3. Local governments and industrial firms should value the enhancement of LCE. Firms and local governments should abandon the development philosophy of "pollution first, treatment later". At the same time, the pertinent departments should establish and refine the negative list of market access systems to strictly restrict those "two-high" firms from entering the market.

However, two points need to be further addressed. First, although this research was processed based on the previous studies, the lack of provincial capital stocks and CO_2 emissions data may have cause biased estimations. Second, considering the data availability, the results cannot be compared with other developed economies such as OECD countries (the provincial LCE results would have relatively been much worse). This outcome leaves a research gap for our further exploration.

REFERENCES

Aghion, P. and Howitt, P., 1992. A model of growth through creative destruction. *Econometrica*, *60*, pp.323-352.

BP, 2019. Statistical review of world energy, London. https://www.nengapp.com/news/detail/2263237, Accessed date: 7 November 2019.

Buzdugan, S. R. and Tüselmann, H., 2018. Making the most of FDI for development: "new" industrial policy and FDI deepening for industrial upgrading. *Transnational Corporations*, *25*(1), pp.1-21.

Chang, Y. T., Zhang, N., Danao, D. and Zhang, N., 2013. Environmental efficiency analysis of transportation system in China: A non-radial DEA approach. *Energy Policy*, *58*(2013), pp.277–283.

Chen, L., Liang, S., Zhang, Y., Liu, M., Meng, J., Zhang, H., Tang, X., Li, Y., Tong, Y., Zhang, W., Wang, X. and Shu, J., 2018. Atmospheric Mercury Outflow from China and Interprovincial Trade. *Environmental Science and Technology*, *52*(23), pp.13792–13800.

Cheng, X., Li, N., Mu, H., Guo, Y. and Jiang, Y., 2018. Study on total-factor energy efficiency in three provinces of Northeast China based on SBM model. *Energy Procedia*, *152*, pp.131–136.

Cherry, T. L., García, J. H., Kallbekken, S. and Torvanger, A., 2014. The development and deployment of low-carbon energy technologies: The role of economic interests and cultural worldviews on public support. *Energy Policy*, *68*, pp.562–566.

Choi, Y., Zhang, N. and Zhou, P., 2012. Efficiency and abatement costs of energy-related CO2 emissions in China: A slacks-based efficiency measure. *Applied Energy*, *98*, pp.198–208.

Cole, M. A. and Elliott, R. J. R., 2003. Determining the trade-environment composition effect: The role of capital, labor and environmental regulations. *Journal of Environmental Economics and Management*, *46*(3), pp.363–383.

Cole, M. A., 2000. Air pollution and 'dirty' industries: How and why does the composition of manufacturing output change with economic development? *Environmental and Resource Economics*, *17*(1), pp.109-123.

Damayanti, M. and Walandouw, P. C. K., 2018. The impacts of population distribution and economic activities towards land value in the capital of Jakarta. *International Journal of Economics and Management*, *12*(S1), pp.259-272.

Dhingra, R. and Das, S., 2014. Life cycle energy and environmental evaluation of downsized vs. lightweight material automotive engines. *Journal of Cleaner Production*, *85*, pp.347–358.

Du, H., Guo, J., Mao, G., Smith, A. M., Wang, X. and Wang, Y., 2011. CO2 emissions embodied in China-US trade: Input-output analysis based on the energy/dollar ratio. *Energy Policy*, *39*(10), pp.5980–5987.

DTI., 2003. Energy White Paper: Our energy future-creating a low carbon economy. DTI, London (In Chinese).

Elhorst, J. P., 2013. *Spatial Econometrics:from Cross-Sectional Data to Spatial Panels.* In Springer, Berlin.

Fan, Y., Liu, L. C., Wu, G., Tsai, H. T. and Wei, Y. M., 2007. Changes in carbon intensity in China: Empirical findings from 1980-2003. *Ecological Economics*, *62*(3–4), pp.683–691.

Färe., R., Grosskopf., S., Norris., M. and Zhang., Z., 1994. Productivity growth, technical progress and efficiency change in African agriculture. *African Development Review*, *84*(1), pp.66–83.

Fessehaie, J. and Morris, M., 2018. *Global value chains and sustainable development goals: What role for trade and industrial policies*. International Centre for Trade and Sustainable Development (ICTSD), Geneva.

Goh, L. T., Rajanee, S. and Lin, W. L., 2020. Crazy rich Asian countries? The impact of FDI inflows on the economic growth of the economies of Asian countries: Evidence from an NARDL approach. *International Journal of Economics and Management*, *14*(1), pp.43-67.

Gregg, J. S., Andres, R. J. and Marland, G., 2008. China: Emissions pattern of the world leader in CO2 emissions from fossil fuel consumption and cement production. *Geophysical Research Letters*, *35*(8), pp.2–6.

Grossman, G. M. and Helpman, E., 1991. Quality ladders in the theory of economic growth. *The Review of Economic Studies*, *58*, pp.43-61.

Gryshova, I., Kyzym, M., Khaustova, V., Korneev, V. and Kramarev, H., 2020. Assessment of the industrial structure and its influence on sustainable economic development and quality of life of the population of different world countries. *Sustainability (Switzerland)*, *12*(5), pp.1–25.

Guan, D., Hubacek, K., Weber, C. L., Peters, G. P. and Reiner, D. M., 2008. The drivers of Chinese CO2 emissions from 1980 to 2030. *Global Environmental Change*, *18*(4), pp.626–634.

Gulen, H. and Ion, M., 2016. Policy uncertainty and corporate investment. *Review of Financial Studies*, *29*(3), pp.523–564.

Guo, X. D., Zhu, L., Fan, Y. and Xie, B. C., 2011. Evaluation of potential reductions in carbon emissions in Chinese provinces based on environmental DEA. *Energy Policy*, *39*(5), pp.2352–2360.

He, J. and Wang, H., 2012. Economic structure, development policy and environmental quality: An empirical analysis of environmental Kuznets curves with Chinese municipal data. *Ecological Economics*, *76*, pp.49–59.

Hubacek, K., Guan, D., Barrett, J. and Wiedmann, T., 2009. Environmental implications of urbanization and lifestyle change in China: Ecological and Water Footprints. *Journal of Cleaner Production*, *17*(14), pp.1241–1248.

Jiang, B., Sun, Z. and Liu, M., 2010. China's energy development strategy under the low-carbon economy. *Energy*, *35*(11), pp.4257–4264.

Kim, H. and Kung, H., 2017. The asset redeployability channel: How uncertainty affects corporate investment. *Review of Financial Studies*, *30*(1), pp.245–280.

Lee, M. Y. and Hashim, H., 2014. Modelling and optimization of CO2 abatement strategies. *Journal of Cleaner Production*, *71*, pp.40–47.

Lee, W. S. and Lee, K. P., 2009. Benchmarking the performance of building energy management using data envelopment analysis. *Applied Thermal Engineering*, *29*(16), pp.3269–3273.

LeSage, J. and Pace, R. K., 2009. Introduction to spatial econometrics. In CRC Press. https://doi.org/10.1111/j.1467-985x.2010.00681_13.x.

Li, H., Fang, K., Yang, W., Wang, D. and Hong, X., 2013. Regional environmental efficiency evaluation in China: Analysis based on the Super-SBM model with undesirable outputs. *Mathematical and Computer Modelling*, *58*(5–6), pp.1018–1031.

Li, L., Di Liu, Hou, J., Xu, D. and Chao, W., 2019. The study of the impact of Carbon finance effect on carbon emissions in Beijing-Tianjin-Hebei region-based on logarithmic mean divisia index decomposition analysis. *Sustainability (Switzerland)*, *11*(1465).

Liang, G., Yu, D. and Ke, L., 2021. An empirical study on dynamic evolution of industrial structure and green economic growth—based on data from china's underdeveloped areas. *Sustainability (Switzerland)*, *13*(15).

Lin, X., Zhu, X., Han, Y., Geng, Z. and Liu, L., 2020. Economy and carbon dioxide emissions effects of energy structures in the world: Evidence based on SBM-DEA model. *Science of the Total Environment*, *729*, p.138947.

Lin, G. P., Long, Z. H., Wu, M., 2006. A spatial investigation of σ-convergence in China. *Journal of Quantitative & Technical Economics (In Chinese)*, *4*, pp.14-21.

Liu, C., Ma, C. and Xie, R., 2020. Structural, Innovation and Efficiency Effects of Environmental Regulation: Evidence from China's Carbon Emissions Trading Pilot. *Environmental and Resource Economics*, *75*(4), pp.741–768.

Liu, H. and Gallagher, K. S., 2010. Catalyzing strategic transformation to a low-carbon economy: A CCS roadmap for China. *Energy Policy*, *38*(1), pp.59–74.

Liu, J., Hou, X., Wang, Z. and Shen, Y., 2021. Study the effect of industrial structure optimization on urban land-use efficiency in China. *Land Use Policy*, *105*, p.105390.

Liu, Y. and Dong, F., 2021. How technological innovation impacts urban green economy efficiency in emerging economies: A case study of 278 Chinese cities. *Resources, Conservation and Recycling*, *169*, p.105534.

Liu, Z., Guan, D., Crawford-Brown, D., Zhang, Q., He, K. and Liu, J., 2013. Energy policy: A low-carbon road map for China. *Nature*, *500*(7461), pp.143–145.

Lu, C., Chiu, Y. H., Shyu, M. K. and Lee, J. H., 2013. Measuring CO2 emission efficiency in OECD countries: Application of the Hybrid Efficiency model. *Economic Modelling*, *32*(1), pp.130–135.

Lu, X., Jiang, X. and Gong, M., 2020. How land transfer marketization influence on green total factor productivity from the approach of industrial structure? Evidence from China. *Land Use Policy*, *95*(1037), p.104610.

Lv, Y., Chen, W. and Cheng, J., 2019. Modelling dynamic impacts of urbanization on disaggregated energy consumption in China: A spatial Durbin modelling and decomposition approach. *Energy Policy*, *133*, p.110841.

Mardani, A., Zavadskas, E. K., Streimikiene, D., Jusoh, A. and Khoshnoudi, M., 1978. A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency. *European Journal of Operational Research*, *2*(6), pp.429–444.

Meng, M. and Qu, D., 2022. Understanding the green energy efficiencies of provinces in China: A Super-SBM and GML analysis. *Energy*, *239*, p.121912.

Moran, P. A. P., 1948. The Interpretation of Statistical Maps. *Journal of the Royal Statistical Society: Series B (Methodological)*, *10*(2), pp.243–251.

Mostafa, M. M., 2009. Modeling the efficiency of top Arab banks: A DEA-neural network approach. *Expert Systems with Applications*, *36*(1), pp.309–320.

Qi, S. Zhou, C., Li, K. and Tang, S., 2021. The impact of a carbon trading pilot policy on the low-carbon international competitiveness of industry in China: An empirical analysis based on a DDD model. *Journal of Cleaner Production*, *281*, p.125361.

Ren, Y., Li, H., Shen, L., Zhang, Y., Chen, Y. and Wang, J., 2018. What is the efficiency of fast urbanization? A China study. *Sustainability (Switzerland)*, *10*(9), pp.1–26.

Romer, M. E., 1990. Endogenous technological change. *Journal of Political Economy*, *98*(5), pp.71-102.

Sadorsky, P., 2010. The impact of financial development on energy consumption in emerging economies. *Energy Policy*, *38*(5), pp.2528–2535.

Schumpeter, J. A., 1934.The Theory of Economic Development. First Published in 1912, English Translation Published in 1934. Harvard University Press, Cambridge, MA.

SCPRC (State Council of the People's Republic of China), 2011. The 12th Five-Year Plan of China (In Chinese). http://www.gov.cn/2011lh/content_1.

Shahbaz, M., Nasir, M. A. and Roubaud, D., 2018. Environmental degradation in France: The effects of FDI, financial development, and energy innovations. *Energy Economics*, *74*, pp.843–857.

Shah Wuh, Yasmeen R, Padda, I. U. H., 2019. An analysis between financial development institutions, and the environment: a global view. *Environmental Science and Pollution Research*, *26*, p.21437e49.

Shan, H., 2008. Reestimating the Capital Stock of China:1952-2006. *Journal of Quantitative & Technical Economics*, *15*, pp.17–31.

Shan, Y., Liu, J., Liu, Z., Xu, X., Shao, S., Wang, P. and Guan, D., 2016. New provincial CO2 emission inventories in China based on apparent energy consumption data and updated emission factors. *Applied Energy*, *184*, pp.742–750.

Shang, Y., Liu, H. and Lv, Y., 2020. Total factor energy efficiency in regions of China: An empirical analysis on SBM-DEA model with undesired generation. *Journal of King Saud University - Science*, *32*(3), pp.1925–1931.

Shi, Y. L., Chen, W. Q., Wu, S. L. and Zhu, Y. G., 2017. Anthropogenic Cycles of Arsenic in Mainland China: 1990-2010. *Environmental Science and Technology*, *51*(3), pp.1670–1678.

Shimada, K., Tanaka, Y., Gomi, K. and Matsuoka, Y., 2007. Developing a long-term local society design methodology towards a low-carbon economy: An application to Shiga Prefecture in Japan. *Energy Policy*, *35*(9), pp.4688–4703.

Song, M., An, Q., Zhang, W., Wang, Z. and Wu, J., 2012. Environmental efficiency evaluation based on data envelopment analysis: A review. *Renewable and Sustainable Energy Reviews*, *16*(7), pp.4465–4469.

Song, M., Song, Y., Yu, H. and Wang, Z., 2013a. Calculation of China's environmental efficiency and relevant hierarchical cluster analysis from the perspective of regional differences. *Mathematical and Computer Modelling*, *58*(5–6), pp.1084–1094.

Stern, N. H., 2006. The stern review: The economics of climate change. HM treasury, London

Teng, X., Liu, F. and Chiu, Y., 2021. The change in energy and carbon emissions efficiency after afforestation in China by applying a modified dynamic SBM model. *Energy*, *216*, p.119301.

Tobler, W. R., 1970. A computer movie simulating urban growth in the Detroit region. *Economic Geography*, *46*, pp.234–240.

Tone, K., 2001. Slacks-Based measure of efficiency. *European Journal of Operational Research*, *130*, pp.498–509.

Tone, K., 2001. A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, *130*(3), p.498e509.

Tone, K., 2002. A slacks-based measure of super-efficiency in data. envelopment analysis. *European Journal of Operational Research*, *143*(1), p.32e41.

Tone, K., 2004. Dealing with Undesirable Outputs in DEA: a Slacks-based Measure (SBM) Approach. Presentation at NAPW III, Toronto, pp. 44e45.

Tran, Q., 2019. Economic policy uncertainty and corporate risk-taking: International evidence. *Journal of Multinational Financial Management*, *52–53*, p.100605.

UNCTAD, 2019. Structural transformation, Industry 4.0 and inequality: Science, technology and innovation policy challenges. United Nations Conference on Trade and Developmen, 14969, 16.

Wang, C., Zhang, X., Vilela, A. L. M., Liu, C. and Stanley, H. E., 2019. Industrial structure upgrading and the impact of the capital market from 1998 to 2015 : A spatial econometric analysis in Chinese regions. *Physica A: Statistical Mechanics Its Applications*, *513*, pp.189–201.

Wang, N. and Chang, Y. C., 2014. The evolution of low-carbon development strategies in China. *Energy*, *68*(2014), pp.61–70.

Wang, Yizhong, Chen, C. R. and Huang, Y. S., 2014. Economic policy uncertainty and corporate investment: Evidence from China. *Pacific Basin Finance Journal*, *26*, pp.227–243.

Wang, Yuan, Wang, W., Mao, G., Cai, H., Zuo, J., Wang, L. and Zhao, P., 2013. Industrial CO2 emissions in China based on the hypothetical extraction method: Linkage analysis. *Energy Policy*, *62*, pp.1238–1244.

Wu, F., Fan, L. W., Zhou, P. and Zhou, D. Q., 2012. Industrial energy efficiency with CO2 emissions in China: A nonparametric analysis. *Energy Policy*, *49*, pp.164–172.

Yashodha, Y., Habibullah, M. S., Mohamed, A. and Sidique, S. F. A., 2018. Investigating the environmental Kuznets Curves through the economic globalization lens: Evidence from middle income countries. *International Journal of Economics and Management*, *12*(S2), pp.599-617.

Yue, W., Cai, Y., Yang, Z., Rong, Q. and Dang, Z., 2018. Structural optmization for industrial sectors to achieve the targets of energy itensity mitigation in the urban cluster of the Pearl River Delta. *Ecological Indicators*, *95*, pp.673-686.

Yu, J., Shi, X., Guo, D. and Yang, L., 2021. Economic policy uncertainty (EPU) and firm carbon emissions: Evidence using a China provincial EPU index. *Energy Economics*, *94*, p.105071.

Yu, N., de Jong, M., Storm, S. and Mi, J., 2013. Spatial spillover effects of transport infrastructure: Evidence from Chinese regions. *Journal of Transport Geography*, *28*, pp.56–66.

Zhang, B., 2015. The Impact of Industrial Structure Adjustment on Economic Growth in Japan. *International Business and Management*, *10*(2), pp.57–63.

Zhang, C. and Zhou, X., 2016. Does foreign direct investment lead to lower CO2 emissions? Evidence from a regional analysis in China. *Renewable and Sustainable Energy Reviews*, *58*, pp.943–951.

Zhang, K., Dong, J., Huang, L. and Xie, H., 2019. China's carbon dioxide emissions: An interprovincial comparative analysis of foreign capital and domestic capital. *Journal of Cleaner Production*, *237*, p.117753.

Zhang, N. and Choi, Y., 2013. Environmental energy efficiency of China's regional economies: A non-oriented slacks-based measure analysis. *Social Science Journal*, *50*(2), pp.225–234.

Zhang, Y., Shen, L., Shuai, C., Tan, Y., Ren, Y. and Wu, Y., 2018. Is the low-carbon economy efficient in terms of sustainable development? A global perspective. *Sustainable Development*, *27*(1), pp.130–152.

Zheng, Q., Wan, L., Wang, S., Wang, C. and Fang, W., 2021. Does ecological compensation have a spillover effect on industrial structure upgrading? Evidence from China based on a multi-stage dynamic DID approach. *Journal of Environmental Management*, *294*(96), p.112934.

Zhou, C., Shi, C., Wang, S. and Zhang, G., 2018. Estimation of eco-efficiency and its influencing factors in Guangdong province based on Super-SBM and panel regression models. *Ecological Indicators*, *86*, pp.67–80.

Zhou, Y., Xing, X., Fang, K., Liang, D. and Xu, C., 2013. Environmental efficiency analysis of power industry in China based on an entropy SBM model. *Energy Policy*, *57*(2013), pp.68–75.

APPENDIX

Appendix A Regional effect verification and effect's decomposition

	Eastern region		Central and Western regions	
	LCE	LCE	LCE	LCE
ISA	0.035		-0.079***	
	(0.73)		(-2.61)	
ISR		0.185***		0.132**
		(5.57)		(2.19)
W × ISA	0.425***		0.116	
	(4.74)		(1.47)	
W × ISR		0.236***		-0.644***
		(4.44)		(-3.47)
Covariables	Yes	Yes	Yes	Yes
Spatial ρ	0.294***	0.023***	0.332***	0.402***
	(3.65)	(0.27)	(2.84)	(3.67)
sigma2_e	0.053***	0.045***	0.004***	0.004***
	(9.08)	(9.19)	(10.40)	(10.35)
L-ratio test	6.027	22.029	287.158	289.967
Direct effects of ISA and ISR on LCE				
ISA	0.084		-0.073**	
	(1.52)		(-2.23)	
ISR		0.188***		0.087
		(5.66)		(1.28)
Indirect effects of ISA and ISR on LCE				
ISA	0.583***		0.130	
	(4.21)		(1.13)	
ISR		0.246***		-0.959***
		(4.96)		(-2.63)
Total effects of ISA and ISR on LCE				
ISA	0.667***		0.057	
	(3.66)		(0.43)	
ISR		0.434***		-0.872**
		(8.48)		(-2.18)
Obs.	169.000	169.000	221.000	221.000
Adj R-squared	0.091	0.174	0.231	0.129

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$; t statistics in parentheses