frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 02 September 2022
DOI 10.3389/fenvs.2022.979177

OPEN ACCESS

EDITED BY
Magdalena Radulescu,
University of Pitesti, Romania

REVIEWED BY
Mihaela Simionescu,
University of Social Sciences, Poland
Alexandra Horobet,
Bucharest Academy of Economic Studies, Romania

*CORRESPONDENCE
Jinye Li,
15299127745@163.com

SPECIALTY SECTION
This article was submitted to Environmental Economics and Management,
a section of the journal
Frontiers in Environmental Science

RECEIVED 27 June 2022
ACCEPTED 26 July 2022
PUBLISHED 02 September 2022

CITATION
Xu J, Li J and Liu C (2022), How does foreign trade affect green total factor energy efficiency? Evidence from China. *Front. Environ. Sci.* 10:979177.
doi: 10.3389/fenvs.2022.979177

How does foreign trade affect green total factor energy efficiency? Evidence from China

Jun Xu, Jinye Li* and Chunyan Liu

School of Economics and Management, Xinjiang University, Urumqi, China

As the largest trading nation in the world, there have been substantial foreign trades (export and import) between China and other countries. Meanwhile, it is also one of the major forces for China's emission reduction. This article applies the panel data of 30 provinces for the period 2004–2017 to investigate the effect of foreign trade on China's green total factor energy efficiency (GTFEE). The slack-based measure (SBM) model is employed to calculate the provincial GTFEEs. Subsequently, the empirical results of the basic linear regression model revealed that both export and import promoted the region's GTFEE, on which the import particularly has more effects than the export. Moreover, the spatial Durbin model (SDM) exhibited that the increase in import will not only present a positive influence on the GTFEE of the region, but also will improve the GTFEEs of the surrounding provinces through the spatial spillover mechanism. Although the increase in export will also exert a positive influence on the GTFEE of the local area, it will impose a significant negative impact on the GTFEEs of the surrounding regions. The results of this study provide important policy implications for the optimization of trade structure and high-quality development of the Chinese economy.

KEYWORDS

foreign trade, green total factor energy efficiency, spatial Durbin model, China, emission reduction

1 Introduction

Since the reform and opening-up, China has already made substantial achievements in economic development to become the second largest economy in the world, and scholars indicate that foreign trade has turned into a powerful engine to continually drive economic growth (Hu and Tan, 2016; Kong et al., 2020). In 2001, China obtained membership in the World Trade Organization (WTO), since which its trade development has achieved remarkable results (Yu and Luo, 2018). In 2010, China became the largest country in trading goods (Jarreau and Poncet, 2012; Caporale et al., 2015). By the end of 2019, China's values of export and import had reached 2.50 and 2.08 trillion dollars, respectively (China's Ministry of Commerce, 2019), ranking first and second in terms of countries. With the rapid economic development, China's environmental problems have become increasingly severe. In 2014, China had become the world's largest CO_2 emitter, whose carbon emissions accounted for about 27.5% of the global emissions (Li and Wang, 2019). According to the Paris Agreement, the intensity of carbon emissions per GDP in China will drop by 60%–65% in 2030 compared with 2005 (Ma et al., 2017; Wang K et al., 2019). Generally speaking, the export-oriented model to drive economic growth is no longer sustainable for China.

At present, how to optimize trade structure and promote the green economy has posed a challenge for China's government. Thus, this article selects the GTFEE to reflect the emissions and economic achievements in China (Wu et al., 2020a). It will focus on studying the impact of foreign trade on China's GTFEE, which attaches great significance to improving the trade structure and achieving the high-quality development of the economy in China.

The contributions of this study are as follows. First, most of the previous research on the export impact on economic growth without considering import separately (Mania and Rieber, 2019; Jalles and Ge, 2020). We attempt to research the impacts of foreign trade on GTFEE. Second, the empirical result of this article draws new conclusions, foreign trade has two ways of exporting and importing, which positively impact China's GTFEE. More importantly, the impacts of import on GTFEE are greater than those of export. Finally, the generalized method of moments (GMM) is used to solve endogeneity problems between variables. The export and import have spatial effects on GTFEE, which are examined with the Spatial Durbin model (SDM).

This article endeavors to provide a better understanding of connections between foreign trade and GTFEE, which is of great significance to the transformation of trade pattern and high-quality development of economy in China.

The remainder of this article is organized as follows: Section 2 presents a literature review. Section 3 introduces the methodology. Section 4 describes the variables and data sources. Section 5 presents an empirical analysis. Section 6 concludes the paper.

2 Literature review

At present, scholars mainly focus on three aspects of the foreign trade impact on GTFEE: carbon emissions, energy efficiency, and technology.

First, scholars have long been concerned with the problem of carbon emissions brought by foreign trade. The impact of foreign trade on global carbon emissions during 1995–2009 was examined by Wang and Ang (2018), whose results showed that a large amount of emissions had been generated. Based on the instrumental variables, Managi et al. (2009) suggested that the influence of foreign trade was significantly heterogeneous among different countries. From the perspective of export effects on carbon emissions, Dietzenbacher et al. (2012) found that ordinary export brought more emissions than the processing trade. Besides, from the regional and industrial perspectives, Yan et al. (2020) calculated the amount of carbon emissions produced by export in China. In summary, scholars have conducted profound studies on the impact of foreign trade on CO2 emissions and generally believed that foreign trade was one of the most important factors affecting carbon emissions.

Second, numerous scholars have also studied the impact of foreign trade on energy efficiency. Most of them focused on exports. Taking Latin America as the research object, Egger and Url (2010) found that the growth of export had become a crucial factor in the lack of energy supply in Austria. Kohler (2013) got the same conclusion when he took South Africa as the object. As for China, the significant correlation between its foreign trade and energy consumption during 1971–2011 was proved by Shahbaz et al. (2013). Besides, Farrow et al. (2018) and Zhang et al. (2017) pointed out that export structure was also an important factor affecting energy efficiency.

Third, Almodovar et al. (2014) firstly researched the effect on technological progress from foreign trade. Since then, it has been regarded as one of the most significant channels for transnational technology spillover (Parrado and De Cian, 2014; Yuan and Ya-Li, 2014; Tientao et al., 2016; Ho et al., 2018). Clerides et al. (1998) and Sharma (2018) indicated that trading enterprises could learn advanced clean technology and management experience from the developed countries through trade. Besides, participating in the fierce international competition required domestic enterprises to continuously improve technology and product quality to meet stricter demands (Revesz, 1992; Korves, 2011).

In addition, the spatial spillover effect on technology is one of the main topics that scholars focus on. By using SDM, Pan et al. (2020a) found that the Outward Foreign Direct Investment (OFDI) exerted a significant spillover effect on the Green Total Factor Productivity (GTFP) of neighboring provinces. With the application of SLM, Zhang et al. (2018) found that carbon productivity also exerted the spatial spillovers effect. Trade is an important way of cooperation, and its technology spillover effect should also attract more attention.

According to the related research above, it is not difficult to discover that many scholars have already studied the relationship between foreign trade and green development from different perspectives. However, few scholars have ever researched the impact of foreign trade on GTFEE and distinguished the heterogeneity between the export and import. Compared with the direct adoption of carbon emissions, energy consumption, and technology as variables, GTFEE could have considered more factors. Meanwhile, studying the impact of foreign trade on GTFEE is more consistent with China's current reality of high-quality economic development. Moreover, this article studies the local and peripheral effects of reverse technology spillovers from foreign trade and whether the export and import can improve the GTFEEs of neighboring areas through a spatial spillover mechanism.

3 Methodology and data

3.1 Calculating method of the GTFEE

Academia has obtained fruitful results in research on energy consumption and efficiency (Wu et al., 2020b). However, the undesired output is rarely included in the indices of energy efficiency at present (Li and Hu, 2012; Li and Lin, 2017). Chung et al. (1997) firstly considered the undesired outputs and named them the Directional Distance Function (DDF). Since then, multiple expansion models continued to be produced, such as the Banker–Charnes–Cooper (BCC) model, the Malmquist index model, and the SBM models (Banker and Cooper, 1984; Tone, 2001; Long and Xiaozhen, 2010; Wang Z et al., 2019). According to the previous research and the reality of China's economic development, this article applies the superefficiency SBM-undesirable model to measure the GTFEEs of 30 provinces in China from 2004 to 2017.

Hypothetically, there are n number of DMUs (provinces in China) at time t, l kinds of input factors to production, M types of desirable outputs, and K types of non-desirable outputs for each DMU. The input set, desirable output set, and non-desirable output set of each DMU are expressed as $x_i = (x_{1k}, x_{2k} \cdots, x_{30k})$, $y_i = (y_{1k}, y_{2k} \cdots, y_{30k})$, and $x_i = (b_{1k}, b_{2k} \cdots, b_{30k})$, respectively. Among them, $l = 3$ corresponds to the capital stock (K), labor (L), and energy consumption (EU). Using the "Perpetual Inventory Method" (PIM) and following the research methods of Dey-Chowdhury (2008) and Dong and Cen (2011), the capital stock is calculated from the fixed-asset investments and their price indexes of every province by the equation presented as follows:

$$K_{i,t} = I_{i,t} + (1 - \delta_{i,t})K_{i,t-1} \tag{1}$$

where $K_{i,t}$, $K_{i,t-1}$, and $I_{i,t}$ denote the capital stock (K) of province i in year t, the capital stock (K) of province i in year t-1, and the values of new capital investment of province i in year t, respectively. δ is the depreciation rate, whereas the research of this article is inclined to set the capital depreciation rate of each province uniformly as 10.96% (Shan, 2008; Liu and Xin, 2019).

In addition, $m = 1$ corresponds to the GDP of each province, whereas $k = 3$ corresponds to the discharge of industrial wastewater, the discharge of industrial solid waste, and carbon emissions.

Finally, this article will be based on the superefficiency SBM-undesirable model, which incorporates undesired outputs into the efficiency study. As shown in formula 2, each province's GTFEE is calculated individually:

$$gtfee^{*} = min\, gtfee \sum_{k=1}^{k} \lambda_k x_{ik} \le gtfee x_n \tag{2}$$
$$s.t. \quad \sum_{k=1}^{k} \sum_{k=1}^{k} \begin{matrix} \lambda_k y_{ik} \ge y_m \\ \lambda_k z_{ik} = y_j \\ \mathrm{n}=1,2\ldots,N; m=1,2\ldots,M; j=1,2\ldots,J; k=1,2\ldots,K \end{matrix}$$

3.2 Econometric model setting

Exploring the impact of foreign trade on GFTEE and following the research of Copeland and Taylor (2004), Chen and Golley (2014), and Li and Wu (2020), this study establishes the specific model as follows:

$$\begin{aligned} GTFEE_{i,t} = \alpha_0 + \alpha_1 Export_{i,t} + \alpha_2 EI_{i,t} + \alpha_3 RD_{i,t} + \alpha_4 IS_{i,t} \\ + \alpha_5 ER_{i,t} + \alpha_6 ER_{i,t}^2 + \alpha_7 UR_{i,t} + \delta_i + v_t + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

$$\begin{aligned} GTFEE_{i,t} = \beta_0 + \beta_1 Import_{i,t} + \beta_2 EI_{i,t} + \beta_3 RD_{i,t} + \beta_4 IS_{i,t} \\ + \beta_5 ER_{i,t} + \beta_6 ER_{i,t}^2 + \beta_7 UR_{i,t} + \delta_i + v_t + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where export and import individually indicate the foreign trade levels, i represents every province, t represents the year, EI indicates the economic development, RD indicates the investment in Research and Development (R&D), IS indicates the industrial structure, ER indicates the environmental regulation, UR indicates the urbanization rate, and α and β are parameters, respectively. Besides, EI is expressed as the scale effect, RD is expressed as the technology effect, IS and UR are expressed as the structure effect, respectively (Feng et al., 2017; Cheng et al., 2018; Yuan and Xiang, 2018).

Based on existing research, the GTFEE may be affected at an earlier stage. According to the method proposed by Wu et al. (2020b), this study also integrates the lagging one-stage variable ($GTFEE_{i,t-1}$) into the following formula:

$$\begin{aligned} GTFEE_{i,t} = \alpha_0 + \alpha_1 GTFEE_{i,t-1} + \alpha_2 Tra_{i,t} + \alpha_3 EI_{i,t} + \alpha_4 RD_{i,t} \\ + \alpha_5 IS_{i,t} + \alpha_6 ER_{i,t} + \alpha_7 ER_{i,t}^2 + \alpha_8 UR_{i,t} + \delta_i + v_t + \varepsilon_{it} \end{aligned} \tag{5}$$

3.2.1 Spatial Durbin model

1) Spatial analysis methods

As mentioned earlier, there are spatial heterogeneity and spatial correlations of foreign trade between different regions. GTFEE of a certain region will be affected not only by the level of its local trade, but also by its neighboring regions. Before performing the spatial econometric analysis, it is essential to test the spatial correlation of these variables (Pan et al., 2019a; Pan et al., 2019b).

The Moran Index (Moran's I) is applied to identify the spatial correlation between the province samples. The calculation method of Moran's I is shown as follows:

$$Moran's\, I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{i,j} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{i,j}}. \tag{6}$$

In formula 6, $S^2 = \sum_{i=1}^{n} (x_i - \bar{x})^2$,$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$. GTFEE of province is represented by x_i and n represents all the 30 provinces. $\bar{x}$ represents the average of GTFEEs, and the variance of GTFEE is represented by S^2. The range of Moran's I is from −1 to 1. When Moran's I > 0, it shows a positive spatial

TABLE 1 The descriptive statistical analysis of variables.

Variables	Sample size	Mean	Std. dev.	Maximum	Minimum
GTFEE	420	0.549	0.174	1.100	0.235
Export	420	14.214	1.673	17.983	10.134
Import	420	13.974	1.748	15.452	12.478
EL	420	10.302	0.683	11.767	8.370
RD	420	1.390	0.010	6.010	0.170
IS	420	46.700	0.081	61.500	27.300
ER	420	1.300	0.0066	4.200	0.300
UR	420	52.400	0.142	89.600	26.500

TABLE 2 China's exports in 2004–2017.

Province	2004	2006	2008	2010	2012	2014	2016	2017	Mean	Rank
Guangdong	32.295	31.170	28.368	28.738	28.066	27.608	28.543	27.519	29.212	1
Jiangsu	14.750	16.559	16.646	17.155	16.062	14.607	15.214	16.053	15.913	2
Zhejiang	9.801	10.415	10.790	11.444	10.977	11.680	12.773	12.677	11.220	3
Shanghai	12.391	11.726	11.828	11.459	10.107	8.979	8.743	8.558	10.589	4
Shandong	6.043	6.049	6.517	6.609	6.293	6.184	6.537	6.500	6.330	5
Fujian	4.955	4.259	3.985	4.534	4.783	4.848	4.944	4.637	4.624	6
Beijing	3.468	3.918	4.021	3.515	2.915	2.664	2.481	2.585	3.289	7
Liaoning	3.188	2.923	2.942	2.733	2.834	2.510	2.053	1.984	2.698	8
Tianjin	3.515	3.457	2.944	2.377	2.362	2.247	2.111	1.925	2.640	9
Hebei	1.574	1.325	1.679	1.430	1.447	1.526	1.458	1.386	1.451	10
Sichuan	0.671	0.684	0.918	1.195	1.881	1.916	1.333	1.659	1.261	11
Chongqing	0.352	0.346	0.400	0.475	1.886	2.709	1.939	1.882	1.189	12
Henan	0.704	0.685	0.750	0.668	1.451	1.683	2.041	2.078	1.183	13
Anhui	0.664	0.706	0.795	0.787	1.308	1.345	1.356	1.347	1.004	14
Hubei	0.570	0.646	0.819	0.916	0.948	1.138	1.242	1.348	0.933	15
Jiangxi	0.336	0.387	0.540	0.851	1.228	1.368	1.421	1.444	0.917	16
Xinjiang	0.514	0.737	1.350	0.822	0.946	1.003	0.743	0.783	0.863	17
Heilongjiang	0.620	0.871	1.175	1.032	0.706	0.741	0.240	0.227	0.734	18
Guangxi	0.402	0.371	0.514	0.609	0.756	1.040	1.093	1.213	0.730	19
Hunan	0.524	0.526	0.588	0.505	0.616	0.852	0.844	1.024	0.643	20
Shaanxi	0.404	0.375	0.376	0.394	0.423	0.595	0.755	1.085	0.501	21
Yunnan	0.377	0.350	0.349	0.482	0.490	0.803	0.548	0.510	0.497	22
Shanxi	0.680	0.427	0.647	0.298	0.343	0.382	0.474	0.451	0.425	23
Jilin	0.289	0.309	0.334	0.284	0.293	0.247	0.200	0.196	0.273	24
Inner Mongolia	0.228	0.221	0.251	0.211	0.194	0.273	0.210	0.218	0.225	25
Guizhou	0.146	0.107	0.133	0.122	0.242	0.402	0.226	0.256	0.206	26
Gansu	0.168	0.156	0.112	0.104	0.175	0.228	0.194	0.081	0.153	27
Hainan	0.184	0.142	0.111	0.147	0.153	0.189	0.101	0.193	0.146	28
Ningxia	0.109	0.097	0.088	0.074	0.080	0.184	0.119	0.161	0.106	29
Qinghai	0.077	0.055	0.029	0.030	0.036	0.048	0.065	0.019	0.043	30
Eastern	0.922	0.919	0.898	0.901	0.860	0.830	0.850	0.840	0.881	1
Central	0.044	0.046	0.056	0.053	0.069	0.078	0.078	0.081	0.061	2
Western	0.034	0.035	0.045	0.045	0.071	0.092	0.072	0.079	0.058	3

Self-calculated and made by the authors.

TABLE 3 China's imports in 2004–2017.

Province	2004	2006	2008	2010	2012	2014	2016	2017	Mean	Rank
Guangdong	29.503	28.464	24.663	23.758	22.546	21.974	22.467	20.847	24.542	1
Beijing	13.188	15.174	18.913	17.640	19.165	18.028	14.508	14.410	16.462	2
Shanghai	15.415	14.397	13.502	13.482	12.641	13.081	15.773	15.345	14.036	3
Jiangsu	14.854	15.615	13.620	13.985	12.068	11.318	11.983	12.378	13.399	4
Shandong	4.422	4.627	5.758	6.083	6.425	6.749	6.126	6.300	5.776	5
Zhejiang	4.823	4.834	5.019	5.234	4.833	4.171	4.328	4.944	4.810	6
Tianjin	3.774	3.914	3.382	3.196	3.702	4.150	3.677	3.770	3.683	7
Fujian	3.231	2.704	2.457	2.671	3.196	3.265	3.348	3.591	3.006	8
Liaoning	2.762	2.536	2.681	2.694	2.537	2.820	2.740	2.964	2.692	9
Hebei	0.746	0.720	1.273	1.397	1.153	1.234	1.014	1.002	1.098	10
Sichuan	0.515	0.556	0.793	0.992	1.137	1.295	1.345	1.661	0.978	11
Henan	0.436	0.399	0.597	0.523	1.213	1.306	1.789	1.662	0.944	12
Jilin	0.905	0.621	0.756	0.886	1.022	1.052	0.898	0.767	0.847	13
Anhui	0.584	0.683	0.779	0.849	0.689	0.903	1.006	1.258	0.814	14
Heilongjiang	0.554	0.559	0.558	0.661	1.273	1.101	0.725	0.743	0.784	15
Hubei	0.603	0.695	0.794	0.823	0.691	0.837	0.841	0.859	0.767	16
Guangxi	0.337	0.389	0.520	0.583	0.771	0.828	1.556	1.617	0.764	17
Chongqing	0.315	0.268	0.335	0.354	0.805	1.635	1.392	1.304	0.724	18
Jiangxi	0.273	0.309	0.520	0.588	0.457	0.546	0.644	0.640	0.480	19
Shaanxi	0.222	0.219	0.260	0.422	0.338	0.686	0.889	0.847	0.476	20
Hunan	0.416	0.286	0.365	0.480	0.514	0.556	0.539	0.699	0.475	21
Yunnan	0.268	0.358	0.407	0.417	0.605	0.552	0.530	0.650	0.444	22
Inner Mongolia	0.422	0.483	0.470	0.386	0.401	0.417	0.456	0.487	0.441	23
Hainan	0.411	0.186	0.260	0.453	0.615	0.584	0.581	0.326	0.429	24
Shanxi	0.240	0.314	0.454	0.564	0.441	0.372	0.424	0.379	0.421	25
Xinjiang	0.461	0.248	0.258	0.298	0.320	0.214	0.129	0.159	0.272	26
Gansu	0.137	0.293	0.397	0.413	0.293	0.169	0.175	0.175	0.271	27
Guizhou	0.115	0.073	0.129	0.088	0.092	0.070	0.060	0.129	0.095	28
Ningxia	0.047	0.062	0.055	0.057	0.032	0.058	0.048	0.075	0.050	29
Qinghai	0.022	0.015	0.024	0.023	0.024	0.030	0.010	0.013	0.021	30
Eastern	0.931	0.932	0.915	0.906	0.889	0.874	0.865	0.859	0.899	1
Central	0.040	0.039	0.048	0.054	0.063	0.067	0.069	0.070	0.055	2
Western	0.029	0.030	0.036	0.040	0.048	0.060	0.066	0.071	0.045	3

Self-calculated and made by the authors.

dependence. When Moran's I < 0, it implies a negative spatial dependence. When Moran's I = 0, it indicates no spatial autocorrelation.

2) Construction of spatial weight matrix

Constructing a spatial weight matrix is the basis for establishing a spatial econometric model. Given the geographical spaces and economic discrepancies between different provinces, there have been three spatial weight matrices to be selected, including the ones of geographic adjacency, geographic distance, and economic distance (Li K et al., 2018) as follows:

Geographic adjacency spatial weight matrix ($W1$).

$$W_{ij} = 1\left(i \neq j\right). \tag{7}$$

In the matrix above, if province i owns a common boundary with province j, it means $W1 = 1$; otherwise, $W1 = 0$.

Geographic distance's spatial weight matrix ($W2$):

$$W_2 = 1\Big/dis_{i,j}. \tag{8}$$

In the matrix above, $dis_{i,j}$ is the straight-line distance between the capitals of provinces i and j.

Economic distance's spatial weight matrix ($W3$):

$$W_3 = 1\Big/\left|\overline{y_i} - \overline{y_j}\right|\left(i \neq j\right). \tag{9}$$

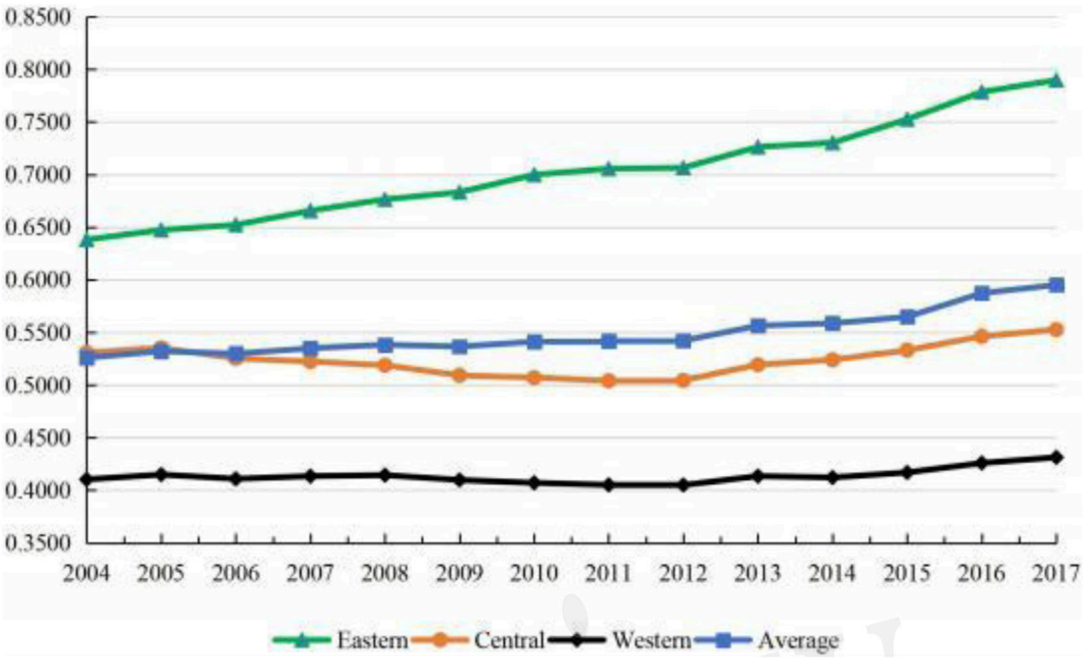

FIGURE 1
Three regional static green total factor energy efficiency.

In the matrix above, y_i and y_j are individually represented as the per capita GDP in provinces i and j and $W3$ is expressed as the reciprocal of the absolute value of the gap between the economic levels of these two provinces.

3) The design of SDM

After the spatial correlation test, this article intends to apply a spatial econometric model to study the spatial effects. There have been three applicable kinds of spatial econometric models: the Spatial Lag Model (SLM), Spatial Error Model (SEM), and SDM. However, as some scholars have argued, SDM can capture the spatial correlation between dependent variables and the spatial spillover effects of independent variables more effectively than SLM and SEM. Thus, this article employs SDM to study the influence of trade on GTFEE and its spillover effects. This model is accordingly established as follows:

$$GTFEE_{i,t} = \alpha + \rho \sum\nolimits_{j=1}^{n} W_{i,j} GTFEE_{j,t} + \beta_1 tra_{i,t} + \beta_2 \sum\nolimits_{j=1}^{n} W_{i,j} tra_{i,j} + \beta_3 X_{i,t} + \delta_i + \upsilon_t + \varepsilon_{it} \quad (10)$$

where $tra_{i,t}$ indicates either export or import; X is a series of control variables; Wi is a spatial weight matrix; and α, ρ, and β are the parameters.

3.3 Data sources and variables selection

3.3.1 Explained variables

Green total factor energy efficiency (GTFEE) is the explained variable in our basic model and SDM model. It is calculated by formula 2 in Section3.1.

3.3.2 Explanatory variables

Foreign trade ($tra_{i,t}$) is the most important explanatory variable in our model, including export and import values. Export mainly refers to the flow of goods from the region to other countries, and import mainly refers to the flow of goods from other countries to the region.

3.3.3 Control variables

We added multiple control variables to the model to minimize or even avoid the estimation bias caused by missing variables. These control variables are explained as follows.

1) Economic development level (EL): the per capita GDP measures the level of provincial economic development (Josep et al., 2005; Hao et al., 2020).

2) Research and Development ((R& D) investment: R&D investment is also one of the important factors in promoting technological progress. The ratio of research investment to GDP is used to measure the R&D ((Lin and Zhao, 2016).

TABLE 4 Estimation results of the basic model for export.

Variables	FE	RE	Ols	DIFF-GMM	SYS-GMM
L.*gftee*				0.612***	0.885***
				(0.000)	(0.000)
Export	0.024***	0.029***	0.041***	0.012***	0.003*
	(0.005)	(0.000)	(0.000)	(0.000)	(0.097)
EI	0.044***	0.010***	0.039***	0.003***	0.004***
	(0.003)	(0.000)	(0.000)	(0.001)	(0.007)
UR	−0.793***	−0.479***	−0.623**	−0.064**	0.111***
	(0.000)	(0.009)	(0.030)	(0.035)	(0.000)
RD	7.463***	8.043***	7.446***	2.502***	0.718***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IS	−0.381***	−0.349***	−0.318***	−0.176***	−0.026*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.059)
ER	−4.815***	−5.638***	−7.446***	−1.426***	−2.599***
	(0.005)	(0.000)	(0.000)	(0.002)	(0.001)
lnreg2	73.640*	88.893***	121.200***	20.980*	38.860**
	(0.073)	(0.006)	(0.006)	(0.058)	(0.042)
_cons	0.301***	0.391***	0.491***	0.501***	0.035***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)
R^2	0.355	0.2855	0.7176		
AR (2)				1.31*	1.40*
				(0.082)	(0.076)
Hansen test				27.98	28.16
				(1.000)	(1.000)
F/Wald test	23.19***	247.93	304.63***	67,853.55***	69,566.06***
N	420	420	420	360	390

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The *p*-value is shown in parentheses.

3) Industrial structure (IS): the share of GDP in the secondary industry is used to measure the industrial structure. The secondary industry is a large energy user. This is the original intention of adding the variables. Thus, the higher the proportion of the total secondary industry, the more the emissions and the lower the GTFEE (Liu and Bae, 2018; Wu et al., 2019; Hao et al., 2020).

4) Environmental regulation (ER): Porter and Linde (1999) put forward the Porter hypothesis, suggesting that the enterprise can achieve a win-win situation between economic growth and environmental protection through ER. Here, the ratio of environmental governance investment to GDP is used to measure the ER (Lanoie et al., 2008; Nesta et al., 2014; Wu et al., 2020a).

5) Urbanization rate (UR): according to the research of Zhang et al. (2015) and Li M et al. (2018), the share of the non-agricultural population relative to the total population is used to measure the UR.

3.3.4 Data sources

The sample data set is the panel data of China's 30 provinces from 2004 to 2017. The main data comes from the China Statistical Yearbook, China Science and Technology Statistics Yearbook, China Energy Statistical Yearbook, China Environmental Statistics Yearbook, Wind Database, and National Bureau of Statistics. Taking into the lack of data in Tibet and the availability of data in Hong Kong, Macau, and Taiwan. The research objects are 30 provinces except for Tibet, Hong Kong, Macau, and Taiwan. In order to eliminate the impact of the price factor on the results, increase the data stability, and reduce size impact, *EI*, export, and import values have been represented by logarithm. Here, the descriptive statistics of the data are given in Table 1.

4 Results and discussions

4.1 Foreign trade in China

4.1.1 Export in China

Table 2 reveals that the proportion of exports in eastern China to the total exports is much higher than that in the central and western regions during the sample period. From 2004 to 2017, the average proportion of exports in eastern China to the

TABLE 5 Estimation results of the basic model for import.

Variables	FE	RE	Ols	DIFF-GMM	SYS-GMM
L.*gftee*				0.613***	0.885***
				(0.000)	(0.000)
Import	0.008***	0.024***	0.044***	0.005***	0.009***
	(0.003)	(0.000)	(0.000)	(0.004)	(0.006)
EI	0.051***	0.002***	0.045***	0.007**	0.002**
	(0.002)	(0.000)	(0.000)	(0.022)	(0.028)
UR	−0.683***	−0.313	−0.083	−0.034	0.115***
	(0.000)	(0.403)	(0.403)	(0.321)	(0.000)
RD	7.626***	7.921***	6.491***	2.491***	0.778***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IS	−0.331***	−0.306***	−0.282***	−0.149***	−0.015*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.092)
ER	−4.719***	−5.806***	−7.743***	−1.588***	−2.501***
	(0.006)	(0.000)	(0.000)	(0.000)	(0.003)
lnreg2	74.050*	97.350**	136.600***	27.2080**	34.690**
	(0.075)	(0.020)	(0.002)	(0.012)	(0.021)
_cons	0.371***	0.443***	0.474***	0.076***	0.036***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.006)
R^2	0.3431	0.3562	0.7509		
AR (2)				1.31**	1.40**
				(0.019)	(0.016)
Hansen test				26.93	27.37
				(1.000)	(1.000)
F/Wald test	28.58***	216.22***	330.22***	47,578.63***	74,919.79***
N	420	420	420	360	390

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The *p*-value is shown in parentheses.

total exports was 89.90%, compared with just 5.50% and 4.50% in central and western China. The top three regions of total exports are Guangdong (29.21%), Jiangsu (15.91%), and Zhejiang (11.22%), respectively, all in eastern China. By contrast, the last three ones are Hainan (0.15%), Ningxia (0.11%), and Qinghai (0. 04%), respectively, all in western China. Obviously, the eastern regions located in the coastal areas play an irreplaceable role in China's exports.

4.1.2 Import in China

Table 3 shows that the average proportion of imports from eastern China in the total is 88.10%, compared with only 6.10% and 5.80% from central and western regions, respectively. More notably, the top three proportions of imports are from Guangdong (24.54%), Beijing (16.46%), and Shanghai (14.04%), all in eastern China. However, the last three proportions of imports are from Guizhou (0.09%), Ningxia (0.05%), and Qinghai (0.02%). Generally speaking, the eastern coastal regions hold a dominant position in China's export and import, which is the main frontier for reform and opening-up. Among all these regions, the development of trade in China is very uneven, which must attract attention and solutions during the process of high-quality economic development.

4.2 China's GTFEE

Based on the calculation methods of GTFEE above, this study has measured the GTFEEs of these three regions[1]. The results are exhibited in Figure 1. From 2004 to 2017, the results show an upward trend in China's average GTFEE from 0.526 to 0.595. From the perspective of the region, both the central and western ones presented the GTFEEs lower than the national level. However, the GTFEE of the eastern region turned out to be higher than the national average. From 2004 to 2017, the gap between GTFEEs of eastern and central regions widened from 0.107 to 0.237, whereas the gap between GTFEEs of eastern and western regions broadened from 0.227 to 0.358. There has been an upward trend in GTFEE moving to the eastern regions from the central and western regions. Although there is a high level of coordination between economic growth and environmental performance in the eastern regions, there remain significant

TABLE 6 Moran's I value of GTFEE during 2004–2017.

Year	Moran'sI(W_1)	*p*-value	Moran's I (W_2)	*p*-value	Moran's I (W_3)	*p*-value
2004	0.365***	0.000	0.223***	0.002	0.164***	0.008
2005	0.370***	0.000	0.221***	0.002	0.168***	0.007
2006	0.363***	0.000	0.215***	0.003	0.172***	0.006
2007	0.379***	0.000	0.235***	0.002	0.206***	0.002
2008	0.361***	0.000	0.241***	0.001	0.240***	0.001
2009	0.345***	0.001	0.238***	0.002	0.248***	0.000
2010	0.337***	0.001	0.233***	0.002	0.262***	0.000
2011	0.330***	0.001	0.241***	0.002	0.270***	0.000
2012	0.359***	0.001	0.269***	0.001	0.286***	0.000
2013	0.358***	0.001	0.273***	0.001	0.290***	0.000
2014	0.403***	0.000	0.317***	0.000	0.314***	0.000
2015	0.388***	0.000	0.307***	0.000	0.311***	0.000
2016	0.435***	0.000	0.380***	0.000	0.327***	0.000
2017	0.425***	0.000	0.375***	0.000	0.321***	0.000

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The *p*-value is shown in parentheses.

regional differences in China, which should be considered when making related policies.

1 According to the No. 33 (2000) document of China, this study divides 30 provinces into three regions: the eastern region (including 11 provinces, i.e., Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangzhou, Hainan, and Liaoning.), the central region (including eight provinces, i.e., Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan, Jilin, and Heilongjiang.), and the western region (including 11 provinces, i.e., Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.).

4.3 Baseline regression results and discussion

According to the methodology, this study applies the regression methods of Fixed Effect (FE) and Random Effect (RE) to estimate the formulas of (3) and (4). Meanwhile, in order to address the possible endogeneity problem between export, import, and GTFEE while improving the robustness of the results, the generalized moment method is adopted to conduct the estimation.

The empirical results are shown in Table 4 and Table 5, respectively. The selection of instrumental variables is reasonable because the Hansen test and the Auto-Regressive AR(2) estimation results present no second-order sequence correlation of the random error terms (Blundell and Bond, 1998). The specifics of the results are as follows: firstly, the coefficients of export and import are both positive and they are both significant at the 1% level. In other words, an improvement in export or import will inhibit an improvement in GTFEE. Secondly, the coefficient of export (0.003) is lower than that of import (0.009), which means that the import impacts GTFEE more significantly than the export trade does. In fact, China has strongly promoted the processing trade since the last century (Byrne et al., 1996; Ma et al., 2014). Processing trade accounts for over 50% of China's total exports (He and Wang, 2020). Some scholars found that an excessive proportion of processing trade was one of the most important factors to lower productivity (Lu et al., 2010; Ma et al., 2014; Dai et al., 2016; Manova and Yu, 2016). Meanwhile, other scholars indicated that the enterprises can absorb advanced technology through import, which was a significant source of technological progress and a key driving force for improving GTFEE (Grossman and Helpman, 1991; Coe and Helpman, 1995; School of Earth Environment, University of Leeds, Leeds, UK, 2016). Thirdly, the sign of the *EI* coefficient among other variables is positive and statistically significant at the 1% level, which shows a higher level of economic development and a higher degree of GTFEE. The sign of the UR coefficients is negative and statistically significant at the 1% or 5% level. With progressive urbanization, China's population and industries have inundated the cities and significantly increased energy consumption and environmental pollution in China (Sheng et al., 2020; Sun and Huang, 2020). The sign of R&D coefficients is also positive and statistically significant at the 1% level, which exhibits that technological innovation considerably reduces carbon emission by improving the GTFEE. The coefficients of the IS are significantly negative at the 1% or 10% level, which indicates that IS plays a significantly negative role in raising the GTFEE. The results

TABLE 7 Estimation of the SDM.

Variables	Export			Import		
	W1	W2	W3	W1	W2	W3
Export	0.0321***	0.0473***	0.0427***			
	(0.000)	(0.000)	(0.000)			
Import				0.0179**	0.0230***	0.0259***
				(0.017)	(0.003)	(0.001)
EI	0.0984***	0.0768**	0.0908***	0.0961***	0.0857**	0.0943***
	(0.002)	(0.018)	(0.003)	(0.003)	(0.011)	(0.003)
UR	−1.111***	−1.271***	−1.100***	−0.898***	−1.135***	−0.928***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RD	8.156***	2.303*	6.077***	8.703***	2.692*	6.802***
	(0.000)	(0.088)	(0.000)	(0.000)	(0.052)	(0.000)
IS	−0.315***	−0.295***	−0.241***	−0.279***	−0.219***	−0.152**
	(0.000)	(0.000)	(0.002)	(0.000)	(0.002)	(0.050)
ER	−3.754**	−5.003***	−2.842*	−3.458**	−4.659***	−2.264
	(0.013)	(0.001)	(0.065)	(0.024)	(0.002)	(0.151)
lnreg2	54.39	71.06**	43.62	53.49	69.59*	35.48
	(0.138)	(0.049)	(0.242)	(0.151)	(0.059)	(0.350)
*W*export*	0.0430**	0.0396***	0.0470***			
	(0.012)	(0.007)	(0.004)			
*W*import*				0.0112**	0.0272**	0.0171**
				(0.025)	(0.015)	(0.037)
Spatial rho	−0.456***	0.299***	0.317***	−0.456***	0.296***	0.271***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.003)
Variance sigma2_e	0.0016***	0.0015***	0.0016***	0.0017***	0.0016***	0.0017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes
N	420	420	420	420	420	420

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The *p*-value is shown in parentheses.

TABLE 8 Effect decomposition.

Spatial weight	Variables	Direct effect	Indirect effect	Total effects
W_1	Export	0.035*** (0.000)	−0.034*** (0.002)	0.001** (0.028)
	Import	0.019**	0.015***	0.034**
		(0.018)	(0.008)	(0.021)
W_2	Export	0.046*** (0.000)	−0.026** (0.025)	0.020** (0.020)
	Import	0.022***	0.029*	0.051**
		(0.005)	(0.056)	(0.031)
W_3	Export	0.041*** (0.000)	−0.08** (0.023)	0.089** (0.031)
	Import	0.026***	0.014**	0.040***
		(0.002)	(0.018)	(0.008)

**, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The *p*-value is shown in parentheses.

also present that the coefficients of ER are negative, and the coefficients of square term (ER^2) are positive, which are both significant at the 1%, 5%, or 10% levels. It indicates a "U-shaped" relationship between the ER and GTFEE. Before the turning point, ER showed a "green paradox" effect and after the turning point, it showed an "emission reduction effect" (Cheng et al., 2017; Huang and Lei, 2021; Wu et al., 2020a).

4.4 Spatial results and analysis

4.4.1 Spatial autocorrelation analysis

Moran's I is an effective tool for explaining spatial correlation. According to formula (6), Moran's I test results of spatial correlation of GTFEE under three different matrices of weights are individually shown in Table 6. During 2004–2017, Moran's I of the GTFEE are positive and statistically significant, which indicates that the GTFEE of China presented significant characteristics of spatial agglomeration.

Moreover, the degree of spatial dependence exhibits a growing uptrend.

4.4.2 Estimation of the SDM model

In order to make the estimation structure more reliable, this study applies three different matrices of spatial weight to estimate the SDM. Following the Hausmann test, this study chooses the FE model in the form of space-fixed, time-fixed, and time-space double-fixed effects. Finally, according to the likelihood function values and goodness of different fixed effects, this study reports the results of the double-fixed one. Its regression results are listed in Table 7.

The coefficients of export and import are all significantly positive under *W1*, *W2*, and *W3*, presenting that both export and import can promote the growth of provincial GTFEEs. From another perspective, no matter what spatial matrix is adopted, the spatial lag terms of export and import are always positively significant, which also passed the significance test of the 1% or 5% level. This finding implies that the growth of provincial export or import will exert a positive effect on promoting the GTFEEs in the surrounding areas. However, this study can only make a preliminary judgment according to Table 7. On the contrary, Lesage (2008) and Yang (2019) pointed out that applying point estimation to test the spillover effects may cause model estimation errors.

4.4.3 Direct and indirect effects

Table 8 reveals that the direct estimations under three different spatial weights of export are all positive and significant, which indicates a positive influence on the region's GTFEE growth. However, the indirect effects of export are negative and significant under three different spatial weights, and all passed the significance test of the 1% or 5% level. This proves that export in this region imposes a significant negative impact on GTFEE in surrounding areas. This occurs mainly for some reasons. China's has obvious development differences between regions and uneven trade development structure between regions,the raw materials and intermediate products with low added-value to the regional source from the surrounding areas, which would generate much energy consumption and emissions and objectively reduce their GTFEEs. For example, China's central and western regions have been crucial sources of energy and labor for the eastern coastal areas. Moreover, compared with competitors in regions with backward trade development, those trading enterprises in developed areas enjoy more opportunities to learn and absorb advanced technology and management experience, which play a significant role in improving their GTFEEs (Poon et al., 2006; Wang and Ang, 2018). In summary, the total effect of export is positive and composed of the most direct impacts.

As shown in Table 8, this article can also find that the direct estimations under three different spatial weights of import are all positive and significant, indicating another positive influence on the region's GTFEE growth. This presents that the growth of imports is conducive to improving the GTFEE. More importantly, the indirect effects of imports are positive and significant under three different spatial weights, and all passed the significance test of the 1%, 5%, or 10% level. This result indicates that the growth of imports in this region will also affect the GTFEEs in surrounding areas. The possible explanations are as follows. On the one hand, the import of capital-intensive and technology-intensive goods can facilitate the imitations and innovations by domestic enterprises, such as pollution-treatment equipment and other high-tech products, which may be called the "technology spillover effect," thus eventually improving the GTFEE (Parrado and De Cian, 2014; Huang et al., 2017; Zhao and Lin, 2019). On the other hand, the import of consumer goods may replace domestic production and therefore reduce domestic energy consumption and emissions (Al-mulali and Sheau-Ting, 2014). Besides, during the fierce international competition, the domestic enterprises may raise their technological levels, which will bring pressure on their competitors in the surrounding regions to improve their production technology. Therefore, the GTFEEs of these adjacent regions could be improved as well.

5 Conclusion and policy recommendations

Based on the previous research, this study applied the panel data of 30 provinces from 2004 to 2017 to calculate the GTFEE with the SBM-undesirable model, based on which this study established the basic linear regression model to empirically test the influences of export and import on GTFEE. In addition, the geographic proximity matrix (*W1*), geographic distance weight matrix (*W2*), and economic, geographic distance weight matrix (*W3*) were introduced, respectively, into this study. The SDM was applied to test the direct and indirect spatial effects of export and import on GTFEE. The conclusions are as follows. Firstly, the inter-provincial GTFEE in China showed a ladder-like distribution pattern of eastern-central-western. Secondly, both export and import improved the regional GTFEEs, but import exhibited more effect than export on the enhancement of GTFEE. Thirdly, in terms of spatial effect, the increase in import would not only exert a positive effect on the GTFEE of the local regions, but also raise the GTFEE of surrounding provinces through the spatial spillover mechanism. Although the increase in export would have a positive influence on the GTFEE of the local regions, it would impose a significant negative impact on the GTFEE of surrounding areas. Based on the above empirical analysis, this study put forward several policy recommendations as follows:

1) The government should focus more on regionally coordinated development and keep narrowing the development gaps between regions, especially between the eastern and central-western regions. Significantly, the old path of "treatment after pollution" concentrated in the central and western regions should be avoided. The road to sustainable development requires drawing lessons from the development experience of the eastern regions. The policy needs to optimize the regional coordination of technologies and innovations and finally improve the GTFEEs in the central and western regions. For example, the government could encourage more investments in universities and scientific research institutions in the central and western provinces.
2) Moreover, the government should greatly enhance the role of imports in improving the quality of economic development, especially the imports of capital goods and high-tech products. Honestly speaking, China has been over-relying on export for numerous years. However, now, the international environment for cooperation has undergone profound changes. Therefore, as the important driving force of economic development, the import should be emphasized more than before, which will optimize the trade structure and promote the GTFEEs.
3) Additionally, the government should also promote the optimization of industrial distributions and encourage the high-tech enterprises and talents to transfer from the eastern regions to the central and western ones. The western and central provinces could fully use the late-comer advantages in trade and strengthen the cooperation with eastern provinces by introducing advanced technology and management experience. Especially for western regions, it is essential to transform their resource advantages into industrial ones, thus effectively promoting their local GTFEEs.

Though this study quantitatively investigated the relationships between export, import, and GTFEE, there remain some limitations, which could become the possible directions of future research. Firstly, the inter-provincial data applied in this study is not adequate and may easily cause some sample bias. Thus, future researchers should gather city-level or firm-level data to conduct precise investigations. Moreover, this study mainly applied total export and import to measure the level of trade. Consequently, the heterogeneity of trading partner countries may be overlooked. Therefore, future research will need to explore deeper into these fields.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Materials. Further inquiries can be directed to the corresponding author.

Author contributions

JL: conceptualization, project administration, formal analysis, writing-review and editing. Jx: conceptualization, writing-review and editing, writing-original draft. CL: writing-review and editing, methodology, validation.

Funding

This study was supported by the National Natural Science Foundation of China (Grant no. 71964032).

Acknowledgments

The authors acknowledge financial support from the National Natural Science Foundation of China (Grant no. 71964032), the Key Project of Philosophy and Social Science of the Ministry of Education of China (Grant no. 17JZD033).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

References

Al- mulali, U., and Sheau-Ting, L. (2014). Econometric analysis of trade, exports, imports, energy consumption and CO2 emission in six regions. *Renew. Sustain. Energy Rev.* 33, 484. doi:10.1016/j.rser.2014.02.010

Banker, R. D., Cooper, A. C. W., and Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manage. Sci.* 30, 1078–1092. doi:10.1287/mnsc.30.9.1078

Blundell, R., and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *J. Econ.* 87, 115

Byrne, J., Shen, B., and Li, X. (1996). The challenge of sustainability: Balancing China's energy, economic and environmental goals. *Energy Policy* 24, 455–462. doi:10.1016/0301-4215(96)00011-0

Caporale, G. M., Sova, A., and Sova, R. (2015). Trade flows and trade specialisation: The case of China. *China Econ. Rev.* 34, 261–273. doi:10.1016/j.chieco.2015.03.010

Chen, S., and Golley, J. (2014). 'Green' productivity growth in China's industrial economy. *Energy Econ.* 44, 89–98. doi:10.1016/j.eneco.2014.04.002

Cheng, Z., Li, L., and Liu, J. (2018). Industrial structure, technical progress and carbon intensity in China's provinces. *Renew. Sustain. Energy Rev.* 81, 2935–2946. doi:10.1016/j.rser.2017.06.103

Cheng, Z., Li, L., and Liu, J. (2017). The emissions reduction effect and technical progress effect of environmental regulation policy tools. *J. Clean. Prod.* 149, 191. doi:10.1016/j.jclepro.2017.02.105

Chung, Y. H., Färe, R., and Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *J. Environ. Manage.* 51, 229–240. doi:10.1006/jema.1997.0146

Coe, D. T., and Helpman, E. (1995). International R&D spillovers. *Eur. Econ. Rev.* 39, 859–887. doi:10.1016/0014-2921(94)00100-e

Dai, M., Maitra, M., and Yu, M. (2016). Unexceptional exporter performance in China? The role of processing trade. *J. Dev. Econ.* 121, 177. doi:10.2139/ssrn.1963652

Dey- Chowdhury, S. (2008). Methods explained: Perpetual inventory method (PIM). *Econ. Lab. Market Rev.* 2, 48–52. doi:10.1057/elmr.2008.140

Dietzenbacher, E., Pei, J., and Yang, C. (2012). Trade, production fragmentation, and China' s carbon dioxide emissions. *J. Environ. Econ. Manage.* 64, 88–101. doi:10.1016/j.jeem.2011.12.003

Dong, J., and Cen, Y. (2011). Measurement of highway capital stock in China: 1952 2009. *J. Transp. Syst. Eng. Inf. Technol.* 11, 20–23. doi:10.1016/s1570-6672(10)60100-6

Egger, P., and Url, T. (2010). Public export credit guarantees and foreign trade structure: Evidence from Austria. *World Econ.* 29, 399–418. doi:10.1111/j.1467-9701.2006.00790.x

Farrow, K., Grolleau, G., and Mzoughi, N. (2018). Less is more in energy conservation and efficiency messaging. *Energy Policy* 122, 1–6. doi:10.1016/j.enpol.2018.07.007

Feng, C., Wang, M., Liu, G., and Huang, J. (2017). Green development performance and its influencing factors: A global perspective. *J. Clean. Prod.* 144, 323–333. doi:10.1016/j.jclepro.2017.01.005

Grossman, G. M., and Helpman, E. (1991). Trade, knowledge spillovers, and growth. *Eur. Econ. Rev.* 35, 517–526. doi:10.1016/0014-2921(91)90153-a

Hao, Y., Gai, Z., and Wu, H. (2020). How do resource misallocation and government corruption affect green total factor energy efficiency? Evidence from China. *Energy Policy* 143, 111562. doi:10.1016/j.enpol.2020.111562

He, L., and Wang, L. (2020). Distinct exporters and the environment: Empirical evidence from China manufacturing. *J. Clean. Prod.* 258, 120614. doi:10.1016/j.jclepro.2020.120614

Ho, C., Wang, W., and Yu, J. (2018). International knowledge spillover through trade: A time-varying spatial panel data approach. *Econ. Lett.* 162, 30–33. doi:10.1016/j.econlet.2017.10.015

Hu, C., and Tan, Y. (2016). Export spillovers and export performance in China. *China Econ. Rev.* 41, 75–89. doi:10.1016/j.chieco.2016.08.008

Huang, J., Du, D., and Tao, Q. (2017). An analysis of technological factors and energy intensity in China. *ENERG POLICY* 109, 1. doi:10.1016/j.enpol.2017.06.048

Huang, L., and Lei, Z. (2021). How environmental regulation affect corporate green investment: Evidence from China. *J. Clean. Prod.* 279, 123560. doi:10.1016/j.jclepro.2020.123560

Jalles, J. T., and Ge, J. (2020). Emissions and economic development in commodity exporting countries. *Energy Econ.* 85, 104572. doi:10.1016/j.eneco.2019.104572

Jarreau, J., and Poncet, S. (2012). Export sophistication and economic growth: Evidence from China. *J. Dev. Econ.* 97, 281–292. doi:10.1016/j.jdeveco.2011.04.001

Josep, L. C. I. S., Tomás, D. B. C., and Enrique, L. B. (2005). Breaking the panels: An application to the GDP per capita. *Econom. J.* 8, 159–175. doi:10.1111/j.1368-423x.2005.00158.x

Kohler, M. (2013). CO_2 emissions, energy consumption, income and foreign trade: A South African perspective. *Energy Policy* 63, 1042–1050. doi:10.1016/j.enpol.2013.09.022

Kong, Q., Peng, D., Ni, Y., Jiang, X., and Wang, Z. (2020). *Trade openness and economic growth quality of China: Empirical analysis using ARDL model.* Financ Res Lett.

Korves, N. (2011). "Is free trade good or bad for the environment? New empirical evidence." in *climate change:socioeconomic effects, edited by Juan Blanco, houshang kheradmand.* London: InTech. doi:10.5772/23008

Lanoie, P., Patry, M., and Lajeunesse, R. (2008). Environmental regulation and productivity: Testing the porter hypothesis. *J. Product. Anal.* 30, 121–128. doi:10.1007/s11123-008-0108-4

Lesage, J. P. (2008). An introduction to spatial econometrics. *rei.* 123, 19–44. doi:10.4000/rei.3887

Li, B., and Wu, S. (2020). Effects of local and civil environmental regulation on green total factor productivity in China: A spatial Durbin econometric analysis. *J. Clean. Prod.* 153, 342. doi:10.1016/j.jclepro.2016.10.042

Li, J., and Lin, B. (2017). Ecological total-factor energy efficiency of China's heavy and light industries: Which performs better? *Renew. Sustain. Energy Rev.* 72, 83–94. doi:10.1016/j.rser.2017.01.044

Li, L., and Hu, J. (2012). Ecological total-factor energy efficiency of regions in China. *Energy Policy* 46, 216–224. doi:10.1016/j.enpol.2012.03.053

Li, S., and Wang, S. (2019). Examining the effects of socioeconomic development on China' s carbon productivity: A panel data analysis. *Sci. Total Environ.* 659, 681–690. doi:10.1016/j.scitotenv.2018.12.409

Li, K, K., Fang, L., and He, L. (2018). How urbanization affects China' s energy efficiency: A spatial econometric analysis. *J. Clean. Prod.* 200, 1130–1141. doi:10.1016/j.jclepro.2018.07.234

Li, M, M., Li, C., and Zhang, M. (2018). Exploring the spatial spillover effects of industrialization and urbanization factors on pollutants emissions in China' s Huang- Huai- Hai region. *J. Clean. Prod.* 19 5, 154. doi:10.1016/j.jclepro.2018.05.186

Lin, B., and Zhao, H. (2016). Technology gap and regional energy efficiency in China's textile industry: A non-parametric meta-frontier approach. *J. Clean. Prod.* 137, 21–28. doi:10.1016/j.jclepro.2016.07.055

Liu, X., and Bae, J. (2018). Urbanization and industrialization impact of CO2 emissions in China. *J. Clean. Prod.* 172, 178. doi:10.1016/j.jclepro.2017.10.156

Liu, Z., and Xin, L. (2019). Has China's belt and road initiative promoted its green total factor productivity？——evidence from primary provinces along the routeEvidence from primary provinces along the route. *Energy Policy* 129, 360–369. doi:10.1016/j.enpol.2019.02.045

Long, Y., and Xiaozhen, H. (2010). Analysis on regional difference and convergence of the efficiency of China' s green economy based on DEA. *Economist* 2, 46–54.

Lu, J., Lu, Y., and Tao, Z. (2010). Exporting behavior of foreign affiliates: Theory and evidence. *J. Int. Econ.* 81, 197–205. doi:10.1016/j.jinteco.2010.03.002

Ma, M., Yan, R., Du, Y., Ma, X., Cai, W., and Xu, P. (2017). A methodology to assess China's building energy savings at the national level: An IPAT – LMDI model approach. *J. Clean. Prod.* 143, 784–793. doi:10.1016/j.jclepro.2016.12.046

Ma, Y., Tang, H., and Zhang, Y. (2014). Factor Intensity, product switching, and productivity: Evidence from Chinese exporters. *J. Int. Econ.* 92, 349–362. doi:10.1016/j.jinteco.2013.11.003

Managi, S., Hibiki, A., and Tsurumi, T. (2009). Does trade openness improve environmental quality? *J. Environ. Econ. Manage.* 58, 346–363. doi:10.1016/j.jeem.2009.04.008

Mania, E., and Rieber, A. (2019). Product export diversification and sustainable economic growth in developing countries. *Struct. Change Econ. D.* 51, 138. doi:10.1016/j.strueco.2019.08.006

Manova, K., and Yu, Z. (2016). How firms export: Processing vs. ordinary trade with financial frictions. *J. Int. Econ.* 100, 120–137. doi:10.1016/j.jinteco.2016.02.005

Nesta, L., Vona, F., and Nicolli, F. (2014). Environmental policies, competition and innovation in renewable energy. *J. Environ. Econ. Manage.* 67, 396–411. doi:10.1016/j.jeem.2014.01.001

Pan, X., Li, M., Wang, M., Chu, J., and Bo, H. (2020). The effects of outward foreign direct investment and reverse technology spillover on China's carbon productivity. *Energy Policy* 145, 111730. doi:10.1016/j.enpol.2020.111730

Pan, X., Uddin, M. K., Han, C., and Pan, X. (2019b). Dynamics of financial development, trade openness, technological innovation and energy intensity: Evidence from Bangladesh. *Energy* 171, 456–464. doi:10.1016/j.energy.2018.12.200

Pan, X., Uddin, M. K., Saima, U., Jiao, Z., and Han, C. (2019a). How do industrialization and trade openness influence energy intensity? Evidence from a path model in case of Bangladesh. *Energy Policy* 133, 110916. doi:10.1016/j.enpol.2019.110916

Parrado, R., and De Cian, E. (2014). Technology spillovers embodied in international trade: Intertemporal, regional and sectoral effects in a global CGE framework. *Energy Econ.* 41, 76–89. doi:10.1016/j.eneco.2013.10.016

Poon, J. P. H., Casas, I., and He, C. (2006). The impact of energy, transport, and trade on air pollution in China. *Eurasian Geogr. Econ.* 47, 568–584. doi:10.2747/1538-7216.47.5.568

Porter, M. E., and Linde, C. V. D. (1999). Green and competitive: Ending the stalemate. *Harv. Bus. Rev.* 28, 128

Revesz, R. L. (1992). *Rehabilitating Interstate Competition: Rethinking the " Race-to- the- Bottom" Rationale for Federal Environmental Regulation*, 67. New York U Law Rev, 1210.

School of Earth Environment, University of Leeds, Leeds, UK (2016). Blowing policy bubbles: Rethinking emissions targets and low- carbon energy policies in the U. K. *J. Environ. Pol. Plan.*, 1–16. doi:10.1080/1523908x.2016.1266931

Shahbaz, M., Khan, S., and Tahir, M. I. (2013). The dynamic links between energy consumption, economic growth, financial development and trade in China: Fresh evidence from multivariate framework analysis. *Energy Econ.* 40, 8–21. doi:10.1016/j.eneco.2013.06.006

Shan, H. J. (2008). Reestimating the capital stock of China: 1952-2006. *J. Quantitative Tech. Econ.* 10, 17–31.

Sheng, P., Zhai, M., Zhang, Y., and Kamal, M. A. (2020). The effects of urbanization on household wastewater emissions in China: Efficient- and inefficient- emissions. *Environ. Pollut.* 267, 115350. doi:10.1016/j.envpol.2020.115350

Sun, W., and Huang, C. (2020). How does urbanization affect carbon emission efficiency? Evidence from China. *J. Clean. Prod.* 272, 122828. doi:10.1016/j.jclepro.2020.122828

Tientao, A., Legros, D., and Pichery, M. C. (2016). Technology spillover and TFP growth : A spatial Durbin model. *Int. Econ.* 145, 21–31. doi:10.1016/j.inteco.2015.04.004

Tone, K. (2001). A slacks- based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* 130, 498–509. doi:10.1016/s0377-2217(99)00407-5

Wang, H., and Ang, B. W. (2018). Assessing the role of international trade in global CO2 emissions: An index decomposition analysis approach. *Appl. Energy* 218, 146–158. doi:10.1016/j.apenergy.2018.02.180

Wang, K, K., Miao, Z., Zhao, M., Miao, C., and Wang, Q. (2019). China ' s provincial total- factor air pollution emission efficiency evaluation, dynamic evolution and influencing factors. *Ecol. Indic.* 10 7, 105578. doi:10.1016/j.ecolind.2019.105578

Wang, Z, Z., Huang, W., and Chen, Z. (2019). The peak of CO_2 emissions in China: A new approach using survival models. *Energy Econ.* 81, 1099–1108. doi:10.1016/j.eneco.2019.05.027

Wu, H., Hao, Y., and Ren, S. (2020a). How do environmental regulation and environmental decentralization affect green total factor energy efficiency: Evidence from China. *Energy Econ.* 9 1, 104880. doi:10.1016/j.eneco.2020.104880

Wu, H., Hao, Y., and Weng, J. (2019). How does energy consumption affect China' s urbanization? New evidence from dynamic threshold panel models. *Energ Policy* 127, 24. doi:10.1016/j.enpol.2018.11.057

Wu, H., Xu, L., Ren, S., Hao, Y., and Yan, G. (2020b). How do energy consumption and environmental regulation affect carbon emissions in China? New evidence from a dynamic threshold panel model. *Resour. Policy* 67, 101678. doi:10.1016/j.resourpol.2020.101678

Yan, B., Duan, Y., and Wang, S. (2020). China ' s emissions embodied in exports: How regional andtrade heterogeneity matter. *Energy Econ.* 87, 104479. doi:10.1016/j.eneco.2019.104479

Yang, Z. (2019). Editorial introduction to the special issue entitled: Spatial econometrics: New methods and applications. *Reg. Sci. Urban Econ.* 76, 1. doi:10.1016/j.regsciurbeco.2019.05.003

Yu, C., and Luo, Z. (2018). What are China's real gains within global value chains? Measuring domestic value added in China's exports of manufactures. *China Econ. Rev.* 47, 263–273. doi:10.1016/j.chieco.2017.08.010

Yuan, B., and Xiang, Q. (2018). Environmental regulation, industrial innovation and green development of Chinese manufacturing: Based on an extended CDM model. *J. Clean. Prod.* 17 (6), 895–908. doi:10.1016/j.jclepro.2017.12.034

Yuan, X. U., and Ya- Li, C. (2014). Technology effect of international trade: Based on the perspective of technology spillover. *Chin. J. Popul. Resour. Environ.* 24 (1), 148–156. doi:10.3969/j.issn.1002-2104.2014.01.021

Zhang, L., Xiong, L., Cheng, B., and Yu, C. (2018). How does foreign trade influence China 's carbon productivity? Based on panel spatial lag model analysis. *Struct. Chang. Econ. Dyn.* 47, 171–179. doi:10.1016/j.strueco.2018.08.008

Zhang, Y., Zhao, Y., Liu, Y., Zhonghua, B., and Wang, S. (2017). Embodied carbon in China' s foreign trade: An online SCI- E and SSCI based literature review. *Renew. Sust. Energy Rev.* 68, 492–519. doi:10.1016/j.rser.2016.10.009

Zhang, Y., Yi, W., and Li, B. (2015). The impact of urbanization on carbon emission: Empirical evidence in beijing. *Energy Procedia* 75, 2963–2968. doi:10.1016/j.egypro.2015.07.601

Zhao, H., and Lin, B. (2019). Will agglomeration improve the energy efficiency in China ' s textile industry: Evidence and policy implications. *Appl. ENERG* 237, 326. doi:10.1016/j.apenergy.2018.12.068