SUSTAINABLE ENERGY PRODUCTION AND CONSUMPTION: SYSTEM ACCOUNTING, INTEGRATED MANAGEMENT, POLICY RESPONSES

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SUSTAINABLE ENERGY PRODUCTION AND CONSUMPTION: SYSTEM ACCOUNTING, INTEGRATED MANAGEMENT, POLICY RESPONSES

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EDITORIAL
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Editorial: Sustainable Energy Production and Consumption: System Accounting, Integrated Management, Policy Responses

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Editorial on the Research Topic

Sustainable Energy Production and Consumption: System Accounting, Integrated Management, Policy Responses

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INTRODUCTION

This Research Topic was proposed with the intent to: 1) share and catalog experiences of how to conduct system accounting for energy production and consumption from different perspectives, 2) to promote a deeper understanding of the resource nexus by considering integrated management of "Energy+" systems, and 3) to encourage critical discussion of policy responses for sustainable energy production and consumption, to connect academic research and practical management. The eventual submissions covered a range of themes, although the Energy+ (or Energy-X-Nexus) approach was less covered. Energy and the potential economic opportunities for reducing greenhouse gas emissions were considered at a variety of scales—national, provincial, sectoral, company—and using various alternative techniques.

ARTICLES

Nine papers have been published under this topic, covering a broad range of areas in the field, but with an overall tendency towards examining macro-economic and sectoral environmental and economic performance, and the influence of factors such as innovation, investment, and subsidization.

Industrial environmental efficiency was focused on by (Sun et al.), who considered overall environmental efficiency as being composed of two serial elements—economic development and environmental governance. They evaluated the two elements, considering the effects of a variety of indicators, including urbanization, and demonstrated that the economic development focus was in general more related to industrial environmental efficiency.

Similarly, the study by (Xie et al.) examined the improvement of environmental performance in resource-based cities in China, demonstrating that the introduction of technology from external sources was not as effective as indigenous technological innovation in improving green transformation. This study suggests that direct research and development investment is an effective tool in achieving the desired outcomes. The effect of research and development investment was also indicated as important for regions to improve total factor coal productivity (Wang et al.). The positive impact of government subsidies on technology innovation up to a certain threshold was demonstrated by (Wang et al.).

The influence and efficiency in value creation for online platform-based companies in transitioning towards more sustainable options was examined by (Xie et al.). This case study on the energy sector tried to model the mechanism of this choice in transition.

Divisia techniques were used to consider sub-sectoral influences and opportunities for improvement in emissions, indicating the strength of the energy structure for Xinjiang Production and Construction Corps (Wang et al.). While (Zeng et al.) considered provincial level opportunities for reducing carbon emissions from electricity production, finding a cooperative model in which provinces could combine or trade efforts in emissions reduction, to be more effective and fair than each province being forced to seek emissions reductions internally.

Energy embodied in trade was analyzed for China at the sectoral and international level by (Zhang et al.), using trade in value-added methods. They show a difference between the sectors that produce the most economic value and those that have the highest embodied energy, thus indicating a potential to create mutual benefit by restructuring the embodied energy export structure.

On a very different topic, (Wei et al.) developed methods to diagnose the performance of hydraulic turbines.

CONCLUDING REMARKS

The editors hope that the published papers will interest the readers and initiate some interesting and informative discussion in the open review process.

AUTHOR CONTRIBUTIONS

The editorial was drafted by BM, checked by XT and JM.

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.

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ORIGINAL RESEARCH
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Innovation or Introduction? The Impact of Technological Progress Sources on Industrial Green Transformation of Resource-Based Cities in China

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With the increasingly prominent problems of global resource consumption and environmental pollution, industrial green transformation has become one of the requirements of China's industrial development in the new era. However, there is a lack of research on the impact of technological innovation and technology introduction on the industrial green transformation of resource-based cities. To bridge this gap, this study uses the panel data of 115 resource-based cities in China from 2003 to 2016, and uses the dynamic panel generalized method of moments (GMM) estimation method to study the impact of technological innovation and technology introduction on industrial green transformation of resource-based cities. The results show that technology introduction has a negative effect on the industrial green transformation of resource-based cities, while technological innovation can have a positive effect. Meanwhile, technology introduction has imparted a greater role to technological innovation in promoting this transformation. In addition, the interactive effects between technological innovation and technology introduction have obvious heterogeneity on the industrial green transformation of different types of resource-based cities. Therefore, resource-based cities should continue to increase investment in scientific research, to constantly improve and consolidate their technological innovation ability, optimize foreign investment strategy in technology introduction, and strengthen the digestion and absorption of imported technology, while increasing technological innovation and personnel training.

Keywords: technological innovation, China, technology introduction, industrial green transformation, resource-based cities

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INTRODUCTION

The Sustainable Development Goals (SDGS) aim to integrate the three dimensions of social, economic, and environmental development from 2015 to 2030, and enable sustainable development (United Nations, 2015). Among them, the goal of SDG7 is to "ensure that all people have access to affordable, reliable, and sustainable modern energy." To achieve this goal, it is necessary to improve energy efficiency and accelerate industrial transformation (Adom and Adams, 2020). After 40 years of reform and opening up, despite the rapid development of its economy and remarkable achievements, environmental problems have always plagued China. China's long-term implementation of an extensive economic growth model, characterized by labor-intensive and resource-intensive production methods (Yi et al., 2013), has caused various environmental problems and hindered sustainable development. The Chinese government has realized the importance of maintaining a balance between the environment and the economy. To achieve the SDG7 goals, China must increase investment in clean energy technology research and upgrade its industrial structure rapidly. Therefore, both the National 13th Five-Year Plan (FYP) and the "Made in China 2025 Plan" (The State Council of the People's Republic of China, 2015), announced the acceleration in developing an ecological civilization and promoting green industrial development. As per the "Industrial Green Development Plan (2016–2020)" (Ministry of Industry and Information Technology, 2016), by 2020, the concept of green development will become the development goal of the whole industry. This will vigorously promote energy efficiency improvement and substantially reduce pollution emissions. The implementation of these measures has effectively promoted the development of clean energy in China. However, according to the world environmental performance index (EPI) ranking in 2018 (Environmental Performance Index, 2018), China scored 50.74 points, ranking 120th among 180 countries in the world, indicating that improving the environment remains China's top priority.

In the past few decades, resource-based cities have played an important role in China's economic growth (Long et al., 2013). According to the National Sustainable Development Plan of Resource-based Cities (2013–2020), there are 262 resource-based cities in China (Liu et al., 2020), with 126 prefecture-level cities, accounting for 43.6% of the total. Resource-based cities rely on the development of local resources to achieve economic development (Li et al., 2013), and resource-intensive industries play a leading role in their economies (Yu et al., 2008). Resource-based cities tend to have higher unemployment rates (Chen et al., 2018b), single employment structure (Tan et al., 2016), lack of growth potential (Li et al., 2013), weak alternative industries (He et al., 2017), lower social insurance (Bo and Hasnat, 2017), and other social and economic problems. Meanwhile, overexploitation and inefficient resource utilization also cause environmental pollution and ecological risks (Ma et al., 2018). However, resource-based cities face more severe crizes in industrial green transformation than do other cities (Yu et al., 2016), which is a global concern. Industry is a major contributor to the economic development of China's resource-based cities, and the major source of environmental pollution. Industrial green transformation is crucial in achieving the sustainable development of resource-based cities (Yuan et al., 2020).

Industrial green transformation refers to improving the efficiency of energy resource utilization, reducing pollutant emissions, reducing environmental impact, improving labor productivity, and enhancing sustainable development capabilities to achieve a win–win situation for both the economy and the environment (Chinese Academy of Social Sciences, 2011). Technological progress is the process of continuous technological development, improvement, and the continuous replacement of old technologies with new ones, which increase energy efficiency and use less polluting technologies in the production process (Kaika and Zervas, 2013). Technological progress is the core of energy efficiency improvement and energy savings (Li and Lin, 2018), and essential for stimulating industrial green transformation. Simultaneously, technological innovation (Guo et al., 2017) and technology introduction (Yang et al., 2017) are the two main paths of technological progress. Technological innovation mainly refers to indigenous innovation (Fu et al., 2011), achieved by increasing scientific research and R&D investment. Technology introduction refers to the acquisition of advanced technical knowledge or equipment from abroad through international technical exchanges and transfers. Developing countries mainly achieve technology introduction through foreign direct investment (FDI). However, there is no consistent conclusion on the role of technological innovation and technology introduction on industrial green transformation.

In the long term, increasing technological innovation input, technological innovation output, and technology introduction are important ways to promote production technology progress (Hu et al., 2020b). In some cases, the input and output of technological innovation and the introduction of technology may not promote the progress of production technology significantly. In other ways, it may not necessarily promote the industrial green transformation of resource-based cities. This is because of the many uncertain intermediate links among the input, output, and technological innovations to the formation of production technology capacity. In terms of technological innovation, on the one hand, there is opportunity cost in technological innovation. The increase in technological innovation input means that the capital invested in production decreases. Therefore, reduced productive investment means reduced output, which may hinder industrial green transformation. In contrast, the high wages of foreign-funded enterprises attract the technical personnel of domestic enterprises and foreign-funded enterprises to merge and participate in domestic enterprises, inducing the R&D investment of the government and enterprises to foreign-funded technology research and development. Therefore, it is not conducive to the improvement of production technology of domestic enterprises, and cannot effectively promote the industrial green transformation of resource-based cities. In terms of technology introduction, local technology, imported technology, and their matching degree will seriously restrict the role of imported technology in the industrial green transformation of resource-based cities. Furthermore, the absorption and digestion capacity determine whether the imported technology can eventually form production technology. Simultaneously, the technology gap is also an important factor, restricting the role of introduced technology in the industrial green transformation of resource-based cities. If the technology gap is too large and the learning ability of the technology importer is low, it will be difficult for local companies to learn. This will result in the hollowing out of imported technology and reduce the level of industrial green transformation.

The above research showed that technological progress could improve the utilization efficiency of natural resources, which is a significant factor in facilitating the industrial green transformation of resource-based cities. However, technological innovation and technology introduction must reflect in the progress of production technology to do so. Therefore, it is necessary to explore the influence of technological innovation and technology introduction on industrial green transformation of resource-based cities. This study examines the impact of technological innovation and technology introduction in detail, which not only has important theoretical significance but also provides valuable decision-making reference in choosing the path of technological progress to achieve industrial green transformation and sustainable development in such cities.

This study contributes to the literature in several ways. First, many existing studies focus on the relationship between a single source of technological progress and industrial green transformation. Guo et al. (2017) studied the impact of technological innovation and regional green performance, and Jin et al. (2019) studied the impact of technological innovation and green total factor efficiency of industrial water resources. Hu et al. (2018) studied the impact of foreign investment and industrial green technology progress. There is no consensus on the impact of technological innovation and technology introduction on industrial green transformation. This present study examines the impact of technological innovation and technology introduction on industrial green transformation. Meanwhile, by constructing the multiplicative term of technological innovation and foreign investment, this study examines the effect of the interaction between technological innovation and technology introduction on industrial green transformation and judges the technological innovation path to promote industrial green transformation. Second, in terms of industrial green transformation, most studies use regional-level (national or provincial)[1] and industry-level data, while some quantitative studies examine cities. For example, Fu et al. (2018) and Chen et al. (2016) measure the dynamic efficiency of industrial green transformation in 30 Chinese mainland provinces. Cheng and Li (2018) empirically test the effects of R&D investment on the green growth of China's manufacturing industry. Simultaneously, resource development creates resource-based cities, and the problem of industrial sustainable development is more prominent than in other cities. Hence, it is more important to study the industrial green transformation of resource-based cities. Therefore, this study uses the panel data of 115 resource-based cities in China from 2003 to 2016 for its research objective. Finally, according to the different stages and the sustainable development ability of resource-based cities, it investigates the heterogeneity of technological innovation and technology introduction on the industrial green transformation of different types of resource-based cities.

This article proceeds as follows: *Literature Review* offers a literature review. *Materials and Methods* introduces the research materials and methods. *Empirical Results and Discussion* contains the empirical results and discussion. Finally, *Conclusion* summarizes the findings and discusses the policy implications of the conclusions.

[1]According to the Constitution of the People's Republic of China, China's administrative regions are divided into four levels. First-level provincial administrative regions include provinces, autonomous regions, and municipalities. Second-level prefecture-level administrative regions include prefecture-level cities and regions. Third-level county-level administrative districts include municipal districts, county-level cities, and counties. Fourth-level township administrative districts include streets and towns.

LITERATURE REVIEW

Impacts of Technological Innovation on Industrial Green Transformation

Many studies consider that technological innovation can promote industrial transformation or industrial green transformation. According to the "Porter hypothesis" (Porter, 1991), technological innovation is mainly to improve resource utilization efficiency through technological progress, thereby promoting industrial green transformation. Simultaneously, "creative destruction" considers that the key to obtain new competitive advantage is to transform through technological innovation (Schumpeter, 1934, p. 10). If an enterprise wants to maintain its competitive advantage, it must constantly perform technological innovation (Veliyath and Shrivastava, 1996). Technological innovation is a continuous source of sustainable development of the contemporary economy and plays a key role in improving resource efficiency and upgrading industrial structure (Ngai and Pissarides, 2007). Some scholars have also shown that advanced technology is conducive to the efficient and clean utilization of energy resources (Yang and Wang, 2013). For example, technological innovation can promote the resource utilization efficiency of both traditional and emerging industries (Miao et al., 2018). In addition, technological innovation plays an important role in promoting the green development of regional economy (OECD, 2011b). Guo et al. (2017) reported that technological innovation has a positive impact on regional green efficiency. Miao et al. (2017) reported that the development of green new products has a major positive effect on the efficiency of natural resource utilization. Therefore, technological innovation can promote the industrial green transformation of resource cities by improving the production technology of traditional industries and increasing the efficiency of resource utilization (Li and Lin, 2018). However, some scholars argue that technological innovation has a negative influence on promoting industrial green transformation. Zhao and Jing (2014) reported that the crowding out effect of technological innovation might shrink enterprises, thereby reducing the efficiency of enterprise resource utilization. Jin et al. (2019) reported that technological innovation has an obvious restraint on the green development of industrial water resources in western China. The above research shows that technological innovation may promote the industrial green transformation of resource-based cities; however, it may also inhibit this process.

Impacts of Technology Introduction on Industrial Green Transformation

Foreign direct investment (FDI) is an important route of technology introduction (Blomstrom and Kokko, 2001). The path of technology introduction through FDI accelerates the transfer of knowledge, technology, and management experience from the home country to the host country (Azman-Saini et al., 2010). Many scholars believe that developing countries have reversed their lack of technological innovation in the early stages of development by using the technology spillover effect of FDI (Barrell and Pain, 1999). Meanwhile, the "Pollution Halo Hypothesis" (Birdsall and Wheeler, 1993) holds that FDI can bring more environment-friendly production standards and technologies to developing countries. FDI has a positive impact on the industrial and ecological environment of host countries through the demonstration effect (List et al., 2003), which means that it is conducive to the productivity improvement, economic growth, and sustainable social development of the host country (Kokko, 1994). Therefore, resource-based cities promote industrial green transformation through the knowledge and technology spillover effects of technology introduction (Doytch and Narayan, 2016). Some scholars have conducted empirical research on this position. For example, Antweiler et al. (2001) reported that FDI is conducive to the improvement of clean technology and green technology in host countries. Albornoz et al. (2009) found that local enterprises in Argentina could improve environmental protection technology by constantly learning and absorbing the advanced environmental management systems of foreign-funded enterprises. Examining the manufacturing industry in China, Hu et al. (2018) found FDI that has a positive spillover effect on the progress rate of green technology.

However, another view holds that technology introduction cannot promote urban economic development and industrial green transformation. The "Pollution Haven Hypothesis" (Cole, 2003) states that relatively developed economies will transfer pollution-intensive enterprises to less developed economies due to the relatively intensive labor force (Taylor and Scott, 2005) and relatively lax environmental regulations in developing countries (Mulatu et al., 2010). These factors cause environmental pollution in developing countries. The empirical results show that the degree of technological development (Dean et al., 2009), strictness of environmental regulation (Kheder and Zugravu, 2012), richness of resources (Dam and Scholtens, 2012) of the host country, and the motivation of multinational enterprises (Rezza, 2013) are the determinants of the pollution refuge hypothesis. China's resource-based cities have abundant resources and low-standard environmental regulations, which may cause the introduction of technology to hinder the industrial green transformation. Jorgenson (2009) studied less developed countries and reported that FDI in the manufacturing sector is positively correlated with industrial water pollution. Meanwhile, scholars have reported that multinational companies transfer pollution-intensive production to developing countries (Chung, 2014), causing serious pollution and inhibiting the green transformation of industry (Acharyya, 2009). In addition, Yan et al. (2019) found the greater foreign investment a resource-based city receives, the lower its energy and technology efficiency. These results show that FDI will have a negative impact on the environment of host countries, which means that technology introduction is not conducive to industrial green transformation in the region. The above research shows that technology introduction may both promote and inhibit the industrial green transformation of resource-based cities.

Measurement of Industrial Green Transformation

Owing to unsustainable industrial development in China in recent years, and increasing resource and environmental problems, industrial green development has gradually become a research hotspot. The characteristics of industrial production activities necessitate that scholars focus on the adverse effects on the environment without losing sight of the potential economic benefits of industry (Zhou et al., 2013). Industrial green transformation will resolve the problems in the industrial development process, such as high energy consumption, heavy environmental pollution, low production efficiency, and weak international competitiveness (Van de Kerk and Manuel, 2008). The region needs an environment-friendly and resource-saving society. This is also the embodiment of a "green economy" (Pearce et al., 1989) in the industrial industry. Improving the efficiency of industrial green transformation is the key to achieving the green development of industry (Pearce, 2013). Consequently, improving the green transformation level of resource-based cities is the key to achieving sustainable development.

Today, more scholars are focusing on the measurement of industrial green transformation. The following technical methods are common for measuring the green transformation of industry. Chen et al. (2016) used the analytic hierarchy process (AHP) to construct an evaluation index system to evaluate the green development of China's industry. Feng et al. (2017) measured the efficiency of China's regional industrial green transformation by combining the hybrid model and window analysis. In addition, many scholars used the data envelopment analysis (DEA) method to study industrial green transformation issues. Cheng and Li (2018) used the nondirectional distance function (NDDF) and meta-frontier methods to measure green growth in China's manufacturing industry. The Organization for Economic Cooperation and Development (OECD) has established a complete green development index system covering all aspects of economy, environment, and human well-being (OECD, 2011a). Li et al. (2016) used the DEA model to evaluate the sustainable development of resource-based cities. Hu et al. (2020a) used the hyperbolic distance function (HDF) model to measure the energy and environment performance of resource-based cities. Hu et al. (2019) used the Super-slack based measure (SBM) function and the Global Malmquist–Luenberger (GML) index to calculate China's manufacturing industrial green total factor productivity.

In general, the above studies adopt a single index to depict technological progress, and do not consider the difference in the effects of different sources of technological progress on industrial green transformation. The new economic growth theory believes that technological innovation can accumulate knowledge and promote process innovation, which provides a steady stream of power and support for sustainable economic growth (Jefferson et al., 2006). International trade theory holds that through the introduction, digestion, and absorption of advanced technologies from developed countries, developing countries could accelerate economic growth and industrial green transformation (Corssman and Helpman, 1991). Combined with the existing theoretical framework, this study analyses the impact of technological innovation and technology introduction on the industrial green transformation of resource-based cities. Simultaneously, this study analyzes the effect of the interaction between technological innovation and technology introduction on industrial green transformation of resource-based cities.

MATERIALS AND METHODS

Model Setting

Global Malmquist–Luenberger Measure for Determining the Green Growth Index

This study focuses on the measurement of industrial green transformation of resource-based cities. [2]The investigators considered the Super-SBM directional distance function of unanticipated outputs, and used the GML index to measure the industrial green transformation of resource-based cities. In empirical applications, existing research uses the GML index to measure the green total factor productivity of the industrial sector (Wang et al., 2020), China's industrial green productivity (Wang and Shen, 2016), and light manufacturing industries (Emrouznejad and Yang, 2016). Meanwhile, the traditional Malmquist–Luenberger (ML) index has two potential disadvantages over the GML index. First, the industrial green transformation measured by the traditional ML index has no multiplicative property. The traditional ML index can only analyze the short-term fluctuations of production efficiency in adjacent periods; it cannot observe the long-term growth trend of production efficiency. This may lead to "technical regression," which is obviously unreasonable. Second, the mixing direction of the SBM function, the output reduction, and the output reduction of the undesired output may lead to infeasible solutions. However, GML indexing can avoid the shortcomings of infeasible solution. The GML index is based on a set of production possibilities over the full-time horizon of all decision-making units (Hu et al., 2019). Therefore, this study chooses the GML index to measure the industrial green transformation of resource-based cities.

Production Possibility Set Considering Environmental Factors

This study assumes that each resource-based city is a decision unit and set as DMU_K, where K represents the number of prefecture-level cities in resource-based cities. $x = (x_1, \ldots, x_n)$ represents N production essentials put into each region, where $x \in R_N^+$, obtain M expected outputs, $y = (y_1, \ldots, y_n) \in R_M^+$, I non-anticipated outputs, $b = (b_1, \ldots, b_n) \in R_I^+$, and x^{kt}, y^{kt}, b^{kt} represent the input and output in the T phase; the production frontier of the DEA's unexpected output can be expressed as follows:

$$P^t(x) = \left\{ \begin{array}{c} (y^t, b^t) : \sum_{k=1}^{K} z_k^t y_{km}^t \geq y_{km}^t,\ \forall m;\ \sum_{k=1}^{K} z_k^t b_{ki}^t = b_{ki}^t,\ \forall i; \\ \sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_{kn}^t,\ \forall n; \sum_{k=1}^{K} z_k^t = 1, z_k^t \geq 0, \forall k \end{array} \right\} \tag{1}$$

where z_k^t represents the weight of the observations of each cross section. However, there will be production technology retrogression in the $P^t(x)$ model. To avoid this, some scholars built a global production possibility set $P^G(x)$ based on $P^t(x)$, which emphasizes the consistency and comparability of the production frontier (Oh, 2010). The model is as follows:

$$P^G(x) = \left\{ \begin{array}{c} (y^t, b^t) : \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t y_{km}^t \geq y_{km}^t,\ \forall m; \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t b_{ki}^t = b_{ki}^t,\ \forall i; \\ \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_{kn}^t,\ \forall n; \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t = 1, z_k^t \geq 0, \forall k \end{array} \right\} \tag{2}$$

Global Super-Slack Based Measure Directional Distance Function

The investigators defined the direction distance function in the energy environment (Fukuyama and Weber, 2009) as follows:

$$\begin{array}{l} \overrightarrow{S_V^t}\left(x^{t,k}, y^{t,k}, b^{t,k}, g^x, g^y, g^b\right) = \max\limits_{s^x, s^y, s^b} \dfrac{\frac{1}{N}\sum_{n=1}^{N} \frac{S_n^x}{g_n^x} + \frac{1}{M+I}\left(\sum_{m=1}^{M} \frac{S_m^x}{g_m^x} + \sum_{i=1}^{I} \frac{S_i^b}{g_i^b}\right)}{2} \\ \text{s.t.} \sum_{k=1}^{K} z_k^t x_{kn}^t + s_n^x = x_{k'n}^t,\ \forall n; \sum_{k=1}^{K} z_k^t y_{km}^t - s_m^y = y_{k'm}^t, \forall m; \\ \quad \sum_{k=1}^{K} z_k^t b_{ki}^t + s_i^b = b_{k'i}^t, \forall i;\ \sum_{k=1}^{K} z_k^t = 1,\ z_k^t \geq 0,\ \forall k;\ s_m^y \geq 0,\ \forall m;\ s_i^b \geq 0,\ \forall i \end{array} \tag{3}$$

In **Eq. (3)**, g^x represents the direction vector of input reduction, g^y represents the direction vector of expected output increase, and g^b represents the direction vector of non-expected output decrease; s_n^x represents the input redundant relaxation vector, s_m^y represents the expected output insufficient relaxation vector, and s_i^b represents the unexpected output excessive relaxation vector. Similarly, the Global SBM direction distance function is as follows:

[2]According to sustainable development plan of resource-based cities in China (2013–2020) issued by the State Council, resource-based cities are those in which the mining and processing of natural resources, such as minerals and forests in the region, are the leading industries (including prefecture-level cities, districts, and other county-level administrative districts). In all, there are 262 resource-based cities, including 126 prefecture-level administrative regions, 62 county-level cities, 58 counties, and 16 municipal districts. Available online at: http://www.gov.cn/zwgk/2013-12/03/content _2,540,070.htm.

$$\overrightarrow{S_V^G}\left(x^{t,k}, y^{t,k}, b^{t,k}, g^x, g^y, g^b\right) = \max_{s^x, s^y, s^b} \frac{\frac{1}{N}\sum_{n=1}^{N}\frac{S_n^x}{g_n^x} + \frac{1}{M+I}\left(\sum_{m=1}^{M}\frac{S_m^x}{g_m^x} + \sum_{i=1}^{I}\frac{S_i^b}{g_i^b}\right)}{2}$$

$$\text{s.t.} \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t x_{kn}^t + s_n^x = x_{k'n}^t, \forall n; \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t y_{km}^t - s_m^y = y_{k'm}^t, \forall m;$$
$$\sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t b_{ki}^t + s_i^b = b_{k'i}^t, \forall i; \sum_{k=1}^{K} z_k^t = 1, \ z_k^t \geq 0, \ \forall k; \ s_m^y \geq 0, \ \forall m; \ s_i^b \geq 0, \ \forall i \tag{4}$$

Global Malmquist–Luenberger Indicator (GML)

This study constructs the GML index (*Gtfp*) through directional distance function SBM to overcome the disadvantage of the ML index often having no solution when solving linear programming. The GML index is further divided into the technical efficiency (*Geffch*) index and technical progress (*Gtech*) index. The specific decomposition of the model is as follows:

$$Gtfp_t^{t+1} = \frac{1 + \overrightarrow{S_V^G}\left(x^t, y^t, b^t; g^x, g^y, g^b\right)}{1 + \overrightarrow{S_V^G}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^x, g^y, g^b\right)} = geffch_t^{t+1} \times gtech_t^{t+1} \tag{5}$$

$$geffch_t^{t+1} = \frac{1 + \overrightarrow{S_V^t}\left(x^t, y^t, b^t; g^x, g^y, g^b\right)}{1 + \overrightarrow{S_V^{t+1}}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^x, g^y, g^b\right)} \tag{6}$$

$$gtech_t^{t+1} = \frac{\left[1 + \overrightarrow{S_V^G}\left(x^t, y^t, b^t; g^x, g^y, g^b\right)\right] \Big/ \left[1 + \overrightarrow{S_V^t}\left(x^t, y^t, b^t; g^x, g^y, g^b\right)\right]}{\left[1 + \overrightarrow{S_V^G}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^x, g^y, g^b\right)\right] \Big/ \left[1 + \overrightarrow{S_V^{t+1}}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^x, g^y, g^b\right)\right]} \tag{7}$$

where the GML index (*Gtfp*) represents the relative change value of $t+1$ based on t period, $\overrightarrow{S_V^t}\left(x^t, y^t, b^t; g^x, g^y, g^b\right)$ and $\overrightarrow{S_V^G}\left(x^t, y^t, b^t; g^x, g^y, g^b\right)$ represent current and Global SBM distance functions, respectively. The GML and its components can be interpreted as follows: i) GML >0 represents the improvement of industrial green transformation; ii) GML < 0 represents the deterioration of industrial green transformation; and iii) GML = 0 represents that industrial green transformation has not changed.

Existing literature generally believes that changes in industrial green technology should be measured by changes in total factor productivity, and usually decomposes GML into technological changes and efficiency changes based on the measurement principle. The change in industrial technology may not only occur from the absorptive capacity of foreign technology and a good foreign production management system but also manifest in the introduction of new technology and technological innovation. Hence, this study considers the GML index to measure industrial green transformation.

Empirical Model

Technological innovation and technology introduction are two important factors influencing the industrial green transformation of resource-based cities. To study the influence of technological innovation and technology introduction on the efficiency of industrial green transformation, this study constructed an econometric model of efficiency and influencing factors of green transformation in resource-based cities as follows:

$$\mathrm{GML}_{it} = \alpha_0 + \alpha_1\mathrm{TI}_{it} + \alpha_2\mathrm{FTI}_{it} + \alpha_3\mathrm{PGDP}_{it} + \alpha_4\mathrm{MD}_{it} + \alpha_5\mathrm{HC}_{it} + \alpha_6\mathrm{ER}_{it} + \alpha_7\mathrm{NET}_{it} + c_i + \mu_{it} \tag{8}$$

where i represents industry, t represents the time, c_i is the city individual fixed effect that does not change with time, and μ_{it} represents the error term. The dependent variable is indexing efficiency of industrial green transformation of resource-based cities, that is, GML. The econometric model has the year 2003 as the base period and converts it to a cumulative growth index.

The existing literature usually constructs the multiplicative term of human capital and foreign investment participation (Xu, 2000) or the multiplicative term of R&D and foreign investment participation (Kokko et al., 1996) to test the impact of local learning and absorption capacity on foreign technology spillovers. The absorptive capacity includes not only the ability to absorb foreign technology but also the ability to imitate learning. Therefore, to investigate whether technology introduction will promote the impact of technological innovation on the industrial green transformation of resource-based cities, this study constructs the multiplicative term of technological innovation and technology introduction (TI∗FTI). The specific form is as follows:

$$\mathrm{GML}_{it} = \beta_0 + \beta_1\mathrm{TI}_{it} + \beta_2\mathrm{FTI}_{it} + \beta_3\mathrm{TI}_{it}*\mathrm{FTI}_{it} + \beta_4\mathrm{PGDP}_{it} + \beta_5\mathrm{MD}_{it} + \beta_6\mathrm{HC}_{it} + \beta_7\mathrm{ER}_{it} + \beta_8\mathrm{NET}_{it} + c_i + \mu_{it} \tag{9}$$

As we know, FTI reflects the digestion, absorption, learning, and imitation of imported technology by local enterprises, and does not focus on the improvement of imported technology. The multiplicative term of technological innovation and technology introduction (TI∗FTI) represents the interactive effects of technological innovation and technology. TI∗FTI may not only indicate the digestion and absorption of imported technology, and learning and imitation of local enterprises, but also through investment in technological innovation, which increases the digestion and absorption of imported technology, reflecting in the improvement of imported technology. Therefore, TI∗FTI includes not only simple imitation but also independent innovation based on introduction and absorption imitation.

Many economic and social phenomena are continuous and interrelated. In the econometric model, the variables are autoregressive and interactive. For example, the present level of industrial green transformation may affect the next level of such transformation. Meanwhile, technological innovation and technology introduction may not only promote industrial green transformation but also may be the result of such transformation. Therefore, it is necessary to solve the endogeneity problem of ordinary panel model estimation. The static panel model **Eqs. (8)** and **(9)** are modified to the dynamic model **Eqs. (10)** and **(11)**, which contain the first order of the explained variables. The final model is as follows:

$$\mathrm{GML}_{it} = \alpha_0 + \varphi\mathrm{GML}_{i,t-1} + \alpha_1\mathrm{TI}_{it} + \alpha_2\mathrm{FTI}_{it} + \alpha_3\mathrm{PGDP}_{it} + \alpha_4\mathrm{MD}_{it} + \alpha_5\mathrm{HC}_{it} + \alpha_6\mathrm{ER}_{it} + \alpha_7\mathrm{NET}_{it} + c_i + \mu_{it} \tag{10}$$

TABLE 1 | Parameters of industrial green transformation.

Variable classification	Variable symbol	Variable definitions
Factor input	LCI	Sum of the number of mining industry employees, manufacturing industry employees, power gas and water supply employees
	CS	Total fixed assets of industrial enterprises
	IEC	Industrial electricity consumption
	IWC	Industrial water consumption
Expected output	GIO	Gross value of industrial output
Unexpected output	SE	Industrial smoke and dust emissions
	DE	Industrial sulfur dioxide emissions
	WE	Industrial wastewater emissions

$$\begin{aligned}\mathrm{GML}_{it} = {} & \beta_0 + \tau \mathrm{GML}_{i,t-1} + \beta_1 \mathrm{TI}_{it} + \beta_2 \mathrm{FTI}_{it} + \beta_3 \mathrm{TI}_{it} * \mathrm{FTI}_{it} \\ & + \beta_4 \mathrm{PGDP}_{it} + \beta_5 \mathrm{MD}_{it} + \beta_6 \mathrm{HC}_{it} + \beta_7 \mathrm{ER}_{it} + \beta_8 \mathrm{NET}_{it} \\ & + c_i + \mu_{it}\end{aligned} \tag{11}$$

Variable and Definition

Industrial Green Transformation

We use the GML index to measure the industrial green transformation of resource-based cities. According to traditional economic growth theory, the basic variables of production function are capital, labor, technology, and output level. However, Weitzman (1995) considers that economic growth mainly includes human capital, physical capital, and natural capital, and proposes that the environment is an important natural capital. This present study considers the rigid constraints of resources and environment of resource-based cities on the scale and speed of industrial economic development, and includes resources and environment in the analysis frame of industrial economic growth. Hence, the investigators constructed the correlative indexes of the expected output, unexpected output, and factor inputs as follows:

Factor inputs: Labor capital investment (LCI), scholars generally use the annual average number of industrial employees to measure, considering that the industrial sector mainly includes the mining industry, manufacturing industry, power, gas and water production, and supply industry. This study uses the sum of the number of mining industry employees, manufacturing industry employees, power gas, and water supply employees (Zhang, et al., 2011) to measure industrial labor input. For capital stock (CS), the investigators used the total fixed assets of industrial enterprises above a designated size for measurement. For energy input (EI), considering that energy consumption and water resource consumption are not the main sources of expected output and it is difficult to obtain the total energy consumption of industry, this study used industrial electricity consumption (IEC) and industrial water consumption (IWC) for the measurement. Expected output: This study sets the gross value of industrial output (GIO) as expected output. Unexpected output: considering the prominent problems of air pollution and water pollution due to industrial development, to measure industrial green transformation comprehensively, the investigators selected industrial smoke and dust emissions (SE), industrial sulfur dioxide emissions (DE), and industrial wastewater emissions (WE) as the unexpected output. **Table 1** summarizes the parameters of industrial green transformation.

Independent Variable

Technological progress is the core driving force in improving the industrial green transformation of resource-based cities. In the long term, the main ways to promote production technology are to increase investment in technological innovation, improve the output of technological innovation (such as patents and scientific papers), and increase the strength of technology introduction. Hence, the core independent variables mainly include technological innovation and technology introduction.

1) Technological Innovation: Technological innovation is a basic method of enhancing resource efficiency and upgrading industrial structure. In general, the existing research reflects the measurement of technological innovation in three aspects. 1) Measuring technological innovation from the perspective of technological innovation investment, scholars mainly adopt R&D expenditure and government investment in science and technology (Kontolaimou et al., 2016). 2) Measured from the perspective of technological innovation output, the variables include patent (Griliches, 1990), product innovations (Cruz-Cazares et al., 2013), and process innovations (Akgün et al., 2009). 3) Constructing a comprehensive index to evaluate and measure technological innovation, for example, measuring technological innovation from two aspects of input and output (Guo et al., 2017). This present study considered the availability and representativeness of data comprehensively, and the investigators used the proportion of science and technology investment to GDP (TI) for the measurement.

2) Technology Introduction: Technology introduction mainly consists of three channels as follows: technology trade, import, and FDI. In most cases, technology transfer Congress controls the trade of advanced technology to maintain its monopoly position. Most of the technology transferred through patents is mature and declining technology. Furthermore, information asymmetry makes it difficult for technology purchasers to acquire all technologies. Imported products may obtain more advanced technology than through technology transfer. However, information asymmetry makes it difficult for importing countries to obtain core technologies through "reverse engineering." For FDI, to occupy the investment market, multinational enterprises may adopt advanced technology for production to gain competitive advantage. Simultaneously, employees of multinational enterprises may flow to local enterprises, and local enterprises will absorb and digest relevant technologies to achieve technological progress. Therefore, FDI is an important method of introducing technology (Blomstrom and Kokko, 2001). The technology spillover of FDI will continuously improve the level of clean energy technology and output levels of local enterprises (Perkins and Neumayer, 2008). However, strict foreign environmental regulations and policies may force enterprises with high levels of

TABLE 2 | Variables' definition.

Variable classification	Variable symbol	Variable definitions
GML	Factor input	Labor capital investment, capital stock, energy input
	Expected output	The gross value of industrial output
	Unexpected output	Industrial smoke and dust emissions, industrial sulfur dioxide emissions and industrial wastewater emissions
Independent variable	TI	Ratio of science and technology investment to GDP
	FTI	Ratio of actual FDI to investment in social fixed assets
Control variable	PGDP	Local per capita GDP, take the natural logarithm
	MD	Ratio of urban individual and private economic employees To the total employment
	HC	Ratio of number of higher education to total population
	ER	Urban residents' disposable, take the natural logarithm
	NET	Number of internet users, take the natural logarithm

energy consumption and pollution to move to developing countries (Deng and Xu, 2015). The investigators used the proportion of actual FDI in the fixed investment of the whole society (FTI) for the measurement.

Control Variable

1) Regional economic development level (PGDP): The growth of the economic aggregate would lead to the adjustment of industrial sectors, promote the transformation of industrial structure, and ultimately improve the efficiency of regional industrial green transformation (Song et al., 2013). This present study uses the local per capita GDP as a proxy index to indicate the level of regional economic development, and the form of logarithm to increase the stationarity of data and eliminate any possible heteroscedasticity. 2) Marketization degree (MD): The higher the degree of marketization, the more conducive is the flow of factors of production to industries with high efficiency. This study measures MD by the proportion of urban individual and private economic employees in total employment. 3) Human capital (HC): Human capital is the core element of technological innovation in industrial enterprises, and education is the guarantee of human capital formation. This study uses the ratio of residents with higher education and the total population in the region for the measurement. 4) Environmental regulation (ER): This is an important factor affecting the innovation of green technology. Antweiler et al. (2001) consider it to be highly correlated with residents' income level. Therefore, this study chooses the urban residents' disposable income as the alternative variable, and uses the logarithmic form to increase the stationarity of the data and eliminate any possible heteroscedasticity. 5) Level of information technology (NET): Selecting the number of Internet users as a measure of the level of information technology, the same form of logarithm. **Table 2** summarizes the variables and their definitions.

TABLE 3 | Descriptive statistics.

Variable	N	Mean	St. dev	Min	Max
LCI	1,610	105,865	74,542	5,600	449,600
CS	1,610	5,387,745	6,468,444	86,045	64,988,164
IEC	1,610	378,827	526,217	1,016	5,195,783
IWC	1,610	5,670	7,910	74	84,440
GIO	1,610	12,709,053	17,734,412	84,543	153,678,749
SE	1,610	43,105	178,135	139	5,168,812
DE	1,610	4,984	4,339	122	29,365
WE	1,610	64,632	56,122	612	337,164
GML	1,610	1.0211	0.1148	0.5721	1.8343
TI	1,610	0.0015	0.0056	4.03E − 08	0.2089
FTI	1,610	0.0238	0.0302	0	0.2824
PGDP	1,610	9.9644	0.8195	4.5951	12.4564
MD	1,610	0.8390	0.7989	0.0066	18.8056
HC	1,610	0.0081	0.0074	0.00003	0.0531
ER	1,610	9.5888	0.4922	8.1303	10.7319
NET	1,610	11.9935	1.05458	8.2815	14.6220

Data and Descriptive Statistics

Based on the Chinese government's plans in 2013 (Council, 2013), and considering the pertinence of the research, continuity of data availability, and comparability between cities, this study selects the data of 115 resource-based cities in China from 2003 to 2016, with 1,610 observations. We derive the related variables from the China City Statistical Yearbook, the China Environment Statistical Yearbook, and the statistical bulletins of national economic and social development in various cities. Meanwhile, the study also uses dataset sources from the Economy Prediction System (EPS) database.[3] Furthermore, this study uses the interpolation method to complete some missing values in the variables. **Table 3** gives a statistical description of the main variables.

EMPIRICAL RESULTS AND DISCUSSION

Basic Model Regression Results

According to the existing literature, there are two methods for estimating dynamic panel models: the difference-GMM (D-GMM) estimation and the system-GMM (S-GMM) estimation. The weak instrumental variables in the D-GMM estimation process may result in serious limited sample bias. However, the S-GMM estimation was based on the D-GMM estimation, which takes the lagged variable of the difference item as the level value of the instrumental variable. Increasing the number of tool variables can effectively resolve the problem of weak tool variables, and the endogenous problem in the model. Simultaneously, the S-GMM estimation can improve estimation efficiency and estimate variable coefficients that do not change

[3]EPS global statistical data/analysis platform is a professional data service platform founded by Beijing Forecast Information Technology Co., Ltd. The EPS data platform has built a series of professional databases, including World Trade Data, China Industry Business Performance Data, the China City Statistical Yearbook, and the China Environment Statistical Yearbook. Available online at http://olaptest.epsnet.com.cn/

TABLE 4 | Estimation results of dynamic panel model.

Variable	GML			
	(1)	(2)	(3)	(4)
TI	0.473***		0.940**	0.071
	(8.98)		(10.86)	(0.25)
FTI		−0.293***	−0.337***	−0.346***
		(−20.52)	(−13.10)	(−8.55)
TI*FTI				120.456***
				(7.76)
PGDP	0.042***	0.031***	0.446***	0.026***
	(21.3)	(8.22)	(18.27)	(7.31)
MD	0.003**	0.003**	0.002	0.004
	(2.51)	(2.54)	(1.74)*	(1.63)
HC	2.046***	2.201***	1.344***	1.590***
	(20.15)	(10.05)	(10.79)	(10.50)
ER	−0.156***	−0.132***	−0.156***	−0.137***
	(−44.52)	(−24.85)	(−28.99)	(−22.97)
NET	0.028***	0.020***	0.024***	0.024***
	(14.26)	(15.23)	(11.98)	(8.83)
AR (1)	−6.59	−6.590	−6.553	−6.502
	(0.000)	(0.000)	(0.000)	(0.000)
AR (2)	−0.959	−0.907	−1.157	−1.145
	(0.338)	(0.364)	(0.258)	(0.252)
Sargan	107.172	110.609	110.162	98.540
	(0.637)	(0.546)	(0.558)	(0.327)

Notes: The value in brackets is the value of t., **, ***, respectively, indicating that the estimated parameters pass the statistical significance test at the 10, 5, and 1% levels, respectively.*

with time. This study mainly used S-GMM to estimate the dynamic panel model that technological innovation and technology introduction affect the green efficiency of resource-based city industry, with **Table 4** presenting the results.

The diagnosis test shows that the results of AR 1) and AR 2) indicate that the first-order residual has a first-order serial correlation; however, no second-order sequence correlation exists; that is, the S-GMM estimator is consistent. Furthermore, the results of Sargan test prove that the selected instrumental variables are reasonable and effective.

First, this study analyzes the effects of technological innovation on industrial green transformation of resource-based cities. The regression results indicate that technological innovation has a significant positive impact on industrial green development. This is probably because the Chinese government has continuously increased investment in scientific and technological research in recent years to improve the independent innovation capabilities of enterprises. Consequently, technological innovation improves the efficiency of enterprise resource utilization, which promotes the green transformation of industry in resource-based cities. Simultaneously, Chen et al. (2016) also show that technological innovation can promote the green development of China's industry.

Second, the results show that technology introduction has a significant inhibitory effect on the industrial green transformation of resource-based cities. The "Pollution Haven Hypothesis" also proves this conclusion. This can be explained in two parts: 1) resource-based cities in China have cheap resources and immature environmental regulations, which attract foreign investment to their high energy consumption and heavy-polluting industries (Yan et al., 2019) and 2) technology introduction may worsen competing domestic companies, and even crowd them out from the market (Hu and Jefferson, 2002). The competitive pressure from foreign investment has squeezed the market share of local enterprises, reducing their profits and R&D capacity. Consequently, it hinders the technological progress of local enterprises and restricts the industrial green transformation of resource-based cities.

Third, the interactions between technological innovation and technology introduction have significantly increased the industrial green transformation of resource-based cities. The results show that technological innovation induced by technology introduction does benefit to improving the efficiency of industrial green transformation in China's resource-based cities. The increasing investment in scientific research has resulted in technological innovation, which promotes the transformation of green industries in resource-based cities through the absorption and imitation of foreign technologies. Increasing investment in scientific research and technological innovation can improve the technological level of enterprises and reduce the technological gap with foreign-funded enterprises, accelerating the transfer of foreign knowledge, technology, and management experience (Azman-Saini et al., 2010).

In addition, this study also analyzes the impact of other control variables on the industrial green transformation of resource-based cities. The regression results show that 1) the regional economic development level (PGDP) of each model shows a significant positive impact. Cities with high economic development levels tend to have stronger financial resources and can use more resources for the green transformation and development of urban industry (Yan et al., 2019). 2) Marketization degree (MD) is always beneficial in promoting green transformation, and the market competition mechanism helps enterprises change the direction of green production, by

TABLE 5 | Results of the robustness test.

Variable	Technical efficiency (TE)		Technical progress (TP)	
	(1)	(2)	(3)	(4)
TI	0.392***	0.249***	0.713**	0.155
	(12.28)	(3.80)	(4.05)	(0.29)
FTI	−0.032**	−0.080***	−0.396***	−0.350***
	(−3.09)	(−6.92)	(−8.18)	(−9.08)
TI*FTI		58.033***		149.538***
		(13.13)		(5.95)
Controlled variables	Yes	Yes	Yes	Yes
AR (1)	−6.770	−6.790	−7.651	−7.687
	(0.000)	(0.000)	(0.000)	(0.000)
AR (2)	−1.716	−1.708	−1.287	−1.233
	(0.086)	(0.088)	(0.198)	(0.217)
Sargan	106.167	104.419	98.332	107.907
	(0.638)	(0.706)	(0.333)	(0.901)

Notes: The value in brackets is the value of t., **, ***, respectively, indicating that the estimated parameters pass the statistical significance test at the 10, 5, and 1% levels, respectively.*

conforming to market demand. 3) The coefficient before HC is significantly positive in all models. As the central link of green technological innovation, the level of HC has an important role in promoting the green industrial transformation of resource-based cities, indicating that HC is an important source of industrial green efficiency improvement in China. 4) Environmental regulation (ER) has a significant positive effect on industrial green transformation of resource-based cities. Other studies on the relationship between environmental policy and industrial green transformation also give consistent results (Lanoie et al., 2011). There may be two reasons. First, the response of local governments and industries to national environmental regulation may be heterogeneous (Zhu et al., 2014). Second, the poor implementation mode and quality of environmental regulations lead to negative impact on green transformation (Jin et al., 2019). 5) The level of information technology (NET) also has a significant positive effect. An improvement in the level of information technology is conducive to the promotion of industrial green transformation of resource-based cities.

Robustness Test

Due to the GML index cannot effectively consider the impact of technological innovation and technology introduction on the technical efficiency and technological progress in promoting total factor productivity. Consequently, this study uses technical efficiency and technological progress index as explanatory variables to examine the impact of technological innovation and technology introduction regression on the industrial green transformation of resource based. **Table 5** shows the specific results.

Under the significance level of at least 1%, the result shows that the technological innovation coefficient is positive, which indicates that technological innovation promotes the green industrial technical efficiency and technological progress of resource-based cities in China. This also shows that technological innovation promotes the industrial green transformation of resource-based cities by improving industrial technical efficiency and technological progress. Meanwhile, the influence of technology introduction on technical efficiency and technological progress is significantly negative. It passes the significance test at the 1% level, indicating that technology introduction will increase the negative influence on technical efficiency and technological progress at the present stage, which is also consistent with previous conclusions. Thus, technology introduction does not bring obvious knowledge and technology spillovers (Li et al., 2017) to resource-based cities. Finally, under the 1% significance level, the interactions between technological innovation and technology introduction promote the improvement of technical efficiency and technological progress of industrial green transformation. This shows that technology introduction can increase the impact of technological innovation on the technical efficiency and technological economy of industrial green transformation. Local enterprises have promoted the improvement in efficiency of the green transformation of resource-based cities by digesting and absorbing technology. This is also consistent with previous conclusions. In conclusion, the sign and significance level of regression coefficients of main variables are essentially the same as the basic model, which proves that the above results are robust.

Heterogeneity Test

According to the "Plan of Sustainable Development for Resource-based Cities in China (2013–2020)" (Council, 2013) issued by the State Council of China, the leading industries of resource-based cities mainly exploit and process natural resources such as minerals and forests in the region. Simultaneously, the state divides resource-based cities into growth-type, maturity-type, recession-type, and regeneration-type, according to the resource support capacity and sustainable development ability. Therefore, according to this classification, this study tests the heterogeneity of technological innovation and technology introduction on the industrial green transformation of different resource-based cities. **Table 6** shows that the result of AR (1), AR (2), and Sargan tests in all models pass the test

TABLE 6 | Results of the heterogeneity test.

Variable	Growth-type		Maturity-type		Recession-type		Regeneration-type	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TI	15.424*	−48.127	9.185***	−2.229***	43.718*	17.201**	2.496	−128.541
	(1.65)	(−0.27)	(11.62)	(−7.77)	(1.85)	(2.42)	(0.37)	(−1.92)*
FTI	3.780	−9.839	−0.054	−0.206***	−0.183	−0.663	0.644*	−3.708
	(0.78)	(−1.06)	(−0.59)	(−3.43)	(−0.18)	(−1.13)	(1.69)	(−1.64)*
TI*FTI		4,643.689		195.43***		−579.049*		3,270.301*
		(1.01)		(9.73)		(−1.76)		(1.99)
Controlled variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR (1)	−2.00	−1.75	−5.11	−5.179	−2.13	−2.69	−6.49	−1.81
	(0.045)	(0.080)	(0.000)	(0.000)	(0.033)	(0.007)	(0.000)	(0.071)
AR (2)	0.58	1.25	−0.86	−0.559	0.12	−2.17	−0.05	−0.13
	(0.563)	(0.212)	(0.387)	(0.576)	(0.908)	(0.030)	(0.963)	(0.899)
Sargan	164.70	100.67	56.98	54.759	281.77	33.62	134.47	97.38
	(0.341)	(0.300)	(0.476)	(0.597)	(0.242)	(0.630)	(0.104)	(0.385)

Notes: The value in brackets is the value of t., **, ***, respectively, indicating that the estimated parameters pass the statistical significance test at the 10, 5, and 1% levels, respectively.*

conditions, indicating that the design of the model is reasonable, and the estimation using the system GMM is effective.

In **Table 6**, the coefficients of different types of resource-based cities before technological innovation are positive, indicating the importance of increasing investment in scientific and technological research and development for the sustainable development of resource-based cities. Therefore, technological innovation can promote the industrial green efficiency of different types of resource-based cities. This proves that increasing investment in technological innovation and promoting production technology are important methods to promote such green transformation in China. In terms of technology introduction, different types of resource-based cities show strong heterogeneity. The technology introduction coefficient of renewable resource-based cities is significantly positive, indicating that renewable resource-based cities can significantly improve the efficiency of regional industrial green transformation. Since regeneration-type essentially eliminates resource dependence, they also have higher levels of opening up and technological innovation. Therefore, renewable resource-based cities can improve the production technology and energy efficiency of local enterprises through foreign technology spillovers. The interactions between technological innovation and technology introduction show significantly positive coefficients of regeneration-type and maturity-type resource-based cities. However, the coefficient before the interactions between technological innovation and technology introduction of recession-type resource-based cities is significantly negative. The results show that technological innovation induced by technology introduction is not conducive to the industrial green transformation improvement. Recession-type cities face problems of resource depletion and relatively backward economic development. This may lead to vicious competition between foreign-funded enterprises and local enterprises, and this may not be conducive to the improvement of regional industrial green efficiency. The above analysis shows that the impact of technological innovation and technology introduction of different types of resource-based cities in China on industrial green transformation has strong heterogeneity.

CONCLUSION

Based on the panel data of 115 resource-based cities in China from 2003 to 2016, this study uses the S-GMM method to empirically analyze the impact of technological innovation and technology introduction on the industrial green transformation of resource-based cities. We draw the following conclusions:

First, technological innovation can improve the level of industrial green transformation of resource-based cities in China. In recent years, the government has continuously increased investment in scientific research, enabling enterprises to improve existing production technologies, energy-conserving techniques, and carbon-reduction technologies (Li et al., 2017). Consequently, energy efficiency improves, pollutant emissions reduce, and the industrial structure optimizes (Wang et al., 2011), which stimulates the industrial green transformation of resource-based cities. Simultaneously, it is necessary for China to implement science and technology innovation strategies and improve regional technological innovation. This study contributes to research on clean energy technologies in resource-based cities, including solar energy, renewable energy, and more advanced and cleaner fossil fuels, which promote the energy efficiency and industrial green transformation of resource-based cities. This discovery also provides a feasible path for industrial green transformation of resource-based cities in developing countries around the world.

Second, technology introduction inhibits the improvement of industrial green transformation level in resource-based cities. There are three possible reasons for this result. 1) Lax environmental regulation in resource-based cities attracts polluting foreign capital (Zhang and Zhou, 2016). This increases the need for energy consumption in resource-based cities, which hinders their green transformation. 2) Foreign investment would employ local technical personnel with high salaries, which may lead to the reverse spillover of technical knowledge to foreign-funded enterprises and reduce the technological innovation ability of local enterprises. It reduces the ability of local companies to develop clean technologies, which fail to improve the resource utilization efficiency of resource-based cities. 3) To gain competitive advantage and maintain a monopoly, foreign-funded enterprises are generally unwilling to transfer their core technologies (Chen et al., 2018a). Developed countries even transfer obsolete technologies to developing countries. Therefore, enterprises cannot obtain advanced clean technology through technology introduction, which cannot effectively improve the energy efficiency and the energy consumption structure of resource-based cities. Consequently, technology introduction is not conducive to the industrial green transformation of resource-based cities.

Third, technology introduction has increased the role of technological innovation in promoting the industrial green transformation of resource-based cities. Enterprises can digest and absorb technology introduced in resource-based cities, which would develop better performing products of higher quality, and obtain more market share than innovators and simple imitators (Shankar et al., 1998). In addition, increasing investment in scientific research and technological innovation can improve the imitative learning and technological innovation capabilities of resource-based urban enterprises. The improvement in enterprises' learning ability can effectively digest and absorb foreign-funded technology, enabling local enterprises to obtain advanced clean technology. This can improve the energy efficiency of resource-based cities and enable the green transformation of resource-based industries.

In addition, the heterogeneity test results show that the impact of technological innovation and technology introduction of different types of resource-based cities on industrial green transformation is different. Specifically, only the technology introduction of regeneration-type resource-based cities can significantly promote the industrial green efficiency of the region. Because regeneration-type resource-based cities have a more mature industrial structure and energy structure, they can effectively absorb the advanced clean technology introduced by technology introduction. Therefore, technology introduction can promote the industrial green transformation of regeneration-type resource-based cities. Simultaneously, for the interactions between technological innovation and technology introduction, technology introduction can effectively increase the impact of technological innovation on the green transformation of regeneration-type and maturity-type resource-based cities. This may be due to a relatively mature industrial structure and energy structure system of regeneration-type and maturity-type resource-based cities. They can continue to promote the green development of the industry by digesting, absorbing, and imitating foreign technologies. However, the coefficient before the interactions between technological innovation and technology introduction of recession-type resource-based cities is significantly negative, indicating that technology introduction will reduce the impact of technological innovation on green transformation. Because of the excessive development of resources and the relatively lagging industrial structure and energy structure in recession-type resource-based cities, local enterprises cannot improve production technology and energy efficiency by absorbing and imitating foreign technologies.

These conclusions have clear policy implications for choosing the path of technological progress in facilitating the industrial green transformation of resource-based cities in China. Simultaneously, the conclusions has certain reference significance for the sustainable development of resource-based cities in developing countries around the world.

First, technological innovation is an important strategic measure to improve the industrial green transformation of resource-based cities and achieve high-quality development. First, governments of developing countries should increase the funds and policy support for the green transformation of resource-based industries, while guiding and encouraging industrial enterprises to adopt green and clean technologies. At the same time, the government can use innovative governance models to promote the construction of a safe, efficient, clean, low-carbon, and green energy system. Second, by increasing investment in basic research, focusing on the self-accumulation of technological innovation knowledge, and seeking original technological innovation, it is possible to achieve competitiveness in the new international environment. Third, to improve the positive effect of technological innovation investment on the industrial green transformation of resource-based cities, the government also needs to improve the technological innovation system, introduce market mechanism, strengthen the protection of intellectual property rights, improve energy efficiency, and actively adjust the industrial structure. Furthermore, policies should encourage the research and development of clean and renewable energy technologies. In terms of energy structure, continuously increasing the proportion of new energy sources such as wind and solar energy and reducing the proportion of fossil fuel consumption will improve the level of green transformation of resource-based cities.

Second, policymakers of developing countries should continue to adhere to the strategy of introducing advanced technology using foreign capital. The technology spillover of foreign capital is an important factor in promoting the industrial green transformation of resource-based cities. China's resource-based cities should strive to improve the technology content of foreign investment, encourage developed countries in Europe and the United States, to invest, encourage foreign enterprises to use advanced technologies in China, and encourage foreign investment to undertake research and development activities. Simultaneously, the governments of resource-based cities should encourage enterprises to promote the introduction, assimilation, and re-innovation of innovation capability (Sun et al., 2012). Independent innovation and imitation innovation can not only improve the competitiveness of local enterprises but also encourage foreign enterprises to transfer technology. Furthermore, resource-based cities should introduce advanced clean energy technologies from abroad, improve the efficiency of clean energy utilization, optimize the industrial structure, and reduce dependence on high-carbon energy.

Finally, policymakers of developing countries should encourage enterprises to strengthen the digestion and absorption of introduced technology and lay a solid foundation for independent innovation, which reduces the technological gap with developed countries. Meanwhile, policymakers should encourage enterprises to integrate and imitate innovation, to accelerate technological innovation knowledge at a lower cost in a short period of time. Based on the introduction–digestion and absorption–imitation innovation, it is necessary to strengthen the ability of independent innovation and improve the level of independent innovation. Consequently, this will develop a new mode of introduction–digestion, absorption–imitation, and innovation-independent innovation. Finally, different policy support can be adopted for different types of resource-based cities. Resource-based cities should strengthen their ability to absorb technology, especially recession-type cities, which will improve low energy use efficiency in resource-based cities.

This study has room for further development and expansion. First, we mainly use a single index for the measurement of technological innovation and technology introduction. Therefore, to obtain more instructive research conclusions, we can consider expanding the indicator system and using more types of indicators. Second, we have analyzed resource-based cities with different attributes (i.e., coal and oil) into a unified framework. Future studies can consider collecting data on resource-based cities with different resource attributes for empirical research, thereby investigating the influencing factors of industrial green transformation of resource-based cities with different resource attributes.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. These data can be found here: China City Statistical Yearbook and Economy Prediction System (EPS) database.

AUTHOR CONTRIBUTIONS

WX performed drafting and writing, TY performed supervision and editing, SX performed supervision and editing, and FC performed editing.

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REFERENCES

Acharyya, J. (2009). FDI, growth and the environment: evidence from India on CO_2 emission during the last two decades. *J. Econ. Dev.* 34, 43. doi:10.35866/caujed.2009.34.1.003

Adom, P. K., and Adams, S. (2020). Technical fossil fuel energy efficiency (TFFEE) and debt-finance government expenditure nexus in Africa. *J. Clean. Prod.* 271, 122670. doi:10.1016/j.jclepro.2020.122670

Akgün, A. E., Keskin, H., and Byrne, J. (2009). Organizational emotional capability, product and process innovation, and firm performance: an empirical analysis. *J. Eng. Technol. Manag.* 26 (3), 103–130. doi:10.1016/j.jengtecman.2009.06.008

Albornoz, F., Cole, M. A., Elliott, R. J., and Ercolani, M. G. (2009). In search of environmental spillovers. *World Econ.* 32, 136–163. doi:10.1111/j.1467-9701.2009.01160.x

Antweiler, W., Copeland, B. R., and Taylor, M. S. (2001). Is free trade good for the environment?. *Am. Econ. Rev.* 91, 877–908. doi:10.1257/aer.91.4.877

Azman-Saini, W. N. W., Law, S. H., and Ahmad, A. H. (2010). FDI and economic growth: new evidence on the role of financial markets. *Econ. Lett.* 107, 211–213. doi:10.1016/j.econlet.2010.01.027

Barrell, R., and Pain, N. (1999). Domestic institutions, agglomerations and foreign direct investment in Europe. *Eur. Econ. Rev.* 43, 925–934. doi:10.1016/S0014-2921(98)00105-6

Birdsall, N., and Wheeler, D. (1993). Trade policy and industrial pollution in Latin America: where are the pollution havens?. *J. Environ. Dev.* 2, 137–149. doi:10.1177/107049659300200107

Blomstrom, M., and Kokko, A. (2001). Foreign direct investment and spillovers of technology. *Int. J. Technol. Manag.* 22, 435–454. doi:10.1504/IJTM.2001.002972

Bo, L., and Hasnat, D. (2017). Efficiency differences among China's resource-based cities and their determinants. *Resour. Policy* 51, 31–38. doi:10.1016/j.resourpol.2016.11.003

Chen, C., Han, J., and Fan, P. (2016). Measuring the level of industrial green development and exploring its influencing factors: empirical evidence from China's 30 provinces. *Sustainability* 8 (2), 153. doi:10.3390/su8020153

Chen, C., Lan, Q., Gao, M., and Sun, Y. (2018a). Green total factor productivity growth and its determinants in China's industrial economy. *Sustainability* 10, 1052. doi:10.3390/su10041052

Chen, W., Shen, Y., and Wang, Y. (2018b). Evaluation of economic transformation and upgrading of resource-based cities in Shaanxi province based on an improved TOPSIS method. *Sustainable Cities and Society* 37, 232–240. doi:10.1016/j.scs.2017.11.019

Cheng, Z., and Li, W. (2018). Independent R and D, technology introduction, and green growth in China's manufacturing. *Sustainability* 10, 311. doi:10.3390/su10020311

Chinese Academy of Social Sciences (CASS) (2011). A study on the green transformation of Chinese industry. *China Ind. Econ.* 4, 5–14. doi:10.19581/j.cnki.ciejournal.2011.04.001

Chung, S. (2014). Environmental regulation and foreign direct investment: evidence from South Korea. *J. Dev. Econ.* 108, 222–236. doi:10.1016/j.jdeveco.2014.01.003

Cole, M. A. (2003). Development, trade, and the environment: how robust is the environmental kuznets curve?. *Environ. Dev. Econ.* 8, 557–580. doi:10.1017/S1355770X0300305

Corssman, G., and Helpman, E. (1991). *Innovation and growth in the world economy*. Cambridge, MA: MIT Press.

Council T. S. (2013). The plan for the sustainable development of resource-based cities in China (2013–2020). China. Available online at: http://www.gov.cn/zwgk/2013-12/03/content_2540070.htm

Cruz-Cazares, C., Bayona-Saez, C., and Garcia-Marco, T. (2013). You can't manage right what you can't measure well: technological innovation efficiency. *Res. Pol.* 42, 1239–1250. doi:10.1016/j.respol.2013.03.012

Dam, L., and Scholtens, B. (2012). The curse of the haven: the impact of multinational enterprise on environmental regulation. *Ecol. Econ.* 78, 148–156. doi:10.1016/j.ecolecon.2012.04.011

Dean, J. M., Lovely, M. E., and Wang, H. (2009). Are foreign investors attracted to weak environmental regulations? Evaluating the evidence from China. *J. Dev. Econ.* 90, 1–13. doi:10.1016/j.jdeveco.2008.11.007

Deng, Y., and Xu, H. (2015). International direct investment and transboundary pollution: an empirical analysis of complex networks. *Sustainability* 7, 3933–3957. doi:10.3390/su7043933

Doytch, N., and Narayan, S. (2016). Does FDI influence renewable energy consumption? An analysis of sectoral FDI impact on renewable and non-renewable industrial energy consumption. *Energy Econ.* 54, 291–301. doi:10.1016/j.eneco.2015.12.010

Emrouznejad, A., and Yang, G.-L. (2016). CO_2 emissions reduction of Chinese light manufacturing industries: a novel RAM-based global Malmquist-Luenberger productivity index. *Energy Pol.* 96, 397–410. doi:10.1016/j.enpol.2016.06.023

Environmental Performance Index (EPI) (2018). Available online at: http://www.epi.yale.edu/

Feng, C., Wang, M., Liu, G.-C., and Huang, J.-B. (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

Fu, J., Xiao, G., Guo, L., and Wu, C. (2018). Measuring the dynamic efficiency of regional industrial green transformation in China. *Sustainability* 10, 628. doi:10.3390/su10030628

Fu, X., Pietrobelli, C., and Soete, L. (2011). The role of foreign technology and indigenous innovation in the emerging economies: technological change and catching-up. *World Dev.* 39, 1204–1212. doi:10.1016/j.worlddev.2010.05.009

Fukuyama, H., and Weber, W. L. (2009). A directional slacks-based measure of technical inefficiency. *Soc. Econ. Plann. Sci.* 43, 274–287. doi:10.1016/j.seps.2008.12.001

Griliches, Z. (1990). Patent statistics as economic indicators: a survey. *J. Econ. Lit.* 28, 1661–1707. doi:10.3386/w3301

Guo, L. L., Qu, Y., and Tseng, M.-L. (2017). The interaction effects of environmental regulation and technological innovation on regional green growth performance. *J. Clean. Prod.* 162, 894–902. doi:10.1016/j.jclepro.2017.05.210

He, S. Y., Lee, J., Zhou, T., and Wu, D. (2017). Shrinking cities and resource-based economy: the economic restructuring in China's mining cities. *Cities* 60, 75–83. doi:10.1016/j.cities.2016.07.009

Hu, A. G. Z., and Jefferson, G. H. (2002). FDI impact and spillover: evidence from China's electronic and textile industries. *World Econ.* 25, 1063–1076. doi:10.1111/1467-9701.00481

Hu, J., Pan, X., and Huang, Q. (2020a). Quantity or quality? The impacts of environmental regulation on firms' innovation-Quasi-natural experiment based on China's carbon emissions trading pilot. *Technol. Forecast. Soc. Change* 158, 120122. doi:10.1016/j.techfore.2020.120122

Hu, J., Wang, Z., Huang, Q., and Zhang, X. (2019). Environmental regulation intensity, foreign direct investment, and green technology spillover-an empirical study. *Sustainability* 11, 2718. doi:10.3390/su11102718

Hu, J., Wang, Z., Lian, Y., and Huang, Q. (2018). Environmental regulation, foreign direct investment and green technological progress—evidence from Chinese manufacturing industries. *Int. J. Environ. Res. Publ. Health* 15, 221. doi:10.3390/ijerph15020221

Hu, Y., Yan, T.-H., and Chen, F.-W. (2020b). Energy and environment performance of resource-based cities in China: a non-parametric approach for estimating hyperbolic distance function. *Int. J. Environ. Res. Public* 17, 4795. doi:10.3390/ijerph17134795

Jefferson, G. H., Huamao, B., Xiaojing, G., and Xiaoyun, Y. (2006). R&D performance in Chinese industry. *Econ. Innovat. N. Technol.* 15, 345–366. doi:10.1080/10438590500512851

Jin, W., Zhang, H.-q., Liu, S.-s., and Zhang, H.-b. (2019). Technological innovation, environmental regulation, and green total factor efficiency of industrial water resources. *J. Clean. Prod.* 211, 61–69. doi:10.1016/j.jclepro.2018.11.172

Jorgenson, A. K. (2009). Foreign direct investment and the environment, the mitigating influence of institutional and civil society factors, and relationships between industrial pollution and human health. *Organ. Environ.* 22, 135–157. doi:10.1177/1086026609338163

Kaika, D., and Zervas, E. (2013). The environmental kuznets curve (EKC) theory-Part A: concept, causes and the CO_2 emissions case. *Energy Pol.* 62, 1392–1402. doi:10.1016/j.enpol.2013.07.131

Kheder, S. B., and Zugravu, N. (2012). Environmental regulation and French firms location abroad: an economic geography model in an international comparative study. *Ecol. Econ.* 77, 48–61. doi:10.1016/j.ecolecon. 2011.10.005

Kokko, A., Tansini, R., and Zejan, M. C. (1996). Local technological capability and productivity spillovers from FDI in the Uruguayan manufacturing sector. *J. Dev. Stud.* 32 (4), 602–611. doi:10.1080/00220389608422430

Kokko, A. (1994). Technology, market characteristics, and spillovers. *J. Dev. Econ.* 43 (2), 279–293. doi:10.1016/0304-3878(94)90008-6

Kontolaimou, A., Giotopoulos, I., and Tsakanikas, A. (2016). A typology of European countries based on innovation efficiency and technology gaps: the role of early-stage entrepreneurship. *Econ. Modell.* 52, 477–484. doi:10.1016/j.econmod.2015.09.028

Lanoie, P., Laurent-Lucchetti, J., Johnstone, N., and Ambec, S. (2011). Environmental policy, innovation and performance: new insights on the porter hypothesis. *J. Econ. Manag. Strat.* 20, 803–842. doi:10.1111/j.1530-9134.2011.00301.x

Li, H., Long, R., and Chen, H. (2013). Economic transition policies in Chinese resource-based cities: an overview of government efforts. *Energy Pol.* 55, 251–260. doi:10.1016/j.enpol.2012.12.007

Li, K., and Lin, B. (2018). How to promote energy efficiency through technological progress in China?. *Energy* 143, 812–821. doi:10.1016/j.energy.2017.11.047

Li, L., Lei, Y., Pan, D., and Si, C. (2016). Research on sustainable development of resource-based cities based on the DEA approach: a case study of Jiaozuo, China. *Math. Probl Eng.* 2016, 1–10. doi:10.1155/2016/5024837

Li, W., Wang, W., Wang, Y., Wang, Y., and Qin, Y. (2017). Industrial structure, technological progress and CO_2 emissions in China: analysis based on the STIRPAT framework. *Nat. Hazards* 88, 1545–1564. doi:10.1007/s11069-017-2932-1

List, J. A., Millimet, D. L., Fredriksson, P. G., and McHone, W. W. (2003). Effects of environmental regulations on manufacturing plant births: evidence from a propensity score matching estimator. *Rev. Econ. Stat.* 85, 944–952. doi:10.1162/003465303772815844

Liu, B., Wang, J., Jing, Z., and Tang, Q. (2020). Measurement of sustainable transformation capability of resource-based cities based on fuzzy membership function: a case study of Shanxi Province, China. *Resour. Pol.* 68, 101739. doi:10.1016/j.resourpol.2020.101739

Long, R., Chen, H., Li, H., and Wang, F. (2013). Selecting alternative industries for Chinese resource cities based on intra- and inter-regional comparative advantages. *Energy Pol.* 57, 82–88. doi:10.1016/j.enpol.2012.10.047

Ma, Y., Yan, J., Sha, J., He, G., Song, C., Fan, S., et al. (2018). Dynamic simulation of the atmospheric environment improved by a focus on clean energy utilization of resource-based cities in China. *J. Clean. Prod.* 192, 396–410. doi:10.1016/j.jclepro.2018.04.247

Miao, C., Fang, D., Sun, L., and Luo, Q. (2017). Natural resources utilization efficiency under the influence of green technological innovation. *Resour. Conserv. Recycl.* 126, 153–161. doi:10.1016/j.resconrec.2017.07.019

Miao, C., Fang, D., Sun, L., Luo, Q., and Yu, Q. (2018). Driving effect of technology innovation on energy utilization efficiency in strategic emerging industries. *J. Clean. Prod.* 170, 1177–1184. doi:10.1016/j.jclepro.2017.09.225

Ministry of Industry and Information Technology (2016). Industrial green development plan (2016–2020). http://www.miit.gov.cn/n1146295/n1652858/n1652930/n3757016/c5143553/content.html

Mulatu, A., Gerlagh, R., Rigby, D., and Wossink, A. (2010). Environmental regulation and industry location in Europe. *Environ. Resour. Econ.* 45, 459–479. doi:10.1007/s10640-009-9323-3

Ngai, L. R., and Pissarides, C. A. (2007). Structural change in a multisector model of growth. *Am. Econ. Rev.* 97, 429–443. doi:10.1257/000282807780323460

OECD (2011b). *Fostering innovation for green growth*. Paris, France: OECD.

OECD (2011a). *Towards green growth: monitoring progress*. Paris, France: OECD.

Oh, D.-h. (2010). A global Malmquist-Luenberger productivity index. *J. Prod. Anal.* 34, 183–197. doi:10.1007/s11123-010-0178-y

Pearce, D. (2013). *Blueprint: greening the world economy*. New York, NY: Routledge.

Pearce, D. W., Markandya, A., and Barbier, E. (1989). *Blueprint for a green economy*. London, UK: Earthscan.

Perkins, R., and Neumayer, E. (2008). Fostering environment efficiency through transnational linkages? Trajectories of CO_2 and SO_2, 1980–2000. *Environ. Plann.* 40, 2970–2989. doi:10.1068/a4089

Porter, M. E. (1991). Towards a dynamic theory of strategy. *Strat. Mgmt. J.* 12, 95–117. doi:10.1002/smj.4250121008

Rezza, A. A. (2013). FDI and pollution havens: evidence from the Norwegian manufacturing sector. *Ecol. Econ.* 90, 140–149. doi:10.1016/j.ecolecon.2013.03.014

Schumpeter, J. (1934). *The theory of economic development: an inquiry into profits, capital, credit, interest, and the business cycle*. Cambridge, MA: Harvard University Press.

Shankar, V., Carpenter, G. S., and Krishnamurthi, L. (1998). Late mover advantage: how innovative late entrants outsell pioneers. *J. Market. Res.* 35, 54–70. doi:10.1177/002224379803500107

Song, M., Song, Y., An, Q., and Yu, H. (2013). Review of environmental efficiency and its influencing factors in China: 1998–2009. *Renew. Sustain. Energy Rev.* 20, 8–14. doi:10.1016/j.rser.2012.11.075

Sun, W., Li, Y., Wang, D., and Fan, J. (2012). The efficiencies and their changes of China's resources-based cities employing DEA and Malmquist index models. *J. Geogr. Sci.* 22, 509–520. doi:10.1007/s11442-012-0943-0

Tan, J., Zhang, P., Lo, K., Li, J., and Liu, S. (2016). The urban transition performance of resource-based cities in northeast China. *Sustainability* 8, 1022. doi:10.3390/su8101022

Taylor, M. S., and Scott, M. (2005). Unbundling the pollution haven hypothesis. *Adv. Econ. Anal. Pol.* 3, 1–28. doi:10.2202/1538-0637.1408

The State Council of the People's Republic of China (2015). Made in China 2025 plan. http://www.gov.cn/zhengce/content/2015-05/19/content_9784.htm

United Nations (2015). *Transforming our world: the 2030 agenda for sustainable development*. New York, NY: Division for Sustainable Development Goals.

Van de Kerk, G., and Manuel, A. R. (2008). A comprehensive index for a sustainable society: the SSI-the sustainable society index. *Ecol. Econ.* 66, 228–242. doi:10.1016/j.ecolecon.2008.01.029

Veliyath, R., and Shrivastava, P. (1996). Hypercompetition: managing the dynamics of strategic Maneuvering hypercompetition: managing the dynamics of strategic maneuvering, by D'AveniRichard A. New york: free press, 1994. *Acad. Manag. Rev.* 21, 291–294. doi:10.5465/AMR.1996.9602161575

Wang, K.-L., Pang, S.-Q., Ding, L.-L., and Miao, Z. (2020). Combining the biennial Malmquist-Luenberger index and panel quantile regression to analyze the green total factor productivity of the industrial sector in China. *Sci. Total Environ.* 739, 140280. doi:10.1016/j.scitotenv.2020.140280

Wang, Y., and Shen, N. (2016). Environmental regulation and environmental productivity: the case of China. *Renew. Sustain. Energy Rev.* 62, 758–766. doi:10.1016/j.rser.2016.05.048

Wang, Z., Yang, Z., Zhang, Y., and Yin, J. (2012). Energy technology patents-CO_2 emissions nexus: an empirical analysis from China. *Energy Pol.* 42, 248–260. doi:10.1016/j.enpol.2011.11.082

Weitzman, M. L. (1995). *The welfare significance of a national product revisited*. Boston: Harvard Institute of Economic Research Working Papers, Harvard - Institute of Economic Research.

Xu, B. (2000). Multinational enterprises, technology diffusion, and host country productivity growth. *J. Dev. Econ.* 62, 477–493. doi:10.1016/S0304-3878(00)00093-6

Yan, D., Kong, Y., Ren, X., Shi, Y., and Chiang, S. (2019). The determinants of urban sustainability in Chinese resource-based cities: a panel quantile regression approach. *Sci. Total Environ.* 686, 1210–1219. doi:10.1016/j.scitotenv.2019.05.386

Yang, L., and Wang, K.-L. (2013). Regional differences of environmental efficiency of China's energy utilization and environmental regulation cost based on provincial panel data and DEA method. *Math. Comput. Model.* 58, 1074–1083. doi:10.1016/j.mcm.2012.04.004

Yang, Z., Shao, S., Yang, L., and Liu, J. (2017). Differentiated effects of diversified technological sources on energy-saving technological progress: empirical evidence from China's industrial sectors. *Renew. Sustain. Energy Rev.* 72, 1379–1388. doi:10.1016/j.rser.2016.11.072

Yi, L., Sun, L., Feng, T., and Zhu, C. (2013). How to reduce energy intensity in China: a regional comparison perspective. *Energy Pol.* 61, 513–522. doi:10.1016/j.enpol.2013.06.007

Yu, C., de Jong, M., and Cheng, B. (2016). Getting depleted resource-based cities back on their feet again—the example of Yichun in China. *J. Clean. Prod.* 134, 42–50. doi:10.1016/j.jclepro.2015.09.101

Yu, J., Zhang, Z., and Zhou, Y. (2008). The sustainability of China's major mining cities. *Resour. Pol.* 33, 12–22. doi:10.1016/j.resourpol.2007.10.001

Yuan, Q., Yang, D., Yang, F., Luken, R., Saieed, A., and Wang, K. (2020). Green industry development in China: an index based assessment from perspectives of both current performance and historical effort. *J. Clean. Prod.* 250, 119457. doi:10.1016/j.jclepro.2019.119457

Zhang, C., and Zhou, X. (2016). Does foreign direct investment lead to lower CO2 emissions? Evidence from a regional analysis in China. *Renew. Sust. Energ. Rev.* 58, 943–951. doi:10.1016/j.rser.2015.12.226

Zhang, J., Deng, S., Shen, F., Yang, X., Liu, G., Guo, H., et al. (2011). Modeling the relationship between energy consumption and economy development in China. *Energy* 36, 4227–4234. doi:10.1016/j.energy.2011.04.021

Zhao, K., and Jing, P. (2014). Resource dependency, effective demand shortage and crowding out of innovation in enterprises: an empirical study based on the data of China's provinces. *Sci. Res. Manag.* 35, 85–93. doi:10.19571/j.cnki.1000-2995.2014.12.011

Zhou, X., Zhang, J., and Li, J. (2013). Industrial structural transformation and carbon dioxide emissions in China. *Energy Pol.* 57, 43–51. doi:10.1016/j.enpol.2012.07.017

Zhu, S., He, C., and Liu, Y. (2014). Going green or going away: environmental regulation, economic geography and firms' strategies in China's pollution-intensive industries. *Geoforum* 55, 53–65. doi:10.1016/j.geoforum.2014.05.004

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Does Urbanization Promote Regional Industrial Environmental Efficiency? A Comparison of Economic Development-Oriented Regions and Environmental Governance-Oriented Regions

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The promotion of industrial environmental efficiency (IEE) has attracted considerable attention from scholars and policymakers. Previous studies have focused on the factors driving IEE without considering the leader-follower relationship between the two stages of IEE and have used aggregated indicators to detect the effect of urbanization on IEE. In this study, we open the "black box" of IEE and regard it as a serial system comprised of the economic development (ED) stage and the environmental governance (EG) stage. We select typical provinces belonging to the ED-oriented regions and EG-oriented regions for our analysis. We quantify IEE by using the slack-based model (SBM), decompose the effect of urbanization into four typical factors and detect the effect of the urbanization-related factors by using a tobit regression model. Next, we compare the effect of the urbanization-related factors in the different regions. The results show that overall, in 2011–2015, IEE in the different regions was low and fluctuating, and it increased in ED-oriented regions while remaining stable in EG-oriented regions. The IEE of the ED-oriented regions was always higher than that of the EG-oriented regions, with the gap increasing over time. The IEE of the two stages varied in each type of region. Urbanization-related factors had different effects on the IEE of the different stages in the two types of region, and the same factor had significantly different effects in different regions.

Keywords: Network DEA, industrial environmental efficiency, two-stage production system, leader-follower relationship, Tobit

INTRODUCTION

Through the process of reform and openness, the industry of China is developing rapidly and is the largest contributor to the economic development of China. **Figure 1** reports the energy consumption in China from 2010 to 2017. A total of 66.3% of total energy, 95% of coal, and 99% of crude oil are consumed in the industrial sectors. In addition, the amount of industrial wastewater discharge reached 18.16 billion tons in 2017, accounting for approximately 23.55% of the total wastewater discharge in China. The extensive development of industry has consumed too much energy and caused serious environmental pollution. Additionally, China is still in a stage of rapid motorization

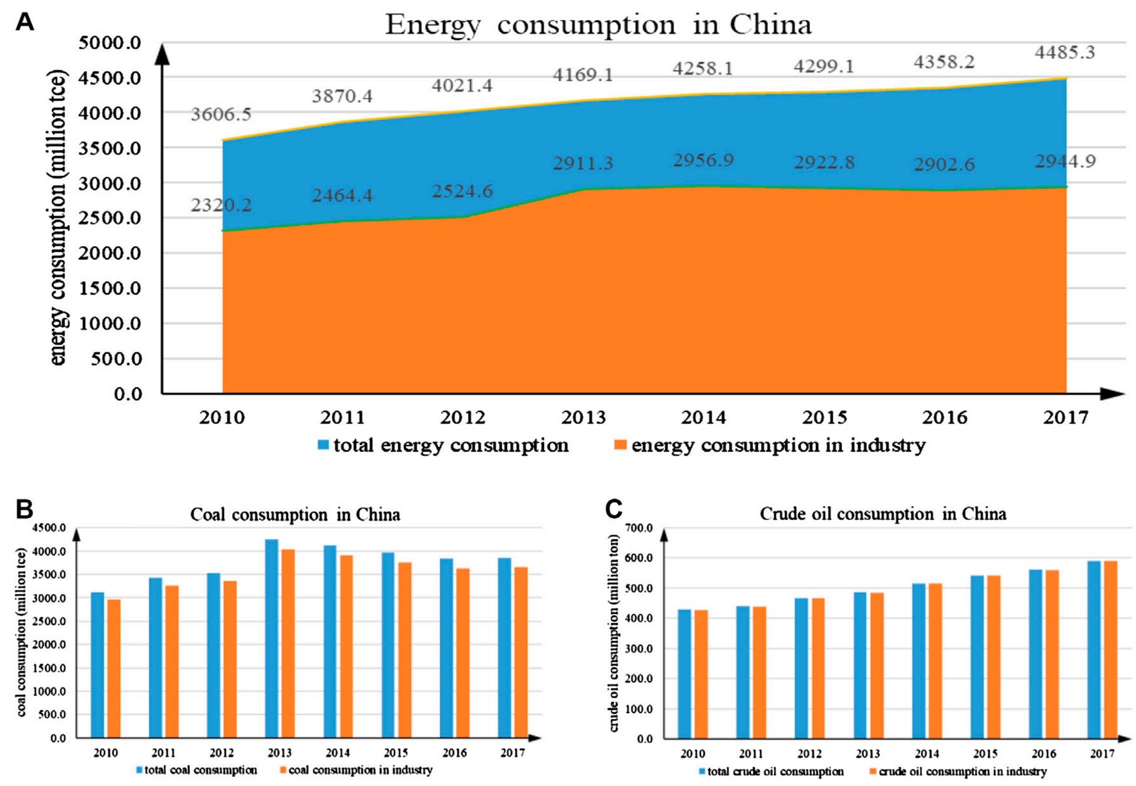

FIGURE 1 | The total and main energy consumption in China.

and urbanization, which indicates that it will consume more energy and its industry will cause more pollution. Therefore, it is of great importance to quantify industrial environmental efficiency (IEE) and detect the factors that drive it.

IEE has been studied continuously by scholars in recent years. Two important issues are related to this topic: quantifying IEE scientifically and identifying the key drivers of IEE.

For the first issue, IEE is an application of environmental efficiency (EE) in industry. After the definition of EE was proposed by the World Business Council for Sustainable Development (WBCSD) in 1992, many scholars attempted to measure the environmental impact that accompanies economic development. EE was defined as the ratio of economic outputs to environmental consumption in earlier studies, which ignored other inputs for economic outputs and could only provide the EE value without determining the measures that promote EE (Aldanondo-Ochoa et al., 2014). To solve these problems, many efficiency analysis techniques have been proposed, and these approaches can be categorized into two types: parametric approaches and nonparametric approaches (Chen et al., 2017). Moreover, stochastic frontier analysis (SFA) is a typical parametric approach, and data envelopment analysis (DEA) is a typical nonparametric approach (Long et al., 2018; Chen et al., 2012). In particular, the DEA method is widely used because it does not require the specification of the functional relations between inputs and outputs of decision-making units (DMUs) (Chen et al., 2017; Cook et al., 2012; Deng et al., 2016).

The traditional DEA model always maximizes outputs and minimizes inputs and does not take environmental pollution into consideration (Feng and Wang, 2018). However, environmental pollution as an undesired output is always accompanied by the desired output. Therefore, we should maximize outputs and minimize inputs and environmental pollution at the same time when quantifying EE. There are some standard methods for dealing with undesired outputs, including regarding the undesired outputs as inputs (Li et al., 2018), changing the undesired outputs into desired outputs by using their reciprocals (Liu et al., 2019), and adjusting the model to account for environmental production technology (Fernández et al., 2018).

In addition to the radial methods mentioned above, a slack-based measurement (SBM) method was proposed by Tone (Tone, 2001), which aimed at minimizing input excesses and desired output shortfalls at the same time. As radial methods can easily lead to many efficient DMUs, the SBM method is believed to be more appropriate for addressing undesired outputs (Park et al., 2018) and has been widely used in EE assessment. For example, Zhang et al. (2019) evaluated the EE of 283 cities in China with the Super-SBM model and compared the EE performance among different regions. Xiao et al. (2018) calculated the energy-environmental efficiency of 31 sectors in China and proposed policy implications from both the microcosmic and macroscopic perspectives. Wang et al. (2019a) measured the EE of a cruise shipping company with the Super-SBM model in a study on corporate social responsibility. Zhang et al. (2016) and Na et al. (2017) performed similar studies.

Although the studies mentioned above have proposed many methods for handling undesired outputs, they still regard EE as the efficiency of environmental pollution discharge. Actually, in the process of industrial production, there are two general stages. In the first stage, raw materials, parts, and other resources are changed into products, and some environmental pollutants are generated at the same time. In the second stage, environmental protection technology, purification equipment, and R&D activities are used to reduce pollution. Therefore, IEE can be decomposed into two components: economic development efficiency and environmental governance efficiency. In this way, we can detect IEE in detail.

Furthermore, although the IEE of each region should include economic development efficiency and environmental governance efficiency, the development goals of each region are substantially different because of imbalanced development in China. Actually, the regional imbalance in development in China has always been serious and is becoming increasingly more serious. Some developing regions have vast environmental capacity and usually aim at growing the economy. However, some developed regions usually face strong calls for environmental protection and focus on environmental governance to attract talent. Therefore, there is a leader-follower relationship between the ED stage and EG stage in each region. However, this relationship has not often been considered in the literature.

For the second issue, many scholars have focused on the industrial structure, FDI, R&D, economic development level, energy structure, and environmental regulations to determine the key drivers that impact IEE (He et al., 2016; Huang and Qiuping, 2015; Li and Qi, 2014; Lyu et al., 2018; Wang et al., 2015; Wang et al., 2018a; Wang et al., 2018b; Wang et al., 2019b). The urbanization of China has grown rapidly in recent decades, and it is believed that urbanization will affect the industrial structure, energy structure, and economic development level and ultimately affect IEE (Chen et al., 2017; Li et al., 2018; Feng and Wang, 2017; Han et al., 2018; Pan et al., 2015; Sanz-Díaz et al., 2017). In this context, it is necessary to determine the effect of urbanization on IEE. Most of the existing literature uses an aggregate index to represent urbanization, e.g., the proportion of the urban population to the total population, and tests for an effect on IEE. However, there are many urbanization-related factors that have different effects on IEE (Bingquan et al., 2018). Therefore, using an aggregate index to represent urbanization can only give the combined effect on IEE and cannot detect the effect of each urbanization-related factor. What is worse, it will lead to irrational efficiency promotion plans and unreasonable urbanization development policies.

In summary, this paper contributes to the literature in two ways. 1) Due to the significantly imbalanced development of regions in China, provinces have different goals for IEE promotion. Some provinces take improving ED as their primary (i.e., leader) goal and improving EG as their secondary (i.e., follower) goal. In other provinces, the opposite is true. In contrast to the existing literature, this paper divides IEE into two stages—the ED stage and EG stage—and divides the provinces into two groups based on their observed leader-follower relationship. Then, an IEE assessment model is proposed based on the leader-follower relationships and SBM to break open the "black box" of IEE. 2) Instead of using an aggregate index to describe urbanization, this paper decomposes the effect of urbanization on IEE into four significant drivers—the population change effect, industrial structure change effect, spatial change effect, and economic growth effect—to detect the detailed effect of urbanization on IEE and provide more precise information for IEE promotion in different provinces.

The rest of the paper is organized as follows. Sector 2 describes the models and data. Sector 3 reports the results and discussions. Sector 4 concludes.

METHODOLOGY

Industrial Environmental Efficiency Assessment Model

According to the industry production process, in the ED stage, energy, materials, and industrial investment are used to generate products and produce environmental pollution. In the EG stage, environmental protection technology and equipment are used to treat the pollutants to meet the standards for discharge. Therefore, IEE can be divided into two stages, and the corresponding process is shown in **Figure 2**.

Suppose there are n DMUs that represent the provinces under assessment. In the ED stage, $S^{ED} = \{(X^{ED}, Y^{ED}, P^{ED})| X^{ED} can\, produce\ (Y^{ED}\ and\ \ P^{ED})\}$. X^{ED} means the inputs for economic development, Y^{ED} means the desired outputs, and P^{ED} means the pollutants, which are undesired outputs. Furthermore, in the EG stage, $S^{EG} = \{(X^{EG}, P^{ED}, Y^{EG})| (X^{EG}\ and\ \ P^{ED}) can\, prodece\, Y^{EG}\}$. X^{EG} means the additional inputs for environmental governance, and Y^{EG} indicates the total amount of treated pollutants.

Although each DMU includes both stages, the development goals of the provinces are different. In developing provinces that have vast environmental capacity, economic growth is the dominant goal, and these provinces are called ED-oriented regions. In developed provinces where the call for environmental protection is stronger, environmental governance is the dominant goal, and these provinces are called EG-oriented regions. In this context, we propose an IEE assessment model based on SBM and the leader-follower relationship between the ED stage and EG stage.

According to network DEA, on the one hand, for the ED-oriented regions, we should maximize the efficiency of the ED stage first and then maximize the efficiency of the EG stage under the constraint that the efficiency of the ED stage does not decrease during this second step (Liu et al., 2019). In this case, the assessment model for the performance of the ED stage is described by **Eq. 1**.

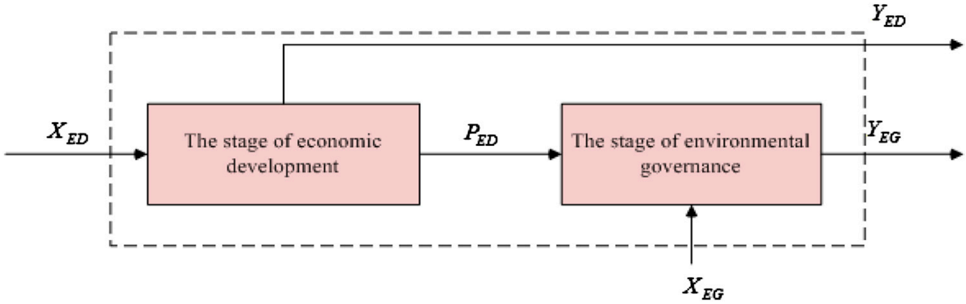

FIGURE 2 | The Stages of IEE.

$$\theta_0^{ED} = \min \frac{1-\frac{1}{m_1}\sum_{i=1}^{m_1}\frac{s_i^-}{X_{ED_0}}}{1+\frac{1}{q_1+z_1}\left(\sum_{k=1}^{q_1}\frac{s_k^+}{Y_{ED_0}}+\sum_{r=1}^{z_1}\frac{s_r^-}{P_{ED_0}}\right)}$$
$$s.t\begin{cases} X_{ED}\lambda^{ED}+s_i^- = X_{ED_0} \\ Y_{ED}\lambda^{ED}-s_k^+ = Y_{ED_0} \\ P_{ED}\lambda^{ED}+s_r^- = P_{ED_0} \\ s_i^- \geq 0; s_k^+ \geq 0; s_r^- \geq 0; \lambda^{ED} \geq 0 \end{cases} \tag{1}$$

In **Eq. 1**, θ_0^{ED} represents the performance of the ED stage; m_1, q_1, and z_1 indicate the number of inputs, desired outputs, and undesired outputs in this stage, respectively. λ^{ED} is a weight vector. s_i^-, s_k^+, and s_r^- are the slack variables for inputs, desired output, and undesired output, respectively.

Let $t = \frac{1}{1+\frac{1}{q_1+z_1}\left(\sum_{k=1}^{q_1}\frac{s_k^+}{Y_{ED_0}}+\sum_{r=1}^{z_1}\frac{s_r^-}{P_{ED_0}}\right)}$; then **Eq. 1** can be transformed into **Eq. 2**, and the model is linearized.

$$\theta_0^{ED} = \min t-\frac{1}{m_1}\sum_{i=1}^{m_1}\frac{S_i^-}{X_{ED_0}}$$
$$s.t\begin{cases} X_{ED}\tau^{ED}+S_i^- = tX_{ED_0} \\ Y_{ED}\tau^{ED}-S_k^+ = tY_{ED_0} \\ P_{ED}\tau^{ED}+S_r^- = tP_{ED_0} \\ t+\frac{1}{q_1+z_1}\left(\sum_{k=1}^{q_1}\frac{S_k^+}{Y_{ED_0}}+\sum_{r=1}^{z_1}\frac{S_r^-}{P_{ED_0}}\right) = 1 \\ S_i^- \geq 0; S_k^+ \geq 0; S_r^- \geq 0; \tau^{ED} \geq 0 \end{cases} \tag{2}$$

where $S_i^- = ts_i^-; S_k^+ = ts_k^+; S_r^- = ts_r^-; \tau^{ED} = t\lambda^{ED}$.

As environmental governance is a secondary goal for ED-oriented regions, the assessment model for the performance of the EG stage can be described by **Eq. 3**.

$$\theta_0^{EG} = \min \frac{1-\frac{1}{m_2+z_1}\left(\sum_{j=1}^{m_2}\frac{s_j^-}{X_{EG_0}}+\sum_{t=1}^{z_1}\frac{s_t^-}{P_{ED_0}}\right)}{1+\frac{1}{q_2}\sum_{l=1}^{q_2}\frac{s_l^+}{Y_{EG_0}}}$$
$$s.t.\begin{cases} X_{EG}\lambda^{EG}+s_j^- = X_{EG_0} \\ P_{ED}\lambda^{EG}+s_t^- = P_{ED_0} \\ Y_{EG}\lambda^{EG}-s_l^+ = Y_{EG_0} \\ \frac{1-\frac{1}{m_1}\sum_{i=1}^{m_1}\frac{s_i^-}{X_{ED}}}{1+\frac{1}{q_1+z_1}\left(\sum_{k=1}^{q_1}\frac{s_k^+}{Y_{ED}}+\sum_{r=1}^{z_1}\frac{s_r^-}{P_{ED_0}}\right)} \geq \theta_0^{ED} \\ P_{ED}\lambda^{ED} = P_{ED}\lambda^{EG} \\ s_j^- \geq 0; s_t^- \geq 0; s_l^+ \geq 0; \lambda^{EG} \geq 0 \\ s_i^- \geq 0; s_k^+ \geq 0; s_r^- \geq 0; \lambda^{ED} \geq 0 \end{cases} \tag{3}$$

In **Eq. 3**, θ_0^{EG} represents the performance of the EG stage; m_2 and q_2 indicate the number of inputs and desired outputs in this stage. z_1 represents the number of undesired outputs from the ED stage that will be treated in the EG stage. λ^{EG} is a weight vector. s_j^-, s_t^+, and s_l^- are the slack variables for inputs, undesired output from the ED stage, and desired output. Specifically, $\frac{1-\frac{1}{m_1}\sum_{i=1}^{m_1}\frac{s_i^-}{X_{ED}}}{1+\frac{1}{q_1+z_1}\left(\sum_{k=1}^{q_1}\frac{s_k^+}{Y_{ED}}+\sum_{r=1}^{z_1}\frac{s_r^-}{P_{ED_0}}\right)} \geq \theta_0^{ED}$ ensures that the performance of the ED stage will not decrease when maximizing the performance of the EG stage, as economic development is the oriented goal for ED-oriented regions. $P_{ED}\lambda^{ED} = P_{ED}\lambda^{EG}$ ensures that the undesired output from the ED stage is fully treated in the EG stage and that the two stages are well linked together.

Similarly, let $\kappa = \frac{1}{1+\frac{1}{q_2}\sum_{l=1}^{q_2}\frac{s_l^+}{Y_{EG_0}}}$; then **Eq. 3** can be transformed into **Eq. 4**, and the model is linearized.

$$\theta_0^{EG} = \min\kappa - \frac{1}{m_2 + z_1}\left(\sum_{j=1}^{m_2}\frac{S_j^-}{X_{EG_0}} + \sum_{t=1}^{z_1}\frac{S_t^-}{P_{ED_0}}\right)$$

$$s.t.\begin{cases} X_{EG}\zeta^{EG} + S_j^- = \kappa X_{EG_0} \\ P_{ED}\zeta^{EG} + S_t^- = \kappa P_{ED_0} \\ Y_{EG}\zeta^{EG} - S_l^+ = \kappa Y_{EG_0} \\ \kappa + \frac{1}{q_2}\sum_{l=1}^{q_2}\frac{S_l^+}{Y_{EG_0}} = 1 \\ \frac{\theta_0^{ED}}{q_1 + z_1}\left(\sum_{k=1}^{q_1}\frac{S_k^+}{Y_{ED_0}} + \sum_{r=1}^{z_1}\frac{S_r^-}{P_{ED_0}}\right) + \frac{1}{m_1}\sum_{i=1}^{m_1}\frac{S_i^-}{X_{ED_0}} \le \left(1 - \theta_0^{ED}\right)\kappa \\ P_{ED}\tau^{ED} = P_{ED}\zeta^{EG} \\ S_j^- \ge 0; S_t^- \ge 0; S_l^+ \ge 0; \zeta^{EG} \ge 0 \\ S_i^- \ge 0; S_k^+ \ge 0; S_r^- \ge 0; \tau^A \ge 0 \end{cases} \tag{4}$$

where $S_j^- = \kappa s_j^-$; $S_t^- = \kappa s_t^-$; $S_l^+ = \kappa s_l^+$; $\zeta^{EG} = \kappa\lambda^{EG}$; $S_i^- = \kappa s_i^-$; $S_k^+ = \kappa s_k^+$; $S_r^- = \kappa s_r^-$; and $\tau^{ED} = \kappa\lambda^{ED}$.

On the other hand, for EG-oriented regions, environmental governance is the dominant goal, and economic development is the secondary goal. Therefore, we should maximize the efficiency of the EG stage first and then maximize the efficiency of the ED stage under the constraint that the efficiency of the EG stage does not decrease. In this context, we maximize the performance of the EG stage using **Eq. 5**.

$$\phi_0^{EG} = \min\frac{1 - \frac{1}{m_2 + z_1}\left(\sum_{j=1}^{m_2}\frac{s_j^-}{X_{EG_0}} + \sum_{t=1}^{z_1}\frac{s_t^-}{P_{ED_0}}\right)}{1 + \frac{1}{q_2}\sum_{l=1}^{q_2}\frac{s_l^+}{Y_{EG}}}$$

$$s.t.\begin{cases} X_{EG}\lambda^{EG} + s_j^- = X_{EG_0} \\ P_{ED}\lambda^{EG} + s_t^- = P_{ED_0} \\ Y_{EG}\lambda^{EG} - s_l^+ = Y_{EG_0} \\ s_j^- \ge 0; s_t^- \ge 0; s_l^+ \ge 0; \lambda^{EG} \ge 0 \end{cases} \tag{5}$$

Let $\eta = \frac{1}{1 + \frac{1}{q_2}\sum_{l=1}^{q_2}\frac{s_l^+}{Y_{EG_0}}}$; then **Eq. 5** can be linearized as shown in **Eq. 6**.

$$\phi_0^{EG} = \min\eta - \frac{\sum_{j=1}^{m_2}\frac{S_j^-}{X_{EG_0}} + \sum_{t=1}^{z_1}\frac{S_t^-}{P_{ED_0}}}{m_2 + z_1}$$

$$s.t.\begin{cases} X_{EG}\delta^{EG} + S_j^- = \eta X_{EG_0} \\ P_{ED}\delta^{EG} + S_t^- = \eta P_{ED_0} \\ Y_{EG}\delta^{EG} - S_l^+ = \eta Y_{EG_0} \\ \eta + \frac{1}{q_2}\sum_{l=1}^{q_2}\frac{S_l^+}{Y_{EG_0}} = 1 \\ S_j^- \ge 0; S_t^- \ge 0; S_l^+ \ge 0; \delta^{EG} \ge 0 \end{cases} \tag{6}$$

where $S_j^- = \eta s_j^-$; $S_t^- = \eta s_t^-$; $S_l^+ = \eta s_l^+$ and $\delta^{EG} = \eta\lambda^{EG}$.

Similarly, the performance of the ED stage of EG-oriented regions can be calculated by **Eq. 7**.

$$\phi_0^{ED} = \min\frac{1 - \frac{1}{m_1}\sum_{i=1}^{m_1}\frac{s_i^-}{X_{ED_0}}}{1 + \frac{1}{q_1 + z_1}\left(\sum_{k=1}^{q_1}\frac{s_k^+}{Y_{ED_0}} + \sum_{r=1}^{z_1}\frac{s_r^-}{P_{ED}}\right)}$$

$$s.t.\begin{cases} X_{ED}\lambda^{ED} + s_i^- = X_{ED_0} \\ Y_{ED}\lambda^{ED} - s_k^+ = Y_{ED_0} \\ P_{ED}\lambda^{ED} + s_r^- = P_{ED_0} \\ \frac{1 - \frac{1}{m_2 + z_1}\left(\sum_{j=1}^{m_2}\frac{s_j^-}{X_{EG_0}} + \sum_{t=1}^{z_1}\frac{s_t^-}{P_{ED_0}}\right)}{1 + \frac{1}{q_2}\sum_{l=1}^{q_2}\frac{s_l^+}{Y_{EG_0}}} \ge \phi_0^{EG} \\ P_{ED}\lambda^{ED} = P_{ED}\lambda^{EG} \\ s_j^- \ge 0; s_t^- \ge 0; s_l^+ \ge 0; \lambda^{EG} \ge 0 \\ s_i^- \ge 0; s_k^+ \ge 0; s_r^- \ge 0; \lambda^{ED} \ge 0 \end{cases} \tag{7}$$

Let $\chi = \frac{1}{1 + \frac{1}{q_1 + z_1}\left(\sum_{k=1}^{q_1}\frac{s_k^+}{Y_{ED_0}} + \sum_{r=1}^{z_1}\frac{s_r^-}{P_{ED}}\right)}$; **Eq. 7** can be linearized as listed in **Eq. 8**.

$$\phi_0^{ED} = \min\chi - \frac{1}{m_1}\sum_{i=1}^{m_1}\frac{S_i^-}{X_{ED_0}}$$

$$s.t.\begin{cases} X_{ED}\Lambda^{ED} + S_i^- = \chi X_{ED_0} \\ Y_{ED}\Lambda^{ED} - s_k^+ = \chi Y_{ED_0} \\ P_{ED}\Lambda^{ED} + s_r^- = \chi P_{ED_0} \\ \frac{1}{m_2 + z_1}\left(\sum_{j=1}^{m_2}\frac{S_j^-}{X_{EG_0}} + \sum_{t=1}^{z_1}\frac{S_t^-}{P_{ED_0}}\right) + \frac{\phi_0^{EG}}{q_2}\sum_{l=1}^{q_2}\frac{S_l^+}{Y_{EG_0}} \le (1 - \phi_0^{EG})\chi \\ P_{ED}\Lambda^{ED} = P_{ED}\Lambda^{EG} \\ S_j^- \ge 0; S_t^- \ge 0; S_l^+ \ge 0; \Lambda^{EG} \ge 0 \\ S_i^- \ge 0; S_k^+ \ge 0; S_r^- \ge 0; \Lambda^{ED} \ge 0 \end{cases} \tag{8}$$

where $S_j^- = \chi s_j^-$; $S_t^- = \chi s_t^-$; $S_l^+ = \chi s_l^+$; $\Lambda^{EG} = \chi\lambda^{EG}$; $S_i^- = \chi s_i^-$; $S_k^+ = \chi s_k^+$; $S_r^- = \chi s_r^-$; and $\Lambda^{ED} = \chi\lambda^{ED}$.

Using the performance of each stage, we can define the IEE of each stage and of the whole process. According to Hu et al. (2006), the IEE of the ED stage can be defined in **Eq. 9**.

$$IEE^{ED} = \frac{Actual\ pollutant\ discharge - slack\ of\ pollutant\ discharge}{Actual\ pollutant\ discharge} \tag{9}$$

Accordingly, the IEE of the EG stage can be defined in **Eq. 10**.

$$IEE^{EG} = \frac{Actual\,pollutant\,treatment}{Actual\,pollutant\,treatment + slack\,of\,pollutant\,treatment} \tag{10}$$

Therefore, the total IEE can be defined in **Eq. 11**.

$$IEE^{total} = \sqrt{IEE^{ED} * IEE^{EG}} \tag{11}$$

In this context, the characteristics of IEE can be analyzed.

(1) If IEE^{ED} (IEE^{EG}) <1, the DMU in the ED stage (EG stage) is inefficient.
(2) If IEE^{ED} (IEE^{EG}) =1, the DMU in the ED stage (EG stage) is efficient.
(3) If and only if $IEE^{ED} = 1$ and $IEE^{EG} = 1$, the DMU is efficient in the whole process.

Regression Analysis of Industrial Environmental Efficiency Determinants

To detect the determinants of IEE in each stage and the whole process, a multiple linear regression model should be constructed. As the values of IEE^{ED}, IEE^{EG}, and IEE^{total} are in the range [0, 1], we use the tobit estimator. In this paper, we treat the IEE of each stage and the whole process as the dependent variables and test the regression specification given in **Eq. 12**.

$$y_i = \begin{cases} x_i\beta + \mu_i, y_i > 0 \\ 0, y_i \le 0 \end{cases} \tag{12}$$

where y_i is the dependent variable, x_i is the independent variable, and β is the regression coefficient, with $\mu_i \sim N(0, \sigma^2)$.

Variables and Data

(1) Inputs and outputs of the IEE assessment model

Based on some existing studies (Huang and Qiuping, 2015; Chen et al., 2017; Feng et al., 2018; Wang et al., 2018), this paper takes industrial investment, industrial employment, and energy consumption as inputs in the ED stage and industrial GDP as the desired output and industrial wastewater discharge, industrial solid waste discharge, and industrial waste gas ("three wastes") as the undesired outputs. In the EG stage, this paper takes the three wastes from the ED stage, investment in treatment for the three wastes as inputs, and takes the actual level of treatment of the three wastes as output. The indicators are listed in **Table 1**.

Determinants of Industrial Environmental Efficiency

The process of urbanization is expected to affect IEE significantly. Specifically, the main effects are listed as follows.

①It is obvious that the population distribution will change with population migration from rural areas to cities. As a result, population density will increase in urban areas and will provide a large supply of labor for industry development. Moreover, the increase in population density will affect environmental capacity and will finally affect IEE. Therefore, we use urban population density (*upd*) to reflect the effect of urbanization due to population change on IEE.
②The development of urbanization requires many industrial products, which promotes the development of the secondary industry. As a result, the proportion of the secondary industry to the national economy will change, especially the manufacturing sector, which will grow rapidly. Meanwhile, along with the development of the manufacturing sector, the consumption of energy and water will increase sharply. Therefore, we use the proportion of the manufacturing sector (*pms*) to the national economy to reflect the effect of urbanization due to changes in the industrial structure on IEE.
③Obviously, the size of urban areas will increase along with the development of urbanization, especially in developing regions. However, sprawl from the built-up areas in urban cities will decrease the space available for industry development. Additionally, disorganized plans for urbanization have caused a seriously disordered spatial layout, which reduces the ability of the urban ecosystem to self-adjust, and this disordered layout has caused serious environmental problems. Therefore, we use the proportion of the built-up area to the total area of the urban city (*pbu*) to reflect the spatial change effect of urbanization on IEE.

TABLE 1 | Indicators for the IEE assessment model.

Types	Indicators	Variables
ED-stage inputs	Investment	Industrial development investment (10^8 yuan)
	Employment	Industrial employment population (10^4)
	Energy	Industrial total energy consumption (10^4 tce)
ED-stage outputs	Industrial output	Industrial GDP (10^8 yuan)
	Environmental pollutants	Industrial wastewater (104 m^3)
		Industrial solid waste (10^4 t)
		Industrial waste gas (104 m^3)
EG-stage input	EG investment	Industrial three wastes treatment investment (10^8 yuan)
EG-stage output	Three wastes treatment	Total level of industrial wastewater treatment (104 m^3)
		Total level of industrial solid waste treatment (10^4 t)
		Total level of industrial waste gas treatment (104 m^3)

TABLE 2 | List of variables for the analysis of the factors driving industrial environmental efficiency.

Factor	Variables
upd	Urban population density (104 people per square kilometer)
pms	Proportion of manufacturing sector (%)
pbu	Proportion of built-up area (%)
pcdi	Per capita disposable income (104 yuan)
rgdp	Per capita GDP (104 yuan)
tie	Total import and export (104 dollar)
res	Research expenditure (104 yuan)
	–

④The income of residents is expected to increase with migration from rural areas to urban areas. As a result, the disposable income of residents will grow. The growth of the income of residents will generate new demand for industrial products, which will promote the development of industry. The environmental awareness of residents will increase when disposable income increases, and the call for environmental governance will become stronger, which will affect IEE. Therefore, we use per-capita disposable income (*pcdi*) to reflect the effect of urbanization due to changes in the income of residents on IEE.

In addition, to control for the effect of other important determinants of IEE, we use per-capita GDP (*rgdp*) to reflect the effect of economic growth, total imports and exports (*tie*) to reflect the effect of international trade, and research expenditure (*res*) to reflect the effect of research investment. These variables are listed in **Table 2**.

The data listed in **Table 1** and **Table 2** are cited from the China Statistical Yearbook (2012–2016) and the China Environmental Statistics Yearbook (2012–2016).

RESULTS AND DISCUSSION

Analysis of Industrial Environmental Efficiency in Different Regions

Overall Analysis of Industrial Environmental Efficiency in Different Regions

We select 16 typical provinces and divide these provinces into two groups: EG-oriented regions and ED-oriented regions, according to their development stage in 2011–2015 and in line with previous studies (Liu et al., 2019; Wang et al., 2018; Wang et al., 2015). The provinces selected are listed in **Table 3**.

Table 4 reports the EE of ED-oriented regions during different stages. **Table 5** reports the EE of EG-oriented regions during different stages.

TABLE 3 | Provinces in different regions.

Region	Provinces
EG-oriented region	Tianjin, Hebei, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Shanxi
ED-oriented region	Hubei, Guangxi, Hainan, Sichuan, Guizhou, Gansu, Qinghai, Xinjiang

Overall, the IEE in the different regions was low, especially in the EG-oriented regions. **Figure 3** presents the changes in the average *IEE* in different regions during 2011–2015. As shown in **Figure 3**, the IEE of both types of regions is low and fluctuates during the observation period. Overall, the IEE of the ED-oriented regions increased, while the IEE of the EG-oriented regions remained stable during 2011–2015. IEE^{ED} increased sharply in ED-oriented regions, while it decreased sharply in EG-oriented regions. IEE^{EG} clearly increased in EG-oriented regions, especially beginning in 2013, while it slowly decreased in ED-oriented regions. In this context, the IEE of ED-oriented regions is significantly dominated by IEE^{ED}, while the IEE of EG-oriented regions is significantly dominated by IEE^{EG}. It is interesting that for ED-oriented regions, IEE^{ED} increased sharply beginning in 2013 and became larger than IEE^{EG} in 2015, indicating the rapid development of industry; meanwhile, IEE^{EG} slowly decreased due to the increase in environmental pollution. Therefore, it is important for ED-oriented regions to introduce green industries and reduce pollution discharge. For EG-oriented regions, the sharp decrease in IEE^{ED} may be because of industrial transfer, which caused a great decline in industrial output.

Comparative Analysis of ED-Oriented Regions and EG-Oriented Regions

To explore the leader-follower relationship in the different regions, this paper further conducts a comparative analysis of the efficiency of the regions in the two stages, as shown in **Figure 4**. It is obvious that the IEE of the ED-oriented regions is always higher than that of the EG-oriented regions during the observation period, and the gap is increasing. This may be due to their different development goals. For ED-oriented regions, economic development is the leader goal, and it is believed that developing industry is particularly helpful for regional economic growth. Meanwhile, for EG-oriented regions, which have experienced rapid industry development and have a better economic base, environmental governance is the leader goal, and many industrial enterprises are removed, especially heavily polluting enterprises. Therefore, the gap may become increasingly larger in the next few years.

It is obvious that the IEE^{ED} of ED-oriented regions gradually caught up with that of EG-oriented regions from 2011 to 2014 and exceeded it in 2015. It is believed that the IEE^{ED} of ED-oriented regions will increase with the development of industry. Meanwhile, the gap in IEE^{EG} between ED-oriented regions and EG-oriented regions decreased in the observation period due to the rapid increase in IEE^{EG} in EG-oriented regions. Hopefully the IEE in the environmental governance stage will improve its performance in the EG-oriented regions.

Analysis of the Determinants

Using a tobit panel regression analysis model, the effects of various factors on *IEE*, IEE^{ED}, and IEE^{EG} are detected, and the results are shown in **Table 6**.

According to **Table 6**, the determinants have significantly different effects on *IEE*, IEE^{ED}, and IEE^{EG}, and the same determinant even has different effects on the *IEE*, IEE^{ED}, and

TABLE 4 | *IEE* of ED-oriented provinces.

ED-oriented region	2011			2012			2013			2014			2015		
	IEE^{ED}	IEE^{EG}	IEE	IEE^{ED}	IEE^{EG}	IEE	IEE^{ED}	IEE^{EG}	IEE	IEE^{ED}	IEE^{EG}	IEE	IEE^{ED}	IEE^{EG}	IEE
Hubei	0.63	0.94	0.77	0.67	1	0.82	0.66	0.56	0.61	0.61	0.79	0.69	1	1	1
Guangxi	0.58	1	0.76	0.58	1	0.76	0.52	1	0.72	1	0.91	0.95	1	0.68	0.83
Hainan	0.65	0.18	0.34	0.69	0.15	0.33	0.49	0.12	0.24	0.55	0.15	0.16	1	0.17	0.41
Sichuan	0.42	0.9	0.61	0.52	0.75	0.63	0.45	0.72	0.57	0.49	0.85	0.64	0.39	0.78	0.56
Guizhou	0.28	1	0.53	0.36	0.69	0.50	0.43	1	0.66	0.47	1	0.68	0.56	0.81	0.67
Gansu	0.54	0.14	0.27	0.40	0.36	0.39	0.44	0.29	0.36	0.44	0.25	0.33	0.35	0.32	0.33
Qinghai	0.48	0.34	0.4	1	0.46	0.68	0.46	0.66	0.55	0.47	0.61	0.54	0.40	0.62	0.5
Xinjiang	0.56	0.43	0.49	0.54	0.36	0.44	0.46	0.37	0.42	0.46	0.32	0.38	0.39	0.46	0.43

IEE^{EG} of different regions, which is especially the case for the urbanization-related determinants. To study the different effects of the same determinant on the *IEE*, *IEE^{ED}*, and *IEE^{EG}* of different regions, we conduct a comparative analysis between the different stages and the different regions.

(1) Comparative analysis of the effect of population change due to urbanization

Obviously, the change in urban population density has a significant effect on the *IEE*, *IEE^{ED}*, and *IEE^{EG}* of ED-oriented regions. Specifically, an increase in urban population density has a significantly positive effect on the *IEE* (significant at the 10% level), *IEE^{ED}* (significant at the 1% level), and *IEE^{EG}* (significant at the 5% level) of ED-oriented regions, indicating that as urbanization develops, an increasing number of people move into cities and provide a large supply of competent industrial workers for each sector of industry, thus promoting the economic growth of industry. The same is true for the EG stage in ED-oriented regions. An increase in population provides many sanitation workers and service staff for environmental governance, thus increasing the amount of pollutants treated.

Interestingly, the change in urban population density only has a significant effect on *IEE^{ED}* (significant at the 5% level) and has no significant effect on the *IEE^{EG}* and *IEE* of EG-oriented regions. In particular, it is negatively related to *IEE^{ED}* (significant at the 5% level), indicating that an increase in population density decreases the IEE of the ED stage in EG-oriented regions. This may be because most of the EG-oriented regions are developed provinces that have experienced rapid industrial development, and many high-pollution and labor-intensive sectors have been transferred to developing regions. Therefore, an increase in population density cannot increase the output of industry. Instead, too many people flooding into cites decreases the environmental carrying capacity and capacity for environmental self-repair of the region, thus decreasing *IEE^{EG}*.

(2) Comparative analysis of the effect of industrial structure change

A change in industrial structure has significantly different effects on *IEE* in both types of regions. For ED-oriented regions, it is positively related to *IEE^{ED}* (significant at the 1% level) and *IEE* (significant at the 10% level), while it is positively related to *IEE^{EG}* but is not significant. This indicates that a change in industrial structure is helpful for increasing IEE, especially *IEE^{ED}* and *IEE*, by increasing the proportion of industry to the national economy. However, it should be noted that increasing the proportion of industry may increase the *IEE^{ED}* and *IEE* in the short term by increasing industrial output for ED-oriented regions because of their excellent environmental carrying capacity. However, *IEE* will decrease with the increase in industrial pollution. Therefore, it is important to introduce environmentally friendly industries into ED-oriented regions.

For EG-oriented regions, the change in industrial structure is negatively related to *IEE^{ED}* (significant at the 5% level), *IEE^{EG}* (significant at the 1% level), and *IEE* (significant at the 5% level), indicating that an increase in the proportion of industry to the national economy will decrease IEE not only in the ED stage but also in the EG stage. This may be because the ecological system is fragile after years of development, and the cost of environmental governance is very high. Therefore, it will be helpful for EG-

TABLE 5 | IEE of EG-oriented provinces.

EG-oriented region	2011			2012			2013			2014			2015		
	IEE^{ED}	IEE^{EG}	IEE	IEE^{ED}	IEE^{EG}	IEE	IEE^{ED}	IEE^{EG}	IEE	IEE^{ED}	IEE^{EG}	IEE	IEE^{ED}	IEE^{EG}	IEE
Tianjin	1.00	0.31	0.55	1.00	0.42	0.65	1.00	0.34	0.59	1.00	0.35	0.59	1.00	0.34	0.58
Hebei	1.00	0.35	0.59	0.95	0.37	0.59	0.89	0.40	0.60	0.85	0.41	0.59	0.86	0.42	0.60
Jiangsu	0.43	0.33	0.38	0.42	0.36	0.39	0.39	0.40	0.40	0.39	0.59	0.48	0.38	0.60	0.48
Zhejiang	0.53	0.38	0.45	0.52	0.37	0.44	0.43	0.32	0.37	0.43	0.38	0.40	0.38	0.37	0.37
Fujian	0.41	0.28	0.34	0.46	0.38	0.42	0.36	0.32	0.34	0.33	0.38	0.35	0.34	0.39	0.36
Shandong	0.70	0.40	0.53	0.65	0.37	0.49	0.62	0.40	0.49	0.63	0.44	0.52	0.46	0.48	0.47
Guangdong	0.69	0.32	0.47	0.55	0.32	0.42	0.53	0.44	0.48	0.54	0.60	0.57	0.43	0.61	0.51
Shanxi	0.85	0.58	0.70	0.72	0.52	0.61	0.50	0.43	0.46	0.45	0.53	0.49	0.36	0.47	0.41

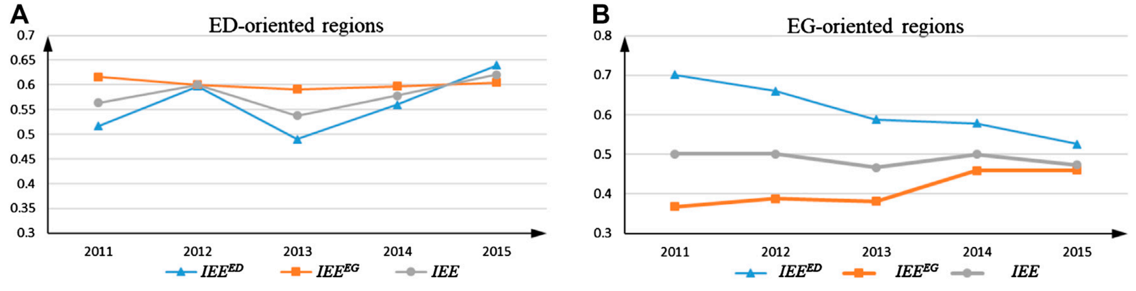

FIGURE 3 | The change of IEE, IEE^{ED} and IEE^{EG} in different regions.

oriented regions to transfer some sectors of industry to other regions and support the development of the service industry.

(3) Comparative analysis of the effect of urban spatial structure change

In ED-oriented regions, the change in urban spatial structure is negatively related to IEE^{ED} (significant at the 1% level), while no significant correlation was observed with IEE^{EG} or *IEE*. This indicates that the IEE of the ED stage decreased with an increase in built-up areas in cities. This may be because the increase in built-up areas was mainly due to real estate development, which occupied the development space that would otherwise have been used by industry. Meanwhile, the blind expansion of urban space has also led to incomplete infrastructure construction and imperfect industrial layouts, which decrease IEE^{ED}. In this context, the rational planning of urban layout and the reservation of development space for industry will be conducive to increasing industry EE for ED-oriented regions.

However, the contrary is true for EG-oriented regions. The change in urban spatial structure is positively related to IEE^{ED} (significant at the 1% level), IEE^{EG} (significant at the 5% level), and *IEE* (significant at the 1% level). This means that the IEE of each stage and the overall efficiency increased with the increase in built-up areas in cities. This is because the urbanization level in EG-oriented regions is high, and there is not much space for industry development or environmental governance. Therefore, an increase in urban area provides space for industry

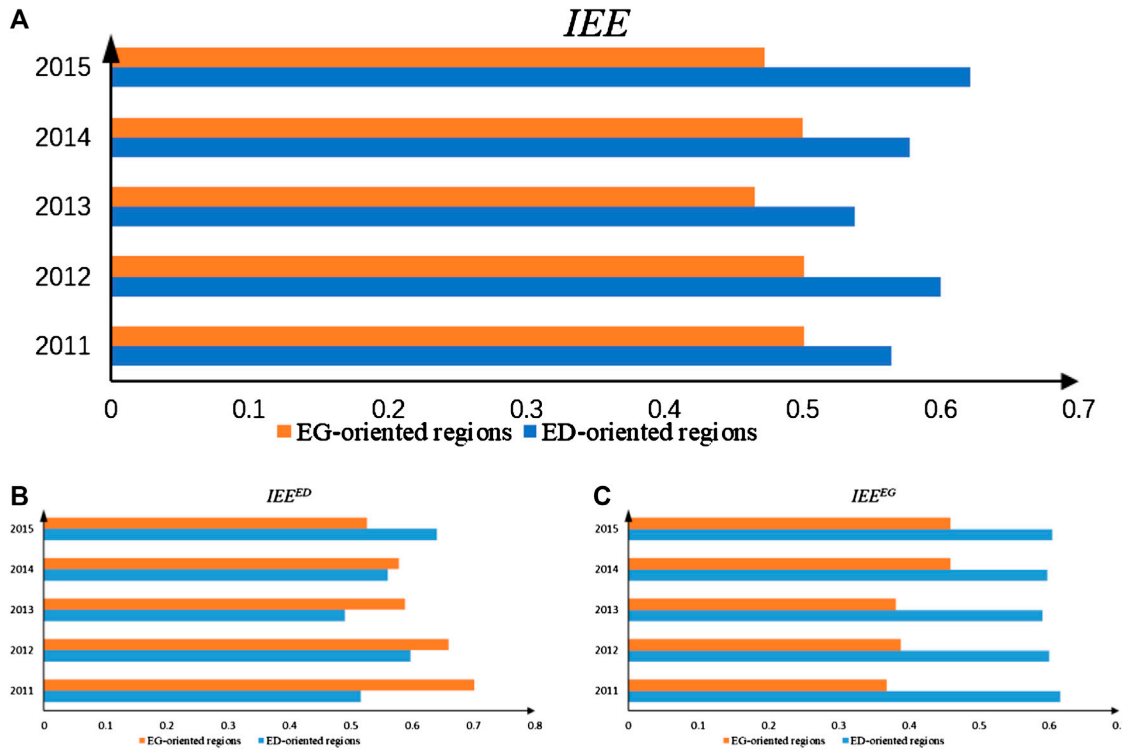

FIGURE 4 | The comparison of IEE, IEE^{ED} and IEE^{EG} in different regions.

TABLE 6 | Regression results for factors impacting IEE.

Variables	ED-oriented regions			EG-oriented regions		
	IEE^{ED}	IEE^{EG}	IEE	IEE^{ED}	IEE^{EG}	IEE
upd	3.215***	2.040**	1.175*	−2.435**	−0.413	−2.378
pms	0.128***	0.013	0.116*	−0.111**	−1.014***	−1.011**
pbu	−1.031***	1.002	1.012	1.034***	1.412**	1.623***
pcdi	2.191***	1.651*	2.164***	−1.337	2.263**	−1.597
rgdp	1.244**	−0.172	−1.054	2.258***	1.068*	1.137***
tie	−2.524**	−2.920*	−3.340**	1.113***	1.049*	2.088*
res	1.830*	2.490**	1.544***	1.399***	1.713***	2.187***
cons	−3.235***	−1.28*	−1.922***	0.561	1.178**	−0.478

*Note: *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively*

development, especially for emerging industrial sectors, which are high value-added and low-pollution sectors. In addition, the increase in urban area provides space for industrial environmental governance, which improves the capacity for environmental governance in the region.

(4) Comparative analysis of the effect of a change in the income of residents

Notably, an increase in the income of residents increased the industry EE of ED-oriented regions. As shown in **Table 6**, the disposable income of residents is positively related to IEE^{ED} (significant at the 1% level), IEE^{EG} (significant at the 10% level), and IEE (significant at the 5% level). This may be because increasingly more people moved to cities because of the increase in income for residents that occurred along with the development of urbanization, and this population increase then provided a large supply of competitive industrial workers. Meanwhile, the growing population also generated a great deal of demand for industrial products, thereby increasing IEE^{ED}.

However, calls from residents for a better environment increased along with the increase in income, which forced the local government to execute rigorous policies to promote environmental quality. Therefore, industrial firms should be required to upgrade their production equipment to reduce pollution emissions and their waste treatment equipment to improve waste treatment capacity. In this context, an increase in the income of residents is positively related to IEE^{EG} not only in ED-oriented regions but also in EG-oriented regions.

(5) Comparative analysis of the effect of control variables

Economic growth (*rgdp*) is positively related to the IEE of each stage in EG-oriented regions but is only positively related to the IEE of the ED stage in ED-oriented regions. This may be because the purchasing power of residents increases along with economic growth, thus generating a great deal of demand for industrial products and thereby increasing the IEE of the ED stage. Additionally, as EG-oriented regions are developed provinces, economic growth can provide many resources for environmental governance, thus increasing the IEE of the EG stage in EG-oriented regions. However, as ED-oriented regions are developing provinces, the resources allocated to environmental governance are few, causing economic growth to have no significant effect on the IEE of the EG stage in ED-oriented regions.

International trade (*tie*) is negatively related to the IEE of each stage in ED-oriented regions, indicating that IEE decreases along with the development of international trade in ED-oriented regions. This may be because parts manufacturing and assembly are dominant sectors in the industry of ED-oriented regions, which are typically high energy-consumption, high-pollution, and low value-added sectors. Therefore, the development of international trade increases pollution emissions and increases the pressure for environmental governance, thus decreasing IEE. However, international trade is positively related to the IEE of each stage in EG-oriented regions. This may be because research and design is the dominant sector in the industry of EG-oriented regions, which is typically low energy-consumption, low-pollution, and high value-added.

Research investment (*res*) is positively related to the IEE of each stage in both types of region, indicating that increasing research investment will upgrade industrial production technology, which can not only increase industrial output but also decrease environmental pollution. Moreover, increased research investment can also upgrade environmental pollution treatment technology, which improves the capacity for environmental governance in the region.

CONCLUSIONS AND POLICY IMPLICATIONS

Conclusion

This paper proposes a two-stage efficiency measurement model based on DEA and the concept of leader-follower relationships to evaluate the IEE of ED- and EG-oriented regions in China. To detect the detailed effect of urbanization on the IEE of each stage and on overall efficiency, a tobit regression model was used, as the values for the efficiency measure were truncated. The main conclusions of this paper are as follows. 1) Overall, the IEE in different regions was low in 2011–2015, especially in EG-oriented regions. Additionally, IEE increased in ED-oriented regions but remained stable in EG-oriented regions. 2) In contrast, the IEE of ED-oriented regions was always higher than that of EG-oriented regions during the observation period, and the gap increased. The

IEE of the ED stage in ED-oriented regions increased, while it decreased sharply in EG-oriented regions, and the IEE of the EG stage decreased slowly in ED-oriented regions, while it obviously increased in EG-oriented regions. 3) Urbanization had different effects on the IEE of the different regions. Moreover, the same factor had significantly different effects in different regions, and the same factor even had significantly different effects on different stages in the same region.

Policy Implications

For ED-Oriented Regions

First, as population density has a significantly positive effect on the IEE of the two stages and on overall efficiency, it is important for local governments in ED-oriented regions to moderately increase population density to provide a large supply of industrial workers for industrial production and governance. Second, due to the positive effect of the industrial structure on the IEE of the ED stage and on overall efficiency, it would be helpful to transfer some low-pollution industrial sectors from EG-oriented regions or other countries to the ED-oriented regions. However, it is worth noting that improving the capacity for environmental governance in advance to match the industrial transfers will be important for ED-oriented regions. Third, blind spatial expansion has a negative effect on the IEE of the ED stage, so it is important to scientifically optimize urban layout, especially through improving the construction of infrastructure. Fourth, growth in income increases the IEE of the two stages and overall efficiency significantly; therefore, guiding residents to green consumption patterns would be conducive to simultaneously increasing the efficiency of both stages. Fifth, it is important to optimize the foreign trade structure, as foreign trade is negatively related to the IEE of the two stages and to overall efficiency. The local government should take measures to decrease the level of labor-intensive and low-end manufacturing but should encourage the export of high-end manufacturing products.

For EG-Oriented Regions

First, population density is negatively related to the IEE of the ED stage. Therefore, purposively guiding some industrial workers to ED-oriented regions or guiding industrial workers to change to other related industries may be helpful for increasing the IEE of the ED stage in EG-oriented regions. Second, the industrial structure is negatively related to the IEE of the two stages and to overall efficiency. Therefore, local governments should slow down the development of the traditional manufacturing sector to decrease the proportion of the manufacturing sector to the national economy and should implement policies to encourage the development of advanced manufacturing industries. Third, the spatial structure is positively related to the IEE of the two stages and to overall efficiency. Therefore, it moderately increases the space available for the development of industry, especially for advanced manufacturing sectors. Urban renewal will be of great importance, as there is not much vacant space in EG-oriented regions. Fourth, income growth is positively related to the IEE of the EG stage, indicating that public scrutiny plays an important role in environmental governance. Therefore, it will be of great importance to open channels for public feedback. Fifth, as international trade was positively related to the IEE of the two stages and to overall efficiency, the local governments of EG-oriented regions should encourage the development of high-tech production, which will help upgrade the industrial structure in China.

For Both Types of Regions

First, research investment can not only lead to upgrades in production technology, thus increasing industrial output and decreasing pollution, but can also improve the level of environmental governance. Therefore, local governments should encourage research institutes and industrial enterprises to increase their investments in research to break through problems in industrial production and environmental governance that have bottlenecked. Second, improving the level of economic development will increase the revenue of governments. In this case, the local governments will be capable of taking measures to encourage the development of advanced manufacturing, eliminate obsolete production technology, and support new technology for industrial production and environmental governance.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

LS writes the manuscript, collects some data YL proposes the IEE assessment model and caculates the results LL revises the manuscript and improves the policy impliaction BL revises the manuscript thoroughly.

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REFERENCES

Aldanondo-Ochoa, A. M., Casasnovas-Oliva, V. L., and Arandia-Miura, A. (2014). Environmental efficiency and the impact of regulation in dryland organic vine production. *Land Use Pol.* 36, 275–284. doi:10.1016/j.landusepol.2013.08.010

Bingquan, L., Tian, C., Li, Y., Huihui, S., and Zhanxin, M. (2018). Research on the effects of urbanization on carbon emissions efficiency of urban agglomerations in China. *J. Clean. Prod.* 197, 1374–1381. doi:10.1016/j.jclepro.2018.06.295

Chen, N., Xu, L., and Chen, Z. (2017). Environmental efficiency analysis of the Yangtze River Economic Zone using super efficiency data envelopment analysis (SEDEA) and tobit models. *Energy* 134, 659–671. doi:10.1016/j.energy.2017.06.076

Chen, P.-C., Chang, C.-C., Yu, M.-M., and Hsu, S.-H. (2012). Performance measurement for incineration plants using multi-activity network data envelopment analysis: the case of Taiwan. *J. Environ. Manag.* 93, 95–103. doi:10.1016/j.jenvman.2011.08.011

Chen, Y., Han, Y., and Zhu, Q. (2017). Energy and environmental efficiency evaluation based on a novel data envelopment analysis: an application in petrochemical industries. *Appl. Therm. Eng.* 119, 156–164. doi:10.1016/j.applthermaleng.2017.03.051

Cook, W. D., Harrison, J., Rouse, P., and Zhu, J. (2012). Relative efficiency measurement: the problem of a missing output in a subset of decision making units. *Eur. J. Oper. Res.* 220, 79–84. doi:10.1016/j.ejor.2012.01.022

Deng, G., Li, L., and Song, Y. (2016). Provincial water use efficiency measurement and factor analysis in China: based on SBM-DEA model. *Ecol. Indicat.* 69, 12–18. doi:10.1016/j.ecolind.2016.03.052

Feng, C., Huang, J.-B., and Wang, M. (2018). Analysis of green total-factor productivity in China's regional metal industry: a meta-frontier approach. *Resour. Pol.* 58, 219–229. doi:10.1016/j.resourpol.2018.05.008

Feng, C., and Wang, M. (2018). Analysis of energy efficiency in China's transportation sector. *Renew. Sustain. Energy Rev.* 94, 565–575. doi:10.1016/j.rser.2018.06.037

Feng, C., and Wang, M. (2017). The economy-wide energy efficiency in China's regional building industry. *Energy* 141, 1869–1879. doi:10.1016/j.energy.2017.11.114

Fernández, D., Pozo, C., Folgado, R., Jiménez, L., and Guillén-Gosálbez, G. (2018). Productivity and energy efficiency assessment of existing industrial gases facilities via data envelopment analysis and the Malmquist index. *Appl. Energy.* 212, 1563–1577. doi:10.1016/j.apenergy.2017.12.008

Han, L., Han, B., Shi, X., Su, B., Lv, X., and Lei, X. (2018). Energy efficiency convergence across countries in the context of China's Belt and Road initiative. *Appl. Energy.* 213, 112–122. doi:10.1016/j.apenergy.2018.01.030

He, F., Dongdong, M., and Zhu, L. (2016). Measurement and factors of environmental technology efficiency in China under the constraint of haze. *R&D Management.* 28, 34–43. doi:10.13581/j.cnki.rdm.20160906.004

Hu, J.-L., Wang, S.-C., and Yeh, F.-Y. (2006). Total-factor water efficiency of regions in China. *Resour. Pol.* 31, 217–230. doi:10.1016/j.resourpol.2007.02.001

Huang, Y., and Qiuping, S. (2015). Research on environmental efficiency and environmental total factor productivity in China's regional economies. *China Population,Resources and Environment.* 25, 25–34. doi:10.3969/j.issn.1002-2104.2015.12.004

Li, J., Huang, X., Kwan, M.-P., Yang, H., and Chuai, X. (2018). The effect of urbanization on carbon dioxide emissions efficiency in the Yangtze River Delta, China. *J. Clean. Prod.* 188, 38–48. doi:10.1016/j.jclepro.2018.03.198

Li, M., and Wang, Q. (2014). International environmental efficiency differences and their determinants. *Energy* 78, 411–420. doi:10.1016/j.energy.2014.10.026

Liu, B., Li, Y., Hou, R., and Wang, H. (2019). Does urbanization improve industrial water consumption efficiency. *Sustainability* 11, 1–11. doi:10.3390/su11061787

Long, X., Chen, B., and Park, B. (2018). Effect of 2008's Beijing Olympic Games on environmental efficiency of 268 China's cities. *J. Clean. Prod.* 172, 1423–1432. doi:10.1016/j.jclepro.2017.10.209

Lyu, K., Bian, Y., and Yu, A. (2018). Environmental efficiency evaluation of industrial sector in China by incorporating learning effects. *J. Clean. Prod.* 172, 2464–2474. doi:10.1016/j.jclepro.2017.11.163

Na, J.-H., Choi, A.-Y., Ji, J., and Zhang, D. (2017). Environmental efficiency analysis of Chinese container ports with CO 2 emissions: an inseparable input-output SBM model. *J. Transport Geogr.* 65, 13–24. doi:10.1016/j.jtrangeo.2017.10.001

Pan, X., Liu, Q., and Peng, X. (2015). Spatial club convergence of regional energy efficiency in China. *Ecol. Indicat.* 51, 25–30. doi:10.1016/j.ecolind.2014.10.026

Park, Y. S., Lim, S. H., Egilmez, G., and Szmerekovsky, J. (2018). Environmental efficiency assessment of U.S. transport sector: a slack-based data envelopment analysis approach. *Transport. Res. Transport Environ.* 61, 152–164. doi:10.1016/j.trd.2016.09.009

Sanz-Díaz, M. T., Velasco-Morente, F., Yñiguez, R., and Díaz-Calleja, E. (2017). An analysis of Spain's global and environmental efficiency from a European Union perspective. *Energy Pol.* 104, 183–193. doi:10.1016/j.enpol.2017.01.030

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, G., Li, K. X., and Xiao, Y. (2019a). Measuring marine environmental efficiency of a cruise shipping company considering corporate social responsibility. *Mar. Pol.* 99, 140–147. doi:10.1016/j.marpol.2018.10.028

Wang, J., Wang, S., Li, S., Cai, Q., and Gao, S. (2019b). Evaluating the energy-environment efficiency and its determinants in Guangdong using a slack-based measure with environmental undesirable outputs and panel data model. *Sci. Total Environ.* 663, 878–888. doi:10.1016/j.scitotenv.2019.01.413

Wang, K., Lijuan, S., Liu, L., Du, Y., Meng, X., and Yang, B. (2018a). Study on the temporal-spatial heterogeneity and driving factors of air environmental efficiency for yangtze river economic zone. *Resources and Environ.Yangtze Basin.* 27, 453–462. doi:10.11870/cjlyzyyhj201803001

Wang, K., Wei, Y.-M., and Huang, Z. (2018b). Environmental efficiency and abatement efficiency measurements of China's thermal power industry: a data envelopment analysis based materials balance approach. *Eur. J. Oper. Res.* 269, 35–50. doi:10.1016/j.ejor.2017.04.053

Wang, Q., Zhao, Z., Shen, N., and Liu, T. (2015). Have Chinese cities achieved the win-win between environmental protection and economic development? From the perspective of environmental efficiency. *Ecol. Indicat.* 51, 151–158. doi:10.1016/j.ecolind.2014.07.022

Xiao, C., Wang, Z., Shi, W., Deng, L., Wei, L., Wang, Y., et al. (2018). Sectoral energy-environmental efficiency and its influencing factors in China: based on S-U-SBM model and panel regression model. *J. Clean. Prod.* 182, 545–552. doi:10.1016/j.jclepro.2018.02.033

Zhang, J., Zeng, W., and Shi, H. (2016). Regional environmental efficiency in China: analysis based on a regional slack-based measure with environmental undesirable outputs. *Ecol. Indicat.* 71, 218–228. doi:10.1016/j.ecolind.2016.04.040

Zhang, Y., Shen, L., Shuai, C., Bian, J., Zhu, M., Tan, Y., et al. (2019). How is the environmental efficiency in the process of dramatic economic development in the Chinese cities?. *Ecol. Indicat.* 98, 349–362. doi:10.1016/j.ecolind.2018.11.006

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Drivers and Policy Choices of Industrial Total-Factor Coal Productivity: Evidence From Eastern China

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Identifying the critical factors of industrial total-factor coal productivity (TCP) and its promotion paths will help achieve the goals of regional energy conservation and pollution reduction. Based on the perspective of total-factor productivity, this paper integrates the methods of stochastic frontier analysis (SFA), Kaya identity, and STIRPAT model to systematically diagnose the temporal and spatial characteristics and the heterogeneous sources of the industrial TCP in 11 provinces of eastern China, and it proposes some differentiated regulatory policies for different provinces. The results show that the TCP is increasing year by year and tends to converge, which indicates that increasing TCP is more and more challenging. Further research shows that there are significant spatial differences in the impact of the economic development level (EDL), industrial economic structure (IES), energy consumption intensity (ECI), and energy consumption structure (ECS) on industrial TCP. As the original driving factors of technological progress, the impact of R&D investment intensity (RII) and R&D investment levels (RIL) on industrial TCP is relatively consistent in different regions. The former has a negative congestion effect on TCP due to the imbalance of R&D investment structure, while the latter has a positive effect on TCP. Therefore, the eastern region should increase R&D expenditure and optimize R&D expenditure structure as a general way to improve TCP in each region and adopt differentiated regulatory policies in economic development and energy utilization according to local conditions.

Keywords: total-factor coal productivity, driving factors, promotion paths, R&D expenditure, STIRPAT model

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INTRODUCTION

With the development of economy and the acceleration of industrialization, problems such as resource shortage and air pollution have become increasingly serious. How to coordinate the development of economy and environment has become a topic of common concern for the whole society. Therefore, while developing the economy, we must also pay attention to energy saving and emission reduction, so as to coordinate economic and environmental benefits. Through previous studies, we know that improving energy efficiency is an essential means of energy saving and emission reduction (Guan et al., 2014; Mardani et al., 2017; Wang et al., 2019a). The key to energy saving is to define the factors that affect the total-factor coal productivity (TCP) in the industrial sector. Besides, affected by industry-dominated industrial structure and coal-dominated energy structure, improving TCP in the industrial sector is related to the economy's sustainable development, and it is an important means to resolve air pollution (Hou et al., 2018; Zhao et al., 2018; Xiong et al., 2019). Based on the above, it is urgent to study how to identify important influencing factors and how to choose the upgrade path of TCP in consideration of regional differences. Therefore, this paper analyzes the evolution trends and regional differences, key factors, and possible improvement paths of industrial coal productivity. It contributes to industrial energy saving and emission reduction and has an important significance for the economic transformation and upgrading.

For energy productivity measurement, single-factor and total-factor energy productivity are usually used. The former, traditionally represented by energy intensity, is used to measure the relationship between energy input and economic output. It is easy to operate but cannot measure the potential technology efficiency and ignores the substitution effect of production factors such as labor and capital on energy (Zhou et al., 2008). In comparison, the substitution elasticity of energy and other production factors is considered, and the defects mentioned above are overcome in the total-factor energy productivity (Wang et al., 2016; Liu and Bae, 2018). As for the measurement methods, the most used methods are non-parametric data envelopment analysis (DEA) and parametric SFA (Chen et al., 2015; Iftikhar et al., 2016; Wang et al., 2018). Comparatively speaking, as the DEA is a mathematical programming method that does not include statistical noise, its estimate of efficiency value may be biased, and its measurement results are easily affected by extreme values (Yang et al., 2011). The SFA method can identify the ineffectiveness of various influencing factors and analyze the factors affecting efficiency while calculating the efficiency, thus avoiding the deficiency of the DEA two-step method (Feng et al., 2017; Gong, 2018). Therefore, considering random noise, the SFA method is applied to measure the industrial TCP in this paper.

There are large spatial differences in China's energy productivity. For example, He et al. (2018) studied the industrial sector's energy productivity and found that the energy productivity in the eastern region was higher than that in the central and western regions. Zhao et al. (2014) studied industrial energy productivity and found that energy productivity gaps in the eastern region were narrowing, while in the west and central regions, they were widening. In studying the economic and environmental efficiency of energy consumption, Lu et al. (2019) found a positive spatial correlation between the economic and environmental efficiency of energy consumption. The productivity of coastal areas in eastern China was relatively high, while that of inland areas in central and western China was relatively low. Overall, energy productivity is high in the eastern region and low in the west and central regions.

As for the influencing factors of energy productivity, energy productivity is affected by technology, energy structure, economic development, industrial structure, and others. However, due to the differences in research methods or samples, different scholars' research conclusions were not the same (Ang and Xu, 2013; Meng et al., 2015). For the technological level, it is generally believed that its improvement will increase energy productivity. For example, Ouyang et al. (2019) found that the technical level was the main driving force for energy efficiency growth. In contrast, Jiang and Zha (2015) found that R&D expenditures from enterprises could improve it, but those from the government would inhibit it. Energy structure is also an important influencing factor in energy productivity. Most scholars believed that the high-carbon energy consumption structure was not beneficial to improving energy productivity (Li and Shi, 2014). For example, Teng et al. (2018) hold that the industrial sector's productivity has not been significantly improved only because the optimization of energy consumption structure and the treatment of emission reduction have reduced pollution emissions. Besides, many scholars were also concerned about the relationship between economic development and energy productivity, but the research results differed. For example, Zhao et al. (2014) and Lu et al. (2019) found that there was a positive correlation between economic development and energy productivity, but Zhou et al. (2018) found that there was a U-shaped relationship. The industrial structure has an important impact on regional energy productivity. In general, the increase in the proportion of the secondary industry characterized by high energy consumption would reduce energy productivity, but the increase in the proportion of the tertiary industry characterized by low energy consumption would increase energy productivity (Wang et al., 2019b).

The spatial evolution trends of industrial coal productivity and the spatial differences of the influence of related factors on TCP need to be further examined. What is more, many scholars used to adopt energy intensity, which was an indicator of output-type technological progress, to explore the influence of technological progress on the TCP. In contrast, few scholars comprehensively consider the impact of input-type and output-type technological progress. Therefore, this paper takes per capita R&D investment and R&D investment proportion as input-type technological progress factors to examine their regional energy efficiency implications.

As for the research methods for the influencing factors of energy productivity, the method of the factor decomposition and the econometric analysis are most widely used. However, data availability often limits the former, and its conclusions can only provide a general direction for policy improvement. Therefore, many scholars use econometric methods to analyze the influencing factors of energy efficiency. Overall, all methods have advantages and disadvantages. For example, the Ordinary Least Square (OLS) method often leads to biased estimation results (Li and Shi, 2014), and the Tobit model is also a commonly used method. But Simar and Wilson (2007) found that the Tobit regression would show inconsistent results with the deterioration in DEA, and the truncated model was more applicable to related research. However, the truncated model has some defects. Liu and Lin (2018) pointed out that the truncated regression would lose some observations and decrease sample size. Generalized-moment-method estimator (GMM) was also a method for analyzing the main factors affecting energy productivity. This method could significantly improve the efficiency of the estimates and solve the endogenous variable. However, compared with other methods, GMM introduces more estimates of the variables. Although this method would improve the estimated results' consistency, it may cause excessive restriction to generate estimated bias (Jiang and Zha, 2015). Considering the spatial differences in the influencing factors of industrial coal productivity, this paper uses a panel data model. This method is more beneficial to revealing the spatial differences and the promotion paths of the influencing factors of regional coal productivity than using time series data or cross-sectional data alone.

Generally speaking, the existing literature has carried out extensive research on energy productivity and put forward many useful insights, but some shortcomings also exist. First, many scholars mostly measure energy productivity by energy intensity, and the result is difficult to reflect the real energy utilization efficiency, while there are few studies on TCP. Second, based on the research objects (provinces, industries, and cities), most scholars do not consider different impacts of heterogeneous factors such as resource endowments, institutional environment, and industrial structure on TCP (Lu et al., 2019). Moreover, the existing research on provincial energy productivity is usually based on the dynamic panel data model, such as system GMM. Although this method can avoid endogenous problems of variables, it leads to overconstraints and thus produces estimation bias, and it is difficult to portray the spatial differences of heterogeneous influencing factors of TCP. Finally, most of the influencing factors of regional energy productivity are selected based on subjective experience or existing literature, lacking a theoretical basis.

The efficient use of coal resources depends on a differentiated policy support system. However, there is still a lack of consistent analysis framework concerning the measurement of the coal utilization efficiency, the description of its internal heterogeneities, and the analysis of related influencing factors within the existing literature. In addition, the previous literature rarely considered the impact of technological progress on TCP in terms of input and output.

Based on the above deficiencies, the contribution of our paper is threefold. First, the TCP in the eastern region is taken as the research object to discuss its influencing factors' spatial differences. China's industrial structure is dominated by the industrial sector, and the energy consumption structure is dominated by coal. The eastern part of China is the center of economic development and energy consumption. At the same time, it is facing problems such as resource shortage and environmental carrying capacity constraints. Therefore, this paper takes 11 provinces in eastern China as the research objects. The results are more targeted and operable for industrial energy saving and emission reduction. Second, based on the expanded Kaya identity, this paper measures energy technology progress from two aspects; that is, it considers the impact of technological progress on total-factor coal productivity comprehensively. Per capita R&D investment and R&D investment proportion are regarded as input-type technological progress, and industrial energy intensity is used as output-type to examine the effect on TCP. Third, based on the STIRPAT model, the spatial differences of various influencing factors in China's eastern region on TCP are empirically analyzed to clarify the possible paths for the improvement of coal productivity and thus to promote the energy saving and emission reduction in the industrial sector and the transformation and upgrade of the regional economy.

The remainder of this paper is organized as follows. **Section 2** describes the research methods and sample data. **Section 3** presents the empirical results. **Section 4** discusses the impact of various influencing factors on the industrial TCP in the eastern region and the differences between regions, and **Section 5** concludes.

METHODOLOGY

Stochastic Frontier Analysis

Stochastic frontier analysis (SFA) is proposed by Aigner et al. (1977). Its main feature is that it adopts a combined error term composed of symmetric random error and new unilateral error. This method can not only capture the random influence of environmental factors but also measure the non-effectiveness. Compared with the traditional DEA method, SFA is more convenient to compare and analyze different objects. Its discriminant ability is stronger, especially in the processing of panel data (Zhang and Lu, 2017). Referring to the modeling ideas of Battese and Coelli (1995), this paper expresses the stochastic frontier production function of TCP as follows.

$$y_{it} = f(x_{it};\beta)\exp(v_{it} - u_{it}) \tag{1}$$

where i and t represent the ith region and tth period, respectively, y_{it} denotes economic output, $f(x_{it};\beta)$ means the production frontier, x_{it} represents the factor input vector, and β is the parameter to be estimated. $(v_{it} - u_{it})$ is the compound error structure, v_{it} is the random disturbance term of the normal distribution, and u_{it} is used to measure the technological non-validity. Technological efficiency can be defined as the ratio of actual output to the maximum possible output:

$$TE_{it} = \frac{y_{it}}{f(x_{it};\beta)\exp(v_{it})} = \exp(-u_{it}) \tag{2}$$

Before measuring the TCP through the stochastic frontier production function, the form of the production function must be determined first. The production functions in the existing literature mainly include the Cobb-Douglas production function and the *trans*-logarithmic production function. In comparison, the latter can reflect the interaction of input factors on output. Therefore, this paper uses the *trans*-logarithmic production function to measure the TCP. Based on the research ideas of Zhang and Lu (2017), this paper sets capital, labor as fixed investment, and industrial coal consumption as a variable input, establishing the *trans*-logarithmic production function as follows:

$$\begin{aligned}\ln IEA_{it} = {} & \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln ICC_{it} + \beta_4 (\ln K_{it})^2 \\ & + \beta_5 (\ln L_{it})^2 + \beta_6 (\ln ICC_{it})^2 + \beta_7 \ln K_{it} \cdot \ln L_{it} \\ & + \beta_8 \ln K_{it} \cdot \ln ICC_{it} + \beta_9 \ln L_{it} \cdot \ln ICC_{it} + v_{it} - u_{it}\end{aligned} \tag{3}$$

where IEA represents the industrial value-added (100 million yuan), K represents the net value of industrial fixed assets (100 million yuan), L represents the total population of industrial employees (10 thousand people), and ICC represents the industrial coal consumption (10 thousand tons). This paper measures TCP by the ratio of IEA to industrial coal consumption (ICC), subtracting lnICC from both sides of model **Eq. 3** simultaneously:

$$\begin{aligned}\ln\left(IEA_{it}/ICC_{it}\right) = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \left(\beta_3 - 1\right)\ln ICC_{it} \\ + \beta_4 \left(\ln K_{it}\right)^2 + \beta_5 \left(\ln L_{it}\right)^2 + \beta_6 \left(\ln ICC_{it}\right)^2 \\ + \beta_7 \ln K_{it} \cdot \ln L_{it} + \beta_8 \ln K_{it} \cdot \ln ICC_{it} \\ + \beta_9 \ln L_{it} \cdot \ln ICC_{it} + v_{it} - u_{it}\end{aligned} \tag{4}$$

Therefore, the industrial TCP can be measured based on model **Eq. 4**.

Kaya Identity

Kaya identity integrates social, economic, energy, environmental, and technological subsystems and is described by a simple mathematical identity (Kaya, 1989). Because of simple structure and intuitive calculation, it is widely used to analyze the influencing factors in greenhouse gas emissions, energy consumption, and other research fields (Lima et al., 2016; Wu et al., 2016). Kaya identity is expanded in this paper to define the influencing factors of TCP, as shown in model **Eq. 5**.

$$\begin{aligned}TCP = \frac{IEA}{ICC} = \frac{IEA}{GDP} \cdot \frac{GDP}{POP} \cdot \frac{POP}{RDI} \cdot \frac{RDI}{GDP} \cdot \frac{GDP}{TEC} \cdot \frac{TEC}{ICC} \\ = IES \cdot EDL \cdot RIL^{-1} \cdot RII \cdot ECI^{-1} \cdot ECS^{-1}\end{aligned} \tag{5}$$

where GDP represents the regional gross domestic product. TEC represents terminal energy consumption. RDI represents internal expenditures for regional research and development. IES indicates the industrial economic structure, represented by the proportion of IEA to GDP. EDL is the per capita GDP to measure the level of economic development. ECS represents the proportion of ICC to TEC to measure the energy consumption structure in the industrial sector. Therefore, a high degree of the ECS means that the industrial sector uses more coal, while other sectors use less. That is, coal resources are concentrated in the industrial sector. It is well known that the industrial sector has high coal utilization efficiency, so increasing the proportion of coal consumption in total energy consumption is more conducive to energy saving and emission reduction. ECI denotes TEC per unit of GDP to measure the level of output-type technological progress. RII is the proportion of R&D expenditures to regional GDP to measure the intensity of R&D expenditures. RIL indicates the R&D investment level, measured by per capita R&D investment. According to model (5), TCP is mainly affected by factors such as industrial economic structure (IES), economic development level (EDL), industrial energy consumption structure (ECS), energy consumption intensity (ECI), R&D investment intensity (RII), and R&D investment level (RIL).

STIRPAT Model

Based on the identification of the influencing factors, the STIRPAT model is used to analyze the asymmetrical impact of IES, EDL, ECS, ECI, RII, and RIL on TCP in this paper. The STIRPAT model facilitates the avoidance of cross-sectional dependence, heterogeneity, and nonlinear transformation of potential integration variables (Liddle, 2015). On this basis, the logarithm on both sides of model **Eq. 6** is taken, and a panel data model **Eq. 7** for influencing factors of industrial coal productivity in eastern China is obtained:

$$TCP_{it} = a \cdot IES_{it}^{b} \cdot EDL_{it}^{c} \cdot ECS_{it}^{d} \cdot ECI_{it}^{e} \cdot RII_{it}^{f} \cdot RIL_{it}^{g} \cdot \varepsilon_{it} \tag{6}$$

$$\begin{aligned}\ln TCP_{it} = \alpha_i + \beta_{1i} \ln IES_{it} + \beta_{2i} \ln EDL_{it} + \beta_{3i} \ln ECS_{it} \\ + \beta_{4i} \ln ECI_{it} + \beta_{5i} \ln RII_{it} + \beta_{6i} \ln RIL_{it} + \mu_{it}\end{aligned} \tag{7}$$

where α, β are coefficients to be evaluated and μ is random error. According to model **Eq. 7**, the factors of industrial TCP mainly involve economic growth (EDL and IES), energy utilization (ECS and ECI), and R&D expenditure (RII and RIL). Furthermore, this paper uses the Hausman test to identify the type of panel data model. This article first sets the following two null hypotheses, namely, H_1 ($\alpha_1 = \alpha_2 = \ldots = \alpha_n$, $\beta_1 = \beta_2 = \ldots = \beta_k$) and H_2 ($\beta_1 = \beta_2 = \ldots = \beta_k$), and then it constructs F_1 and F_2 statistics, respectively.

$$F_1 = \frac{(S_3 - S_1)/[(n-1)(k+1)]}{S_1/[nT - n(k+1)]} \sim F[(n-1)(k+1), n(T-k-1)] \tag{8}$$

$$F_2 = \frac{(S_2 - S_1)/[(n-1)k]}{S_1/[nT - n(k+1)]} \sim F[(n-1)k, n(T-k-1)] \tag{9}$$

where n is the number of cross-section objects; k is the number of explanatory variables; T is the number of periods. S_1, S_2, and S_3 represent the sum of squares of residuals of the variable coefficient model, variable intercept model, and constant-coefficient model, respectively. If the model accepts hypothesis H_1, it means that the model should be set as the constant coefficient model. If H_1 is rejected, it is necessary to check further whether H_2 is received. If H_2 is accepted, the local boundary model should be selected; otherwise, it should be set as the variable coefficient model.

This paper uses this method to determine the type of panel data and then empirically analyzes the influencing factors of industrial TCP of 11 provinces in eastern China.

Sample and Data

Affected by industry-dominated industrial structure and coal-dominated energy structure, energy consumption in the east of China has increased dramatically in recent years (Wang et al., 2020; Xu et al., 2020). Therefore, studying the industrial TCP in the region and its influencing factors will help formulate differentiated energy saving measures and paths. This paper takes the data from 2000 to 2018 in 11 provinces in eastern China as samples (Beijing City, Tianjin City, Hebei Province, Liaoning Province, Shanghai City, Jiangsu Province, Zhejiang Province, Fujian Province, Shandong Province, Guangdong Province, and Hainan Province). The indexes of GDP, industrial value-added (IEA), and the net value of industrial fixed K are derived from the "China Statistical Yearbook (2000–2019)", and K is calculated by subtracting the

TABLE 1 | Results of TCP in eastern China from 2000 to 2018.

Year	Beijing	Tianjin	Hebei	Liaoning	Shanghai	Jiangsu	Zhejiang	Fujian	Shandong	Guangdong	Hainan
2000	0.258	0.300	0.432	0.304	0.376	0.502	0.458	0.381	0.490	0.555	0.177
2001	0.289	0.332	0.464	0.336	0.409	0.532	0.489	0.413	0.521	0.583	0.205
2002	0.321	0.365	0.495	0.369	0.441	0.561	0.520	0.446	0.550	0.610	0.235
2003	0.354	0.398	0.526	0.401	0.473	0.589	0.550	0.477	0.579	0.637	0.265
2004	0.387	0.430	0.555	0.434	0.504	0.617	0.578	0.508	0.607	0.661	0.297
2005	0.419	0.462	0.584	0.465	0.534	0.642	0.606	0.538	0.633	0.685	0.329
2006	0.451	0.493	0.611	0.497	0.563	0.667	0.632	0.568	0.658	0.707	0.362
2007	0.483	0.524	0.637	0.527	0.591	0.690	0.657	0.596	0.682	0.729	0.395
2008	0.514	0.554	0.662	0.557	0.618	0.712	0.681	0.622	0.704	0.748	0.427
2009	0.544	0.582	0.686	0.585	0.644	0.733	0.704	0.648	0.726	0.767	0.459
2010	0.573	0.610	0.708	0.612	0.669	0.753	0.725	0.672	0.746	0.785	0.491
2011	0.600	0.636	0.729	0.638	0.692	0.771	0.745	0.695	0.765	0.801	0.521
2012	0.627	0.661	0.749	0.663	0.714	0.789	0.764	0.717	0.782	0.816	0.551
2013	0.652	0.684	0.768	0.687	0.735	0.805	0.782	0.738	0.799	0.830	0.580
2014	0.677	0.707	0.785	0.709	0.754	0.820	0.798	0.757	0.814	0.844	0.607
2015	0.699	0.728	0.801	0.730	0.773	0.834	0.814	0.775	0.828	0.856	0.633
2016	0.716	0.747	0.817	0.748	0.791	0.846	0.828	0.792	0.842	0.869	0.659
2017	0.733	0.765	0.832	0.767	0.808	0.858	0.842	0.809	0.856	0.884	0.686
2018	0.748	0.783	0.847	0.786	0.824	0.869	0.854	0.825	0.871	0.897	0.714

accumulated depreciation from the original value of the fixed assets of industrial enterprises above designated size. For excluding the price factor, GDP, IEA, and K of each province have been deflated to constant price referring to 2019.

Because of the availability of data, POP represents the average employee number of industrial enterprises above designated size; the data is derived from "China Industrial Statistical Yearbook (2000–2019)"; the missing data are obtained from the statistical yearbooks of each province; terminal energy consumption (TEC) and industrial coal consumption (ICC) are sourced from the regional energy balance sheet in "China Energy Statistical Yearbook"; R&D investment intensity (RII) and R&D investment level (RIL) are derived from "China Science and Technology Statistical Yearbook (2000–2019)".

RESULTS

Calculation Results of TCP in Eastern China

Based on the SFA model, this paper calculates the industrial total factor coal productivity of 11 provinces in eastern China from 2000 to 2018, and the results are shown in **Table 1**. On the whole, the industrial TCP in the east of China has been increasing year by year, but there are obvious spatial and temporal differences in the annual average growth rate and cumulative increment of industrial TCP.

As shown in **Table 1**, the industrial TCP of 11 provinces shows growth trends from 2000 to 2018. However, due to the heterogeneity of regional social and economic development, there are obvious regional differences in industrial TCP of various provinces. For example, the industrial TCP in Guangdong, Jiangsu, Shandong, Zhejiang, and Hebei provinces is obviously higher than the average level in the eastern region, which indicates that the industrial TCP in these provinces has limited potential for improvement in the future. In contrast, the industrial TCP of the four provinces of Liaoning, Tianjin, Beijing, and Hainan is significantly lower than the average level of eastern China, which indicates that the TCP of these provinces has great potential for improvement in the future.

In terms of the change trends, the regional differences in TCP tend to decrease. As shown in **Figure 1**, its growth rate and the increment are significant in Beijing, Tianjin, Liaoning, and Hainan provinces during the inspection period. For example, the TCP in Hainan province increased from 0.177 in 2000 to 0.714 in 2018, and its average annual growth rate reached 8.06%. In contrast, due to the relatively large base of the TCP in Hebei, Zhejiang, Jiangsu, Shandong, Guangdong, and other provinces, its growth rate and the increment are not significant. However, their TCP is still at a relatively high level. Besides, the regional gap in TCP in the eastern region decreases year by year, and its growth rate tends to converge. The maximum inter-provincial gap in TCP was 0.378 in 2000, and the maximum inter-provincial gap in 2018 was 0.183. Meanwhile, the regional differences in the growth rate of TCP fell from 10.77% to 2.86%, and the growth rate showed convergence trends, which means that China's regional energy productivity has astringency (Zhang and Lu, 2017).

In general, there are great regional differences in the industrial TCP in eastern China. All regions' TCP increases year by year. The changes in its growth rate and the increment value tend to converge, which means that the potential for improvement in the industrial TCP is relatively limited. As we all know, the different levels of economic development lead to different industrialization processes in various regions, so the energy utilization technology and utilization efficiency of each region are also different (Steven, 1997). The reason why Hainan Province has the largest growth rate at the beginning is because the base number is small and it is in the growth period, while the other regions are in the mature or decline period of the life cycle and the TCP base is relatively large, so the growth rates and increments are not significant. Therefore, it is necessary to identify the key influencing factors and improvement paths that affect regional TCP.

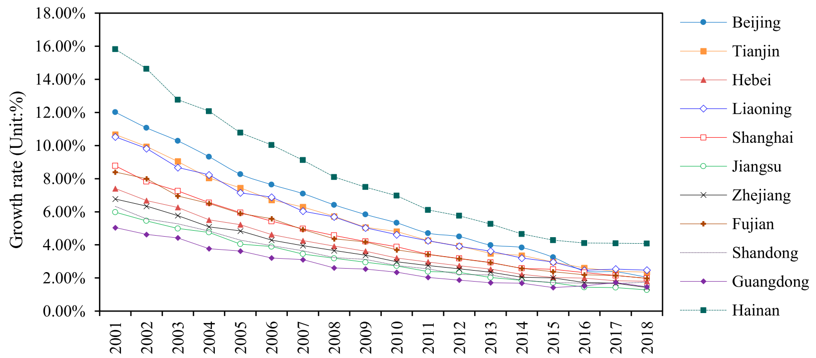

FIGURE 1 | Changes in the annual growth rate of TCP in eastern China.

TABLE 2 | The results of the unit root test.

Index	IPS	Fisher-ADF	Fisher-PP	Stationarity
ln *TCP*	−2.9820[b]	18.7286[a]	0.0496	No
Δ ln *TCP*	−12.7601[a]	115.3870[a]	88.5362[a]	Yes
ln *IES*	3.6472	11.6710	3.4914	No
Δ ln *IES*	−2.9398[b]	46.3082[b]	89.0702[a]	Yes
ln *EDL*	3.1670	9.9395	9.8583	No
Δ ln *EDL*	−2.3400[b]	43.4766[a]	58.6162[a]	Yes
ln *ECS*	0.8804	13.8137	10.0288	No
Δ ln *ECS*	−4.9269[a]	58.7223[a]	87.1128[a]	Yes
ln *ECI*	1.7520	15.2304	11.6352	No
Δ ln *ECI*	−7.5163[a]	86.6457[a]	104.9300[a]	Yes
ln *RII*	−0.8554	24.9478	25.5056	No
Δ ln *RII*	−9.0698[a]	100.9880[a]	135.7480[a]	Yes
ln *RIL*	1.9537	25.7019	22.6375	No
Δ ln *RIL*	−5.7128[a]	71.9536[a]	131.9630[a]	Yes

Note: Δ represents first difference.
[a]$p < 0.01$.
[b]$p < 0.05$.
[c]$p < 0.10$.

TABLE 3 | Results of covariance analysis and Hausman test.

Residual sums of square	F statistics	Critical value (0.05)	Chi-sq. statistic	Prob
S_3 = 6.035987	F_1 = 139.63	F (70,132) = 1.40	176.03	0
S_2 = 0.868,801	F_2 = 22.03	F (60,132) = 1.42		
S_1 = 0.060526				

Empirical Results of TCP Influencing Factors

The unit root test is usually used to judge the data stationarity to avoid spurious regression (Harris et al., 2020). According to the IPS, Fisher-ADF, and Fisher-PP tests, the results in **Table 2** show that the first-order difference terms of all variables are stationary. Further, the results of the Kao test show that the null hypothesis of "no co-integration relationship" is rejected at 1% significant level, so the co-integration relationship exists among the variables.

On this basis, this article uses the Hausman test to determine the type of panel data model. According to the test results in **Table 3**, $F_1 > F_{0.05}$ (70,132), $F_2 > F_{0.05}$ (60,132). Therefore, this paper chooses the variable coefficient model to analyze the influencing factors of industrial TCP.

Because of the serial correlation and the cross-sectional heteroskedasticity of panel data, this paper uses the CS-SUR method to make an empirical test on the panel data of 11 eastern provinces from 2000 to 2018. The results show that the model passes the F-statistic at the 1% significance level, and most of the estimated coefficients in the panel data model pass the *t*-test, which indicates that the model fits well (**Table 4**).

Overall, there are noticeable regional differences in the influence of different factors on industrial TCP. From the perspective of the contribution of various factors to TCP, the coal consumption structure and R&D investment level have a positive effect on the industrial TCP; the energy intensity and R&D investment intensity have a negative effect on the industrial TCP; and the impact of industrial economic structure and economic development level has large regional differences. The contribution of each influencing factor is discussed in detail below.

DISCUSSION

Influencing Factors of TCP in Eastern China

Based on the empirical test results, this article further discusses the influencing factors of the industrial TCP in eastern China to clarify the possible paths for the promotion of regional TCP.

Regional Differences in the Impact of EDL on TCP

From the test results, the economic development level (EDL) has significant impacts on the TCP. Its influence effect is positive in some provinces such as Beijing, Tianjin, Hebei, Guangdong, and Hainan, and the elasticity coefficients are 0.415, 0.633, 0.599, 0.097, and 1.219, respectively. In contrast, the EDL of Shanghai, Jiangsu, Zhejiang, Fujian, and Shandong provinces has inhibited the increase in industrial TCP, and the elasticity coefficients were −0.511, −0.481, −0.406, −2.313, and −1.464, respectively.

TABLE 4 | Regression coefficient test results of influencing factors of TCP.

Regions	C	Δ ln *IES*	ln *EDL*	Δ ln *ECS*	Δ ln *ECI*	Δ ln *RII*	ln *RIL*
Beijing	−11.076[a]	−0.312[a]	0.415[b]	0.147	−0.078	−0.257	0.538[a]
	(−16.595)	(−5.382)	(2.584)	(1.511)	(−0.994)	(−1.553)	(3.504)
Tianjin	−9.754[a]	−0.065	0.633[a]	0.105[a]	−0.033	−0.290[a]	0.133
	(−12.115)	(−0.830)	(6.415)	(3.770)	(−0.777)	(−3.253)	(1.443)
Hebei	−6.420[a]	−0.392[a]	0.599	0.278[a]	−0.058	0.012	−0.072
	(−8.509)	(−3.358)	(1.572)	(3.287)	(−1.157)	(0.024)	(−0.144)
Liaoning	−6.344[a]	−0.295[b]	−1.675	−0.010	0.134	−2.063	2.316
	(−8.049)	(−2.163)	(−0.576)	(−0.099)	(1.453)	(−0.692)	(0.790)
Shanghai	−6.432[a]	0.101[b]	−0.511[a]	−0.191[a]	0.160[a]	−0.836[a]	1.165[a]
	(−5.187)	(1.994)	(−3.016)	(−3.401)	(2.938)	(−4.080)	(6.223)
Jiangsu	−1.824[a]	0.171[a]	−0.481[a]	0.077[a]	−0.057[a]	−0.522[a]	0.680[a]
	(−12.831)	(12.346)	(−5.869)	(4.289)	(−5.803)	(−6.453)	(8.386)
Zhejiang	−2.576[a]	−0.004	−0.406[a]	0.044	−0.039	−0.505[a]	0.664[a]
	(−3.707)	(−0.098)	(−3.520)	(0.923)	(−1.139)	(−4.195)	(5.795)
Fujian	−3.680[a]	0.301[a]	−2.313[a]	−0.138[a]	0.136[a]	−2.599[a]	2.704[a]
	(−12.662)	(3.239)	(−9.415)	(−4.363)	(6.924)	(−10.920)	(11.237)
Shandong	−2.201[a]	0.100[b]	−1.464[a]	0.060[b]	−0.014	−1.572[a]	1.697[a]
	(−6.675)	(2.267)	(−4.597)	(2.389)	(−0.958)	(−4.959)	(5.351)
Guangdong	−2.727[a]	0.381[a]	0.097[a]	0.030	−0.047[b]	−0.092[a]	0.187[a]
	(−12.376)	(7.530)	(3.319)	(1.253)	(−2.525)	(−3.227)	(7.095)
Hainan	−11.457[a]	0.624[a]	1.219[c]	0.275[b]	−0.121[c]	−0.004	−0.110
	(−9.531)	(6.985)	(1.616)	(2.434)	(−1.700)	(−0.005)	(−0.149)

Note: t-statistics are given in parentheses.
[a]$p < 0.01$.
[b]$p < 0.05$.
[c]$p < 0.10$.

In fact, due to the regional differences in the industrial structure, resource endowments, and economic development of eastern China, the U-shaped relationship between economic development and energy efficiency is usually not uniform in different regions and economic planning period (Huang and Wang, 2017; Zhou et al., 2018). Meanwhile, the impact of the EDL on TCP in Liaoning Province does not pass the significance test, and it may be caused by data falsification in recent years.

Regional Differences in the Impact of IES on TCP

According to the empirical results, the influence of industrial economic structure (IES) on TCP shows significant regional differences. It can be seen that, in Tianjin and Zhejiang, the IES is not a critical factor affecting TCP, while in other provinces, the IES is an essential factor affecting TCP. In comparison, IES greatly influences the industrial TCP in Beijing, Hebei, Liaoning, Fujian, Guangdong, and Hainan provinces, but it has relatively small effects in Shanghai, Jiangsu, and Shandong provinces. As shown in **Table 4**, the IES of Shanghai, Jiangsu, Fujian, Shandong, Guangdong, and Hainan provinces significantly promoted the improvement of industrial TCP, while it had a negative impact on Beijing, Hebei, and Liaoning provinces. **Table 4** shows that there are significant regional differences in the promotion effect of industrialization on total-factor coal productivity.

The root cause lies in the different stages of industrialization in 11 provinces in eastern China. When the degree of industrialization is not high enough, regional development pursues more economic development, ignoring the utilization of coal resources and the protection of the ecological environment (Long et al., 2016). In the post-industrial stage, the economic level reaches a certain height. The region pays more attention to the improvement of coal resource productivity and the coordinated development of social economy, energy utilization, and ecological environment (Li and Dewan, 2017).

Regional Differences in the Impact of ECS on TCP

From the empirical results, there are spatial differences in the impact of ECS on TCP. The ECS in Shanghai, Liaoning, and Fujian Province has a negative impact on the TCP, while the ECS in other provinces has a positive impact on the TCP. It is found that the ECS of Hebei and Hainan provinces has a greater impact on the TCP, while the ECS of Jiangsu and Shandong provinces has a relatively small effect on the TCP. According to the definition, the ECS represents the proportion of coal consumption in total energy consumption. The larger the ECS, the higher the proportion of industrial coal consumption in the total energy consumption, which means that the degree of centralized utilization of coal resources will be greater. In fact, the centralized utilization of coal resources is more conducive to promoting and applying energy saving technology and improving energy efficiency (Li and Dewan, 2017).

In comparison, the impact of ECS in Shanghai and Fujian does not meet the theoretical expectations. As shown in **Figure 2**, with the rapid development of high-tech industries in Shanghai, the economic status of the secondary industry gradually gives way to the tertiary industry, and the industrial economic structure reached 26.61% in 2018. Meanwhile, the energy consumption structure is gradually optimizing in Shanghai, and the coal consumption structure is declining year by year and concentrates in the industrial sector. According to statistics,

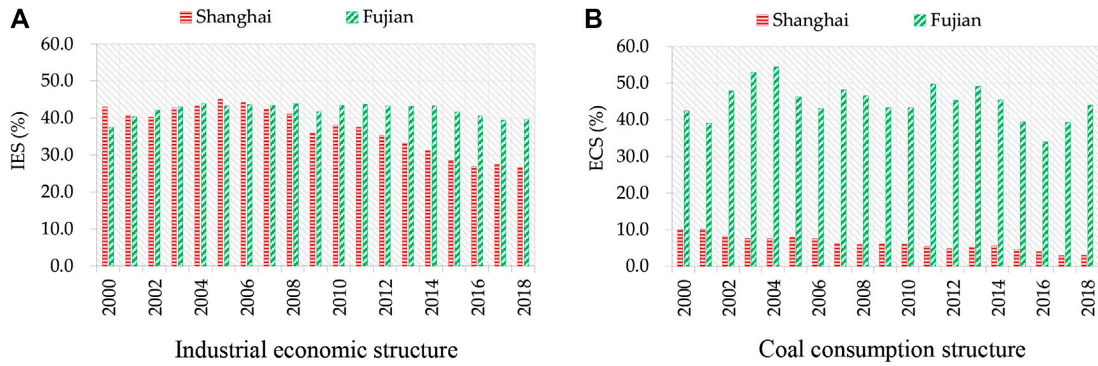

FIGURE 2 | Comparison of IES and ECS between Shanghai and Fujian Province. **(A)** Industrial economic structure. **(B)** Coal consumption structure.

the coal consumption of Shanghai's industrial sector in 2018 was 31.51 million tons of standard coal, accounting for 99.78% of the total coal consumption and 3.02% of the total energy consumption. It can be argued that, in Shanghai, the shrinkage of economic structure and the centralized utilization of coal resources in the industrial sector are the reasons that cause the coal consumption structure to have a negative impact on the industrial TCP.

For Fujian Province, the industrial economic structure changed slightly during the investigation period, from 37.50% in 2000 to 39.61% in 2018. In terms of the coal consumption structure, coal consumption in Fujian Province is mainly concentrated in the industrial sector. In 2018, the industrial sector's total coal consumption was 57.50 million tons of standard coal, accounting for 44.04% of the total terminal energy consumption and 66.36% of the total industrial energy consumption. It can be considered that the excessive concentration and scale effect of the industrial coal consumption are the fundamental reasons for the negative impact of the ECS on the industrial TCP. Therefore, promoting economic transformation and intensive utilization of coal resources are the important ways to improve the industrial TCP in Fujian Province (Xie et al., 2015).

Regional Differences in the Impact of *ECI* on TCP

According to **Table 4**, there are noticeable regional differences in the impact of ECI on industrial TCP in eastern China. The impact of ECI on TCP has not passed the significance test in sample areas such as Beijing, Tianjin, Hebei, Liaoning, Zhejiang, and Shandong provinces, which shows that whether the energy efficiency driven by technological innovation in these regions can improve the industrial TCP has not been supported by empirical data.

In comparison, the ECI in Shanghai, Jiangsu, Fujian, Guangdong, and Hainan has significant effects, but there are noticeable regional differences. The ECI of Jiangsu, Guangdong, and Hainan has negative impacts, which is in accord with theoretical expectations, while the ECI in Shanghai and Fujian has positive impacts. According to the analysis, ECI is a biased single-factor indicator of energy efficiency, with the implicit assumption that economic growth is mainly driven by energy consumption and technological progress, without considering the substitution elasticity of various production factors and energy input structures for economic growth (Norman, 2017; Adom et al., 2018). According to the empirical results of Shanghai and Fujian, the increase in ECI leads to an increase in the industrial TCP. Considering the bias of energy intensity indicators, the reduction of regional energy efficiency does not mean the decrease of industrial TCP (Cao et al., 2017).

Regional Differences in the Impact of RII on TCP

As we all know, advanced equipment utilization and higher technological input help reduce inefficient energy systems, which is beneficial in improving total-factor energy productivity (Beyzanur et al., 2018). According to the test results, the impact of RII on TCP in Hebei, Liaoning, and Hainan provinces does not pass the significance test. In contrast, the RII in other provinces has a significant negative effect on the TCP, which does not meet the theoretical expectations.

There are two reasons for this result. On the one hand, the utilization efficiency of R&D investment in the eastern provinces is relatively low. The transformation and application of R&D achievements are relatively few, leading to the fact that the industrial TCP does not improve with the growth of RII. Especially in Hebei, Liaoning, and Hainan provinces, RII has no significant impact on TCP, and their RII is less than the national average of 2.07% (as shown in **Figure 3**), which indicates that RII needs to cross a certain threshold to promote the increase in TCP significantly. Therefore, improving the utilization efficiency of R&D funds and promoting the transformation and application of R&D achievements are important ways to improve the industrial TCP (Medina et al., 2016). On the other hand, the imbalance of the investment structure of R&D expenditure is also not conducive to the increase in TCP. In fact, the R&D expenditure in the eastern regions is mainly for high-tech industries and emerging industries. In contrast, the proportion of the total R&D expenditure in the energy-intensive industrial sector is relatively small. In other words, due to the imbalance of the input structure of R&D funding, high-tech industries have a certain crowding-out effect on energy-intensive industries in terms of total-factor energy efficiency improvement.

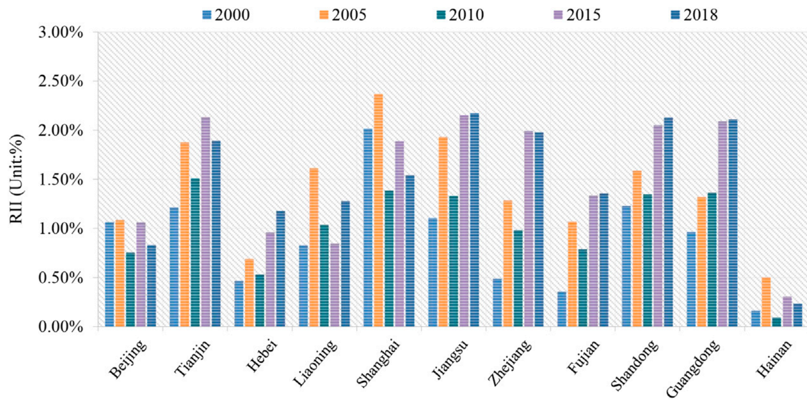

FIGURE 3 | Regional comparison of RII in eastern China.

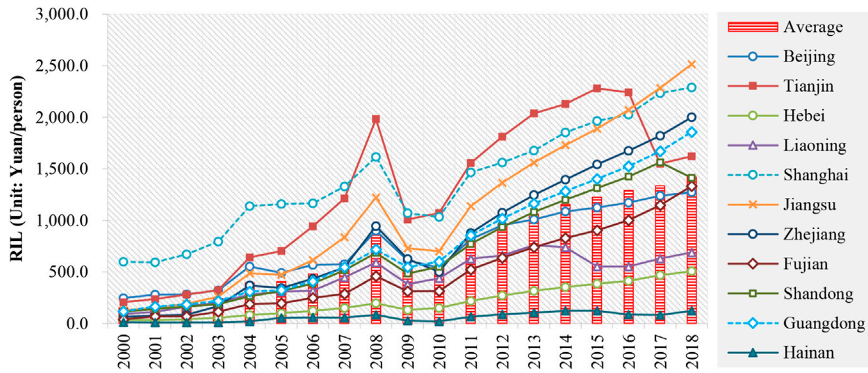

FIGURE 4 | Changes in RIL in eastern China in 2000–2018.

TABLE 5 | Analysis of the critical paths to improving the industrial TCP in eastern China.

Provinces	*IES*	*EDL*	*ECS*	*ECI*	*RII*	*RIL*
Beijing	↓	↑				↑↑
Tianjin		↑↑	↑		↓	↑
Hebei	↓		↑			
Liaoning	↓			↑		
Shanghai	↑	↓↓	↓	↑	↓↓	↑↑↑
Jiangsu	↑	↓	↑	↓	↓↓	↑↑
Zhejiang		↓			↓↓	↑↑
Fujian	↑	↓↓↓	↓	↑	↓↓↓	↑↑↑
Shandong	↑	↓↓↓	↑		↓↓↓	↑↑↑
Guangdong	↑	↑		↓	↓	↑
Hainan	↑↑	↑↑↑	↑	↓		

Note: ↑ and ↓ indicate that some factors promote or inhibit TCP, respectively. The number of ↑ or ↓ indicates the fluctuation range of elasticity coefficient $|\beta_i|$, ☆/★ indicates $0 < |\beta_i| \le 0.5$, ☆☆/★★ indicates $0.5 < |\beta_i| \le 1.0$, and ☆☆☆/★★★ indicates $|\beta_i| > 1.0$.

Regional Differences in the Impact of RIL on TCP

According to the empirical results, the RIL of Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, and Guangdong provinces has significantly positive effects on industrial TCP, while in Hebei, Liaoning, and Hainan provinces, the RIL does not pass the significance test. As shown in **Figure 4**, the R&D expenditure of 11 provinces in eastern China has increased year by year, but each province's growth rate is quite different. The RIL of Beijing, Tianjin, and Shanghai is relatively large, while that of Hebei, Liaoning, and Hainan is relatively low. Taking 2018 as an example, the RIL of Hebei, Liaoning, and Hainan was 505.55, 689.61, and 121.74 yuan per capita, respectively, being far lower than the average level of 1,419.53 yuan per capita in eastern China. It implies that the quantitative changes will cause qualitative changes; that is, when R&D expenditure reaches a certain scale, it can promote the increase in industrial TCP. Therefore, we can conclude that increasing R&D investment is an important way to improve the industrial TCP.

Promotion Paths for TCP in Eastern China

Determining the critical factors of industrial TCP and its upgrade path will help achieve the win-win goals of energy conservation and pollution reduction in eastern China. According to the empirical results, due to the regional differences in economic development, energy utilization, and R&D investment in the 11 eastern provinces of China, there are significant regional differences in the impact of various influencing factors on industrial TCP. We compared the contribution of various influencing factors to TCP, and the results are shown in **Table 5**.

According to **Table 5**, it can be seen that the contribution of the influencing factors of industrial TCP in eastern China is not consistent. Overall, the IES, EDL, ECS, and ECI have heterogeneous effects on industrial TCP in the 11 provinces in eastern China. The RII has a negative inhibitory effect, while RIL has a positive promotion effect. Promoting R&D investment and the transformation of scientific research results are the generic ways to increase the industrial TCP. Therefore, to improve the TCP of the industrial sector in eastern China, differentiated adjustment policies should be formulated in law and market according to local conditions (Liu et al., 2016). In terms of the 11 provinces in eastern China, each province has a different critical path to promote the industrial TCP.

- For Beijing, the IES, EDL, and RIL have a significant impact on TCP. Therefore, the key to improving industrial TCP in Beijing lies in optimizing its industrial structure, promoting economic development, and increasing R&D investment.
- For Tianjin, the factors EDL, ECS, and RII have a significant impact on industrial TCP. Therefore, the key to improving industrial TCP in Tianjin is to accelerate economic development, promote the centralized utilization of coal resources, and increase R&D investment and the transformation and application of its achievements.
- For Hebei Province, considering the significant impact of IES and ECS on industrial TCP, the key to improving industrial TCP in Hebei Province is to optimize the economic structure and the coal consumption structure in its industrial sector.
- For Liaoning Province, the impact of IES and ECI on industrial TCP is slightly significant. Therefore, the key to improving industrial TCP in Liaoning Province is to optimize the industrial structure and intensive utilization of energy.
- For Liaoning Province, the impact of IES on industrial TCP is more significant, while the impact of ECI on TCP is slightly significant. Therefore, the key to enhancing industrial TCP in Liaoning Province in the future is to optimize the industrial structure and pay attention to the intensive utilization of energy resources.
- For the Shanghai Municipality and Fujian Province, the industrial TCP is mainly affected by EDL, RII, and RIL. Therefore, accelerating economic development, increasing R&D expenditures, and accelerating the transformation and application of R&D results are the critical paths to improve their industrial TCP.
- For Jiangsu and Shandong Province, the key influencing factors of industrial TCP in the two provinces are roughly the same. The key to improving industrial TCP lies in accelerating economic development, optimizing the coal consumption structure, and increasing the R&D investment and its achievement transformation.
- For Zhejiang Province, industrial TCP is mainly affected by EDL, RII, and RIL. The key to improving industrial TCP lies in further promoting economic development, increasing R&D investment, and achievement transformation.
- For Guangdong Province, the TCP is relatively high and has a rapid growth rate. The empirical results show that, except for ECS, other factors significantly impact TCP, but these factors have relatively limited potential for industrial TCP improvement. Comparatively speaking, the factors IES and RIL have a great influence on TCP. Therefore, the critical path of upgrading industrial TCP in Guangdong Province lies in optimizing the economic structure and increasing R&D investment.
- For Hainan Province, the empirical results show that IES, EDL, ECS, and ECI significantly impact industrial TCP. Therefore, the key to enhancing industrial TCP in Hainan Province lies in the improvement of industrial economic structure and economic development level, as well as the intensive utilization of coal resources in industrial sectors.

Conclusions and Policy Implications

During the inspection period, the industrial TCP in 11 provinces of eastern China increases year by year, but the regional differences in growth margin and growth rate decrease and show a convergence trend. The growth margin and growth rate of the industrial TCP in Beijing, Tianjin, Liaoning, and Hainan provinces are relatively large. In contrast, those in Hebei, Zhejiang, Jiangsu, Shandong, and Guangdong provinces are not obvious, but their industrial TCP ranks first in eastern China.

The EDL and IES in eastern China have a significant impact on industrial TCP, and there are spatial differences in this impact. The EDL in Beijing, Tianjin, Hebei, Guangdong, Hainan, and other provinces positively affects the industrial TCP. In contrast, the EDL in Shanghai, Jiangsu, Zhejiang, Fujian, and Shandong has a negative inhibitory effect. As for IES, this factor has a positive effect on TCP in Shanghai, Jiangsu, Fujian, Shandong, Guangdong, and Hainan provinces, while that of Beijing, Hebei, and Liaoning provinces does not promote the improvement of industrial TCP. The heterogeneity of the regional industrial structure, resource endowments, and economic development mode are the root causes of this result.

There are spatial differences in the effect of the ECS on the industrial TCP. The ECS in Liaoning, Zhejiang, and Guangdong provinces has no significant impact on TCP. In contrast, ECS in Beijing, Tianjin, Hebei, Jiangsu, Shandong, and Hainan provinces positively affects TCP. By contrast, the ECS in Shanghai and Fujian has a negative impact on industrial TCP. In general, the greater the degree of centralized utilization of coal resources in the industrial sector, the more conducive to the intensive use of coal resources and the improvement of industrial TCP. Therefore, promoting the intensive use of coal resources is a critical way to improve industrial TCP.

As the source of energy technology progress, R&D investment has a relatively consistent impact on industrial TCP in all provinces. The RIL plays a positive role in promoting industrial TCP, while RII has a negative impact on industrial TCP. The root cause lies in the imbalance of R&D investment structure, low efficiency of R&D investment, and fewer applications of R&D results. As the output of energy technology progress, the impact of ECI on industrial TCP has great regional differences. The impact of ECI on TCP is not significant in Beijing, Tianjin, Hebei, Liaoning, Zhejiang, Shandong, and other places. In Jiangsu, Guangdong, and Hainan, ECI has a significant negative impact on TCP, while in Shanghai and Fujian provinces, ECI positively impacts TCP. Considering the bias of energy intensity indicators, the promotion of regional energy efficiency does not mean the decrease of industrial TCP.

There are noticeable regional differences in the key influencing factors of industrial TCP in 11 provinces of eastern China. Therefore, it is necessary to adopt differentiated adjustment policies to improve the industrial TCP according to local conditions. Meanwhile, increasing the R&D expenditures, optimizing R&D investment structure, improving R&D utilization efficiency, and promoting the transformation and application of R&D results are generic ways to improve the industrial coal productivity in the eastern region.

It is necessary to note that RIL has different effects on industrial TCP. For example, RIL in Hainan is lower than that in eastern China, while RIL in Shanghai is higher than average level. Only when RIL is higher than the average R&D level, it will have a significant impact on industrial TCP, which indicates that RIL may have a threshold effect on TCP. This problem deserves further study. In addition, due to the close economic and trade relationship in the eastern region, whether the spatial spillover effect of technological progress will affect TCP also needs further research. Therefore, spatial measurement or threshold cointegration can be considered to test the interactive effects of spatial heterogeneity in our next study.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

DW and YZ were responsible for conceptualization; DW, YZ, and ZZ for methodology; DW, YZ, ZZ, and XY for writing; YZ, ZZ, and XY for results; DW, XY, and XW for validation. XW was responsible for artwork. All authors contributed to the article and approved the submitted version.

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REFERENCES

Adom, P. K., Amakye, K., Abrokwa, K. K., and Quaidoo, C. (2018). Estimate of transient and persistent energy efficiency in Africa: a stochastic Frontier approach. *Energy Convers. Manag.* 166, 556–568. doi:10.1016/j.enconman.2018.04.038

Aigner, D., Lovell, C. A. K., and Schmidt, P. (1977). Formulation and estimation of stochastic Frontier production function models. *J. Econom.* 6, 21–37. doi:10.1016/0304-4076(77)90052-5

Ang, B. W., and Xu, X. Y. (2013). Tracking industrial energy efficiency trends using index decomposition analysis. *Energy Econ.* 40, 1014–1021. doi:10.1016/j.eneco.2013.05.014

Battese, G. E., and Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic Frontier production function for panel data. *Empir. Econ.* 20, 325–332. doi:10.1007/BF01205442

Beyzanur, C. E., Selim, Z., and Dursun, D. (2018). A two-stage analytical approach to assess sustainable energy efficiency. *Energy.* 164, 822–836. doi:10.1016/j.energy.2018.08.213

Cao, L., Qi, Z., and Ren, J. (2017). China's industrial total-factor energy productivity growth at sub-industry level: a two-step stochastic metafrontier malmquist index approach. *Sustainability.* 9, 1384. doi:10.3390/su9081384

Chen, Z. F., Barros, C. P., and Borges, M. R. (2015). A Bayesian stochastic Frontier analysis of Chinese fossil-fuel electricity generation companies. *Energy Econ.* 48, 136–144. doi:10.1016/j.eneco.2014.12.020

Feng, C., Wang, M., Liu, G. C., and Huang, J. B. (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

Gong, B. (2018). The shale technical revolution - cheer or fear? Impact analysis on efficiency in the global oil field service market. *Energy Pol.* 112, 162–172. doi:10.1016/j.enpol.2017.09.054

Guan, D., Su, X., Zhang, Q., Peters, G. P., Liu, Z., Lei, Y., et al. (2014). The socioeconomic drivers of China's primary PM2.5 emissions. *Environ. Res. Lett.* 9, 24010. doi:10.1088/1748-9326/9/2/024010

Harris, D., Kew, H., and Taylor, A. M. R. (2020). Level shift estimation in the presence of non-stationary volatility with an application to the unit root testing problem. *J. Econom.* 219, 354–388. doi:10.1016/j.jeconom.2020.03.008

He, Y., Liao, N., and Zhou, Y. (2018). Analysis on provincial industrial energy efficiency and its influencing factors in China based on DEA-RS-FANN. *Energy.* 142, 79–89. doi:10.1016/j.energy.2017.10.011

Hou, Y. L., Long, R. Y., Chen, H., and Zhang, L. L. (2018). Research on the sustainable development of China's coal cities based on lock-in effect. *Res. Pol.* 59, 479–486. doi:10.1016/j.resourpol.2018.09.002

Huang, H. F., and Wang, T. (2017). The total-factor energy efficiency of regions in China: based on three-stage SBM model. *Sustainability.* 9, 1664. doi:10.3390/su9091664

Iftikhar, Y., He, W. J., and Wang, Z. H. (2016). Energy and CO_2 emissions efficiency of major economies: a non-parametric analysis. *J. Clean. Prod.* 139, 779–787. doi:10.1016/j.jclepro.2016.08.072

Jiang, C. L., and Zha, Y. (2015). Research on the influences of self-R&D activities on the industrial energy efficiency in China. *China Popul. Resour. Environ.* 25, 82–87. doi:10.3969/j.issn.1002-2104.2015.11.011

Kaya, Y. (1989). *Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios*. Paris, France: IPCC

Li, B., and Dewan, H. (2017). Efficiency differences among China's resource-based cities and their determinants. *Res. Pol.* 51, 31–38. doi:10.1016/j.resourpol.2016.11.003

Li, H., and Shi, J. F. (2014). Energy efficiency analysis on Chinese industrial sectors: an improved Super-SBM model with undesirable outputs. *J. Clean. Prod.* 65, 97–107. doi:10.1016/j.jclepro.2013.09.035

Liddle, B. (2015). What are the carbon emissions elasticities for income and population? Bridging STIRPAT and EKC via robust heterogeneous panel estimates. *Global Environ. Change.* 31, 62–73. doi:10.1016/j.gloenvcha.2014.10.016

Lima, F., Nunes, M. L., Cunha, J., and Lucena, A. F. P. (2016). A cross-country assessment of energy-related CO 2 emissions: an extended Kaya index decomposition approach. *Energy.* 115, 1361–1374. doi:10.1016/j.energy.2016.05.037

Liu, J. P., Wang, L., Qiu, M. H., and Zhu, J. (2016). Promotion potentiality and optimal strategies analysis of provincial energy efficiency in China. *Sustainability.* 8, 741. doi:10.3390/su8080741

Liu, W. S., and Lin, B. Q. (2018). Analysis of energy efficiency and its influencing factors in China's transport sector. *J. Clean. Prod.* 170, 674–682. doi:10.1016/j.jclepro.2017.09.052

Liu, X., and Bae, J. (2018). Urbanization and industrialization impact of CO_2 emissions in China. *J. Clean. Prod* 172, 178–186. doi:10.1016/j.jclepro.2017.10.156

Long, R. Y., Wang, H. Z., and Chen, H. (2016). Regional differences and pattern classifications in the efficiency of coal consumption in China. *J. Clean. Prod.* 112, 3684–3691. doi:10.1016/j.jclepro.2015.07.025

Lu, C. Y., Meng, P., Zhao, X. Y., Jiang, L., Zhang, Z. L., and Xue, B. (2019). Assessing the economic-environmental efficiency of energy consumption and spatial patterns in China. *Sustainability.* 11, 591. doi:10.3390/su11030591

Mardani, A., Zavadskas, E. K., Streimikiene, D., Jusoh, A., and Khoshnoudi, M. (2017). A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency. *Renew. Sustain. Energy Rev.* 70, 1298–1322. doi:10.1016/j.rser.2016.12.030

Medina, A., Cámara, Á., and Monrobel, J. (2016). Measuring the socioeconomic and environmental effects of energy efficiency investments for a more sustainable Spanish economy. *Sustainability.* 8, 1039. doi:10.3390/su8101039

Meng, M., Shang, W., Zhao, X. L., Niu, D. X., and Li, W. (2015). Decomposition and forecasting analysis of China's energy efficiency: an application of three-dimensional decomposition and small-sample hybrid models. *Energy.* 89, 283–293. doi:10.1016/j.energy.2015.05.132

Norman, J. B. (2017). Measuring improvements in industrial energy efficiency: a decomposition analysis applied to the UK. *Energy.* 137, 1144–1151. doi:10.1016/j.energy.2017.04.163

Ouyang, X. L., Mao, X. Y., Sun, C. W., and Du, K. R. (2019). Industrial energy efficiency and driving forces behind efficiency improvement: evidence from the pearl river delta urban agglomeration in China. *J. Clean. Prod.* 220, 899–909. doi:10.1016/j.jclepro.2019.02.206

Simar, L., and Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *J. Econom.* 136, 31–64. doi:10.1016/j.jeconom.2005.07.009

Steven, K. (1997). Industry life cycles. *Ind. Corp. Change.* 6, 145–181. doi:10.1093/icc/6.1.145

Teng, X. Y., Lu, L. C., and Chiu, Y. (2018). Considering emission treatment for energy-efficiency improvement and air pollution reduction in China's industrial sector. *Sustainability.* 10, 4329. doi:10.3390/su10114329

Wang, D., He, W., and Shi, R. Y. (2019a). How to achieve the dual-control targets of China's CO_2 emission reduction in 2030? Future trends and prospective decomposition. *J. Clean. Prod.* 213, 1251–2163. doi:10.1016/j.jclepro.2018.12.178

Wang, K. Y., Wu, M., Sun, Y. P., Shi, X. P., Sun, A., and Zhang, P. (2019b). Resource abundance, industrial structure, and regional carbon emissions efficiency in China. *Res. Pol.* 60, 203–214. doi:10.1016/j.resourpol.2019.01.001

Wang, N. N., Chen, J., Yao, S. N., and Chang, Y. C. (2018). A meta-frontier DEA approach to efficiency comparison of carbon reduction technologies on project level. *Renew. Sustain. Energy Rev.* 82, 2606–2612. doi:10.1016/j.rser.2017.09.088

Wang, Q. W., Hang, Y., Sun, L. C., and Zhao, Z. Y. (2016). Two-stage innovation efficiency of new energy enterprises in China: a non-radial DEA approach. *Technol. Forecast. Soc.* 112, 254–261. doi:10.1016/j.techfore.2016.04.019

Wang, S. B., Liu, H. M., Pu, H. X., and Yang, H. (2020). Spatial disparity and hierarchical cluster analysis of final energy consumption in China. *Energy.* 197, 117195. doi:10.1016/j.energy.2020.117195

Wu, Y., Shen, J., Zhang, X., Skitmore, M., and Lu, W. (2016). The impact of urbanization on carbon emissions in developing countries: a Chinese study based on the U-Kaya method. *J. Clean. Prod.* 135, 589–603. doi:10.1016/j.jclepro.2016.06.121

Xie, W., Sheng, P. F., and Guo, X. H. (2015). Coal, oil, or clean energy: which contributes most to the low energy efficiency in China? *Util. Pol.* 35, 67–71. doi:10.1016/j.jup.2015.05.003

Xiong, S. Q., Ma, X. M., and Ji, J. P. (2019). The impact of industrial structure efficiency on provincial industrial energy efficiency in China. *J. Clean. Prod.* 215, 952–962. doi:10.1016/j.jclepro.2019.01.095

Xu, G., Schwarz, P., and Yang, H. (2020). Adjusting energy consumption structure to achieve China's CO_2 emissions peak. *Renew. Sustain. Energy Rev.* 122, 109737. doi:10.1016/j.rser.2020.109737

Yang, M., Yang, F. X., and Chen, X. P. (2011). Effects of substituting energy with capital on China's aggregated energy and environmental efficiency. *Energy Pol.* 39, 6065–6072. doi:10.1016/j.enpol.2011.07.006

Zhang, D. G., and Lu, Y. Q. (2017). Impact of market segmentation on energy efficiency. *China Popul. Resour. Environ.* 27, 65–72. doi:10.3969/j.issn.1002-2104.2017.01.008

Zhao, C. H., Zhang, H. N., Zeng, Y. R., Li, F. Y., Liu, Y. X., Qin, C. J., et al. (2018). Total-factor energy efficiency in BRI countries: an estimation based on three-stage DEA model. *Sustainability.* 10, 278. doi:10.3390/su10010278

Zhao, X. L., Yang, R., and Ma, Q. (2014). China's total factor energy efficiency of provincial industrial sectors. *Energy.* 65, 52–61. doi:10.1016/j.energy.2013.12.023

Zhou, M., Wang, T., Yan, L., and Xie, X. B. (2018). Has economic competition improved China's provincial energy ecological efficiency under fiscal decentralization? *Sustainability.* 10, 2483. doi:10.3390/su10072483

Zhou, P., Ang, B. W., and Pohm, K. (2008). A survey of data envelopment analysis in energy and environmental studies. *Eur. J. Oper. Res.* 189, 1–18. doi:10.1016/j.ejor.2007.04.042

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How Does the Efficiency of Value Realization on a Platform Influence Sustainability Transition? A Case of the Power Industry in China

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In the era of the digital economy, for platform-based actors making a transition from one business field harmful for the sustainable development of society to a new field, their efficiency in value realization (EVR) has become inseparable from the digital platform used. The relationship between EVR on a platform and business transitions is a topic that has not been fully discussed, especially from the perspective of the platform service system. Also, few studies have explored transaction costs and opportunity costs using queuing theory. To fill these gaps and to inform transitions to sustainability, this paper applied a system dynamics method and proposed a framework for analyzing the relationship between EVR and the transition ratio. Findings suggest that improvements in the EVR lead to decreases in response time and may lead to an improved transition ratio. The ratio between EVR and the "entry rate" is important for predicting the transition ratio. However, preference, platform maturity, and the feedback of the transition ratio cause the effect of EVR to dynamically change. Based on this mechanism, the government can take incentive measures to maintain an acceptable transition ratio. For the power industry, the case simulated for this study, the transition can be improved by effectively transmitting a phasing-out policy for platforms and actors, and by guiding power exchange platforms to set reasonable rules, service levels, and growth rates.

Keywords: sustainability transition, efficiency of value realization, value preference, time-varying cost, platform maturity

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INTRODUCTION

The sustainability transition (ST), such as the transition from fossil energy power generation to renewable energy power generation, is an important topic for sustainable development. In the digital economy era, a time when platform-driven mechanisms and societies are further emerging, ST should be discussed in terms of an actor's operation on a platform[1] (Mattila and Seppälä, 2018; Egana-delSol and Flanders, 2019; Kloppenburg and Boekelo, 2019; Kolk and Ciulli, 2020).

[1]The platform, which usually exists in the form of a trading market, is a system that allows participants to engage in value-adding activities, and serves as a digital economics organizer with economic and value goals. These platforms can connect, match, design, coordinate, and oversee the market, accelerating innovation and value creation, and influencing the operation of platform-based actors. Source: Egana-delSol PA and Flanders S. 2019. Platform economy and sustainable energy. In: Leal Filho W, Azul AM, Brandli L, *et al.* (Eds), Affordable and clean energy. Springer International Publishing, Cham, pp.1-9, Mattila J and Seppälä T. 2018. Distributed governance in multi-sided platforms: A conceptual framework from case: Bitcoin. In: Smedlund A, Lindblom A and Mitronen L (Eds), Collaborative value co-creation in the platform economy. Springer, Singapore, pp.183-205.

Platforms can simultaneously influence transition and operational decisions of actors operating on the platform, both in terms of the business field being phased out of and the new niche area. For example, the power exchange center of China has been curbing the trading rate of fired power, by setting priorities that ensure renewable energy consumption[2]. Integrated energy service platforms can automatically make decisions and allocate task orders to specific providers, based on their ranking and comprehensive scores (Wang, 2019). Ranking and scoring, which are directly affected by the platform, influence the velocity of participants' transactions. In these examples, as the platform can accelerate the velocity of transactions, actors can obtain profits from transactions at a higher speed. That is, the input resource can generate a faster increase in value. This leads to changes in an actor's investment in different business fields and can impact the state of the actor's transition. In this process, transaction velocity is closely related to the core concept of the "efficiency of value realization" (EVR[3]).

EVR is a key factor connecting an actor's operations on a platform and an actor's decision to transition. First, EVR, which measures an actor's operational efficiency, is a conjunction between platform and actors. That is, EVR is used to measure the velocity at which the actor's input[4] gains an increase in value at a certain ratio[5] through that platform. EVR is also used to describe the "service rate"[6] of the platform from a service system perspective. Second, EVR influences an actor's decision on transition because this "service rate" influences the actor's response time[7] and time-varying cost (the cost incurred during the response time). This consequently influences actor's profit and investment decisions, which are associated with transition decisions.

In addition, EVR serves as a key factor for ST because the platform changes the actors' transition decisions and behavior mainly in two ways. First, it directly affects the velocity of actors' value realization by offering service and related rules. Second, its services change the actors' business environment, impacting their utility. Overall, the influence from the platform to the actors' business environment can be largely attributed to the impact on the EVR in each period; however, the influence varies over time. In summary, EVR is a key factor connecting the platform, the actor's operation, and transition. This makes it important to study the influencing mechanism of EVR in the platform operation background in order to accelerate transition.

To analyze the relationship between EVR and transition, and explore a new way of managing ST in the platform economy, we addressed the following question: What is the mechanism shaping the effect of the EVR on the transition ratio[8] in the background of the platform?

To explore this mechanism, we raised a second relevant question. In this relationship, how do two factors - value preference and platform maturity - change the effect of the EVR and affect the transition ratio, shaping the dynamic relationship? This question is raised based on two considerations.

First, when considering sustainable development, the government has a "preference" with respect to different actors' activity and their output. This is usually measured by profit or the index of GDP. This preference is described as a "value preference"[9]. Through ST policies or government outreach, the social value preference is transmitted to the platform. As a result, the platform provides different services for different actors or projects forming different EVRs on the platform. Also, in response to the social value preference, actors form judgements about the importance of output from different business fields (actor's value preference[10]), directly influencing their decision on transition.

Secondly, platform maturity[11] is another important factor, because it is closely related to the effect of platform service. As the ability and influence of a platform grows stronger, the platform service is more powerful in changing EVR, and the effect of EVR on the transition dynamically changes. Thus, value preferences and platform maturity play an important role in the mechanism with respect to EVR and the transition ratio.

By answering these two questions, this study identifies an approach to co-governance between the government and the

[2]Notice on Issuing the Rules for the Implementation of Middle-term and Long-term Transactions across Regions and Provinces in Beijing Power Exchange Center. No .51[2018].http://www.bj-px.com.cn/html/main/col14/2018-08/30/20180830102119626314055_1.html.

[3]EVR is the amount of objects that gains an increase in value per unit time. "EVR on a platform" is the velocity of the increase in an actor's value on a platform.

[4]The "input" can be capital, product, resources, or affairs to be dealt with.

[5]This ratio is an achievable or target percentage called the "ratio of an increase in value" which is described in notations (**Table 1**). For example, if 50% of the input capital$\mathbf{I}_1$ can increase at an expected ratio $\mathbf{r}_1$ in one year, then the EVR is $0.5 \cdot \mathbf{I}_1$. For a transaction platform system, the EVR can be estimated by observing the amount of trade.

[6]The platform service is an "increase in value" detailed as a transaction or management service. The velocity of the increase in value is the quantity of objects being served by the platform system per unit time. Thus, the efficiency of platform-based value realization discussed in this study is the same as the platform's service rate.

[7]Response time: In queuing theory, response time refers to the time between customer arrival and the completion of service, or the total time when a customer stays in the system. In this study, response time is defined as the time of value realization, or the time when the resources that receive added value stay in the system. More specifically, it is the time when the resource passes through a platform system to achieve an increase in value at certain ratio. In a broad sense, it is the time when goals can be achieved through the system.

[8]The actor's decision about investments in different business fields shapes the transition ratio. This ratio is the proportion of a resource that an actor in transition transfers from the original business field to a new business field.

[9]Value preference refers to the evaluation on the importance of profit or output value coming from different value creation activities. The evaluation is made under certain values and criterions. Under the value preference, the wealth originally measured by money and labor time changes according to an assessment of "importance" and becomes the utility value. Under a certain value preference, policies or measures exerted on favored and unsupported fields will differ. It is measured by the coefficient of value preference, shown as notations of $\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2$ in **Table 1**.

[10]The value preference discussed in this paper includes the value preference of society, that of platform, and that of the actor. The societal preference is also called social value preference in this paper, while the actor's preference is also called strategic preference.

[11]Platform maturity refers to the capability and influence of platform at different development stages.

platform to accelerate the transition to sustainability. Specifically, by providing a mechanism that reflects the change in the transition ratio, it informs innovative policies with respect to value preference, platform growth, service level, efficiency of value increase, and actor behavior management during a transition.

The rest of this paper is structured as follows. The next section provides the literature review. **Methodology** presents the process of modeling using System Dynamics. **Simulation Result** provides a numerical analysis, using the transition of China's power industry as an illustration. The last section concludes the paper.

LITERATURE REVIEW

Platform Maturity and Preference

Platform maturity and preference are two important factors influencing the platform's service level and the effect of the platform service, respectively. First, platforms have social and environmental values (Martin et al., 2017) and make their own value judgments. Kloppenburg and Boekelo (2019) posited that platforms tend to generate exclusions. Platforms do this by making judgments about the right type of energy production and consumption, raising barriers for new entrants. The values are preset or hidden in the design process, as platforms are established based on an idea, concept, or certain requirements resulting from an analysis by platform operator (Abdelkafi et al., 2019). Platforms affect actors' behavior by offering services, and their value judgments influence their service levels and further change actors' operational efficiency (Xie and Jawad Sajid, 2019).

These studies highlight the presence of preferences and value judgements in the platform system, impacting the platform's behavior and actor's operation. However, the studies do not offer a method or tool for analyzing the influence on platform services and the actor's operation in the context of ST. To fill this gap, we apply the concept of the "value preference" to describe the new decision criteria, including considerations of profit and sustainability. We also offer a tool to explain the decisions related to the platform, society, and the actor in the ST context.

Second, the effect of a platform service is influenced by its maturity. Kim et al. (2018) proposed that a platform experiences three stages in its development: the pre-platform stage, the transitioning stage, and the stabilizing stage. Gawer (2014) noted that the development stage of a platform should include: internal research and development, becoming a supply chain platform, and then becoming an industrial platform. Loux et al. (2020) classified the maturity level of a platform into the nascent stage and mature stage. That study noted that the platform can evolve from a two-sided platform at a nascent stage, bringing together merchants and buyers, to a mature multi-sided platform, bringing together application developers, banks, and advertisers (Loux et al., 2020). Mature and nascent platforms are mainly classified according to age and influence sales differently (Landsman and Stremersch, 2011). Lee (2019) described the maturity level of platform as follows: the start of construction, the perfection of function, the expansion of the application, the exploration in a certain industry, and the establishment of an ecosystem.

Most scholars agree that the platform's maturity refers to its capability level and influence at different development stages. Because the development stage of a platform is often defined based on its capability and influence, the level of development stage is often consistent with its maturity level. In summary, the platform's maturity reflects the level of its capability and influence. When the platform is at a higher stage and of greater maturity, it exerts a stronger effect on the market and stakeholders. At that point, measures taken by the platform generate more influence and as a result, it can significantly increase the actors' operational efficiency.

In conclusion, the preference and maturity of the platform affect its service and the actor's operation. Thus, they are considered to be key factors in the mechanism explored by this study.

Sustainability Transition Theory Related to Phasing Out Activities

Sustainability transition theory mainly discusses how transitions evolve over time and provides policy recommendations to support a progressive transition (Vincent et al., 2016). Widely applied sustainability transition theories include the theory of multi-level analysis and the theory of transition management. Multi-level analysis explains the transition process from three perspectives: niche, institution, and prospect (Geels, 2019; Geels et al., 2017; Köhler et al., 2019; Li and Strachan, 2019). The theory of transition management combines long-term thinking with short-term action (Lachman, 2013; Shum, 2017; Williams et al., 2017).

These theories offer an analytical framework for understanding sustainability transitions. Using a multi-level analysis, Vögele et al. (2018) highlighted possible phase-out pathways for coal-related technologies, highlighting that these processes are influenced by economic, political, technical elements, and social factors. Oei et al. (2020) illustrated the effects of different phase-out pathways for power plants, using an input-output model and regional macroeconomic model. Oei et al. (2019) pointed out that, from a macro perspective, a phase-out path can be jointly managed using a polycentric approach by city, regional, national, and international governments and institutions. Rosenbloom (2018) illustrated how ideas, interests, institutions, and infrastructure interact to create pathways that eliminate coal. Rentier et al. (2019) clarified the impact of different market economies on carbon lock-in and phase-out processes. Rentier et al. (2019) emphasized that strategic interactions, employment protections, government ownership, market price, and profit are important factors affecting a phase-out path. Gloria Baigorrotegui (2019) analyzed destabilizations over short periods, noting that the phasing-out mechanism is formed by three factors: pressure, obstruction, and public overflow to trace the activities. The sustainability transition theories relevant to the phase-out pathway demonstrate the framework, approaches, pathways, influencing factors, and policies. These inform a discussion about transition, considering different sides and factors. However, less attention has been paid to the effect of platform on sustainability transition and related mechanisms.

The Method of System Dynamics Used in Sustainability Transition

Many methodologies have been adopted to analyze the dynamic complex systems in the field of sustainability transition. Examples include extensive sensitivity analysis and Monte Carlo simulations (Banos-Gonzalez et al., 2018), scenario analyses based on the co-simulation method (El-Baz et al., 2019), the fuzzy cognitive mapping-system dynamics approach (Kokkinos et al., 2018; Pereira et al., 2020), differential equation modeling natural experiments (Curseu and Schruijer, 2020), agent-based modeling (Kieckhaefer et al., 2017; Shafiei et al., 2013), and system dynamics modeling (SD modeling) (Bautista et al., 2019, Cavicchi, 2018; Cosenz et al., 2020; Graziano et al., 2019, Papachristos, 2011; Tan et al., 2018).

Of these approaches, SD is a good method for reflecting the systemic interactions among variables (Tan et al., 2018), and is especially useful for analyzing feedback relationships. Ma and Hu (2018) combined SD and coupled game theory to analyze the eco-innovation mechanism and policy in the pulp and paper industry. Bautista et al. (2019) assessed biodiesel production based on a SD model and systems theory. Cavicchi (2018) analyzed the influence of power, institutions, and expectations on the bioenergy transition process by applying qualitative system dynamics and interviewing local actors. Cosenz et al. (2020) conceptualized an approach using dynamic business modeling for sustainability, combining an adapted sustainable business model canvas and system dynamics modeling. Kieckhäfer et al. (2017) studied the system of vehicle, energy, and consumers based on SD and agent modeling. Papachristos (2011) tested the dynamic consistency of the "Multi-Level Perspective" substitution pathway based on the MLP framework and SD modeling.

Two important applications of SD emerge from these studies. First, SD is usually used in mechanism analysis and framework building; one example is the model built by Cosenz et al. (2020). Second, SD is used in scenario simulations and to inform policy recommendations, as in the analysis given by Tan et al. (2018). SD modeling is often integrated with another method; this approach is also shown in this paper. That is, the framework and scenarios analyses in this paper are based both on SD and on the integration of queuing theory.

Studies focusing on platforms and sustainability transitions have consistently explored the ST or platform separately. Only a few papers have linked sustainability with the platform. Specifically, Paundra et al. (2020) studied the environmental impact of ridesharing platforms, based on the interplay of access-based and ownership-based consumption mechanisms. Kloppenburg and Boekelo (2019) and Kolk and Ciulli (2020) discussed the relationship between platform, energy system, and ST. Kolk and Ciulli (2020) also proposed a research agenda for the study of ST by linking society, platform, and actors. However, these theories do not consider the relationship between EVR and transition in the context of the platform. Further, none of these studies have analyzed the perspective of the platform queuing system. Finally, few studies have examined the relationship between ST, platform, society, and actors based on SD modeling and the time-based cost analysis. Based on the research agenda advanced by Kolk and Ciulli (2020) and theories about platform preference and maturity, this study focused on the dynamic mechanism between EVR on platform and transition ratio, considering the influence from value preference and platform maturity. This study applied the SD method to describe this complex feedback relationship.

METHODOLOGY

This study applied the method of system dynamics, which is a science that combines system science theory with simulations to study feedback structures and system behavior. The method complements the dominant multi-level perspective and the transition management approach, by providing a middle ground between emphasizing agency or structure (Vincent et al., 2016). Because there is feedback in this study's transition model, system dynamics is an effective approach. The system dynamics method includes the following steps. First, the problem is articulated or conceptualized for a dynamic hypothesis. Second, the model is formulated. Third, the model is tested and analyzed (Espinoza et al., 2017; Homer, 2019). In the modeling process, Little's Law in queuing theory is used to analyze the time-varying cost (transaction cost and opportunity cost) which relates to the platform service. The value preference is used to analyze the investment decision in the context of ST. This methodology is shown is **Figure 1**.

Notations

To clarify the model and equations in this study, relevant notations are listed in **Table 1**.

Hypothesis and Model Boundary

The essence of the problem discussed in this paper is the relationship between the input resource, the increase in value of that resource, and the allocation of the resource in the background of the platform's operation. This relationship can be described as a dynamic feedback event: an actor in transition invests resources in different fields. Based on the influence of the platform, the resources placed in different fields lead to increases in value at different EVRs, leading to different profit levels. Given the effects of the profit and value preference, the transition ratio emerges and influences a new round of resource investments.

To make the research about this relationship implementable, five hypotheses (H1–H5) are included in the model. H1: The actors in transition are considered as a whole (A). There are two kinds of business fields for the actor: a new business field ($\mathbf{A_1}$) and the original business field, such as fired power generation ($\mathbf{A_2}$). H2: The social value preference can affect the platform's preference and actor through publicity, education, rules, policy tools, and laws. Also, preference affects utility; in other words, the utility from different business fields is determined by profits and by preference. H3: The influence of quality and competition on the EVR is not considered. In the context of China's power system, the product "power" can be considered homogeneous with respect to problems related to peaks and valleys and can be solved through the regulation and control of social power system.

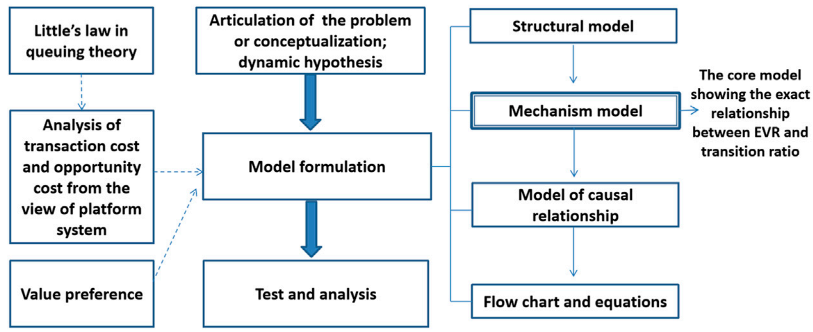

FIGURE 1 | Research method.

This assumption is consistent with the current reality of the power system. H4: The quantity of the supply changes according to demand. H5: The profit from a project in the current period influences the resources to be invested in the next period.

The model boundaries were set as follows: A's new business field ($\mathbf{A_1}$), A's original business field ($\mathbf{A_2}$), and the decision relates to A's investment in a transition. The modeled period covered 20 years (2016–2036). The system of sustainability transition includes three parts: i) the realization of value on the platform in $\mathbf{A_1}$; ii) the realization of value on the platform in $\mathbf{A_2}$; and iii) A's decision-making related to the investment in the transition.

The model boundaries and the overall relationship among the three parts are presented in the general structure in **Figure 2**. The main relationship between the three parts was as follows. The actor's decision-making determines the transition ratio and the resource allocation between $\mathbf{A_1}$ and $\mathbf{A_2}$. Then, by determining the response time, cost and profit, the value realization systems of $\mathbf{A_1}$ and $\mathbf{A_2}$ affect the transition ratio. This interaction relationship is affected by value preference and platform maturity. These feedback relationships are fully explained in the next section.

Dynamic Feedback Mechanism Between EVR and Transition Ratio

The structural model shows the main constituents and general relationship in the transition system. However, the dynamic feedback mechanism between EVR and transition ratio is not precisely related. This is shown as the model illustrating the mechanism involved (**Figure 3**) and is explained as follows.

First, a change in the EVR leads to a change in the transition ratio. The EVR is the consequence of a platform's effect on an actor, however, it is also a driving force advancing the transition. The EVR is influenced by the platform service, platform maturity, and annual input resource. The EVR and entry rate determined the value of the response time (time of value realization). The response time has a direct relationship, with time-driven variations in costs, such as transaction and opportunity costs. Time-driven variations in cost influence profit, which affects resource allocation decisions and the transition ratio in the next period. The value preference impacts this relationship in two main ways. The social value preference affects the value preference of the platform, which is directly associated with the platform's service level. Also, the social value preference affects the actor's strategic preference, impacting the transition ratio.

Second, the transition ratio generates feedback, which causes this relationship dynamic. Changes in the transition ratio lead to changes in the resources invested into different fields, creating fluctuations in the entry rate. The change in the entry rate results in a change in the EVR. This is because the input resource and subsequent output commodities to be traded during each period are related to the number of objects ultimately traded each period (EVR). In addition, a change in the entry rate also causes changes in the time-driven variations in cost, because the quantity of input resources is closely associated with opportunity and transaction costs.

Design of Causal Relationship and Flow Chart

Causal relationships and the development of the flow chart are necessary steps in the simulation based on system dynamics. First, based on the general structure model and the model illustrating the mechanisms involved, the feedback relationships can be analyzed and a chart outlining the casual relationships can be generated. The model illustrating the mechanism illustrates three classes of feedback. The first class of feedback is "EVR → response time → time-varying cost → profit → transition ratio → input resource → entry rate → EVR." This feedback relationship exists both in $\mathbf{A_1}$ and $\mathbf{A_2}$. It is detailed as "$\boldsymbol{\mu_1 \to W_1 \to X_1 \to \Pi_1} \to k \to \boldsymbol{I_1 \to \lambda_1 \to \mu_1}$" in $\mathbf{A_1}$, and is shown as "$\boldsymbol{\mu_2 \to W_2 \to X_2 \to \Pi_2} \to k \to \boldsymbol{I_2 \to \lambda_2 \to \mu_2}$" in $\mathbf{A_2}$. The second class of feedback is "time-varying cost→ profit → transition ratio → input resource → entry rate → time-varying cost per unit time → time-varying cost". Feedback from this second class is specified in $\mathbf{A_1}$ and $\mathbf{A_2}$ as "$\boldsymbol{A_1{:}X_1 \to \Pi_1} \to k \to \boldsymbol{I_1 \to \lambda_1 \to C_1 \to X_1}$" and "$\boldsymbol{A_2{:}X_2 \to \Pi_2} \to k \to \boldsymbol{I_2 \to \lambda_2 \to C_2 \to X_2}$," respectively. The third class of feedback is "input resource → profit → transition ratio → Input resource." This class is specified as "$\boldsymbol{I_1 \to \Pi_1} \to k \to \boldsymbol{I_1}$" for $\mathbf{A_1}$, and as "$\boldsymbol{I_2 \to \Pi_2} \to k \to \boldsymbol{I_2}$" for $\mathbf{A_2}$. Based on the feedback relationship between these factors, **Figure 4** provides a chart showing the causal relationships.

Second, based on the casual relationships, more detailed relationships of the factors are described using equations and

TABLE 1 | Notation definitions.

Notation	Explanation
A	Phasing-out actor, such as companies in the fired power industry
$\mathbf{A_1}$	Phasing-out actor's new business field, such as renewable energy sourced power generation
$\mathbf{A_2}$	Phasing-out actor's original business field, such as fired power generation
$\mathbf{I}$	Total resources placed in $\mathbf{A_1}$ and $\mathbf{A_2}$ each period
$\mathbf{I_1}, \mathbf{I_2}$	Resources placed in $\mathbf{A_1}$ and $\mathbf{A_2}$, respectively
$\mathbf{I_{1\,(t)}}, \mathbf{I_{1\,(t+1)}}$	Resources placed in $\mathbf{A_1}$ in the current period and the next period, respectively. The variables t and t+1 represent the current period and the next period, respectively
μ_1	Efficiency of value realization in $\mathbf{A_1}$ denoting the velocity at which $\mathbf{I_1}$ achieves an increase in the value on the platform, namely the service rate of the platform
μ_2	Efficiency of value realization in $\mathbf{A_2}$
λ_1, λ_2	The entry rate[a] of $\mathbf{A_1}$ and $\mathbf{A_2}$, respectively
$\mathbf{r_1}, \mathbf{r_2}$	Ratio of the increase in value[b], the rate of return on investment without considering the transaction and opportunity cost caused by response time
uc	Unit cost of fired power electricity
M	A large amount of input capital waiting for an increase in value, the value of which should be selected as the largest trade volume to adjust the unit
θ_1, θ_2	Coefficients of factors influencing μ_1 and μ_2, respectively
$\mathbf{L_1}, \mathbf{L_2}$	The service level provided for $\mathbf{A_1}$ and $\mathbf{A_2}$ by the platform, respectively
$\mathbf{L_{10}}, \mathbf{L_{20}}$	The service level provided for $\mathbf{A_1}$ and $\mathbf{A_2}$ by the platform when the platform preference is neutral, respectively
$\mathbf{L_m}$	Basic service level of platform
$\Delta\mathbf{L_1}, \Delta\mathbf{L_2}$	Changes in service level as a result of changes in the value preference of the platform
Π	A's total profit
Π_1	A's profit in the new business field
Π_2	A's profit in the original business field
α_1, α_2	Coefficient of social value preference, used to measure the importance of output value from $\mathbf{A_1}$ and $\mathbf{A_2}$ judged by society, respectively. α_1 and α_2 affect the utility of society (e.g., the sum of $\alpha_1 \cdot \Pi_1$ and $\alpha_2 \cdot \Pi_2$ represents the utility of society). The variables α_1 and α_2 are determined using expert-based methods, such as the Delphi method; and can be revealed based on the target ratio of resource allocation or target quota established by the government
α_{1s}, α_{2s}	Phasing-out actor's strategic preference coefficients for $\mathbf{A_1}$ and $\mathbf{A_2}$, respectively, in the context of a sustainability transition. They are affected by social value preference
α_{1p}, α_{2p}	The coefficient of platform's value preference for $\mathbf{A_1}$ and $\mathbf{A_2}$ respectively. They are affected by social value preference
γ_1, γ_2	The coefficients denoting the change of service level $\mathbf{L_1}$and $\mathbf{L_2}$, respectively, when the coefficient of platform preference deviates from the neutral state for one unit
η_1, η_2	Consistency coefficients of value preference, reflecting the degree of consistency between platform preference and social value preference
$\mathbf{P_m}$	Platform maturity
$\mathbf{P_g}$	The growth rate of platform maturity
$\mathbf{W_1}$	The total response time of all the input resources in $\mathbf{A_1}$
$\mathbf{W_2}$	The total response time of all the input resources in $\mathbf{A_2}$
$\mathbf{C_1}, \mathbf{C_2}$	Transaction and opportunity costs per unit time in $\mathbf{A_1}$ and $\mathbf{A_2}$, respectively
$\mathbf{P_g}$	The growth rate of platform maturity
k	A's transition ratio, referring to the proportion of resource that the actor transfers from the original business field to the new business field
ρ_1, ρ_2	Coefficients measuring the influence from marginal capital utility on the decision of $\mathbf{I_{a1}}$
ρ_0	The influence coefficients of $\mathbf{I}$ have on $\mathbf{I_1}$
$\mathbf{X_1}, \mathbf{X_2}$	Time-varying cost, the cost incurred during response time $\mathbf{W_1}$ and $\mathbf{W_2}$, respectively. This reflects the time-driven variations in cost, referring to the transaction cost (searching cost, information cost, bargaining cost, oversight cost, etc.) and opportunity cost (opportunity cost of holding currency) in the simulation
η_{1s}, η_{2s}	Coefficients measuring the influence from social value preferences α_1 and α_2 on an actor's strategic preferences α_{1s} and α_{2s}, respectively
r	Ratio of time-varying cost per unit time, a coefficient describing relationship between input resource ($\mathbf{I_1}$or$\mathbf{I_2}$) and the time-varying cost incurred in unit time
q	A target ratio of society, specified as output of photovoltaic power divided by the total output of photovoltaic power and fired power in the simulation
D	Demand of electricity, specified as the total demand of photovoltaic power and fired power in the simulation

[a]*Entry rate: the entry rate of the platform is the quantity of objects accessing the platform system and waiting for an increase in value per unit time. Specifically, "object" refers to a resource, such as capital placed in production. "An increase in value" is the "service" of platform system and is often actualized through transactions. The unit of object entering system was adjusted to make statistics conform to a Poisson distribution.* $\mathbf{Adjusted\ entryrate} = \mathbf{the\ amount\ of\ capital\ entering\ the\ platform\ system\ per\ time\ unit} \div \mathbf{M}$.

[b]*The ratio of the increase in value is the return ratio of input resource without considering the response time (response time is explained in the seventh footnote) and time-driven variations in cost such as transaction cost and opportunity cost.* $\mathbf{ratio\ of\ the\ increase\ invalue\ increase} = (\mathbf{revenue} - \mathbf{costirrelevanttoresponsetime}) \div \mathbf{inputcapital}$. *The equation is simplified as* $(\mathbf{P} - \mathbf{uc}) \div \mathbf{uc}$ *in the simulation. In the equation, "cost unrelated to response time" is the cost that cannot be influenced by the platform, mainly referred to as the production cost in this paper. When discussing the power system, it includes depreciation of fixed assets, operation cost, maintenance cost, financial cost, and tax.*

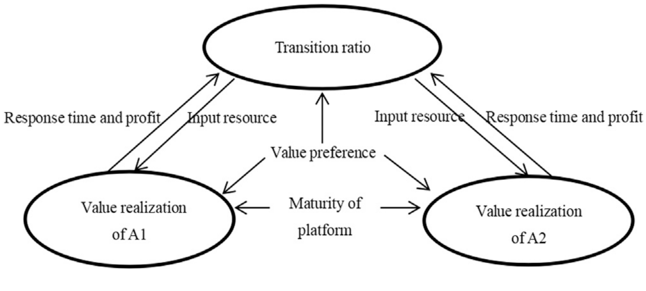

FIGURE 2 | General structure.

$$\mu_1 = \theta_1 \cdot \lambda_1 \cdot L_1 \cdot P_m \tag{1}$$

$$\mu_2 = \theta_2 \cdot \lambda_2 \cdot L_2 \cdot P_m \tag{2}$$

The EVR on the platform is associated with three factors. The first factor is λ_1. This is because if the production plan is developed according to demand, society generally needs the output. As such, the quantity of the supplied products waiting to be traded on the platform each period is related to the volume of products that can be traded through the platform each period. This study considers the case of the power system. As the output of power generation is usually needed and consumed by society, the capacity and quantity of electricity supply each period relates to the quantity traded each period. Thus, the resource used to produce electricity supplied to the platform waiting for a transaction each period (entry rate) relates to the production resource resulting in the electricity finally traded on the platform each period (EVR). In this case, when λ_2 and λ_1 changes, the platform can create different queuing systems in different years.

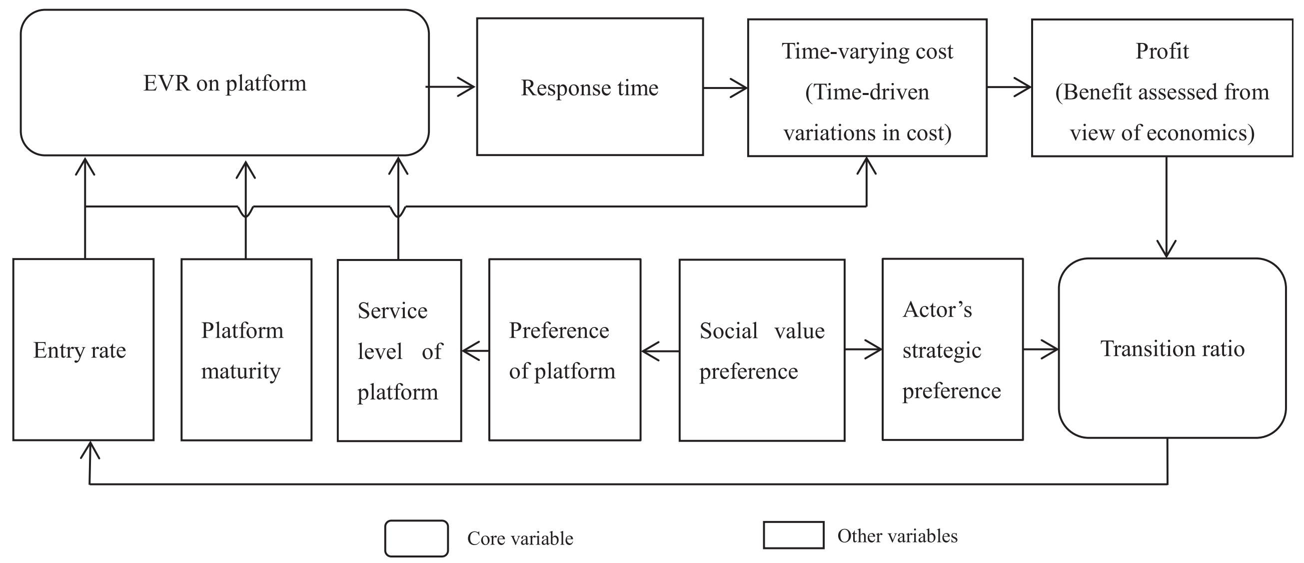

FIGURE 3 | Model illustrating the mechanism between EVR and transition ratio.

a flow chart. The variables I_1 are established as state variables. The changing rate of I_1 is expressed as $I_{1\,(t+1)} - I_{1\,(t)}$. Other variables are established as auxiliary variables. Based on this, a flow chart is drawn to run the simulation (**Figure 5**). In this graph, the transition ratio (k) can influence and be influenced by the value realization systems of A_1 and A_2. The relationships of factors in the flow chart are described using equations explained in **Equations**.

Equations

Based on the structural model, relationship model, flow chart, and the chart of causal relationships, we developed equations related to the value realization and transition ratio.

Equations Relevant to Value Realization

Important variables related to value realization include EVR (μ_1, μ_2), entry rate (λ_2, λ_1), value preference $(\alpha_1, \alpha_2, \alpha_{1p}, \alpha_{2p})$, platform maturity (P_m), time of value realization (W_1, W_2), cost (X_1, X_2), and profit (Π_1, Π_2). Their equations are expressed as follows.

The second factor associated with EVR is the service level of the platform. Platform service refers to all the measures taken by a platform that influence the value realization of the actor's input resource, specified as the transaction service in the simulation. The level of service is an assessment or planning level of the platform's influence on different businesses, marked as level 1, level 2,. . .. The level of service can be estimated using information or recommended statistics (Xie and Jawad Sajid, 2019); rules used to prioritize different businesses; or indexes related to transaction services, payment service, or derivative services (Yu, 2017). A higher level of service reflects a beneficial influence given by the platform. If more objects are traded, there is a greater increase in the resource inputs and increased gains in the value. This leads to a higher EVR.

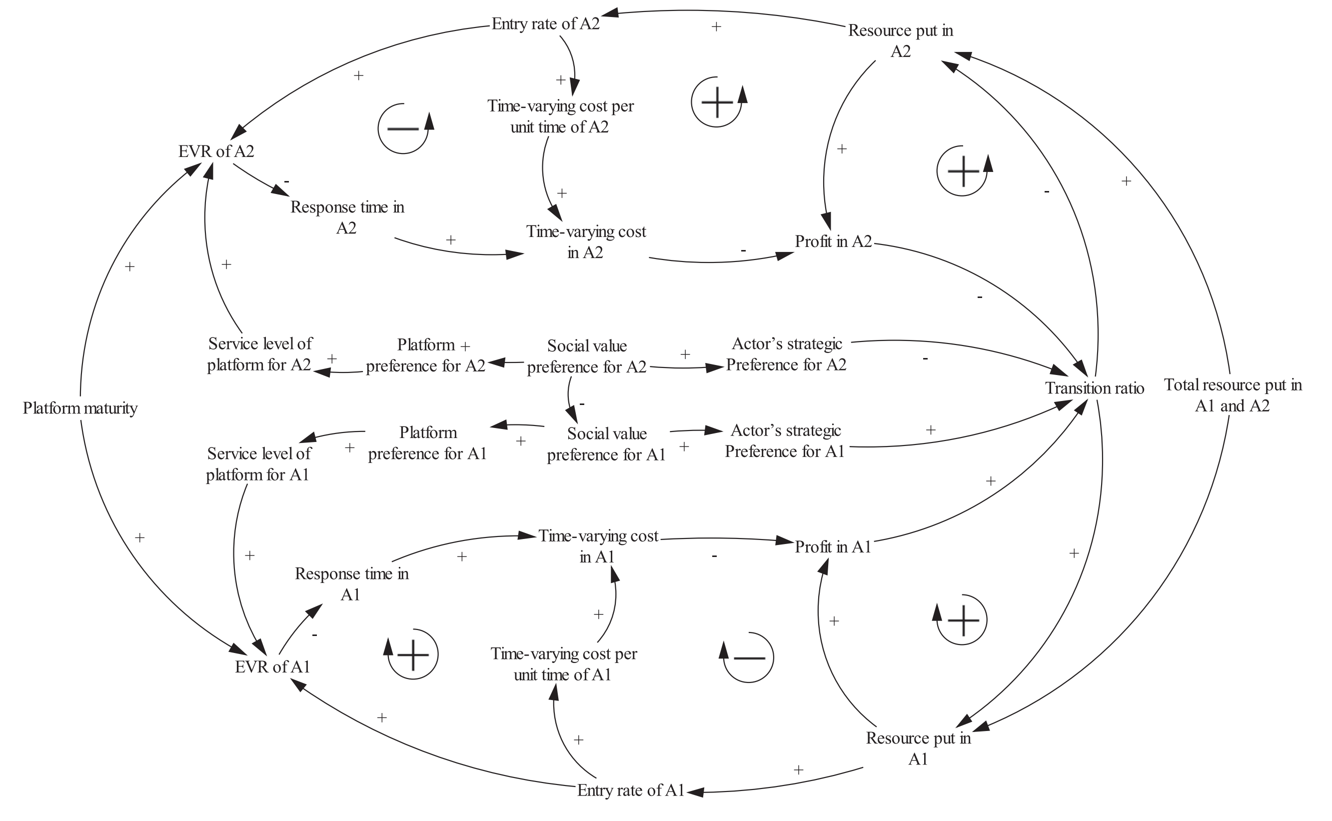

FIGURE 4 | Causal relationship.

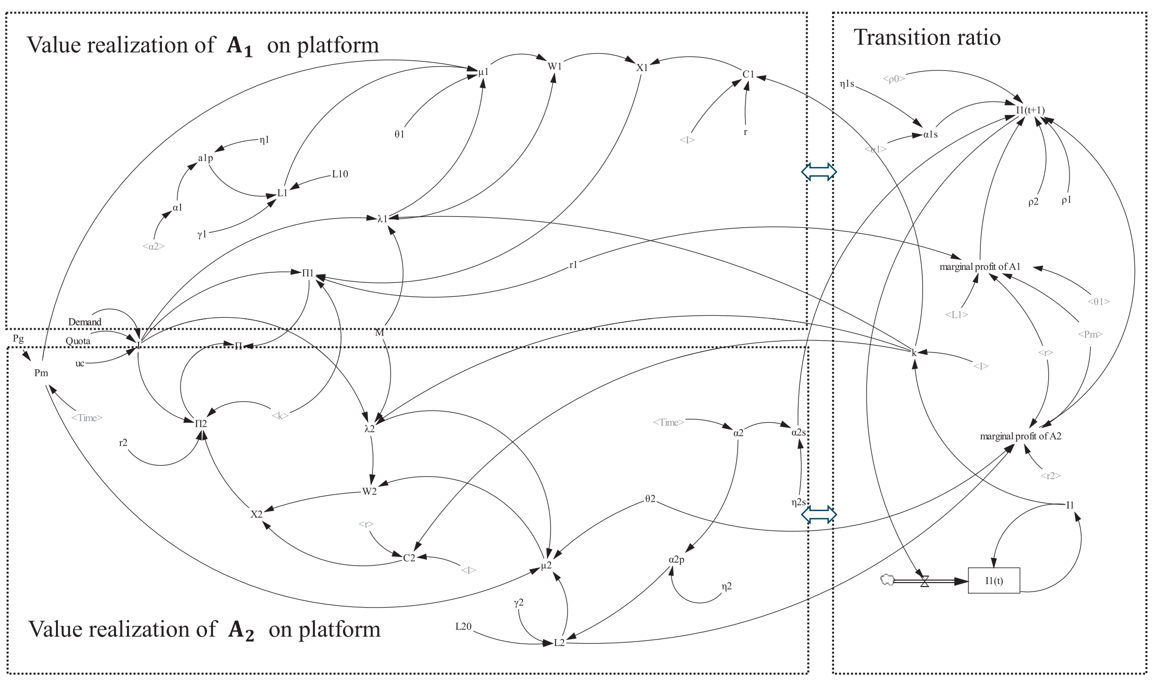

FIGURE 5 | Flow chart.

The third factor associated with EVR is $\mathbf{P_m}$, an accelerator for EVR. As described above, a higher $\mathbf{P_m}$ corresponds to a higher level of technology and higher platform capability. Platform service is based on the technology, operation, and ability of the platform. Superior technology and higher platform capabilities will enhance the efficiency of platform service, which is directly associated with EVR. More specifically, the same level of service affects the EVR differently when comparing a newborn platform ($\mathbf{P_m}$ is low) and a platform with years of development ($\mathbf{P_m}$ is high). For example, improvements in EVR differed for the top level of service offered by the famous platform Alibaba in 1997 compared to 2020. Platform service influences EVR by accelerating or decelerating the value realization of objects entering the platform system. A higher platform maturity enhances the effect of the platform service on value realization.

Service level $(\mathbf{L_1}, \mathbf{L_2})$, value preference $\boldsymbol{\alpha}_{\mathbf{1p}}, \boldsymbol{\alpha}_{\mathbf{1p}}$, $\boldsymbol{\alpha}_1$, $\boldsymbol{\alpha}_2$, and platform maturity $\mathbf{P_m}$ are described in **Eqs. 3–7**.

$$\mathbf{L_1} = \mathbf{IF\ THEN\ ELSE}\left(\mathbf{L_{10}} + \left(\boldsymbol{\alpha}_{\mathbf{1p}} - 0.5\right) \cdot \boldsymbol{\gamma}_1 \le \mathbf{L_m}, \mathbf{L_m}, \mathbf{L_{10}} + \left(\boldsymbol{\alpha}_{\mathbf{1p}} - 0.5\right) \cdot \boldsymbol{\theta}_1\right) \tag{3}$$

$$\mathbf{L_2} = \mathbf{IF\ THEN\ ELSE}\left(\mathbf{L_{20}} + \left(\boldsymbol{\alpha}_{\mathbf{2p}} - 0.5\right) \cdot \boldsymbol{\gamma}_2 \le \mathbf{L_m}, \mathbf{L_m}, \mathbf{L_{20}} + \left(\boldsymbol{\alpha}_{\mathbf{2p}} - 0.5\right) \cdot \boldsymbol{\theta}_2\right) \tag{4}$$

$$\boldsymbol{\alpha}_{\mathbf{1p}} = \boldsymbol{\alpha}_1 \cdot \boldsymbol{\eta}_1 \tag{5}$$

$$\boldsymbol{\alpha}_{\mathbf{2p}} = \boldsymbol{\alpha}_2 \cdot \boldsymbol{\eta}_2 \tag{6}$$

$$\mathbf{P_m} = \mathbf{Time} \cdot \mathbf{P_g} + 1 \tag{7}$$

These equations show that $\mathbf{L_1}$ is determined by a platform's value preference with respect to different objects to be served and the platform's utility. Generally speaking, when the platform attaches more importance and preference to certain behaviors, operations, and their output, the platform provides a higher level of service for the object[12]. For example, the power exchange center of China focuses more attention on renewable energy-sourced power compared to fired power. As such, it prioritizes renewable energy-sourced power transactions to ensure that form of energy is traded and consumed first[13]. In this case, the platform provides a high level of service for renewable energy-sourced power transactions, accelerating the velocity of that transaction. The platform acts as an intermediary, and provides a fair-trade environment. Thus, it must provide a basic service level $(\mathbf{L_m})$ for the actor's operation. In **Eqs. 3, 4**, factors $\mathbf{L_{10}}$ and $\mathbf{L_{20}}$ represent the service level of the platform when the platform's preference is neutral ($\boldsymbol{\alpha}_{\mathbf{1p}} = \boldsymbol{\alpha}_{\mathbf{2p}} = 0.5$). The coefficients of value preference usually changed in the range of $[0, 1]$ in the simulation; therefore, the preference was neutral when the values of coefficients $\boldsymbol{\alpha}_{\mathbf{1p}}, \boldsymbol{\alpha}_{\mathbf{2p}}$ were both 0.5.

The entry rate, response time, and cost are explained based on "Little's Law" in queuing theory, as shown in **Eqs. 8–13**.

$$\boldsymbol{\lambda}_1 = \frac{\mathbf{I_1}}{\mathbf{M}} \tag{8}$$

$$\boldsymbol{\lambda}_2 = \frac{\mathbf{I_2}}{\mathbf{M}} \tag{9}$$

According to Little's Law, key factors such as platform service, objects to be served, entry rate, and the service rate were first clarified and the response time was calculated. The platform service can be specifically described as "helping an actor's invested resource gain an increase in value at a certain ratio." For example, the service can be detailed as matching, sales promotion, coordination of operation, quality, or fame certification. The variables $\mathbf{I_1}$ and $\mathbf{I_2}$ represented the resources invested in $\mathbf{A_1}$ and $\mathbf{A_2}$, respectively; these were considered to be the objects served by the platform. This means that $\mathbf{I_1}$ and $\mathbf{I_2}$ experienced increases in value after the outputs of $\mathbf{A_1}$ and $\mathbf{A_2}$ were traded on the platform. Assume that M is a value larger than the maximum value of a single transaction. The expressions $\frac{\mathbf{I_1}}{\mathbf{M}}$ and $\frac{\mathbf{I_2}}{\mathbf{M}}$ represent the quantity of objects (measured in unit M) entering the platform, and waiting for service, each period. The quantity of objects measured by M conformed to the Poisson distribution. Based on this, the entry rate is described in **Eqs. 8, 9**. The service rate was also the EVR, as explained in **Introduction**. The total response time of all the input objects being served was calculated using **Eqs. 10, 11**.

$$\mathbf{W_1} = \frac{\boldsymbol{\lambda}_1}{\boldsymbol{\mu}_1 - \boldsymbol{\lambda}_1} \tag{10}$$

$$\mathbf{W_2} = \frac{\boldsymbol{\lambda}_2}{\boldsymbol{\mu}_2 - \boldsymbol{\lambda}_2} \tag{11}$$

For commodities such as electricity, society generally needs the supply. Thus, this study considered an electricity transaction system without congestion. The variable $\boldsymbol{\mu}_2$ was usually more than $\boldsymbol{\lambda}_2$. Therefore, the response time per unit of input resource in $\mathbf{A_1}$ and $\mathbf{A_2}$ was calculated as $\frac{1}{\boldsymbol{\mu}_1 - \boldsymbol{\lambda}_1}$ and $\frac{1}{\boldsymbol{\mu}_2 - \boldsymbol{\lambda}_2}$, respectively. Based on this, the response time of all resources placed in $\mathbf{A_1}$ per year was described as $\frac{\boldsymbol{\lambda}_1}{\boldsymbol{\mu}_1 - \boldsymbol{\lambda}_1}$; the response time of all the resources placed in $\mathbf{A_2}$ per year was described as $\frac{\boldsymbol{\lambda}_2}{\boldsymbol{\mu}_2 - \boldsymbol{\lambda}_2}$.

Costs are described in **Eqs. 12–15**.

$$\mathbf{X_1} = \mathbf{W_1} \cdot \mathbf{C_1} \tag{12}$$

$$\mathbf{X_2} = \mathbf{W_2} \cdot \mathbf{C_2} \tag{13}$$

$$\mathbf{C_1} = \mathbf{I_1} \cdot \mathbf{r} \tag{14}$$

$$\mathbf{C_2} = \mathbf{I_2} \cdot \mathbf{r} \tag{15}$$

More goods to be traded and more resources awaiting an increase in value in one period led to higher transaction and opportunity costs in the period; as such, $\mathbf{C_1}$ and $\mathbf{C_2}$ increased with increases in the input resource $\mathbf{I_1}$ and $\mathbf{I_2}$, respectively.

In addition, two other formulas of $\mathbf{X_1}$ and $\mathbf{X_2}$ were derived from **Eqs. 1**, **2**, **12–15** as follows.

$$\mathbf{X_1} = \mathbf{k} \cdot \mathbf{I} \cdot \mathbf{r} \cdot \frac{1}{\boldsymbol{\theta}_1 \cdot \mathbf{L_1} \cdot \mathbf{P_m} - 1} \tag{16}$$

$$\mathbf{X_2} = (1 - \mathbf{k}) \cdot \mathbf{I} \cdot \mathbf{r} \cdot \frac{1}{\boldsymbol{\theta}_2 \cdot \mathbf{L_2} \cdot \mathbf{P_m} - 1} \tag{17}$$

A's profit is divided into two parts: $\boldsymbol{\Pi}_1$ and $\boldsymbol{\Pi}_2$.

[12]"Object" can be goods, resource, capital, or other items waiting to gain value by the operation on the platform. It is specified as the input resource, measured in production cost in simulation.

[13]Notice on Issuing the Rules for the Implementation of Middle-term and Long-term Transactions across Regions and Provinces in Beijing Power Exchange Center. No. 51 [2018]. http://www.bj-px.com.cn/html/main/col14/2018-08/30/20180830102119626314055_1.html.

$$\mathbf{\Pi}_1 = \mathbf{k} \cdot \mathbf{I} \cdot \mathbf{r}_1 - \mathbf{X}_1 \tag{18}$$

$$\mathbf{\Pi}_2 = \mathbf{I} \cdot (1 - \mathbf{k}) \cdot \mathbf{r}_2 - \mathbf{X}_2 \tag{19}$$

Equations Reflecting the Transition Ratio

The investment in $\mathbf{A}_1$ is described in **Eqs. 20–23**. Based on this, the transition ratio is expressed in **Eq. 23**. The resource placed in $\mathbf{A}_2$ is described in **Eq. 24**.

$$\mathbf{I}_{1\,(t+1)} = \boldsymbol{\rho}_1 \cdot \frac{\partial(\boldsymbol{\alpha}_{1s} \cdot \mathbf{\Pi}_1)}{\partial \mathbf{I}_1} - \boldsymbol{\rho}_2 \cdot \frac{\partial(\boldsymbol{\alpha}_{2s} \cdot \mathbf{\Pi}_2)}{\partial \mathbf{I}_2} + \boldsymbol{\rho}_0 \cdot \mathbf{I} \tag{20}$$

Factors on the right side of the equation are assigned a value in period t, that is, the value of the factors at the current time. The factor $\mathbf{I}_{1\,(t+1)}$ represents the value of $\mathbf{I}_1$ in the next period (period t+1).

An actor's decision to invest in $\mathbf{A}_1$ and the corresponding transition ratio is determined both by profit and sustainable strategic preference. This is because from an economic view, profit plays an important role in resource allocations. However, resource allocations and transition decisions do not always depend on profit, especially with respect to sustainable development. The variables $\mathbf{I}_1$ and k are influenced by the actor's sustainable strategic preference, which refers to the actor's evaluation of the importance of different businesses fields with respect to sustainability. This means that even if two business fields create the same profit for A, they have different effects on A's long-term development and transition, due to government's phasing-out policy and other factors influencing the actor's business environment.

The product of profit and preference "$\boldsymbol{\alpha}_{1s} \cdot \mathbf{\Pi}_1$" and "$\boldsymbol{\alpha}_{2s} \cdot \mathbf{\Pi}_2$" represented the utility for $\mathbf{A}_1$ and $\mathbf{A}_2$, respectively. The expressions $\frac{\partial(\boldsymbol{\alpha}_{1s} \cdot \mathbf{\Pi}_1)}{\partial \mathbf{I}}$ and $\frac{\partial(\boldsymbol{\alpha}_{2s} \cdot \mathbf{\Pi}_2)}{\partial \mathbf{I}}$ represented the marginal capital utility of $\mathbf{A}_1$ and $\mathbf{A}_2$, respectively. The values of the coefficients $\boldsymbol{\rho}_1, \boldsymbol{\rho}_2, \boldsymbol{\rho}_0$ were determined by the importance of relevant factors (marginal capital utility and **I**) in the decision-making process. Of course, the concrete expression of k could also be determined through optimization and other methods; however, this does not change the key point of the study: the actor makes decisions on the transition ratio based on profit and strategic preference.

$$\mathbf{I}_1 = \mathbf{I}_{1\,(t)} \tag{21}$$

$$\mathbf{I}_1 = \mathbf{INTEG}\left(\mathbf{I}_{1\,(t+1)} - \mathbf{I}_{1\,(t)}, \mathbf{I}_{1\,(t)}\right) \tag{22}$$

Setting "$\mathbf{I}_{1\,(t+1)} - \mathbf{I}_{1\,(t)}$" as a rate variable, the function of $\mathbf{I}_1$ is expressed in **Eq. 22**. Every time the function of $\mathbf{I}_1$ was assigned a new value, a new period began.

$$\mathbf{k} = \frac{\mathbf{I}_1}{\mathbf{I}} \tag{23}$$

$$\mathbf{I}_2 = (1 - \mathbf{k}) \cdot \mathbf{I} \tag{24}$$

The transition ratio is a ratio of resource allocation. It describes the portion of resource transferred from an actor's original field to a new field, as shown in **Eq. 23**.

Specific Equations of Value Preference

These equations do not discuss the concrete forms of $\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2$. The changing trends in social value preferences were described based on the simulation background's "transition of power industry," shown in **Eqs. 25, 26**.

$$\boldsymbol{\alpha}_2 = \mathbf{Time} \cdot (-0.01) + 0.3 \tag{25}$$

$$\boldsymbol{\alpha}_1 = 1 - \boldsymbol{\alpha}_2 \tag{26}$$

Only two business fields are discussed here ($\mathbf{A}_1, \mathbf{A}_2$); as such, societal resources were allocated in these two fields. Thus, the relationship between $\boldsymbol{\alpha}_1$ and $\boldsymbol{\alpha}_2$ was expressed as $\boldsymbol{\alpha}_1 + \boldsymbol{\alpha}_2 = 1$. The initial value of $\boldsymbol{\alpha}_2$ was set at 0.3 and was assigned different values in the following simulation. Due to a gradual depletion of fossil energy, there was a weakening in the degree of social preference for fired power generation. As such, $\boldsymbol{\alpha}_2$ decreased year by year. Consequently, the degree of social preference to switch from fired power generators to other approaches gradually increased (such as higher levels of renewable energy generation, integrated energy services, or electricity sales). As a result, $\boldsymbol{\alpha}_1$ increased year by year.

SIMULATION RESULT

Description of the Simulation Environment

According to the feedback mechanism between EVR and the transition ratio that influences the platform and social value preference, as shown in **Methodology**, **Figure 3**, a numerical study was completed, taking the transition of China's power system toward sustainability as the context. This allowed for the visual observation and exploration of the dynamic relationship of the above factors.

In China, it is important to promote the phasing-out of fossil-sourced power generation[14]. The Government has introduced a quota system to ensure that a proportion of electricity is generated for consumption using different energy sources[15]. Rules and policies provide better trading conditions for renewably sourced energy for electricity and ensure the speed of its transaction and consumption[16]. This creates competitive pressure on conventional power suppliers. All of this indicates that the government has different value preference with respect to different sourced power generations. Meanwhile, the platform creates pressure for fossil sourced power generators because of its inherent responsibilities and as a result of government rules. Founded in 2016, the platform was specified as the power trading center of China, and was a not-for-profit platform managed by state-owned power grid corporations[17].

[14]The Energy Administration, together with the Development and Reform Commission, issued "Suggestions on further promoting supply-side structural reform and further eliminating backward coal-sourced power generator to promote the optimization and upgrading of coal and electricity industry" No. [2019]431 (http://www.nea.gov.cn/2020-05/22/c_139077597.htm).

[15]Notice of the National Energy Administration on the Implementation of Renewable Energy Power Quota System (http://www.nea.gov.cn/2018-11/15/c_1)

[16]Circular of the Energy Bureau of the National Development and Reform Commission (NDRC) on the mechanism of consumption and security for renewable energy sourced electricity. NDRC [2019] No. 807 (http://zfxxgk.ndrc.gov.cn/web/iteminfo.jsp?id=16176).

[17]The platform is responsible for the construction and operation of the electricity market, the implementation of national policies, the conduct of electricity transactions, the promotion of clean energy consumption, and the future development of electricity financial transactions; it is also responsible for making basic rules for electricity transactions in cooperation with relevant government departments; and the establishment of technical, operational and management standards for the electricity market.

According to government rules, the power trading center ensures that the renewable energy sourced power is transacted and used first. It also facilitates the trading of non-fossil sourced energy power by setting bidding and trading rules. For example, the ranking rule was that when the seller's price was the same, renewable energy sourced power was prioritized. Next, the power generated in a manner that benefitted energy conservation and environmental protection was prioritized. In addition, by offering a special platform service for trading the "power" of electricity generation, the trading center promoted the supply of electricity transferred from conventional fossil sourced power generators to renewable energy sourced power generators. These services promoted the production and consumption of non-fossil sourced power, somewhat hindered the use of fossil sourced power generator, and promoted the transformation of fossil-sourced power generators. In summary, both the government and this not-for-profit platform pressured fossil-sourced power generators. These power suppliers' operational efficiency on the platform and the transition decisions were formed in this environment. How would these conventional power suppliers change their transition ratio in this environment, and how transition could be managed in this type of complex relationship was explored in the simulation.

In the simulation, the "phasing-out" actor A was specified as the collective group of fired power plants. The variable $\mathbf{I}$ represented A's total resources placed into production based on demand. The total input resource was specified as the cost of electricity production, calculated by "multiplying unit cost (Kilowatt-hour cost) by output." The variable $\boldsymbol{\mu}_1$ was specified as the quantity of resources placed in $\mathbf{A}_1$ per unit time. The entry rate of $\mathbf{A}_2$ was specified as the production cost (the input resource) of the electricity supplied for trading on the platform per unit time. The variable $\boldsymbol{\mu}_2$ was the production cost of the electricity ultimately traded on the platform per unit time. In addition, because power exchange centers serve as the example in this study, the platform services can only affect electricity transactions, not production. Parameters and data sources are included in the attached **Table A1**.

Model Validation

A series of checks were performed to verify the applicability of the SD model: a structural check, extreme value check, reality check, sensitivity check, and unit check. First, the integral causal diagram and flow chart were checked according the mechanism and reality, and a unit check was also performed. The structure was consistent with the model description. Second, for the extreme value check and reality check, irregularities were not found in the system, as shown in **Figures 6**, **7** Third, the sensitivity check found that the transition ratio was not sensitive to "the ratio of time-varying cost per unit time" (r), as shown in **Figure 8A**. However, it is very sensitive to the ratio of the increase in value $(\mathbf{r}_1, \mathbf{r}_2)$ and the value preference $(\boldsymbol{\alpha}_2)$, as shown in **Figures 8B–D**. Besides, although the growth rate of platform maturity is not a sensitive factor for the transition ratio, the change of growth rate causes the significant time-varying cost change, as shown in **Figures 8E–G**. All these results were consistent with real-world conditions and platform systems. Detailed tests and analysis of value preference and growth rate are shown in Results and Discussion.

Results and Discussion

After checking the model, the dynamic relationships among factors such as EVR and transition ratio were analyzed (Test 1). Then, the dynamic changes in the transition ratio (k) were analyzed when the EVR changed with the social value preference (Test 2). Finally, changes in the transition ratio were analyzed when the EVR changed with platform maturity (Test 3). The simulation results were as follows.

Test 1 Changes in the EVR, cost, and transition ratio in the current state.

The EVR and entry rate jointly affected the cost, profit, and transition ratio. **Figures 9A–D** shows that $\boldsymbol{\mu}_1$ increased while $\boldsymbol{\mu}_2$ decreased, leading to a decrease in $\mathbf{W}_1$ and increase in $\mathbf{W}_2$. This result generated the force of increasing $\mathbf{X}_2$ and decreasing $\mathbf{X}_1$. However, influenced by a increase in the entry rate $\boldsymbol{\lambda}_1$ and a decrease in $\boldsymbol{\lambda}_2$, both of which were caused by the feedback of an increasing transition ratio (k), both $\mathbf{X}_1$ and $\mathbf{X}_2$ showed a downward trend. As a result of the synthetic influence from the current transition ratio and time-driven variations in cost, $\boldsymbol{\Pi}_1$ went up, while $\boldsymbol{\Pi}_2$ went down. Influenced by profit $(\boldsymbol{\Pi}_1, \boldsymbol{\Pi}_2)$ and preference, the transition ratio (k) continued to rise.

To reduce the cost in $\mathbf{A}_1$ and to continuously improve the transition ratio, the $\boldsymbol{\mu}_1$ can be improved by changing value preferences, or by raising the platform maturity. This would positively influence the EVR on the transition ratio and would mitigate the negative influence caused by feedback with respect to the transition ratio. This approach was implemented in Test 2 and Test 3. Test 2 showed a better result for changing the costs and improving the transition ratio.

Test 2 Preference varies causing the effect of EVR on transition ratio to change.

The social value preference can be changed using approaches such as implementing phasing-out policies. Changes in the relevant variables were seen when the initial values of $\boldsymbol{\alpha}_2$ were set at 0.1, 0.3, and 0.5. When the initial value of $\boldsymbol{\alpha}_2$ was 0.1, the transition ratio rose sharply to 1 in the first year. This would be nearly impossible in reality; as such, we compared the situation when the initial value of $\boldsymbol{\alpha}_2$ was set at 0.3 and 0.5. A lower $\boldsymbol{\alpha}_2$ led to a lower $\boldsymbol{\mu}_2$ and a higher $\boldsymbol{\mu}_1$, generating the force of an increasing $\boldsymbol{\Pi}_1$ and decreasing $\boldsymbol{\Pi}_2$. Subsequently, the synthetic action of value preference and profit increased the transition ratio. However, the transition ratio generated feedback, resulting in more resources placed in $\mathbf{A}_1$ and fewer resources placed in $\mathbf{A}_2$. This trend is shown in **Figures 10H,I**. After that, the synthetic action of entry rate and EVR led to a higher $\mathbf{X}_1$ and a lower $\mathbf{X}_2$. This relationship coincided with **Eqs. 12–15**. Test 2 shows that reducing $\boldsymbol{\alpha}_2$ and increasing $\boldsymbol{\alpha}_1$ led to a higher $\boldsymbol{\mu}_1$, lower $\boldsymbol{\mu}_2$, higher $\boldsymbol{\Pi}_1$, lower $\boldsymbol{\Pi}_2$, and a higher transition ratio. However, it may also lead to a higher $\mathbf{X}_1$ and lower $\mathbf{X}_2$ as a result of the feedback effect.

Test 3 With different platform maturity, the state of transition varies.

The transition state was tested when $\mathbf{P_g}$ was set at values of 0.01, 0.05, and 0.1. The results show that when $\mathbf{P_g}$ was higher, the EVR of both $\mathbf{A}_1$ and $\mathbf{A}_2$ was higher and both the time-varying cost of $\mathbf{A}_1$ and $\mathbf{A}_2$ were lower. With the change in cost, the profit and transition ratio changed. A special outcome was that the transition ratio decreased slightly as $\mathbf{P_g}$ increased (see **Table 2**). This can be explained as follows. As $\mathbf{P_m}$ rose, $\mathbf{X}_2$ decreased significantly more than $\mathbf{X}_1$ because the input resource of $\mathbf{A}_1$ kept increasing. This led to a sharp rise in $\mathbf{C}_1$ and decrease in $\mathbf{C}_2$. As the time-varying cost $(\mathbf{X}_1, \mathbf{X}_2)$ changed in this way, the marginal profit of $\mathbf{A}_2$ rose more than $\mathbf{A}_1$. This led to a decrease in the transition ratio. However, the change in the transition ratio was not evident as $\mathbf{P_g}$ changed in this test, because time-varying cost only made up a small proportion of the full benefit. When ratio of the time-varying cost per unit time (r) rose and time-varying costs consequently occupied a higher proportion of the profit, the transition ratio significantly decreased as $\mathbf{P_g}$ increased. This is shown in **Figure 11H**. Although improvements in platform maturity improved the benefit of $\mathbf{A}_1$, this improvement did not ultimately improve the transition ratio when the time-varying cost of $\mathbf{A}_2$ was reduced more than $\mathbf{A}_1$.

Further Discussion and Policy Implications

Further Discussion

The results of each test were discussed in Results and Discussion; however, there remain issues related to multiple tests or equations that deserve further discussion. In addition, the analysis highlights a number of policy implications.

First, according to Test 2 and Test 3, improvements in the EVR for $\mathbf{A}_1$ did not always lead to a decrease of $\mathbf{X}_1$ in the feedback effect of the transition ratio. When the platform grew at a low rate of 0.01, or if the preference for $\boldsymbol{\alpha}_2$ was at a relatively high level of 0.5, there was an increasing trend in $\mathbf{X}_1$ (the slope of $\mathbf{X}_1 > 0$), as shown in **Figures 10F**, **11C**. This means that when $\mathbf{P_g}$ was low or $\boldsymbol{\alpha}_2$ was high enough, the positive power from $\boldsymbol{\mu}_1$ to $\mathbf{X}_1$ could be weaker than the negative power of the feedback about the rising transition ratio on $\mathbf{X}_1$, leading to an increase in $\mathbf{X}_1$. This result indicates that platform development should not be too slow, or it may prevent an improved transition ratio and result in a decreasing trend of $\mathbf{X}_1$. Also, the government should show a relevant low preference for $\mathbf{A}_2$ and higher preference for $\mathbf{A}_1$ using measures such as phasing-out policies, to affect the preference of the platform and to promote $\boldsymbol{\mu}_1$.

Second, **Eqs. 20, 23** indicate that marginal profit $\frac{\partial \boldsymbol{\Pi}_1}{\partial \mathbf{I}_1}$ and $\frac{\partial \boldsymbol{\Pi}_2}{\partial \mathbf{I}_2}$ can be respectively specified as

$$\frac{\partial \boldsymbol{\Pi}_1}{\partial \mathbf{I}_1} = \boldsymbol{r}_1 - \frac{\boldsymbol{r}}{\frac{\mu_1}{\lambda_1} - 1} \tag{27}$$

and

$$\frac{\partial \boldsymbol{\Pi}_2}{\partial \mathbf{I}_2} = \boldsymbol{r}_2 - \frac{\boldsymbol{r}}{\frac{\mu_2}{\lambda_2} - 1} \tag{28}$$

These expressions are directly related to the transition ratio. From the view of a queuing system, $\frac{\mu_1}{\lambda_1}$ and $\frac{\mu_2}{\lambda_2}$ in **Eqs. 27, 28**, respectively, represent the reciprocal values of the traffic intensity in systems $\mathbf{A}_1$ and $\mathbf{A}_2$, respectively. The increase of $\frac{\mu_1}{\lambda_1}$ or decrease of $\frac{\mu_2}{\lambda_2}$ may enhance the transition ratio. This implies that even if $\boldsymbol{\lambda}_1$ is low and $\boldsymbol{\lambda}_2$ is high at the beginning of the transition, a satisfactory transition ratio could be achieved by adjusting $\frac{\mu_1}{\lambda_1}$ and $\frac{\mu_2}{\lambda_2}$. This leads to the conclusion that EVR and the ratio between EVR and entry rate should be observed, predicted, and influenced to help manage the transition.

Third, the simulation specified actor A as the collective representation of phasing-out actors. However, the framework that analyzed the preference, an actor's resource allocation, and the platform system could also be used to analyze a special actor's transition. Ultimately, the transition ratio is, in essence, a resource allocation ratio, and the platform is a system which can record the entry rate and service rate. As such, the feedback mechanism of the transition ratio can be used to explain other problems related to resource allocations, if the entry rate of the input resource and service rate of the operation system can be recorded or estimated.

Policy Implications

Based on these results and discussions, this section proposes policies for better managing ST. First, the government should analyze changes in time-varying cost, profit, and transition ratios by observing and estimating the EVR and the entry rate, with the help of platform information systems. Based on this, incentive measures can be used to adjust the value preference. The efficiency of value realization and platform growth can be simulated, compared, and selected to maintain changes in the transition ratio within an acceptable range. The result can be predicted by analyzing the change in the transition ratio given the mechanisms described in this study.

Second, the government can help form appropriate social value preferences taking measures such as phasing-out policies, financial policies, consumption policies, and outreach. Also, the government should effectively transmit preferences to platforms and actors and encourage them to conform to expected preferences to accelerate transition.

In addition, platforms should be guided to set reasonable rules and service levels, consistent with expectations about social value preferences and with a coherent transition strategy. For example, platforms may offer new queuing or ranking rules which do not benefit the low qualified actors who are phasing-out. Meanwhile, they could offer services that help phasing-out actors to enter and operate in $\mathbf{A}_1$. Also, platforms should be incentivized to maintain a not-overly-slow growth rate to significantly reduce the cost in $\mathbf{A}_1$ when the EVR in $\mathbf{A}_1$ improves, allowing for effective EVR measures. However, purely improving platform growth may not be effective for a transition if the time-varying cost of $\mathbf{A}_2$ improves to a larger extent compared to $\mathbf{A}_1$ as a result of improving platform maturity. Through all these efforts, a path to sustainability transition can be established through co-governance between the government and the platform. This can lead to the harmonious development of society and actors in a digital platform economy.

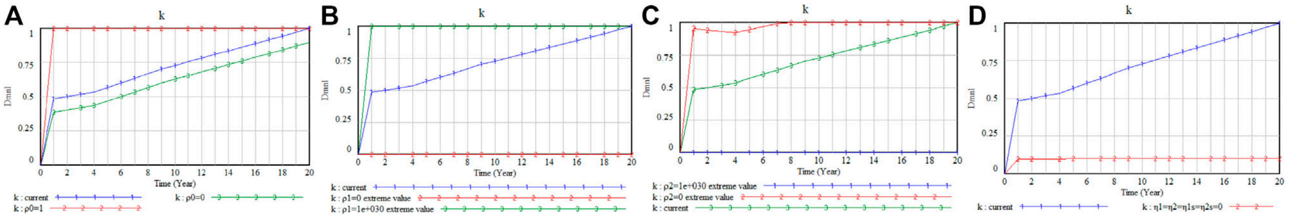

FIGURE 6 | Extreme value check: **(A)** Extreme value check on ρ0; **(B)** Extreme value check on ρ1; **(C)** Extreme value check on ρ2; **(D)** Extreme value check on η1, η2, η1s and η2s.

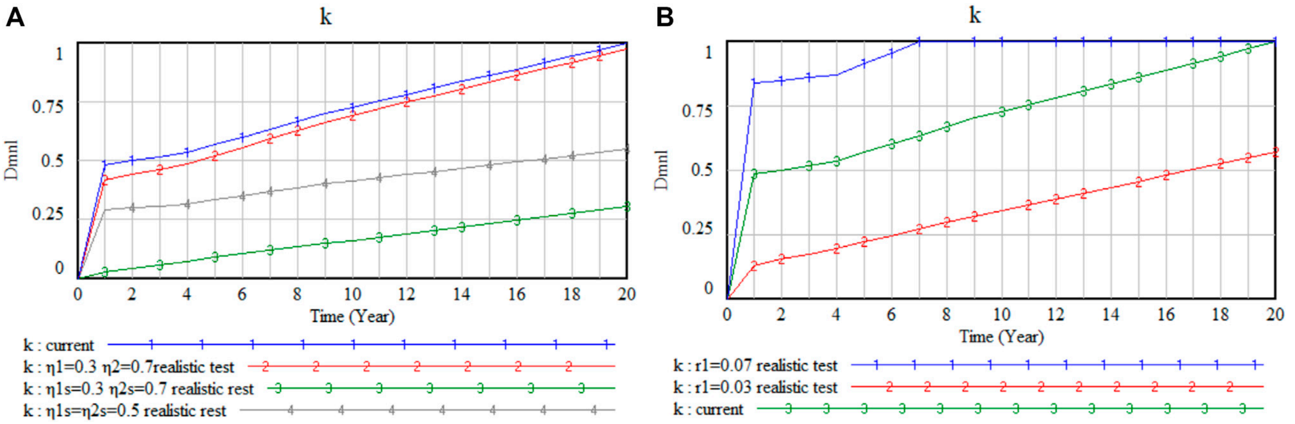

FIGURE 7 | Reality check: **(A)** Reality check on η1, η2, η1s and η2s; **(B)** Reality check on r1.

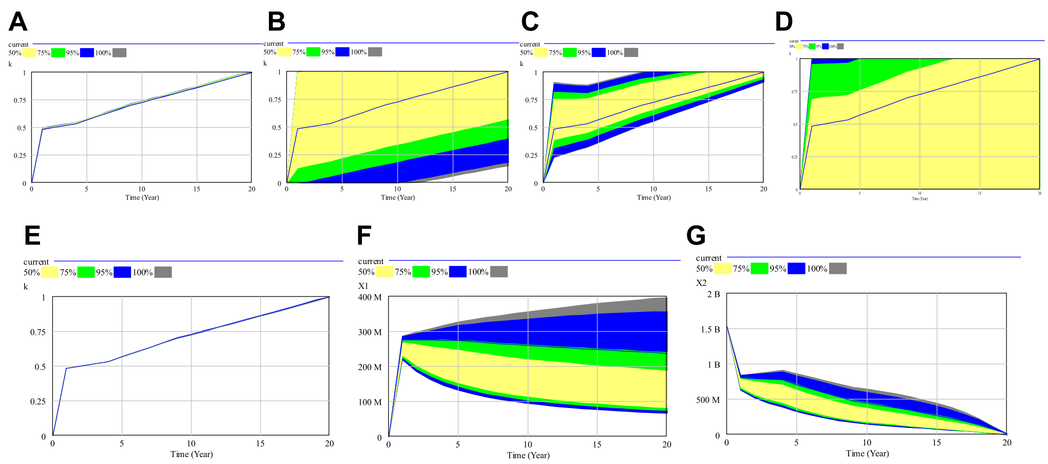

FIGURE 8 | Sensitivity test: **(A)** Sensitivity test on r; **(B)** Sensitivity test on $\mathbf{r}_1$; **(C)** Sensitivity test on $\mathbf{r}_2$; **(D)** Sensitivity test on $\boldsymbol{\alpha}_2$; **(E–G)** Sensitivity test on $\mathbf{P}_\mathbf{g}$.

CONCLUSION

This study explored the mechanisms associated with EVR, time-varying costs, actors' resource allocation, and the transition ratio. Co-governance measures were also explored.

First, sustainability transitions were found to be influenced by EVR and entry rate, especially the ratio reflecting the "reciprocal of traffic intensity." By improving EVR in $\mathbf{A}_1$ and reducing EVR in $\mathbf{A}_2$, the response time and time-driven variations in costs changed, leading to an improved transition ratio. However, the ultimate change in the transition ratio also depended on the entry rate, which changed dynamically as a result of feedback about the transition ratio.

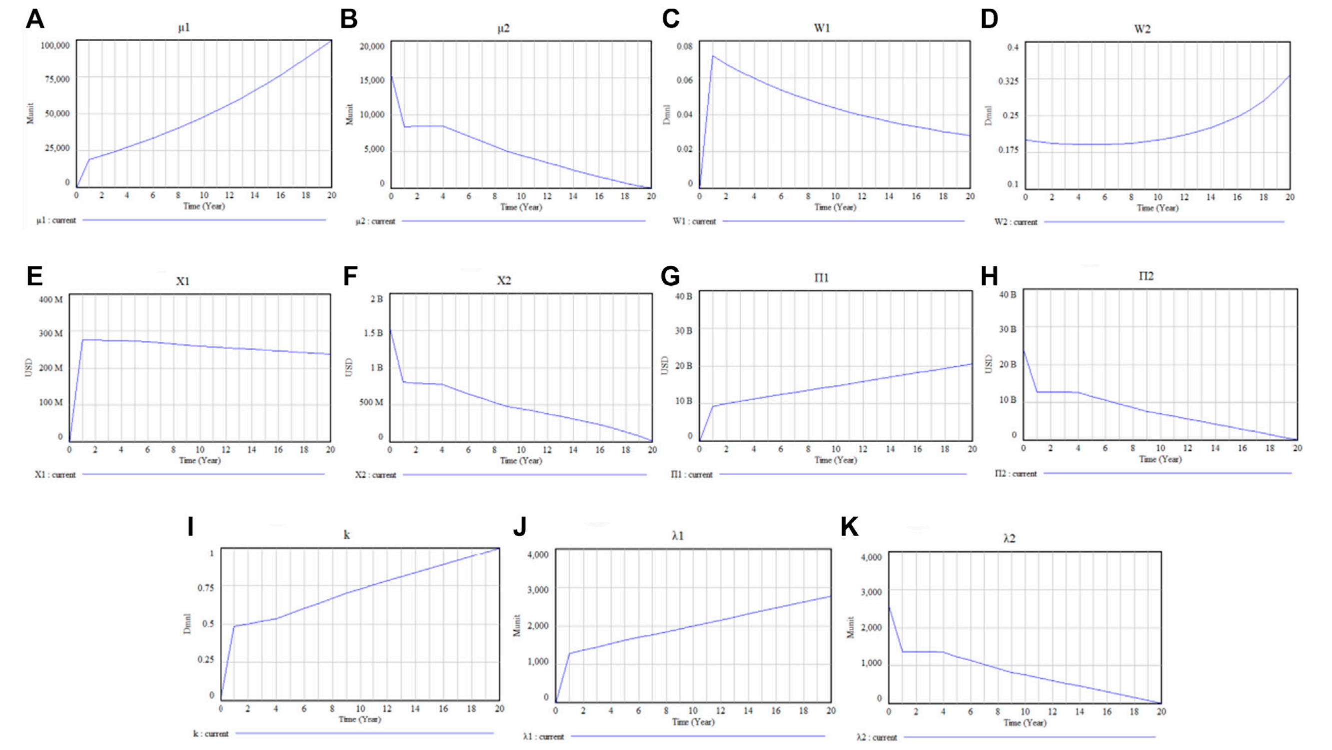

FIGURE 9 | Dynamic relationship between EVR and transition ratio: **(A)** The trend of μ1; **(B)** The trend of μ2; **(C)** The change of W1; **(D)** The change of W2; **(E)** The change of X1; **(F)** The change of X2; **(G)** The change of Π1; **(H)** The change of Π2; **(I)** The change of k; **(J)** The change of λ1; **(K)** The change of λ2.

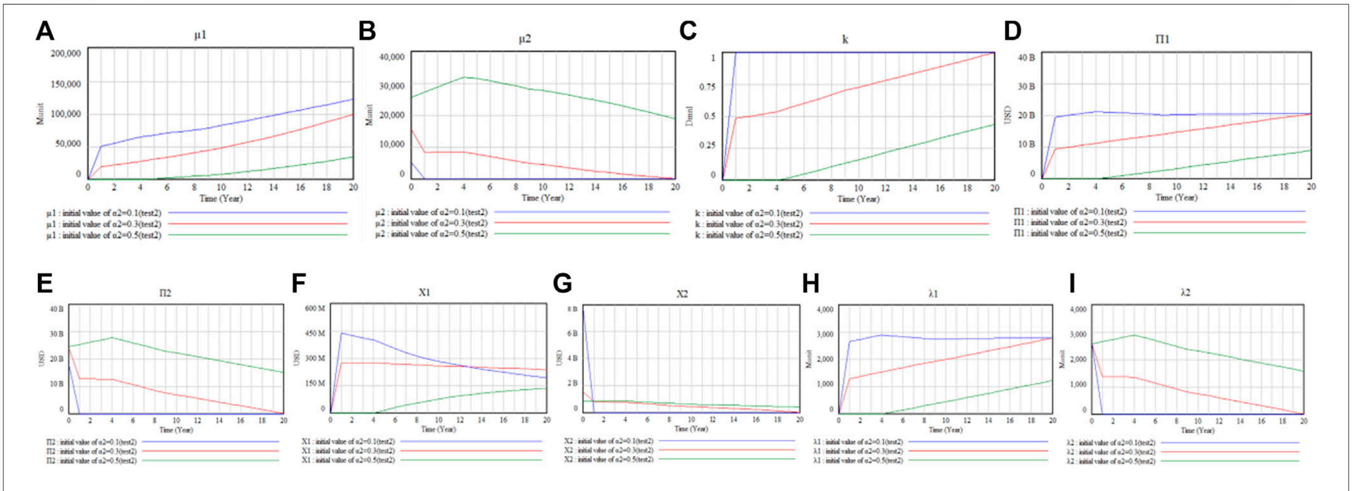

FIGURE 10 | Changes in the factors as preference varies: **(A)** The change of μ1; **(B)** The change of μ2; **(C)** The change of k; **(D)** The change of Π1; **(E)**: The change of Π2; **(F)** The change of X1; **(G)** The change of X2; **(H)** The change of λ1; **(I)** The change of λ2.

Second, the value preference transmitted from the government to the platform and actor played an important role in determining the effect of EVR on the transition. When the social value preference for $\mathbf{A}_2$ decreased, the EVR of $\mathbf{A}_1$ rose, and the $\mathbf{A}_2$ declined. This improved the transition ratio.

Third, both the EVR of $\mathbf{A}_1$ and $\mathbf{A}_2$ improved when there was a higher growth in platform maturity. This led to an increase of profit for both $\mathbf{A}_1$ and $\mathbf{A}_2$. Nevertheless, this simultaneous increase in the EVRs in different fields may not improve the transition ratio and could even lead it to decline. The ultimate change in the transition ratio is decided both by the extent of the improved profits in

TABLE 2 | The value of transition ratio with different values of $\mathbf{P_g}$ (r = 0.02).

Time (Year)	0	1	2	3	4	5	6	7
k ($\mathbf{P_g}$ = 0.01)	0	0.4828	0.4999	0.5164	0.5326	0.5682	0.601	0.6344
k ($\mathbf{P_g}$ = 0.05)	0	0.4828	0.4996	0.5159	0.5319	0.5673	0.5997	0.6330
K ($\mathbf{P_g}$ = 0.1)	0	0.4828	0.4993	0.5155	0.5312	0.5665	0.5989	0.6320

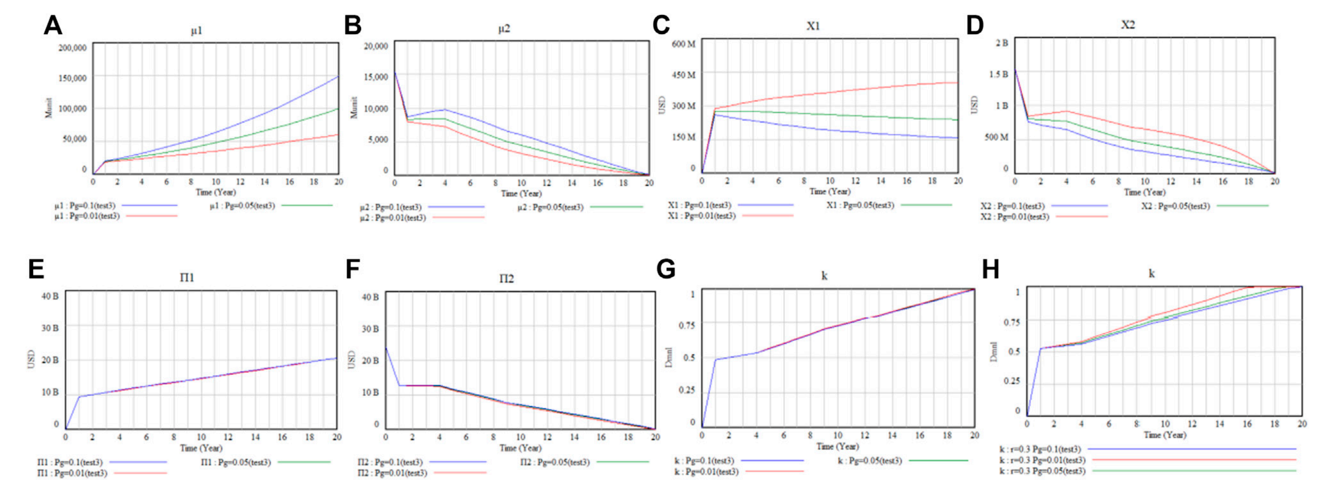

FIGURE 11 | Changes in the factors as platform maturity varies: **(A)** The change of μ1; **(B)** The change of μ2; **(C)** The change of X1; **(D)** The change of X2; **(E)** The change of Π1; **(F)** The change of Π2; **(G)** The change of k; **(H)** The change of k.

different fields as a result of platform maturity improvements, and the ratio between time-varying cost and profit.

The main contributions of this paper are as follows. First, the study illustrated the analysis path from the EVR on a platform to the transition ratio during the dynamic change of multiple factors. This allowed for a model to be established that illustrated an actor's operation and investment decisions, amidst the background of a digital platform economy and sustainability transitions. Second, the EVR and time-driven variations in costs, such as transaction and opportunity costs, were analyzed from the new perspective of the platform service system. Little's Law was used to analyze those costs. This extended the application of queuing theory to investments, transaction costs, and transitions to sustainability. It also linked the method of SD with another field, involving stochastic methods. For research on the platform-driven economy, the problem of judging the efficiency and value of digital service may be solved from a new perspective (the value increase of object) and by a new tool (EVR and response time). Third, the transmission of value preference was integrated into the framework of analysis with respect to ST. By introducing the "value preference" to the field of ST, profit was converted into utility, impacting transition decisions. The coefficient of value preference was introduced to describe evaluations about the utility of output, wealth creation, and the increase in the value of a resource. This ST mechanism, which considers value preferences, may reflect the first attempt in this new field to manage value preferences and the relevant resource allocations through co-governance with digital platforms. Such an exploration of the mechanisms involved in value preference and in public affairs such as ST may contribute to reducing the negative effects of a purely profit-driven market mechanism.

Some limitations remain in this study's model. For example, the model did not consider competition when analyzing the EVR. The transition of the power system in China was used as an example for the simulation. As such, the problems of power peaks and valleys were assumed to be addressed using the social power system, and the power products were considered to be nearly homogeneous. However, when products are heterogeneous, the EVR is affected by operations and competition. In other words, if competition is considered, a relatively low cost may lead to a higher EVR. This study, in contrast, assumed a stable competitive environment. In the future, the function of EVR could be expanded, and correlative factors such as production and operation could be included to address other transition problems in a different context. In addition, the study simulation only considered the situation where the social value preference could be effectively transferred to the platform and the actor. When the consistency coefficient of value preference varies, relevant variables also change.

Future research should include a multi-platform analysis. In addition, the relationship between the EVR and transition ratio could be studied in a more specific way, by considering production and operational conditions on specific platforms, or by discussing specific policies and actors. This could help explore more concrete policies for sustainability transitions.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

JX: Conceptualization, software, writing TL: Conceptualization, supervision, funding acquisition PT and YL: Supervision and editing XL: Software QL and MS: Editing.

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REFERENCES

Abdelkafi, N., Raasch, C., Roth, A., and Srinivasan, R. (2019). Multi-sided platforms. *Electron. Mark.* 29, 553–559. doi:10.1007/s12525-019-00385-4

Banos-Gonzalez, I., Martínez-Fernández, J., Esteve-Selma, M. Á., and Esteve-Guirao, P. (2018). Sensitivity analysis in socio-ecological models as a tool in environmental policy for sustainability. *Sustainability.* 10(8), 2928. doi:10.3390/su10082928

Bautista, S., Espinoza, A., Narvaez, P., Camargo, M., and Morel, L. (2019). A system dynamics approach for sustainability assessment of biodiesel production in Colombia. Baseline simulation. *J. Clean. Prod.* 213, 1–20. doi:10.1016/j.jclepro.2018.12.111

Cavicchi, B. (2018). The burden of sustainability: limits to sustainable bioenergy development in Norway. *Energy Policy.* 119, 585–599. doi:10.1016/j.enpol.2018.05.015

Cosenz, F., Picanco Rodrigues, V., and Rosati, F. (2020). Dynamic business modeling for sustainability: exploring a system dynamics perspective to develop sustainable business models. *Business Strategy Enviro.* 29 (2), 651–664. doi:10.1002/bse.2395

Curseu, P. L., and Schruijer, S. G. L. (2020). Participation and goal achievement of multiparty collaborative systems dealing with complex problems: a natural experiment. *Sustainability.* 12 (3), 987. doi:10.3390/su12030987

Egana-delSol, P. A., and Flanders, S. (2019). "Platform economy and sustainable energy," in *Affordable and clean energy*. Editors W. Leal Filho, A. M. Azul, L. Brandli, et al. (Cham: Springer International Publishing), 1–9.

El-Baz, W., Tzscheutschler, P., and Wagner, U. (2019). Evaluation of energy market platforms potential in microgrids: scenario analysis based on a double-sided auction. *Front. Energy Res.* 7, 13. doi:10.3389/fenrg.2019.00041

Espinoza, A., Bautista, S., Narváez, P. C., Alfaro, M., and Camargo, M. (2017). Sustainability assessment to support governmental biodiesel policy in Colombia: a system dynamics model. *J. Clean. Prod.* 141, 1145–1163. doi:10.1016/j.jclepro.2016.09.168

Gawer, A. (2014). Bridging differing perspectives on technological platforms: Toward an integrative framework. *Res. Pol.* 43 (7), 1239–1249. doi:10.1016/j.respol.2014.03.006

Geels, F. W., Sovacool, B. K., Schwanen, T., and Sorrell, S. (2017). The socio-technical dynamics of low-carbon transitions. *Joule.* 1 (3), 463–479. doi:10.1016/j.joule.2017.09.018

Geels, F. W. (2019). Socio-technical transitions to sustainability: a review of criticisms and elaborations of the multi-level perspective. *Curr. Opin. Environ. Sustainability.* 39, 187–201. doi:10.1016/j.cosust.2019.06.009

Gloria Baigorrotegui, B. (2019). Destabilization of energy regimes and liminal transition through collective action in Chile. *Energy Res. Soc. Sci.* 55, 198–207. doi:10.1016/j.erss.2019.05.018

Graziano, M., De Groot, G. S., Daniela Pilato, L., and Laura Sánchez, M. (2019). Fostering urban transformations in Latin america: lessons around the ecological management of an urban stream in coproduction with a social movement (buenos aires, Argentina). *Ecol. Soc.* 24. doi:10.5751/es-11226-240413

Homer, J. (2019). Best practices in system dynamics modeling, revisited: a practitioner's view. *Syst. Dynam. Rev.* 35, 177–181. doi:10.1002/sdr.1630

Kieckhäfer, K., Wachter, K., and Spengler, T. S. (2017). Analyzing manufacturers' impact on green products' market diffusion - the case of electric vehicles. *J. Clean. Prod.* 162, S11–S25. doi:10.1016/j.jclepro.2016.05.021

Kim, H., Lee, D., and Hwang, J. (2018). The effect of online platform maturity on the efficiency of offline industry. *Telematics Inf.* 35, 114–121. doi:10.1016/j.tele.2017.10.003

Kloppenburg, S., and Boekelo, M. (2019). Digital platforms and the future of energy provisioning: Promises and perils for the next phase of the energy transition. *Energy Res. Soc. Sci.* 49, 68–73. doi:10.1016/j.erss.2018.10.016

Köhler, J., Geels, F. W., Kern, F., Onsongo, E., Wieczorek, A., Alkemade, F., et al. (2019). An agenda for sustainability transitions research: state of the art and future directions. *Environ. Innovation Societal Transitions.* 31, 1–32. doi:10.1016/j.eist.2019.01.004

Kokkinos, K., Lakioti, E., Papageorgiou, E., Moustakas, K., and Karayannis, V. (2018). Fuzzy cognitive map-based modeling of social acceptance to overcome uncertainties in establishing waste biorefinery facilities. *Front. Energy Res.* 6, 25. doi:10.3389/fenrg.2018.00112

Kolk, A., and Ciulli, F. (2020). The potential of sustainability-oriented digital platform multinationals: a comment on the transitions research agenda. *Environ. Innovation Societal Transitions.* 34, 355–358. doi:10.1016/j.eist.2019.12.008

Lachman, D. A. (2013). A survey and review of approaches to study transitions. *Energy Policy.* 58, 269–276. doi:10.1016/j.enpol.2013.03.013

Landsman, V., and Stremersch, S. (2011). Multihoming in two-sided markets: an empirical inquiry in the video game console industry. *J. Mark.* 75 (6), 39–54. doi:10.1509/jm.09.0199

Lee, J. (2019). Assessment research on industrial internet platform from the maturity aspect. *Sci. Technol. Manage. Res.* 39, 43–47. doi:10.3969/j.issn.1000-7695.2019.02.007

Li, F. G. N., and Strachan, N. (2019). Take me to your leader: using socio-technical energy transitions (stet) modelling to explore the role of actors in decarbonisation pathways. *Energy Res. Soc. Sci.* 51, 67–81. doi:10.1016/j.erss.2018.12.010

Loux, P., Aubry, M., Tran, S., and Baudoin, E. (2020). Multi-sided platforms in b2b contexts: the role of affiliation costs and interdependencies in adoption decisions. *Ind. Market. Manag.* 84, 212–223. doi:10.1016/j.indmarman.2019.07.001

Ma, L., and Hu, J. (2018). An analysis of the eco-innovation mechanism and policies in the pulp and paper industry based on coupled game theory and system dynamics. *Sustainability.* 10 (10), 3482. doi:10.3390/su10103482

Martin, C. J., Upham, P., and Klapper, R. (2017). Democratising platform governance in the sharing economy: an analytical framework and initial empirical insights. *J. Clean. Prod.* 166, 1395–1406. doi:10.1016/j.jclepro.2017.08.123

Mattila, J., and Seppälä, T. (2018). "Distributed governance in multi-sided platforms: a conceptual framework from case: Bitcoin," in *Collaborative value co-creation in the platform economy*. Editors A. Smedlund, A. Lindblom, and L. Mitronen (Singapore: Springer), 183–205.

Oei, P-Y., Hermann, H., Herpich, P., Holtemöller, O., Lünenbürger, B., and Schult, C. (2020). Coal phase-out in Germany-implications and policies for affected regions. *Energy.* 196, 1–19. doi:10.1016/j.energy.2020.117004

Oei, P-Y., Brauers, H., and Herpich, P. (2019). Lessons from Germany's hard coal mining phase-out: policies and transition from 1950 to 2018. *Clim. Pol.* 20 (8), 963–979. doi:10.1080/14693062.2019.1688636

Pan, Y., and Chi, D. (2017). Comparison and prediction of the lcoe of coal-fired power generation projects and large-scale pv projects in China. *Sino Global Energy.* 22, 1–7 [In Chinese]. Available at: https://www.cnki.net/.

Papachristos, G. (2011). A system dynamics model of socio-technical regime transitions. *Environ. Innovation Societal Transitions.* 1 (2), 202–233. doi:10.1016/j.eist.2011.10.001

Paundra, J., van Dalen, J., Rook, L., and Ketter, W. (2020). Ridesharing platform entry effects on ownership-based consumption in Indonesia. *J. Clean. Prod.* 265, 121535. doi:10.1016/j.jclepro.2020.121535

Pereira, I. P. C., Ferreira, F., Pereira, L. F., and Govindan, K., Meidutė-Kavaliauskienė, L., and Correia, R. J. C. (2020). A fuzzy cognitive mapping-system dynamics approach to energy-change impacts on the sustainability of small and medium-sized enterprises. *J. Clean. Prod.* 256. doi:10.1016/j.jclepro.2020.120154

Rentier, G., Lelieveldt, H., and Jan Kramer, G. (2019). Varieties of coal-fired power phase-out across europe. *Energy Policy.* 132, 620–632. doi:10.1016/j.enpol.2019.05.042

Rosenbloom, D. (2018). Framing low-carbon pathways: a discursive analysis of contending storylines surrounding the phase-out of coal-fired power in ontario. *Environ. Innovation Societal Transitions.* 27, 129–145. doi:10.1016/j.eist.2017.11.003

Shafiei, E., Ingi Ásgeirsson, E., Davidsdottir, B., and Stefansson, H. (2013). Integrated agent-based and system dynamics modelling for simulation of sustainable mobility. *Transport Rev.* 33 (1), 44–70. doi:10.1080/01441647.2012.745632

Shum, K. L. (2017). Renewable energy deployment policy: a transition management perspective. *Renew. Sustain. Energy Rev.* 73, 1380–1388. doi:10.1016/j.rser.2017.01.005

Tan, Y., Jiao, L., Shuai, C., and Shen, L. (2018). A system dynamics model for simulating urban sustainability performance: a China case study. *J. Clean. Prod.* 199, 1107–1115. doi:10.1016/j.jclepro.2018.07.154

Vincent, d. G., Rouwette, E., van Kranenburg, H., Freeman, E., and van Breen, H. (2016). Sustainability transition dynamics: towards overcoming policy resistance. *Technol. Forecast. Soc. Change.* 111, 135–145. doi:10.1016/j.techfore.2016.06.019

Vögele, S., Kunz, P., Rübbelke, D., and Stahlke, T. (2018). Transformation pathways of phasing out coal-fired power plants in Germany. *Energy Sustainability Soc.* 8, 25. doi:10.1186/s13705-018-0166-z

Wang, Z. (2019). Research on building synthesis energy ecological platform for large-scale network collaboration and data intelligent application. *Power Demand Side Manage.* 21, 77–82. doi:10.3969/j.issn.1009-1831.2019.04.016

Williams, A., Kennedy, S., Philipp, F., and Whiteman, G. (2017). Systems thinking: a review of sustainability management research. *J. Clean. Prod.* 148, 866–881. doi:10.1016/j.jclepro.2017.02.002

Xie, J., and Jawad Sajid, M. (2019). Utility evaluation index system of cross border e-commerce platform and the innovation of service and strategy. *J. Jiangnan Univ. Humanit. Soc. Sci. Ed.* 18, 97–107 [In Chinese]. Available at: https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CJFD&filename=WXQS201902014&dbname=CJFDLAST2019.

Yu, G. (2017). Evaluation e-commerce service level based on variable basis analysis method. *Oper. Res. Manage. Sci.* 26, 163–184 [In Chinese]. Available at: https://www.cnki.net/.

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APPENDIX

TABLE A1 | Value of the parameters in numerical study.

Parameter	Value	Data sources
uc	Initial year 2016: **uc** = 0.04 (USD/KWH). The changing rate of **uc** is calculated based on Pan and Chi (2017)	Comparison and prediction of the LCOE of coal-fired power generation projects and large-scale pv projects in China (Pan and Chi, 2017)
D	1.23 e+013KWH	Calculated using power industry statistics from 2009 to 2018 provided by China's Electricity council http://www.cec.org.cn/guihuayutongji/tongjxinxi/niandushuju/
q	The value is 0.24 in the starting year. The rate of change is 0.01	According to the "Notice of the National Energy Administration on the implementation of renewable Energy power quota system" and statistical statements and measurements from the power industry in China from 2016 to 2018 http://www.nea.gov.cn/2018-11/15/c_1
I	Unit cost (**uc**) multiplied by the quantity of output	In the simulation, the resources placed into power production is measured by cost, so the value of **I** is calculated by multiplying the unit cost with the quantity of output
$\mathbf{r}_{\mathbf{a}1}$	0.05	Simulated data
$\mathbf{r}_{\mathbf{a}2}$	0.0661	The calculation is based on the financial index of industrial enterprises from 2016 to 2018 (Central People's government of the PRC) http://www.gov.cn/xinwen/2017-01/26/content_5163619.htm http://www.gov.cn/xinwen/2018-01/26/content_5260850.htm http://www.gov.cn/xinwen/2019-01/28/content_5361707.htm
r	0.02	Simulated data
$\boldsymbol{\alpha}_2$	$\boldsymbol{\alpha}_2 = \mathbf{Time} \cdot (-0.01) + 0.3$	Simulated data. For the fired power plants that are considered "phasing-out actors,"$\boldsymbol{\alpha}_2 \leq 0.5$.According to this scope, tests were conducted when the value of $\boldsymbol{\alpha}_2$ is as follows $\boldsymbol{\alpha}_2 = \mathbf{Time} \cdot (-0.01) + 0.3$, $\boldsymbol{\alpha}_2 = \mathbf{Time} \cdot (-0.01) + 0.1$, $\boldsymbol{\alpha}_2 = \mathbf{Time} \cdot (-0.01) + 0.5$
$\boldsymbol{\eta}_1$ $\boldsymbol{\eta}_2$	1	Since the power exchange center of China is currently a public not-for-profit platform, it is believed that the value preference of this platform is highly consistent with social value preference
$\boldsymbol{\alpha}_{\mathbf{1s}}$ $\boldsymbol{\alpha}_{\mathbf{2s}}$	$\boldsymbol{\alpha}_{\mathbf{1s}} = \boldsymbol{\alpha}_1 \cdot \boldsymbol{\eta}_{\mathbf{1s}}$ $\boldsymbol{\alpha}_{\mathbf{2s}} = \boldsymbol{\alpha}_2 \cdot \boldsymbol{\eta}_{\mathbf{2s}}$ The variables $\boldsymbol{\eta}_{\mathbf{1s}}$ and $\boldsymbol{\eta}_{\mathbf{1s}}$ are the consistency coefficients between the social value preference and the actor's strategic preference. $\boldsymbol{\eta}_{\mathbf{1s}} = \boldsymbol{\eta}_{\mathbf{2s}} = 1$	Simulated data. The simulation assumed that the social value preference can be effectively transmitted to the actors through outreach and policies from the government of China
$\mathbf{P_g}$	$\mathbf{P_g} = 0.05$ In simulation, the level of platform maturity in the starting year is marked as the standard value 1. It increases at rate $\mathbf{P_g}$	Simulated data. Three levels, $\mathbf{P_g} = 0.01, 0.05, 0.1$, were simulated
$\boldsymbol{\theta}_1$ $\boldsymbol{\theta}_2$	10	Simulated data
M	1.49622e+008	Data are based on trading volume information collected from the trading announcement of Beijing power Exchange center from January 2017 to October 2019 https://pmos.sgcc.com.cn/pmos/index/infoList.jsp?itemid = 213000&title = %E4%BA%A4%E6%98%93%E5%85%AC%E5%91%8A&curpage = 1
$\boldsymbol{\rho}_1$ $\boldsymbol{\rho}_2$	1e+013	Simulated data
$\boldsymbol{\gamma}_1$ $\boldsymbol{\gamma}_2$	2	Simulated data
$\mathbf{L}_{10}$ $\mathbf{L}_{20}$	1	Simulated data
$\mathbf{L_m}$	0.1	Simulated data

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Application of Rough Set and Neural Network in Water Energy Utilization

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In water energy utilization, the damage of fault occurring in the power unit operational process to equipment directly affects the safety of the unit and efficiency of water power conversion and utilization, so fault diagnosis of water power unit equipment is especially important. This work combines a rough set and artificial neural network and uses it in fault diagnosis of hydraulic turbine conversion, puts forward rough set theory based on the tolerance relation and defines similarity relation between samples for the decision-making system whose attribute values are consecutive real numbers, and provides an attribute-reducing algorithm by making use of the condition that approximation classified quality will not change. The diagnostic rate of artificial neural networks based on a rough set is higher than that of the general three-layer back-propagation(BP) neural network, and the training time is also shortened. But, the network topology of an adaptive neural-fuzzy inference system is simpler than that of a neural network based on the rough set, the diagnostic accuracy is also higher, and the training time required under the same error condition is shorter. This algorithm processes consecutive failure data of the hydraulic turbine set, which has avoided data discretization, and this indicates that the algorithm is effective and reliable.

Keywords: decision analysis, rough set, neural network, water energy utilization, sustainable energy

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INTRODUCTION

With the continuous expansion in the scale of wind power, hydroelectric power, and other clean energy types, the hydraulic power generation system structure is also becoming increasingly complex, and the power generation unit of the hydropower station develops towards large scale and automation (Duy and Ozak, 2014; Liu and Packey, 2014). Hence, once a fault occurs, both power generation efficiency and unit safety will be affected, which will have harmful effects on the national economy and cause significant economic loss. The likelihood of malfunctions increases as the complexities of systems grow (Gokmen et al., 2013). The occasional occurrence of fault during the daily operation of hydropower units requires increasingly high reliability and safety of unit operation (Tang et al., 2010; Gao et al., 2016) The fault-diagnosis technology is also increasingly valued by people and has developed to be one comprehensive interdiscipline. Generally, the fault-diagnosis method consists of creating a real fault into the physical system and evaluating its effect on different measured variables (Attoui and Omeiri, 2014). In the current hydropower unit fault prediction and diagnosis, expert-system fault-diagnosis technology has been widely applied to the actual system, and excellent effects have been achieved (Lu et al., 2016a; Lu et al., 2016b). However, the inherent defect of the symbol information processing mechanism on which the expert system is based causes many traditional expert-system problems.

Scholars and engineering technicians put forward many technologies and methods of power system fault diagnosis to quickly and accurately recognize fault and judge the location and type of faulty components under various complicated conditions. The diagnoses are mainly including expert systems, optimization algorithms, fuzzy set theory, and multiagent technology (Pawlak, 1982; Chen et al., 2006; Clark et al., 2014; and Clark et al., 2015). Rough set theory has been widely applied in artificial intelligence, decision support, rule extraction, data mining, machine learning, etc., due to its strong capacity to handle uncertain information. In hydraulic power generation system fault diagnosis, to judge faulty components or areas based on actuating signal of protection and circuit breaker, it is possible to express the fault phenomenon and component state by pattern classification. It is appropriate to utilize the decision table method of rough set theory for this purpose (Pedrycz et al., 2008). However, in hydraulic power generation system fault diagnosis, fault-diagnosis rules of the power system correspond to attribute reduction of rough set theory. Therefore, in the case of a power system fault diagnosis with the rough set method, it is necessary to reduce the rough set decision table, which is an NP-complete problem (Wang et al., 2012). The work of Wang et al. (2013) and Cerrada et al. (2015) combine rough set theory and clone algorithm; the work of Foithog et al. (2012) and Hu et al. (2010) applied a self-adaptive genetic algorithm in attribute reduction of the rough set. The studies mentioned above mainly focus on rules extraction after using rough set theory; however, attribute reduction of the rough set itself is an NP problem.

This paper will utilize the rough set theory and neural network. The advantage of this methodology is to gain knowledge from data or input and output of living examples, and it does not require knowing the mathematical description of input and output. An artificial neural network is a model based on the human brain. It has a neuron system composed of many neurons, which has the advantages of massive parallelism, distributed processing, self-organization, and self-learning. Among these models, the BP neural network is currently the most popular neural network model in application. It has the universal advantages of all neural networks, self-learning and self-adaptive ability, nonlinear mapping ability, and high fault-tolerance rate (Yang et al., 2019). The BP algorithm's main idea is to divide the learning process into two stages; the first stage is the forward propagation process. The given input information is to pass through the input layer and subject to the hidden layer node process and calculate the actual output value of every element. The second stage is a backward process; if the expected output value is not obtained at the output layer, it is necessary to carry out the recursive calculation of the difference between the actual output value and expected output value layer by layer to adjust the weight value based on the error.

This article establishes two kinds of neural network models under a rough set and fuzzy set. One model is the rough neural network, using a rough set to handle front-end data of neural network input and using rough set mining rules to replace the conventional adaptive-network-based fuzzy inference system (ANFIS). Utilizing this algorithm to handle the hydraulic power generation unit's continuous fault data, ultimate results show the effectiveness of this algorithm.

GLOBAL SIMILARITY MEASUREMENT AND ATTRIBUTE REDUCTION ALGORITHM

Improved General Discrimination of Attribute

Definition 1: a decision-making and information system S=(U,A,V,f) is given, where $A = C \cup \{d\}, C$ refers to the condition attribute set, and d refers to the decision attribute. Ud = d1,d2,. . .,drd, ∀a∈C, and the general importance degree of attribute a is defined as

$$\sigma_g(a) = \begin{cases} 1 - \dfrac{1}{C^2_{r(d)}} \sum_{i,j=1}^{r(d)} {}_{i \neq j} \dfrac{a(d_i) \cap a(d_j)}{maxcross[a(d)]} & \text{other} \\ \forall \text{i, j}, a(d_i) \cap a(d_j) = \Phi & \end{cases}, \quad (1)$$

where $C^2_{r(d)}$ refers to the combination with 2 taken out from r(d) numbers, $a(d_i) \cap a(d_j) \subset V$ represents the intersection between the subset of the attribute value of decision value d_i relevant to attribute a and subset of the attribute value of relevant decision value dj relevant thereto, and $maxcross[a(d)] \subset V$ indicates the maximum interval encircled by all intersections of subsets of attribute values of two decision values relevant to attribute *a*, degree of general importance and measurement of the attribute. The general importance of the attribute measures indicates the global decision-making ability, rather than the impact of certain decision elements.

Suppose a decision table of absolute value, as shown in **Table 1**, with six objects.

$$U/d = \{d_1, d_2, d_3\} = \{\{x_1, x_2\}, \{x_3, x_3\}, \{x_5, x_6\}\}.$$

1) Subset interval of the attribute value of decision d_i relevant to attribute a_1 is [1.5,2.1], [1.8,3.3], and [2.0,2.7], respectively. The degree of importance of its general attribute calculated according to **Eq. 1** is as follows:

$$\sigma_g(a_1) = 1 - \frac{1}{C_3^2} \sum_{i \neq j}^{3} \frac{a(d_i) \cap a(d_j)}{[2.0, 2.7]}$$
$$= 1 - \frac{1}{3} \left(\frac{[1.8, 2.1] + [2.0, 2.1] + [2.0, 2.7]}{[2.0, 2.7]} \right) = 0.479.$$

TABLE 1 | Decision table of absolute value.

U	a1	a1'	a2	a3	d
x1	1.5	0.0	0.4	5.6	1
x2	2.1	2.1	0.5	6.7	1
x3	1.8	1.8	0.4	5.1	2
x4	3.3	8.0	0.5	4.6	2
x5	2.0	2.0	0.5	6.8	3
x6	2.7	2.6	0.6	7.3	3

2) Subset interval of the attribute value of decision d_i relevant to attribute a_1, is [0,2.1], [1.8,8], and [2.0,2.7], respectively, and the degree of importance of its general attribute is as follows:

$$\sigma_g\left(a'_1\right) = 1 - \frac{1}{C_3^2}\sum_{i \neq j}^{3}\frac{a(d_i)\cap a\left(d_j\right)}{[2.0, 2.7]}$$
$$= 1 - \frac{1}{3}\left(\frac{[1.8, 2.1] + [2.0, 2.1] + [2.0, 2.7]}{[2.0, 2.7]}\right) = 0.479.$$

Although, attribute a_1 and attribute a'_1 are different in terms of subset interval of the attribute value of decision d_i, since

$$a_1(d_1)\cap a_1(d_2) = a'_1(d_1)\cap a'_1(d_2) = 0.3,$$
$$a_1(d_1)\cap a_1(d_3) = a'_1(d_1)\cap a'_1(d_3) = 0.2,$$
$$a_1(d_2)\cap a_1(d_3) = a'_1(d_2)\cap a'_1(d_3) = 0.9, \quad \text{and}$$
$$maxcross[a_1(d)] = maxcross\left[a'_1(d)\right] = 0.9.$$

Therefore, they are identical in terms of the degree of importance of general attribute, namely, $\sigma_g(a_1) = \sigma_g(a'_1)$. For attribute a_1, its degree of influence on $\frac{a_1(d_1)\cap a_1(d_2)}{[1.6,2.2]} = \frac{0.3}{0.6} = 0.5$, and the degree of influence of a_1 on d_1 is $\frac{a_{1'}(d_1)\cap a_{1'}(d_2)}{[0,2.2]} = \frac{0.3}{2.2} = 0.136$.

Accordingly, for different subset intervals of the attribute value, the intersection between the subset of d_i relevant to a_1 and a'_1 and the subset d_j relevant to it has different degrees of influence on the respective attribute subset interval.

Consequently, the concept about the degree of importance of improved general attribute is put forward, with the influence of intersection between subsets of attribute value on the respective attribute subset interval taken into consideration.

Definition 2: given the decision-making system $S = (U, C\cup d, V, f), U/d = \{d_1, d_2, \ldots d_{r(d)}\}, \quad \forall a \in C,$ an improved general discrimination of attribute a is defined as follows:

$$\sum_g(a) = \begin{cases} 1 - \frac{1}{C_{r(d)}^2}\sum_{i=1}^{r(d)}\frac{\sum_{j=1}^{\substack{r(d)\\ i\neq j}}\varphi_1\left[a(d_i), a\left(d_j\right)\right]}{|a(d_{imax}) - a(d_{imin})|}, & (d_{imax}) \neq a(d_{imin}) \\ 1 - \frac{1}{C_{r(d)}^2}\sum_{i=1}^{r(d)}\frac{\sum_{j=1}^{\substack{r(d)\\ i\neq j}}\varphi_2\left[a(d_i), a\left(d_j\right)\right]}{|a(d_{imax})|}, & (d_{imax}) = a(d_{imin}) \end{cases}, \tag{2}$$

where

$$\varphi_1\left[a(d_i), a\left(d_j\right)\right] = \frac{a(d_i)\cap a\left(d_j\right)}{|r(d) - 1|},$$
$$\varphi_2\left[a(d_i), a\left(d_j\right)\right] = \begin{cases} \frac{a\left(d_j\right)}{|r(d) - 1|}, & a(d_{imax}) \in a\left(d_j\right) \\ & a(d_{imax}) \notin a\left(d_j\right) \end{cases}.$$

$C_{r(d)}^2$ represents the combination with 2 taken out from $r(d)$ numbers, $a(d_i)\cap a(d_j) \subset V$ refers to the intersection between the subset of the attribute value of decision value d_i $\mathrm{d_i}$ relevant to attribute a and subset of the attribute value of decision value d_j relevant thereto, and $a(d_{imax})$ and $a(d_{imin})$ are the maximum and minimum of decision value $\mathrm{d_i}$ relevant to attribute a, respectively. According to the calculation based on formula, $\sigma_g(a_1) = 0.6827, \sigma_g(a'_1) = 0.8171$.

Global Similarity Measurement of the Attribute

Definition 3: given a decision-making system $S = (U, A, V, f) \quad \forall a \in A,\ x, y \in U$, different similarity relations may be defined for different attributes, and this work defines the similarity of attribute a for objects x and y as follows:

$$SIM(x, y) = 1 - \frac{\left|a(x) - a\left(y\right)\right|}{|a_{\max} - a_{\min}|}, \tag{3}$$

where $a_{\max}$ and $a_{\min}$ are the maximum and minimum of attribute a, respectively.

Given a decision-making system $S = (U, A, V, f)$ for attribute subset $P \subseteq A, \quad \forall x, y \in U$ in case that they satisfy the following formula:

$$\frac{\sum_{a\in P}k*SIM_a(x, y) + (1 - k)*\sigma_g(a)}{|P|} \geq \tau, \tag{4}$$

where $k \in [0.5, 1]$ and then $(x, y) \in SIM(x, y)_{p,\tau}$, which is the global similarity threshold. It gives the global similarity degree of the similarity class to take not only the similarity of the object but also the global decision-making ability of the attribute into consideration.

Definition 4: $SIM_{p,\tau} = \{y \in U\left|(x, y) \in SIM_{p,\tau}\right.$ intolerance class.

Definition 5: tolerance class of object $x \in U$ and lower approximation $(P_\tau X)$ and upper approximation $(\overline{P}_\tau X)$ of tolerance relation object set X are defined as follows:

$$\underline{P}_\tau X = \left\{x\middle|SIM_{P,\tau}(x)\subseteq X\right\},$$
$$\overline{P}_\tau X = \left\{x\middle|SIM_{P,\tau}(x)\cap X\varnothing\right\}.$$

They are referred to as the lower approximation of $SIM_{P,\tau}$ and upper approximation of $SIM_{P,\tau}$ of X, respectively.

Definition 6: if $P, Q \subseteq A$, then p (positive threshold) $POS_p(Q)$ and the degree of dependence k_τ of Q are defined as follows:

$$POS_{P,\tau}(Q) = U_{x\subseteq U|Q}\underline{P}_\tau X,$$
$$k_\tau(Q) = \gamma_{P,\tau}(Q) = \frac{\left|POS_{P,\tau}(Q)\right|}{|U|}. \tag{5}$$

Attribute Reduction Algorithm Based on the Tolerance Relation

Attribute reduction of an information system often starts from the calculation of the attribute set to save much time (Min and Liu, 2009; Sun et al., 2017) since positive threshold change based on the global similarity relation is irregular; therefore, it is advisable to add the current foremost attribute from the empty set. The initial range of system threshold is $[\tau, 0.99]$ with threshold reduced by 0.01 from 0.99 every time to calculate the degree of dependence of the condition attribute

TABLE 2 | Diagnosis results of the two kinds of network.

Type of network	Network structure	Training time	Diagnosis results
General neural network	11-21-1	2.242	14/16
Rough neural network	3-16-1	0.913	15/16

set on the decision attribute set till the degree of dependence is unchanged (Sun et al., 2019).

Input: information system $S = (U, C \cup D, V, f)$, and the number of condition attributes is n

Output: reduced set of the attribute of S

APPLICATION ANALYSIS

To analyze various performance indexes of hydropower unit operation at the hydropower station and monitor the state of the hydropower unit during the operation process, the power plant explores the dependency relationship between equipment in various unordered measured data by record and statistics of equipment operating data of the power generation unit. Knowledge discovery means the method of finding a dependency relationship between variables from these data and reporting the model found to the user in the form of a function or rule (Peng et al., 2011; Grbovic et al., 2012; Shang et al., 2017). Production rules are widely applied in knowledge representation because they are simple in form and are easy to understand by the user.

Haa and Xu (2001) provide water turbine fault-diagnosis data of a hydropower station, as shown in **Supplementary Table SA1** in the appendix. Based on the fault-diagnosis system of the rough set, this work takes certain hydropower station data in western China as an example to carry out an experimental simulation study of fault diagnosis. Firstly, using the fuzzy membership function to disperse data with an equal-width discretization method, the membership function parameters generate automatically according to the given fuzzy membership grade. This method has good self-adaptability, and the fuzzification can be omitted in the ANFIS system (Tabakhi et al., 2014; Zhang and Min, 2016; Zhang et al., 2016). In this example, the membership grade is 4. Then, a rough set is utilized to prehandle data to obtain the core attribute, namely, the minimum attribute set {5, 6, 9}, determine the hidden node number of the BP network, repeat the training 10 times with consideration of network training time and the sum of squared errors (SSE), and get the average value of all training by giving the same training step.

With an increase in the hidden layer node number, network convergence error is reduced, but the training time is lengthened (Raileanu and Stoffel, 2004; Shi et al., 2015). The hidden node number is taken as 17 with comprehensive consideration of these two factors. When directly constructing a neural network without rough set handling, 12 input nodes are needed, and more hidden layer nodes are needed for network convergence. The same method is used to find the optimum hidden node number of original data free from dimensionality reduction.

TABLE 3 | Rule table of rough set mining.

No. of rule	Condition attribute			Decision attribute	Rule support
	5	6	9		
1	1	—	—	1	22
2	—	3	—	1	6
3	—	—	3	1	7
4	3	—	2	0	4
5	—	1	—	1	13
6	—	4	—	1	5
7	2	2	—	0	16
8	2	—	1	0	2
9	4	—	—	1	1
10	—	—	4	1	2

Table 2 compares the differences between the two kinds of networks (general neural network and rough neural network). As it is clear, the rough neural network has advantages over those of general neural networks. The two kinds of the network are respectively applied to bearing fault-diagnosis examples. The diagnosis data are shown in **Supplementary Table SA2** in the appendix.

It can be seen from **Table 2**, that the rough neural network has advantages over the general neural networks from network structure, training time, and diagnosis results. But, the two kinds of diagnosis results are not complete in **Table 2**, and only relying on two reasons may cause the incompleteness through analysis. One reason may be that training samples exclude the "model" of tested samples, namely, that faulty reasoning is made about samples not tested. The other reason may be that the noise-resistance capacity of the neural network is not strong enough. More training samples are required for the former one to make a network cover sample space as much as possible (Klepaczko and Materka, 2010; Moradi and Rostami, 2015). But, in most cases, fault data information is pretty little, and normal formation is more, or in tests, it takes high risks to get fault data, so sometimes, an immune algorithm is adopted to diagnose the fault, namely, fault diagnosis by studying pretty much normal data to have immunity to abnormal data. For the latter one, it can be considered to utilize a fuzzy neural network to improve the corresponding noise-resistance capacity. The ANFIS diagnosis process is briefly introduced in the following part of this section. Rough set mining rules are utilized to obtain 10 rules, as shown in **Table 3**. The last item is rule support, namely, the rule repeatability rate in training samples: the higher the repeatability rate is, the more important the rule is.

The full connection method is adopted in general fuzzy neural network construction. For three-input and four-membership grade, $4^3 = 64$ nodes are needed for expression at the rule

TABLE 4 | Diagnosis comparison of the rough neural network and ANFIS.

Type of network	Network structure	SSE	Training time	Diagnosis result
Rough neural network	3-16-1	0.047	0.913	15/16
ANFIS	3-12-10-10-1	0.047	0.561	16/16

input layer. The ANFIS system in this work uses rough set mining rules to replace original rules, which reduces its connection weight, and it can be seen from the table that rules include irrelevant items. The complexity of this example with 13 connection weights and 10 nodes via this connection is greatly reduced when compared with the general network with $4^4 = 256$ connection weights and 64 nodes. Rules obtained with a rough set are used to replace the original rule represented by full connection by modifying the source code of the genfis function provided by the Matlab fuzzy logic toolbox (Aquil and Banerjee, 2008; Grzymala-Busse, 2008). Function anfis is utilized for training in the aspect of network training.

It can be seen from **Table 4** that ANFIS based on a rough set further improves the accuracy of fault diagnosis. Under the same SSE conditions, the training time is shortened, which is attributed to the operation adopted in the intermediate layer. Also, certain noise-resistance capacity is possessed due to the adoption of the fuzzy method.

CONCLUSION

1) A rough neural network and self-adaptive neural-fuzzy inference system (ANFIS) are established by combining a rough set, neural network, and other methods to diagnose hydropower unit fault. The rough neural network has a simpler structure, shorter training time, and higher diagnostic accuracy than the general neural network by comparing their diagnosis results.
2) The hydropower unit fault-prediction and -diagnosis system during the hydroenergy conversion process based on rough set data overcome the problem of traditional expert-system knowledge acquisition bottleneck. In the rough set method, knowledge discovered is described directly, and it is very easy to convert the knowledge into useful rules.
3) A reduction algorithm based on rough classification rules is put forward, and good effects are achieved. Also, a hydropower unit fault-prediction and -diagnosis system based on rough set data mining is enabled. The system is capable of giving an output of high confidence, possesses strong fault-tolerance capability, and deserves a promotion.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**; further inquiries can be directed to the corresponding authors.

AUTHOR CONTRIBUTIONS

MW conceptualized the work, conducted formal analysis, and was responsible for the methodology; XB curated data and wrote the original draft; ZZ conducted investigation and obtained the resources; ZZ and JL were responsible for software; FT-H performed validation; and JL and FT-H reviewed and edited the manuscript.

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REFERENCES

Aquil, K., and Banerjee, M. (2008). Formal reasoning with rough sets in multiple-source approximation systems. *Int. J. Approx. Reason* 49 (2), 466–477. doi:10.1016/j.ijar.2008.04.005

Attoui, I., and Omeiri, A. (2014). Modeling, control and fault diagnosis of an isolated wind energy conversion system with a self-excited induction generator subject to electrical faults. *Energy Convers. Manag.* 82, 11–26. doi:10.1016/j.enconman.2014.02.068

Cerrada, M., Vinicio Sánchez, R., Cabrera, D., Zurita, G., and Li, C. (2015). Multi-stage feature selection by using genetic algorithms for fault diagnosis in gearboxes based on vibration signal. *Sensors (Basel).* 15, 23903–23926. doi:10.3390/s150923903

Chen, D. G., Zhang, W. X., Daniel, Y., and Tsang, E. C. C. (2006). Rough approximations on a complete completely distributive lattice with applications to generalized rough sets. *Inf. Sci.* 176, 1829–1848. doi:10.1016/j.ins.2005.05.009

Clark, P. G., Grzymala-Busse, J. W., and Rzasa, W. (2014). Mining incomplete data with singleton, subset and concept probabilistic approximations. *Inf. Sci.* 280, 368–384. doi:10.1016/j.ins.2014.05.007

Clark, P. G., Grzymala-Busse, J. W., and Rzasa, W. (2015). Consistency of incomplete data. *Inf. Sci.* 322, 197–222. doi:10.1016/j.ins.2015.06.011

Duy, T. V. T., and Ozak, T. (2014). A decomposition method with minimum communication amount for parallelization of multi-dimensional FFTs[J]. *Comput. Phys. Commun.* 185 (1), 153–164. doi:10.1016/j.cpc.2013.08.028

Foithong, S., Pinngern, O., and Attachoo, B. (2012). Feature subset selection wrapper based on mutual information and rough sets. *Expert Syst. Appl.* 39, 574–584. doi:10.1016/j.eswa.2011.07.048

Gao, S., Mao, C., Wang, D., and Lu, J. (2016). Dynamic performance improvement of DFIG-based WT using NADRC current regulators. *Int. J. Electr. Power Energy Syst.* 82 (11), 363–372. doi:10.1016/j.ijepes.2016.03.026

Gokmen, N., Karatepe, E., Silves tre, S., Celik, B., and Ortega, P. (2013). An efficient fault diagnosis method for PV systems based on operating voltage-window. *Energy Convers. Manag.* 73 (5), 350–360. doi:10.1016/j.enconman.2013.05.015

Grbovic, M., Li, W., Xu, P., Usadi, A. K., Song, L., and Vucetic, S. (2012). Decentralized fault detection and diagnosis via sparse PCA based decomposition and Maximum Entropy decision fusion. *J. Process Control.* 22 (4), 738–750. doi:10.1016/j.jprocont.2012.02.003

Grzymala-Busse, J. W. (2008). Three approaches to missing attribute values: a rough set perspective. *Stud. Comput. Intell.* 118, 139–152. doi:10.1007/978-3-540-78488-3_8

Hao, L., and Xu, X. (2001). The application of rough set neural network system in fault diagnosis. *Control Theory Appl.* 5 (18), 681–685.

Hu, Q., Yu, D., and Guo, M. (2010). Fuzzy preference based rough sets. *Inf. Sci.* 180, 2003–2022. doi:10.1016/j.ins.2010.01.015

Klepaczko, A., and Materka, A. (2010). "Artifical intelligence and soft computing," in 10th International Conference, Icaisc, Zakopane, Poland, June 13–17, 2010. (Berlin, Heidelberg: Springer Berlin Heidelberg).

Liu, Y., and Packey, D. J. (2014). Combined-cycle hydropower systems - the potential of applying hydrokinetic turbines in the tailwaters of existing conventional hydropower stations. *Renew. Energy.* 66 (6), 228–231. doi:10.1016/j.renene.2013.12.007

Lu, S., Wang, J., and Xue, Y. (2016a). Study on multi-fractal fault diagnosis based on EMD fusion in hydraulic engineering. *Appl. Therm. Eng.* 103, 798–806. doi:10.1016/j.applthermaleng.2016.04.036

Lu, S., Zhang, X., Bao, H., and Skitmore, M. (2016b). Review of social water cycle research in a changing environment. *Renew. Sust. Energy Rev.* 63, 132–140. doi:10.1016/j.rser.2016.04.071

Min, F., and Liu, Q. (2009). A hierarchical model for test-cost-sensitive decision systems. *Inf. Sci.* 179, 2442–2452. doi:10.1016/j.ins.2009.03.007

Moradi, P., and Rostami, M. (2015). A graph theoretic approach for unsupervised feature selection. *Eng. Appl. Artif. Intell.* 44, 33–45. doi:10.1016/j.engappai.2015.05.005

Pawlak, Z. a. (1982). Rough sets. *Int. J. Comput. Inf. Sci.* 11 (5), 341–356. doi:10.1007/bf01001956

Pedrycz, W., Skowron, A., and Kreinovich, V. (2008). *Handbook of granular computing*. West Sussex, United Kingdom: John Wiley and Sons

Peng, F., Yu, D., and Luo, J. (2011). Sparse signal decomposition method based on multi-scale chirplet and its application to the fault diagnosis of gearboxes. *Mech. Syst. Signal Process.* 25 (2), 549–557. doi:10.1016/j.ymssp.2010.06.004

Raileanu, L. E., and Stoffel, K. (2004). Theoretical comparison between the Gini index and information gain criteria. *Ann. Math. Artif. Intell.* 41, 77–93. doi:10.1023/b:amai.0000018580.96245.c6

Shang, Y., Lu, S., Li, X., Hei, P., Lei, X., Gong, J., et al. (2017). Balancing development of major coal bases with available water resources in China through 2020. *Appl. Energy* 194, 735–750. doi:10.1016/j.apenergy.2016.07.002

Shi, H., Li, Y., Han, Y., and Hu, Q. (2015). Cluster structure preserving unsupervised feature selection for multi-view tasks. *Neurocomputing* 175, 686–697. doi:10.1016/j.neucom.2015.11.001

Sun, B., Ma, W., and Xiao, X. (2017). Three-way group decision making based on multigranulation fuzzy decision-theoretic rough set over two universes. *Int. J. Approx. Reason.* 81, 87–102. doi:10.1016/j.ijar.2016.11.001

Sun, L., Zhang, X., Xu, J., and Zhang, S. (2019). An attribute reduction method using neighborhood entropy measures in neighborhood rough sets. *Entropy (Basel).* 21 (2), 155. doi:10.3390/e21020155

Tabakhi, S., Moradi, P., and Akhlaghian, F. (2014). An unsupervised feature selection algorithm based on ant colony optimization. *Eng. Appl. Artif. Intell.* 32, 112–123. doi:10.1016/j.engappai.2014.03.007

Tang, J., Shi, Y., Zhang, W., and Zhou, L. (2010). Nonlinear analog circuit fault diagnosis using wavelet leaders multifractal analysis method. *J.Control Decis.* 25 (4), 605–609.

Wang, L., Yang, X., Yang, J., and Wu, C. (2012). Relationships among generalized rough sets in six coverings and pure reflexive neighborhood system. *Inf. Sci.* 207, 66–78. doi:10.1016/j.ins.2012.03.023

Wang, S., Zhu, W., Zhu, Q., and Min, F. (2013). Four matroidal structures of covering and their relationships with rough sets. *Int. J. Approx. Reason.* 54, 1361–1372. doi:10.1016/j.ijar.2013.07.001

Yang, C., Li, Z., Guo, X., Yu, W., Jin, J., and Zhu, L. (2019). Application of BP neural network model in risk evaluation of railway construction. *Complexity* 12, 1–12. doi:10.1155/2019/2946158

Zhang, H.-R., and Min, F. (2016). Three-way recommender systems based on random forests. *Knowl. Based Syst.* 91, 275–286. doi:10.1016/j.knosys.2015.06.019

Zhang, X., Miao, D., Liu, C., and Le, M. (2016). Constructive methods of rough approximation operators and multigranulation rough sets. *Knowl. Based Syst.* 91, 114–125. doi:10.1016/j.knosys.2015.09.036

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Modeling Interprovincial Cooperative Carbon Reduction in China: An Electricity Generation Perspective

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As the world faces great challenges from climate change, carbon reduction has become China's basic national policy. However, as the main model for carbon reduction in China, the non-cooperative carbon reduction model (NCCRM) is a simple regulation mode, which is not beneficial for optimization of electricity generation capacity structure and cannot effectively motivate carbon reduction at the provincial level. Therefore, we propose an interprovincial cooperative carbon reduction model (CCRM) from the perspective of electricity generation, which provides a mechanism integrating two fundamental principles of efficiency and fairness. The CCRM consists of two parts: (1) an optimal model of carbon reduction with the object of minimizing the carbon emission of the cooperation union to determine the optimal annual electricity generation for each participating province and (2) a model that distributes the economic benefits of the cooperation among the provinces in the cooperation based on the Shapley value method. We applied the CCRM to the case of an interprovincial union of Shanghai, Sichuan, Shanxi, and Gansu in China. The results, based on the data from 2014 to 2017, show that cooperation can significantly reduce the carbon emission of the union by 425.78×10^8 kg, 11.06%; meanwhile, Shanghai, Sichuan, Shanxi, and Gansu can, respectively, get 2.79×10^8, 11.11×10^8, 4.07×10^8, and 3.19×10^8 CNY of extra benefits from carbon reduction. To test the impact of different parameter values on the results of the CCRM, a sensitivity analysis was conducted. Some policy recommendations are proposed to promote the implementation of the CCRM.

Keywords: optimal model, carbon reduction, Shapley value, game, interprovincial cooperation

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INTRODUCTION

The world is facing great challenges from climate change and environmental pollution. On November 30, 2015, at the United Nations Conference on Climate Change, President Xi Jinping promised to the world that "China pledges to peak CO_2 emissions by around 2030," "and by 2030, reduce CO_2 per unit of GDP by 60–65% over the 2005 level" (Zeng et al., 2018). China is under great

Abbreviations: CCRM, cooperative carbon reducing model; CNY, China Yuan; CO_2, carbon dioxide; FYP, five-year plan; GS, Gansu; KWh, kilowatt-hour; MCCRB, model of collective cooperation and reallocation of benefits; MCRS, minimum-cost-remaining savings; NCCRM, non-cooperative carbon reducing model; SC, Sichuan; SH, Shanghai; SX, Shanxi.

pressure of carbon reduction, which has forced China to develop a carbon reduction strategy. Carbon reduction has become China's basic national policy, and guidelines for China's carbon reducing policies have been issued in the 12th and 13th Five-Year Plan (FYP).

The special energy structure of China determines that optimizing the electricity generation structure is not only effective to carbon reduction but also critical to pollution abatement and energy security. Firstly, electricity power is one of the main forms of energy consumption. Secondly, the structure of electricity generation capacity in China is dominated by coal-fired power generation. Therefore, this paper attempts to resolve the problem of carbon reduction from the perspective of electricity generation so as to get a multi-win effect.

In China, the distributions of economic development and renewable energy resources in different provinces present significant differences. In general, the provinces which abound in renewable energy resources are less developed in economy. This situation means that the provinces with abundant renewable energy resources have great potential of carbon reduction. However, the current model of carbon reduction in China cannot exploit this potential. The current model of carbon reduction is as follows: the central government establishes the carbon reduction goals for the whole country and each province, and at the end of the performance period, which is the Five-Year Plan period, the central government examines the carbon reduction performance of each province. For example, the overall goal for CO_2 emission per unit of GDP set by the Twelfth FYP is a 17% reduction over the 2010 level for the whole country. By province, for example, for Shanghai, Jiangsu, it is 19%; for Beijing, Hebei, 18%; for Sichuan, Fujian, 17.5%; for Shanxi, Jilin, 17%; for Guizhou, Gansu, 16%; for Hainan, Xinjiang, 11%; and for Qinghai, Tibet, 10%. If the carbon reduction goal is not achieved, the leaders of the province will lose promotion opportunities or even their jobs. The current non-cooperative carbon reduction model (NCCRM), under which the carbon reduction performance of each province is examined respectively, may result in huge waste of carbon reduction capability and potential. For example, these years, capacity of renewable energy power generation has made great development in north China, northwest China, and northeast China, but most provinces in these regions cannot consume the renewable energy power electricity entirely for the mismatch between economic development and renewable resources under the NCCRM; as a result, serious wind and solar curtailment has taken place in these regions.

To make full use of the capacity of renewable energy and exploit the potential of renewable energy resources so as to promote carbon reduction more effectively and efficiently, this paper proposes an interprovincial cooperative carbon reduction model (CCRM) for China from the perspective of electricity generation. Under the CCRM, the central government examines the performance of carbon reduction of the union as a whole instead of each province. The carbon reducing union in this model is composed of a few provinces. Considering the differences in structure of electricity generation capacity among provinces in a union, and based on meeting the electricity consumption for socioeconomic development of each province in the union, the carbon reducing union reallocates the quota of electricity generation to each member to minimize the carbon emission of the union from electricity generation so as to maximize the benefits of the union from carbon reducing. The benefits from cooperative carbon reduction are then allocated fairly and reasonably to each province according to the Shapley value method. Under the CCRM, renewable energy capacity will be utilized more efficiently and benefits from carbon reduction will be improved significantly.

The remainder of this paper is organized as follows: the related literatures are reviewed in Section 2. Section 3 constructs the interprovincial CCRM, which consists of two parts: (1) an optimization model that calculates the optimal quantities of electricity generation for each participating province and (2) a model that allocates the cooperation benefits based on the Shapley value method. Then, Section 4 presents the case study on a cooperative union composed of four provinces in China: Shanghai, Sichuan, Shanxi, and Gansu. To test the impact of parameter values on the calculation results of the CCRM, a sensitivity analysis was conducted in Section 5. The final section provides conclusions, policy recommendations, and directions for further study.

LITERATURE REVIEW

With the widespread acceptation that climate change is one of the most important global environmental issues, a great number of researchers have been attracted to solve this problem from the perspective of carbon reduction management and policy. Among them, the relationship between carbon emission or carbon-emission reduction and economic development, as well as the relationship between electricity production and carbon emission, is a widely concerned issue.

At first, the relationship between carbon emission or carbon-emission reduction and economic development is a fundamental concern by researchers and governments. Chen et al. (2007) studied the impact of China's carbon mitigation strategies and corresponding impacts on the social welfare, GDP, investment, and consumption at the national level by applying three MARKAL family models. Zhang et al. (2016) compared the impact of carbon reduction policy on the development of transport sector through carbon tax scenario analyses. Iftikhar et al. (2018) analyzed energy and CO_2 emission efficiency of major economies in terms of economic and distributive efficiency. Zou et al. (2020) through the establishment of a spatial Durbin model discussed the relationship between economic growth and CO_2 emissions. Wu et al. (2021) by establishing the Cobb–Douglas production function and Kaya function studied carbon emissions and economic growth in China at the national level and regional level. These studies have shown that economic development is an important factor of carbon emissions; in turn, carbon reduction policies affect the development of the economy.

Secondly, given the strong relationship between electricity production and carbon emission, a great deal of researches on carbon reduction is carried out from the perspective of electricity generation. On the one hand, to identify critical industries and sectors for reduction efforts, many researchers carried out inventory analysis on carbon emission, verifying that the energy industry and energy-intensive industries, such as electric power industry and the iron and steel industry, are the main contributors to carbon emission (Munksgaard and Pedersen, 2001; Satterthwaite, 2008; Xi et al., 2011; Guo et al., 2012, 2018; Wang et al., 2013; Liu et al., 2015; Wu et al., 2016, 2020). On the other hand, to formulate effective carbon mitigation policy, a number of carbon reduction studies related to electricity generation have been conducted at multiple levels. At the industry level, Cui et al. (2018) explored the comprehensive policy implications of carbon reduction for the power industry in China from both macro and micro perspectives. Li et al. (2018) used the dynamic computable general equilibrium model to quantitatively analyze the impact of carbon-emission trading on the power industry. At the regional level, Xie et al. (2019) established a risk measurement model considering carbon-capture technology and carbon-emission reduction targets to study the power system management in the Xinjiang Autonomous Region. Chang et al. (2017) took Shanghai as an example to study the path of clean production of power enterprises under emission restriction. Li et al. (2020) used provincial data to study the carbon-emission reduction potential of China's coal-fired power plants. At the national level, Liu et al. (2014) answered the question of whether China can realize its carbon reduction target from the perspective of China's thermal power development. At the global level, Cabal et al. (2017) analyzed the application of nuclear fusion technology, which contributes to carbon reduction, in global power systems. These studies show that carbon-emission reduction is closely related to electricity production, and the perspective of electricity generation is a crucial one for carbon-emission reduction research.

Furthermore, both for the world and China, the most important problem for policymakers is to initiate programs that not only will mitigate the global buildup of GHG but also will facilitate cooperation and be perceived as fair (Rose and Tietenberg, 1993). That is to say, an effective policy should embody the two fundamental principles: efficiency and fairness, which are reflected in the UNFCCC principle of "common but differentiated responsibilities." Based on the fairness principle, nations for the world and provinces for China have the equal entitlements of carbon emission. Following the principal of fairness, several organizations (e.g., the Intergovernmental Panel on Climate Change (IPCC), United Nations Development Program, and Organization for Economic Cooperation and Development) and scholars proposed global carbon-emission burden allocation programs (Intergovernmental Panel on Climate Change (IPCC), 2007; United Nations Development Programme (UNDP), 2007; Organisation for Economic Cooperation and Development (OECD), 2008; Ding et al., 2010), and many researchers put forward a number of provincial allocation proposals on carbon-emission reduction target for China (Yu et al., 2014; Zhang et al., 2014; Hao et al., 2015; Miao et al., 2016; Dong et al., 2018; Wang et al., 2018; Pan et al., 2020; Wen and Wang, 2020). Based on the efficiency principle, a few policy instruments or management programs are explored and designed, such as tradable carbon emission permits (Chang and Wang, 2010; Zhou et al., 2013; Zhao et al., 2018; Tan et al., 2019; Zheng et al., 2020; Foramitti et al., 2021), carbon tax (Mori, 2012; Ouchida and Goto, 2014; Zhao et al., 2018), policies to promote household carbon reduction (Bore et al., 2018), and policies facilitating inter-firm collaborations on carbon reduction (Dong et al., 2014; Zhang and Wang, 2014). Although tradable carbon emission permits have gotten successful implementation effects in different countries and regions, China's carbon-emission trading systems are still at the stage of pilot experiments; Raufer and Li (2009) argued that the market-based emission trading schemes may not be suitable for China.

Considering the close relationship between carbon reduction and economic development, the crucial role of electricity generation in carbon reduction, and the importance of effective policy on carbon reduction practice, all these researches are necessary and significant. However, previous studies paid little attention on the macro cooperative carbon reduction mechanism from the perspective of power generation. Although very few studies on carbon reduction embodied the cooperation concept (Qin et al., 2020), research on cooperative carbon reduction from the macro management perspective is in its infancy and needs more efforts. In reality, different provinces in China differ greatly in resource endowments (including renewable energy-resource endowments), industrial structures, and economic development levels; effective policy instruments promoting interprovincial cooperation on carbon reduction have great potentials of economic performance. Furthermore, a cooperative carbon reduction mechanism which embodies efficiency and fairness principles is crucial to global optimization of electricity generation capacity structure and potential release of carbon reduction.

This study extends the current literature in the following aspects: (1) This paper constructs an interprovincial CCRM from the perspective of electricity utilization, which can minimize the carbon emission of the cooperation union and improve the carbon-reducing benefits of each member. Differing from the market-based mechanism, this paper attempts to construct an interprovincial CCRM based on the administration coordination mechanism. (2) The CCRM embodies well the principles of efficiency and fairness. An optimization model that calculates the optimal quantities of electricity generation for each participating province to meet the joint carbon reduction goal is constructed based on the optimization theory, which embodies the principle of efficiency, and a model that distributes the economic benefits of carbon reduction among the members is constructed based on the Shapley value method, which embodies the principle of fairness.

MATERIALS AND METHODS

The mechanism of the interprovincial cooperative carbon reduction includes two aspects: (1) The mechanism of optimizing the benefits of the whole union. If the cooperation union cannot generate additional benefits, cooperation makes no sense. Through optimization of the electricity generation of each participating province, the interprovincial CCRM minimizes the carbon emission of the whole union to maximize the cooperative carbon reduction benefits. (2) Rational allocation mechanism of cooperation benefits. Each participating province has the motivation to get as much benefits from the cooperation as possible, so how to allocate cooperative benefits among the provinces scientifically and reasonably is the key to the interprovincial cooperative carbon reduction. Applying the Shapley value method, which distributes cooperative benefits according to the contribution of each member, the interprovincial CCRM fairly allocates the cooperative carbon reduction benefits. As a result, CCRM consists of an optimal model of carbon reduction to determine the optimal annual electricity generation for each province in the cooperation union and a model to allocate the benefits of cooperation to each province in the union.

Table 1 summarizes the variables and parameters and their definitions that will be used in the CCRM.

The Optimal Model of Carbon Reduction

This paper defines the amount of CO_2 emitted by producing a unit of electricity power by an electricity-generation method as the carbon intensity of this electricity-generation method, and the average amount of CO_2 emitted by producing a unit of electricity power in a province as the integrated carbon intensity of electricity generation in this province. Therefore, the annual CO_2 emission by electricity generation in a province is not only determined by the annual electricity generation but also determined by the integrated carbon intensity. So we built the function of annual CO_2 emission by electricity generation in a province as follows:

$$C_i = b_i * E_i \tag{1}$$

Here E_i is the annual electricity generation in province i, and b_i is the integrated carbon intensity of electricity production in province i. b_i is determined by the capacity structure of electricity production in province i and the carbon intensity of each electricity-generation method, which can be described as:

$$b_i = \sum_{k=1}^{5} a_{ik} * \eta_k \tag{2}$$

Here $k = 1$ denotes the method of thermal power generation, $k = 2$ denotes the method of hydroelectric generation, $k = 3$ denotes the method of solar power generation, $k = 4$ denotes the method of wind power generation, and $k = 5$ denotes method of nuclear power generation. a_{ik} is the capacity proportion of electricity generation method k in province i and satisfies the following two constraints:

$$0 \le a_{ik} \le 1 \tag{3}$$

$$\sum_{k=1}^{5} a_{ik} = 1 \tag{4}$$

Consequently, the function of the quantity of CO_2 emitted by electricity generation in the whole union can be built as follows:

$$C = \sum_{i=1}^{n} C_i = \sum_{i=1}^{n}\sum_{k=1}^{5} \eta_k * a_{ik} * E_i \tag{5}$$

Each province has its own electricity generation capacity range. When all electricity generation facilities in the province work at their full capacity, the maximum quantity of electricity generation in this province can be achieved. The annual electricity generation upper limit is represented as $\xi_{ui} * M_i$. On the other hand, the electricity generation facilities will always produce at least some electricity power. This electricity generation lower limit is represented as $\xi_{li}{}^{*}M_i$. Therefore, the annual electricity generation range for a province is as follows:

$$\xi_{li}{*}M_i \le E_i \le \xi_{ui} * M_i \tag{6}$$

The sum of annual CO_2 emission by electricity generation of all the provinces in the union should be less than or equal to the target set by the central government. Therefore, we obtain the constraints:

$$\sum_{i=1}^{n} C_i \le \sum_{i=1}^{n} q_{ci} \tag{7}$$

To meet the demands of socioeconomic development, the total annual electricity generation in the union should not be less than the sum of the annual quota of the electricity generation of all the provinces in the union:

$$\sum_{i=1}^{n} E_i \ge \sum_{i=1}^{n} q_{ei} \tag{8}$$

Based on the above analysis, we establish the optimal cooperative carbon-reducing model for the whole union, which aimed to minimize the carbon emission by optimizing the amount of electricity generation of each province in the union. For any province i and any electricity generation method k, $i \in I = \{1, 2, \ldots, n\}$, $k \in K = \{1, 2, 3, 4, 5\}$, and the optimal cooperative carbon-reducing model in a given union can be written as follows:

$$\min_{E_i} C = \sum_{i=1}^{n}\sum_{k=1}^{5} \eta_k * a_{ik} * E_i \tag{9}$$

s.t.

$$\left\{\begin{array}{ll} \sum_{i=1}^{n}\sum_{k=1}^{5} \eta_k * a_{ik} * E_i \le \sum_{i=1}^{n} q_{ci} & (10) \\ 0 \le a_{ik} \le 1 & (11) \\ \sum_{k=1}^{5} a_{ik} = 1 & (12) \\ \xi_{li}{*}M_i \le E_i \ \xi_{ui} * M_i & (13) \\ \sum_{i=1}^{n} E_i \ge \sum_{i=1}^{n} q_{ei} & (14) \end{array}\right.$$

TABLE 1 | Definitions of variables and parameters.

Variables and parameters	Definitions	Unit
E_i	Annual electricity generation in province *i*	10^8 kwh
Sh_i	The transferred benefits from utilization of electricity out/into province i during 1 year	10^8 CNY
C_i	The quantity of CO_2 emitted by electricity generation in province i	tCO_2
b_i	The integrated carbon intensity of electricity generation in province i	gCO_2/kwh
a_{ik}	The capacity proportion of electricity generation method k in province i	Dimensionless
η_k	The carbon intensity of electricity generation method k	gCO_2/kwh
C	The quantity of CO_2 emitted by electricity generation in the whole union	tCO_2
M_i	The maximum capacity of electricity generation in province i	10^8 kwh
ξ_{ui}	The upper bound coefficient of electricity production for province i	Dimensionless
ξ_{li}	The lower bound coefficient of electricity production for province i	Dimensionless
q_{ci}	Annual quota of the maximum quantity of CO_2 emitted by electricity generation in province i (calculated according to carbon-reducing target set by the central government for province i)	tCO_2
q_{ei}	Annual quota of the electricity generation in province i (calculated according to carbon-reducing target set by the central government for province i)	tCO_2

Cooperative Carbon-Reducing Benefit Allocation Model

In the optimal model, the cooperative carbon-reducing union meets the national carbon-reducing target through cooperative efforts and minimizes the carbon emission by electricity generation, which will create carbon-reducing benefit by selling the available emission right. Each province tries to get more benefits from the cooperation. The allocation of these benefits greatly affects implementation of CCRM. The Shapley value method distributes cooperative benefits according to scientific calculation of the contribution of each member in a cooperation union. Since the Shapley value method has been proved to be highly effective in distributing cooperative benefits (Lozano et al., 2013; Wu et al., 2017; Zeng et al., 2018), this paper apply this method to allocate interprovincial cooperative carbon reduction benefits.

Set $N = \{1, 2, \cdots, n\}$ as the collection of the n provinces in mainland China. For any subset of N, S (any combination of m provinces), if there exists a real-valued function $\mu(S)$ that satisfies $\mu(\phi) = 0$, $\mu\left(S_i \bigcup S_j\right) \geq \mu(S_i) + \mu\left(S_j\right)$, where $S_i \bigcap S_j = \phi$, then *[N, μ]* is the cooperation strategy for the n provinces, μ is the characteristic function for the strategy, and $\mu(S)$ is the benefit for cooperation union S. The Shapley value, denoted by $f = (f_1, f_2, \cdots f_n)$, represents the allocation strategy for interprovincial cooperative game benefit that can be a weighted distribution based on the characteristic function μ, which is referred to as

$$f_i(\mu) = \sum_{S \in N} \mathrm{H}(|S|)[\mu(S) - \mu(S \backslash \{i\})]\ i = (1, 2, \cdots, n) \quad (15)$$

$$\mathrm{H}(|S|) = \frac{\left(n-k\right)!\left(k-1\right)!}{n!} \quad (16)$$

where $|S|$ is the number of elements (cooperating provinces) in subset S, $\mathrm{H}(|S|)$ is the weighed factor, and $\mu(S \backslash \{i\})$ is the cooperation benefit that does not include province i. In this way, the cooperation benefit is allocated to each participant according to each participant's contribution. The participant who contributes most is rewarded most. Each participant gains economic benefit from the cooperation. As a result, the economic benefit could serve as an incentive to encourage cooperation among participating provinces.

RESULTS AND DISCUSSION

Based on the complementarity in economic development, energy-resource endowments, and capacity structure of power generation, this paper selects Shanghai, Sichuan, Shanxi, and Gansu as case study samples for cooperative carbon-reducing model.

Shanghai is one of the most advanced provincial regions in economic development, and its pillar industries include information industry, financial industry, commercial circulation industry, automobile industry, and so on. However, Shanghai is scarce in natural resources, and its power generation capacity is dominated by thermal power generation.

Sichuan is a major economic province, and its pillar industries mainly include metallurgic industry, chemical engineering industry, and hydropower industry. Sichuan is rich in natural resources especially in hydroelectric resource, and its main power generation capacity is hydroelectric generation.

Shanxi is an economically less-developed province, and its pillar industries are mainly heavy industries such as coal industry and metallurgic industry. As one of the most important coal bases in China, Shanxi provides a large proportion of thermal power to the whole country.

Gansu is an economic backward province, and its pillar industry includes petrochemical industry, electricity industry, and so on. Gansu is rich in energy resources and has a variety of energy resources. As a result, Gansu has a diversified capacity structure of power generation.

The four provinces are highly complementary in energy-resource endowments, capacity structure of power generation, and industrial structures, which provide great space and potential for cooperative carbon reduction. Here we denote Shanghai as SH, Sichuan as SC, Shanxi as SX, and Gansu as GS. To demonstrate CCRM, we take the four provinces as a cooperative carbon union for the case study.

SH–SC–SX–GS Optimal Model of Carbon Reduction

To determine the capacity structure of electricity production in SH, SC, SX, and GS in 2017, we first obtained the data of installed capacity of all kinds of electricity-generation method in these provinces from China electricity power statistical yearbook 2018.

Then, we calculated the annual available time for each kind of electricity-generation method in each province (**Table 2**) according to the following rules and assumptions:

(1) For each kind of electricity-generation method, for each year from 2014 to 2017, for each province of Chinese mainland, based on data from China electricity power statistical yearbook 2015 to 2018, calculate the actual annual mean utilization time of all the electricity-generation facilities of this method;
(2) For thermal power generation, calculate the four maximums of the actual annual mean utilization time from the 31 provinces and then find the maximum from the four values. The maximum is assumed as the annual available time of thermal power generation for all provinces;
(3) For wind power generation in each province, choose the maximum from the four actual annual mean utilization time as the annual available time for this province;
(4) For hydroelectric generation and solar power generation, take the same rule for wind power generation.

Finally, according to the data of installed capacity and annual available time of each kind of electricity-generation method, we get the capacity level and capacity proportion of each method in the sample provinces, shown in **Table 3**.

According to data from the National Energy Administration, we obtained the standard coal consumption rate of power supply in 2017 in China so that we calculated the carbon intensity of thermal power generation method as 770.44 gCO_2/kwh. We denote the carbon intensity of hydroelectric generation, solar power generation, and wind power generation as 0.

With these data, we calculated the integrated carbon intensity of electricity production in the four provinces and then constructed the function of annual CO_2 emission by electricity generation in SH, SC, SX, and GS, as **Table 4** shows.

According to the carbon-reducing target set by the central government and the data of GDP and electricity generation, we calculated the annual quotas of the maximum CO_2 emission by generation and quantity of electricity generation for SH, SC, SX, and GS.

To determine the lower limit and upper limit of the electricity generation of the four provinces (**Table 5**), we make assumptions about the value of ξ_{li} and ξ_{ui}:

(1) The upper limit of the electricity generation of each province is the maximum capacity of electricity generation, so the value of ξ_{ui} is assumed as 1.

(2) Each province will always generate some electric power by itself to meet the needs of science and economy, so the value of ξ_{ui} is assumed as 0.3.

TABLE 4 | Function of annual CO_2 emission by electricity generation.

	Function of annual CO_2 emission by electricity generation
SH	$C_1 = 755.65E_{P1}$
SC	$C_2 = 158.17E_{P2}$
SX	$C_3 = 711.89E_{P3}$
GS	$C_4 = 475.28E_{P4}$

TABLE 2 | Annual available time of electricity-generation facilities (h).

	Thermal power generation	Hydroelectric generation	Wind power generation	Solar power generation
SH	5,026.34	-	2,394.37	919.54
SC	5,026.34	4,125.03	1,680.00	1,185.19
SX	5,026.34	1,721.31	1,892.20	949.15
GS	5,026.34	4,361.18	1,466.46	967.85

TABLE 3 | Capacity structure of electricity-generation in sample provinces.

	Capacity level (10^8 kwh)					Capacity proportion			
	Thermal power generation	Hydroelectric generation	Wind power generation	Solar power generation	Total	Thermal power generation	Hydroelectric generation	Wind power generation	Solar power generation
SH	1,141.48	0	17.00	5.33	1,163.81	98.08%	0.00%	1.46%	0.46%
SC	835.38	3,182.05	35.28	16.00	4,068.71	20.53%	78.21%	0.87%	0.39%
SX	3,199.77	42.00	165.00	56.00	3,462.77	92.40%	1.21%	4.76%	1.62%
GS	1,034.92	378.55	188.00	76.07	1,677.55	61.69%	22.57%	11.21%	4.53%

TABLE 5 | The limits of electricity generation in 2017 (108 kwh).

	SH	SC	SX	GS
Upper limit of electricity generation	1,163.81	4,068.71	3,462.77	1,677.55
Lower limit of electricity generation	349.14	1,220.61	1,038.83	503.26

Based on the above analysis, we established the optimal carbon-reducing model for SH–SC–SX–GS cooperative carbon-reducing union as follows:

$$minC = 755.65E_1 + 158.17E_2 + 711.89E_3 + 475.28E_4 \quad (17)$$

s.t.

$$\begin{cases} \sum_{i=1}^{4} E_i \geq 8512.72 & (18) \\ 755.65E_1 + 158.17E_2 + 711.89E_3 & \\ + 475.28E_4 \leq 3914622 & (19) \\ 349.14 \leq E_1 \leq 1163.81 & (20) \\ 1220.61 \leq E_2 \leq 4068.71 & (21) \\ 1038.83 \leq E_3 \leq 3462.77 & (22) \\ 503.26 \leq E_4 \leq 1677.55 & (23) \end{cases}$$

We applied Lingo 16.0 to solve the model and obtained the optimal amount of electricity generation and carbon emission by generation for each province in the union in 2017. On this basis, this paper applied CNY 49.70/tCO_2, the carbon-emission trading price of Beijing pilot in China's average annual carbon trading network in 2017, and calculated the cooperative carbon-reducing benefit. The amount of electricity generation and the carbon-reducing benefits in these provinces under NCCRM and CCRM are shown in **Table 6**.

Contrasting the carbon emission by generation under two models, we found that the carbon emission of the whole union would decrease greatly by 425.78×10^8 kg, 11.06%, while the total amount of electricity generation was the same. Furthermore, SC and GS, the two provinces with high proportion of renewable energy generation capacity, reached their upper limit of electricity generation, which meant that the renewable energy generation capacity could be fully utilized and almost no renewable energy curtailment would take place in the two provinces. However, SC and GS would emit more CO_2 from the optimal model. So if there is no further allocation of the benefits, SC and GS would not take part in the cooperation and the union cannot be formed.

SH–SC–SX–GS Cooperative Carbon-Reducing Benefit Allocation Model

Because the cooperative carbon-reducing union consists of four provinces, there are 12 possible combinations for the cooperation. To obtain Shanghai's reward from the carbon-reducing cooperation, we firstly calculated the values of μ (S) for all the combinations that involved Shanghai (**Table 7**) and then calculated the corresponding cooperation benefits if Shanghai does not participate (μ ($S\backslash\{SH\}$)). In the final step, based on the benefit allocation strategy in Equations (15), (16), we obtained Shanghai's reward from the cooperation benefits:

$$f_{SH}(v) = 0+1.26+0.09+0.38+0.09+0.59+0.09+0.28 = 2.79\ (10^8\ \text{CNY}) \quad (24)$$

That is, Shanghai would get CNY 2.79×10^8 by participating in the CCRM. In the same way, we obtained the benefit allocation for Sichuan, Shanxi, and Gansu: CNY 11.11×10^8, CNY 4.07×10^8, and CNY 3.19×10^8, respectively.

Table 8 summarizes the main results of allocation of benefits among the four provinces in 2014 based on their carbon-reducing cooperation. At first, it is clear that both the union and each participant province would get extra benefits from cooperative carbon reduction under the CCRM. The union would get 2.12 billion CNY cooperation benefits in total, and in the end, SH, SC, SX, and GS would get 0.28, 1.11, 0.41, and 0.32 billion CNY cooperation benefits, respectively, based on the Shapley value method under the CCRM. Secondly, **Table 8** shows the money transferred among the four provinces in 2017 according to the actual carbon-reducing benefit before allocation and the Shapley value. SH would need to pay CNY 16.37×10^8, and SX would need to pay CNY 10.31×10^8 to SC and GS, respectively; meanwhile, SC and GS would get CNY 15.73×10^8 and CNY 10.95×10^8 from SH and SX, respectively.

From a perspective of implementation, the differences in capacity structure of electricity generation among the four provinces allow this cooperation. SC and GS have a much higher proportion of renewable energy generation capacity than SH and SX, which makes it possible for the interprovincial union to reduce the carbon emission greatly from electricity generation while SC and GS generate more electricity power and SH and SX generate less than that under the NCCRM. Given the extra

TABLE 6 | Amounts of electricity generation and carbon emission under two models.

	NCCRM		CCRM		
	Amount of electricity generation (10^8 kwh)	Carbon emission by generation (10^8 kg)	Amount of electricity generation (10^8 kwh)	Carbon emission by generation (10^8 kg)	Carbon-emission reduction (%)
SH	859.25	649.29	349.14	263.83	59.37%
SC	3,480.38	550.50	4,068.71	643.55	−16.90%
SX	2,823.94	2,010.33	2,417.32	1,720.87	14.40%
GS	1,349.15	641.23	1,677.55	797.31	−24.34%
Total	8,512.72	3,851.34	8,512.72	3,425.56	11.06%

TABLE 7 | Calculation of the benefit allocation under CCRM for Shanghai in 2017.

	Benefit created by reducing of carbon (10^8 CNY)							
	(SH)	(SH, SC)	(SH, SX)	(SH, GS)	(SH, SC, SX)	(SH, SC, GS)	(SH, SX, GS)	(SH, SC, SX, GS)
μ(S)	0	15.15	1.11	4.58	17.30	16.38	4.97	21.16
μ(S-{SH})	0	0	0	0	16.19	9.27	3.86	20.05
μ(S)-μ(S-{SH})	0	15.15	1.11	4.58	1.11	7.11	1.11	1.11
|S|	1	2	2	2	3	3	3	4
H(|S|)	1/4	1/12	1/12	1/12	1/12	1/12	1/12	1/4
H(|S|)[μ(S)-μ(S-{SH})]	0	1.26	0.09	0.38	0.09	0.59	0.09	0.28

TABLE 8 | Allocation of benefits from cooperative carbon reduction (10^8 CNY).

	SH	SC	SX	GS	Total
B1: Benefits from carbon reduction under NCCRM	0	0	0	0	0
B2: Cooperation benefit allocation based on the Shapley value method	2.79	11.11	4.07	3.19	21.16
B3: Actual benefit from carbon reduction under the CCRM (before benefit allocation)	19.16	−4.62	14.38	−7.76	21.16
B4: Monetary payment to other provinces: B4 = B3-B2	16.37	−15.73	10.31	−10.95	0.00
B5: Added benefit from carbon reduction under CCRM: B5 = B2-B1	2.79	11.11	4.07	3.19	21.16

TABLE 9 | Results of the sensitivity for CCRM.

	$[\xi_{li}, \xi_{ui}]$	Carbon emission by generation (10^8 kg)					Actual benefit from carbon reduction (10^8 CNY)					
		SH	SC	SX	GS	Total	Reduction	SH	SC	SX	GS	Total
Base	[0.30,1.00]	263.83	643.55	1,720.87	797.31	3,425.56	11.06%	19.16	−4.62	14.38	−7.76	21.16
Change ξ_{li}	[0.40,1.00]	351.77	643.55	1,638.02	797.31	3,430.64	10.92%	14.79	−4.62	18.50	−7.76	20.91
	[0.35,1.00]	307.80	643.55	1,679.44	797.31	3,428.09	10.99%	16.97	−4.62	16.44	−7.76	21.03
	[0.25,1.00]	219.86	643.55	1,762.29	797.31	3,423.00	11.12%	21.34	−4.62	12.33	−7.76	21.29
Chang;8e ξ_{ui}	[0.30,1.05]	263.83	675.73	1,516.33	837.17	3,293.05	14.50%	19.16	−6.22	24.55	−9.74	27.74
	[0.30,0.95]	263.83	611.37	1,925.41	757.44	3,558.04	7.62%	19.16	−3.02	4.22	−5.78	14.58
	[0.30,0.90]	263.83	579.19	2,129.93	717.58	3,690.53	4.18%	19.16	−1.43	−5.94	−3.79	7.99

benefits from carbon trading, the four provinces are willing to take part in cooperative carbon-reducing union.

In fact, the essence of the cooperative carbon reduction is that the conventional thermal power generation transfers the market to the renewable energy generation through administration coordination, so as to get carbon-reducing benefits. Since the extra benefits of carbon reduction come from the joint efforts of the conventional thermal power generation and the renewable energy generation, these benefits should be allocated to both kinds of power generation plant; that is, these benefits should be used to support the phasing out of backward production capacity in conventional thermal power generation and the running and development of renewable energy generation. Through reasonable allocation of benefits at provincial level and plant level, the CCRM provides an incentive way for the government to optimize the capacity structure of electricity generation, which, in turn, will promote carbon reduction fundamentally in the long run.

Besides carbon reduction, the CCRM can bring additional good effects. Under the CCRM, the provinces with high proportion of renewable energy generation capacity would generate more electricity power, and vice versa. Thus, the CCRM can help to solve the current serious solar and wind energy curtailment in the three north regions and hydro-energy curtailment in the southwest region in China. In addition, the implementation of the CCRM will help the province with high proportion of thermal power generation capacity to alleviate air pollution, such as SX. According to the report published by the Ministry of Ecology and Environment of China, SX accounted for five of 20 rated among the dirtiest cities in China. Less thermal power generation and optimized power generation structure will improve the air quality in SX.

Sensitivity Analysis

The parameters ξ_{li} and ξ_{ui} in formulas (20)–(23) were set as 0.30 and 1 according to China's situation. ξ_{li} and ξ_{ui} denote the lower and upper bound coefficients of electricity production for province i. To study the impact of different values of these parameters on the CCRM calculation results, a sensitivity analysis was carried out for the SH–SC–SX–GS union in 2017. **Table 9** presents the different calculation results (carbon emission by generation and actual benefit from carbon reduction under the CCRM) in each sample province and the whole union.

ξ_{li}, being the lower bound coefficient of electricity production for province i, determines the potential for province i to transfer electricity generation quota out to other provinces. The smaller ξ_{li} is, the more potential province i has to transfer electricity generation quota out to other provinces; more electricity might be generated by low-carbon energy, and greater cooperation carbon reduction benefit could then be generated. Therefore, when ξ_{li} was reduced from 0.30 to 0.25, the total CO_2 emission by generation decreased slightly from 342.556 to 342.300 million tons, the total carbon reduction increased from 11.06% a bit to 11.12% with contrast to the NCCRM, and the total benefit from carbon reduction increased from 2.116 to 2.129 billion CNY. By comparison, when ξ_{li} increased from 0.30 to 0.35 and 0.4, which meant less electricity generation could transfer SH out, the total CO_2 emission by generation improved slightly from 342.556 to 342.809 and 343.064 million tons, the total carbon reduction decreased from 11.06% to 10.99% and 10.92%, and the total benefit from carbon reduction also went down from 2.116 to 2.103 and 2.091 billion CNY. Generally speaking, the CCRM is not sensitive to changes in ξ_{li}.

ξ_{ui}, as a parameter to calculate the upper limit of electricity generation in province i, decides the potential for province i to accept electricity generation quota from other provinces. The bigger ξ_{ui} is, the more potential province i has to accept electricity generation quota from other provinces, the provinces with low integrated carbon intensity of electricity production could generate more electricity, and greater cooperation benefit would be generated. As a result, when ξ_{ui} rose from 1 to 1.05, the total CO_2 emission by generation decreased from 342.556 to 329.305 million tons, the total carbon reduction increased from 11.06% to 14.50%, and the total benefit from carbon reduction increased from 2.116 to 2.774 billion CNY. By contrast, when ξ_{ui} decreased from 1 to 0.95 and 0.9, which represented tightening the constraint in formulas (20)–(23) of the optimization model and less electricity generation quota transferring, the total CO_2 emission by generation improved moderately from 342.556 to 355.804 and 369.053 million tons, the total carbon reduction decreased from 11.06% to 7.62% and 4.18% correspondingly, and the total benefit from carbon reduction also went down temperately from 2.116 to 1.458 and 0.799 billion CNY. To sum up, for SH–SC–SX–GS union, the calculation results of CCRM are moderately sensitive to changes in λ_{ui}.

CONCLUSIONS AND POLICY RECOMMENDATIONS

Optimizing the electricity generation structure through improving the proportion of renewable energy can get a multi-win effect of carbon reduction, pollution abatement, and improving energy security. In view of the widespread interprovincial differences in China's renewable energy-resource endowment, this paper proposed an interprovincial CCRM, a mechanism embodying both principles of efficiency and fairness, so as to improve the current carbon reduction mode. We applied the CCRM to the case study of Shanghai–Sichuan–Shanxi–Gansu union. Results showed that the total carbon emission of the whole union would decrease greatly and every participated province would get substantial extra benefits from cooperative carbon reduction. Furthermore, the implementation of CCRM provides not only an incentive way for the regional government to achieve the carbon reduction goal and an effective solution to solve the current serious renewable energy curtailment in China in the short time, but also a feasible path to realize long-term carbon reduction strategy for the central government.

As the differences in renewable energy-resource endowment and the consequent differences in cost of renewable energy power are not only universal between provinces in China but also universal between different scales of administrative regions such as different counties, different cities, and even different countries, the CCRM proposed in this paper can be widely applied to cooperative carbon reduction in these situations. As a result, the CCRM provides a cooperative carbon reduction mechanism integrating two fundamental principles of efficiency and fairness for both China and other countries.

To promote the implementation of interprovincial cooperative carbon reduction in China, it is necessary to propose the following policy recommendations:

Firstly, the central government should allow and encourage cooperative carbon reduction among provinces. Although the central government and the local governments have realized that the current carbon reduction policy and management system cannot exploit the carbon reduction potential in some provinces, they have not realize the importance of the CCRM as they pay more attention to the fairness of carbon reduction responsibility among different provinces. The CCRM can not only help the provinces get carbon reduction benefits as much as possible by optimizing the electricity generation structure in the short term but also facilitate the implementation of long-term carbon reduction strategies in China by optimizing the capacity structure of electricity generation in each province. Therefore, the central government should develop policies and measures to promote the implementation of the CCRM.

Secondly, to effectively apply the CCRM, there should be an authority or a department of the central government to be responsible for the administration issues of cooperative carbon reduction such as determining the members of the cooperation union, coordinating the allocation of cooperation benefits, evaluating the performance of the union, and so on. These administrative issues require organizational support.

Thirdly, both the provinces with high proportion of thermal power generation capacity, such as Shanxi and Shanghai, and the provinces with high proportion of renewable energy generation capacity, such as Sichuan and Gansu, should be proactive in finding cooperation partners. The CCRM is a win–win mode for both kinds of province as both of them will get extra carbon reduction benefits. For provinces with high proportion of thermal power generation capacity, the extra benefits from cooperative carbon reduction should be mainly used to support the phasing out of backward thermal power generation capacity so as to optimize the capacity structure of electricity generation and be helpful to long-term carbon reduction. For the provinces with high proportion of renewable energy generation capacity, these benefits should be mainly used to support the development of renewable energy so as to exploit their resource advantages; in addition, it is because there exist large funding gaps in renewable energy subsidies in China.

Fourthly, this paper applied the contribution-based Shapley value method to allocate the cooperation benefits, which provides a reference for determining the practical benefit distribution principles or compensation standards. In addition, this paper is based on complementarity in economic development, energy-resource endowments, and capacity structure of power generation to select the research samples, which ensures enough cooperation space potentials and provides rules and principals for determining the members of the cooperation union. In practical application, the situation may be more complicated, and more factors should be taken into account, such as technology of electricity-generation facilities for benefit distribution, the electric grid structure for determining the union members, and so on.

Finally, it is worth noting that this paper only considered the benefits from carbon-emission permit trading under CCRM. In fact, interprovincial cooperative carbon reduction can create much more benefits from reducing air pollution and the subsequent health benefits by generation with low-carbon and cleaner energy. If these benefits are calculated in the CCRM, the results will be much more incentive. Future research could extend this analysis to include these benefits.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

LZe performed conceptualization, methodology, drafting, and writing. WD performed the review and editing. LZh performed the conceptualization and supervision. ZS performed review. All authors contributed to the article and approved the submitted version.

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REFERENCES

Bore, S., Marta, B., Carlo, A., Andersson, C., Herrmann, A., Amelung, D., et al. (2018). Household preferences to reduce their greenhouse gas footprint: a comparative study from four european cities. *Sustainability* 10:4044. doi: 10.3390/su10114044

Cabal, H., Lechon, Y., Bustreo, C., Gracceva, F., Biberacher, M., Ward, D., et al. (2017). Fusion power in a future low carbon global electricity system. *Energy Strategy Rev.* 15, 1–8. doi: 10.1016/j.esr.2016.11.002

Chang, Y. C., and Wang, N. (2010). Environmental regulations and emissions trading in China. *Energy Policy* 38, 3356–3364. doi: 10.1016/j.enpol.2010.02.006

Chang, Z., Wu, H. X., Pan, K. X., Zhu, H., and Chen, J. (2017). Clean production pathways for regional power-generation system under emission constraints: a case study of Shanghai. China. *J. Clean. Prod.* 143, 989–1000. doi: 10.1016/j.jclepro.2016.12.021

Chen, W., Wu, Z., He, J., Gao, P., and Xu, S. (2007). Carbon emission control strategies for China: a comparative study with partial and general equilibrium versions of the China MARKAL model. *Energy* 32, 59–72. doi: 10.1016/j.energy.2006.01.018

Cui, H., Zhao, T., and Wu, R. R. (2018). CO_2 emissions from China's power industry: policy implications from both macro and micro perspectives. *J. Clean. Prod.* 200, 746–755. doi: 10.1016/j.jclepro.2018.07.330

Ding, Z. L., Duan, X. N., Ge, Q. S., and Zhang, Z. Q. (2010). On the major proposals for carbon emission reduction and some related issues. *Sci. China Earth Sci.* 53, 159–172. doi: 10.1007/s11430-010-0012-4

Dong, F., Long, R. Y., Yu, B. L., Wang, Y., Dai, Y., Yang, Q., et al. (2018). How can China allocate CO 2 reduction targets at the provincial level considering both equity and efficiency? Evidence from its Copenhagen Accord pledge. *Resour. Conserv. Recycl.* 130, 31–43. doi: 10.1016/j.resconrec.2017.11.011

Dong, H., Ohnishi, S., Fujita, T., Geng, Y., Fujii, M., and Dong, L. (2014). Achieving carbon emission reduction through industrial & urban symbiosis: a case of Kawasaki. *Energy* 64, 277–286. doi: 10.1016/j.energy.2013.11.005

Foramitti, J., Ivan, S., and van den Bergh, J. C. J. M. (2021). Emission tax vs. permit trading under bounded rationality and dynamic markets. *Energy Policy* 148(Pt B):112009. doi: 10.1016/j.enpol.2020.112009

Guo, J., Zhang, Z., and Meng, L. (2012). China's provincial CO_2 emissions embodied in international and interprovincial trade. *Energy Policy* 42, 486–497. doi: 10.1016/j.enpol.2011.12.015

Guo, P., Qi, X., Zhou, X., and Wei, L. (2018). Total-factor energy efficiency of coal consumption: an empirical analysis of China's energy intensive industries. *J. Clean. Prod.* 172, 2618–2624. doi: 10.1016/j.jclepro.2017.11.149

Hao, Y., Liao, H., and Wei, Y. M. (2015). Is China's carbon reduction target allocation reasonable? An analysis based on carbon intensity convergence. *Appl. Energy* 142, 229–239. doi: 10.1016/j.apenergy.2014.12.056

Iftikhar, Y., Wang, Z., Zhang, B., and Wang, B. (2018). Energy and CO_2 emissions efficiency of major economies: a network DEA approach. *Energy* 147, 197–207. doi: 10.1016/j.energy.2018.01.012

Intergovernmental Panel on Climate Change (IPCC) (2007). *Climate Change 2007: The Physical Science Basis*. New York, NY: Cambridge university press.

Li, J. J., Zhang, Y. L., Tian, Y. J., Cheng, W., Yang, J., Xu, D., et al. (2020). Reduction of carbon emissions from China's coal-fired power industry: insights from the province-level data. *J. Clean. Prod.* 242:118518. doi: 10.1016/j.jclepro.2019.118518

Li, W., Zhang, Y. W., and Lu, C. (2018). The impact on electric power industry under the implementation of national carbon trading market in China: a dynamic CGE analysis. *J. Clean. Prod.* 200, 511–523. doi: 10.1016/j.jclepro.2018.07.325

Liu, H., Liu, W., Fan, X., and Liu, Z. (2015). Carbon emissions embodied in value added chains in China. *J. Clean. Prod.* 103, 362–370. doi: 10.1016/j.jclepro.2014.09.077

Liu, L., Zong, H., Zhao, E., Chen, C., and Wang, J. (2014). Can China realize its carbon emission reduction goal in 2020: from the perspective of thermal power development. *Appl. Energy* 124, 199–212. doi: 10.1016/j.apenergy.2014.03.001

Lozano, S., Moreno, P., Adenso-Díaz, B., and Algaba, E. (2013). Cooperative game theory approach to allocating benefits of horizontal cooperation. *Eur. J. Oper. Res.* 229, 444–452. doi: 10.1016/j.ejor.2013.02.034

Miao, Z., Geng, Y., and Sheng, J. (2016). Efficient allocation of CO_2 emissions in China: a zero sum gains data envelopment model. *J. Clean. Prod.* 112, 4144–4150. doi: 10.1016/j.jclepro.2015.07.035

Mori, K. (2012). Modeling the impact of a carbon tax: a trial analysis for Washington State. *Energy Policy* 48, 627–639. doi: 10.1016/j.enpol.2012.05.067

Munksgaard, J., and Pedersen, K. A. (2001). CO_2 accounts for open economies: producer or consumer responsibility? *Energy Policy* 29, 327–334. doi: 10.1016/s0301-4215(00)00120-8

Organisation for Economic Cooperation and Development (OECD) (2008). *Environmental Outlook to 2030*. Paris: OECD Publishing.

Ouchida, Y., and Goto, D. (2014). Do emission subsidies reduce emission? In the context of environmental R&D organization. *Econ. Model.* 36, 511–516. doi: 10.1016/j.econmod.2013.10.009

Pan, X. X., Liu, H., Huan, J. J., Sui, Y., and Homg, H. (2020). Allocation model of carbon emission permits for the electric power industry with a combination subjective and objective weighting approach. *Energies* 13:706. doi: 10.3390/en13030706

Qin, Q., Liu, Y., and Huang, J. P. (2020). A. cooperative game analysis for the allocation of carbon emissions reduction responsibility in China's power industry. *Energy Econo.* 92:104960. doi: 10.1016/j.eneco.2020.104960

Raufer, R., and Li, S. (2009). Emissions trading in China: a conceptual 'leapfrog' approach? *Energy* 34, 904–912. doi: 10.1016/j.energy.2009.03.011x

Rose, A., and Tietenberg, T. (1993). An international system of tradable CO_2 entitlements: implications for economic development. *J. Environ. Dev.* 2, 1–36. doi: 10.1177/107049659300200102

Satterthwaite, D. (2008). Cities' contribution to global warming: notes on the allocation of greenhouse gas emissions. *Environ. Urban.* 20, 539–549. doi: 10.1177/0956247808096127

Tan, M., Chen, Y., Su, Y. X., Li, X. H., and Li, H. (2019). Integrated optimization model for industrial self-generation and load scheduling with tradable carbon emission permits. *J. Clean. Prod.* 210, 1289–1300. doi: 10.1016/j.jclepro.2018.11.005

United Nations Development Programme (UNDP) (2007). *Human Development Report 2007/2008—Fighting Climate Change: Human Solidarity in a Divided World*. New York, NY: Palgrave Macmillan.

Wang, K., Zhang, X., Wei, Y. M., and Yu, S. (2013). Regional allocation of CO_2 emissions allowance over provinces in China by 2020. *Energy Policy* 54, 214–229. doi: 10.1016/j.enpol.2012.11.030

Wang, X. C., Tang, X., Zhang, B. S., McLellan, B. C., and Lv, Y. (2018). Provincial carbon emissions reduction allocation plan in China based on consumption perspective. *Sustainability* 10:1342. doi: 10.3390/su10051342

Wen, W., and Wang, Q. (2020). Re-examining the realization of provincial carbon dioxide emission intensity reduction targets in China from a consumption-based accounting. *J. Clean. Prod.* 244:118488. doi: 10.1016/j.jclepro.2019.118488

Wu, D., Geng, Y., and Pan, H. Y. (2021). Whether natural gas consumption bring double dividends of economic growth and carbon dioxide emissions reduction in China? *Renew. Sustain. Energy Rev.* 137:110635. doi: 10.1016/j.rser.2020.110635

Wu, F., Huang, N. Y., Zhang, F., Niu, L., and Zhang, Y. (2020). Analysis of the carbon emission reduction potential of China's key industries under the IPCC 2 °C and 1.5 °C limits. *Technol. Forecast. Soc. Chang.* 159:120198. doi: 10.1016/j.techfore.2020.120198

Wu, Q., Ren, H., Gao, W., Ren, J., and Lao, C. (2017). Profit allocation analysis among the distributed energy network participants based on Game-theory. *Energy* 118, 783–794. doi: 10.1016/j.energy.2016.10.117

Wu, R., Geng, Y., Dong, H., Fujita, T., and Tian, X. (2016). Changes of CO_2 emissions embodied in China–Japan trade: drivers and implications. *J. Clean. Prod.* 112, 4151–4158. doi: 10.1016/j.jclepro.2015.07.017

Xi, F., Geng, Y., Chen, X., Zhang, Y., Wang, Z., Xue, B., et al. (2011). Contributing to local policy making on GHG emission reduction through inventorying and attribution: a case study of Shenyang. China. *Energy Policy* 39, 5999–6010. doi: 10.1016/j.enpol.2011.06.063

Xie, Y. L., Fu, Z. H., Xia, D. H., Lu, W., Huang, G., and Wang, H. (2019). Integrated planning for regional electric power system management with risk measure and carbon emission constraints: a case study of the Xinjiang Uygur autonomous region. China. *Energies* 12:601. doi: 10.3390/en12040601

Yu, S., Wei, Y. M., and Wang, K. (2014). Provincial allocation of carbon emission reduction targets in China: an approach based on improved fuzzy cluster and Shapley value decomposition. *Energy Policy* 66, 630–644. doi: 10.1016/j.enpol.2013.11.025

Zeng, L., Zhao, L., Wang, Q., Wang, B., Ma, Y., Cui, W., et al. (2018). Modeling interprovincial cooperative energy saving in China: An electricity utilization perspective. *Energies* 11:241. doi: 10.3390/en11010241

Zhang, B., and Wang, Z. (2014). Inter-firm collaborations on carbon emission reduction within industrial chains in China: practices, drivers and effects on firms' performances. *Energy Economics* 42, 115–131. doi: 10.1016/j.eneco.2013.12.006

Zhang, H., Chen, W., and Huang, W. (2016). TIMES modelling of transport sector in China and USA: comparisons from a decarbonization perspective. *Appl. Energy* 162, 1505–1514. doi: 10.1016/j.apenergy.2015.08.124

Zhang, Y. J., Wang, A. D., and Da, Y. B. (2014). Regional allocation of carbon emission quotas in China: evidence from the Shapley value method. *Energy Policy* 74, 454–464. doi: 10.1016/j.enpol.2014.08.006

Zhao, X. L., Yao, J., Sun, C. Y., and Pan, W. (2018). Impacts of carbon tax and tradable permits on wind power investment in China. *Renew. Energy* 135, 1386–1399. doi: 10.1016/j.renene.2018.09.068

Zheng, J. J., Yang, M. M., Ma, G., Xu, Q., and He, Y. (2020). Multi-agents-based modeling and simulation for carbon permits trading in China: a regional development perspective. *Int. J. Environ. Res. Public Health* 17:301. doi: 10.3390/ijerph17010301

Zhou, P., Zhang, L., Zhou, D. Q., and Xia, W. J. (2013). Modeling economic performance of interprovincial CO_2 emission reduction quota trading in China. *Appl. Energy* 112, 1518–1528. doi: 10.1016/j.apenergy.2013.04.013

Zou, S. H., Zhang, T., and Hong, W. C. (2020). CO_2 emissions, energy consumption, and economic growth Nexus: evidence from 30 provinces in China. *Math. Problems Eng.* 2020:8842770.

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The Effect of Technology Innovation on Corporate Sustainability in Chinese Renewable Energy Companies

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Technology innovation has become the main driving force of China's economic growth. Sustainable development highlights the harmonious symbiosis of the economy and the ecological environment. Renewable energy companies characterized by technology-intensive and environmental friendliness are playing an increasingly important role in achieving economic development while alleviating environmental pressure. Therefore, this paper selects the A-share renewable energy listed companies in China between 2014 and 2019 as samples, using the fixed-effect model and the logit model to explore the effect of technology innovation on corporate sustainability. We find that technology innovation has a positive effect on both financial sustainability (FS) and social and environmental sustainability (SES). Due to the imbalance of regional social and environmental development and different degrees of emphasis placed on environmental and social responsibility, the positive impact of technology innovation on SES is heterogeneous between the east and the central and west regions. Moreover, as the strategic emerging industry, although the renewable energy industry is granted lots of subsidies from the government, the results show that when government subsidies exceed the threshold, the effect of technology innovation on FS is weakened. Government subsidies have a negative moderating effect on the relationship between innovation and SES. Furthermore, we subdivide government subsidies into government subsidies beforehand (GSB) and government subsidies afterwards (GSA). We reveal that the threshold effect of government subsidies mainly comes from GSA, while the moderating effect of government subsidies is caused by GSA and GSB. This paper is an expansion and enrichment of current studies on sustainable development and also puts forward feasible suggestions for the government to formulate precise and effective subsidy policies to stimulate technology innovation.

Keywords: corporate sustainability, technology innovation, government subsidies, renewable energy company, threshold effect

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INTRODUCTION

After 40 years of reform and opening up, China's economy has entered a "new era," the mode of economic development has shifted from extensive growth based on scale and speed to intensive growth based on quality and efficiency, and the driving force of development has also been converted from factors and investment to innovation. The 19th National Congress of the

Communist Party of China requires economic development to be compatible with the carrying capacity of resources and the environment. The development of renewable energy is regarded as the most effective way to alleviate environmental problems on the premise of ensuring economic development (PA Østergaard and Sperling, 2014; Wang et al., 2018), and technology is the essence of renewable energy development (Wang et al., 2020). Therefore, the technology innovation of renewable energy companies should not only stimulate corporate economic growth but also have a positive effect on the environment and society, which can be concluded as realizing the sustainable development of economy, society, and environment.

Although there is a consensus that technology innovation is important to sustainable development (Cancino et al., 2018; UNCTAD, 2018), different scholars have given different opinions on the real effect of technology innovation. Some scholars consider that the corporate sustainable competitive advantage comes from their resources, which are difficult to imitate (Wernerfelt, 1984; Barney, 1991; Xu et al., 2019), and the scarce resources that companies cannot imitate come from the creation of R&D activities (Bakar and Ahmad, 2010; Jawad and Mustafa, 2019). They believe that innovation is an important tool to achieve economic growth, environmental protection, and social development at the same time, and is the best way to use resources (Klewitz and Hansen, 2014; Akwesi, 2019). However, some scholars hold different views. They think that innovation investment can easily bring serious financial burdens (Beason and Weinstein, 1996; Nitsch, 2009), which inhibits rather than promotes corporate financial performance (Diaz Arias and van Beers, 2013). Moreover, some scholars consider that the relationship between technology and financial sustainability (FS) is different from its impact on social and environmental sustainability (SES) (Saunila et al., 2019). The first objective this paper intends to accomplish is to investigate the relationship between technology innovation and corporate sustainability. Furthermore, due to the imbalance of regional social and environmental development in China, whether the relationship between them has regional heterogeneity is also worthy to be explored.

Companies' technology innovation activities have positive externalities of improving resource efficiency and promoting economic development (Long and Summers, 1991; Yudi et al., 2019). However, technology innovation also has risks such as long investment return cycle and competitors' imitation (Staw and Dutton, 1981; McKinley et al., 2014), and government subsidies have always been an important means to compensate for such loss of technology spillover (Arrow, 1971; Kang and Park, 2012; Lim et al., 2017; Qiao and Su, 2020). As a pillar of China's strategic emerging industries, the renewable energy industry has been strongly supported by the government. However, according to the public budget expenditure for renewable energy published by the China Energy Administration (see **Figure 1**), public funding subsidies for renewable energy have shown a gradual reduction process from 2013 to 2017. There is an upward trend after 2018, but it has not reached the original height, and the subsidies for the renewable energy industry are gradually receding. Although the purpose of subsidies is to guide innovation and achieve development, scholars have not reached a consensus on the effect of government subsidies. Some scholars consider that government subsidies are common tools to reduce the loss of private profits brought by technology spillovers and encourage companies to increase R&D investment (Batlle, 2011; Zhang et al., 2014; Su and Zhou, 2019). Nevertheless, government subsidies can also inhibit the development of companies, because government subsidies may focus more on political gains rather than economic benefits, resulting in excessive production and efficiency losses and affecting the development of companies (Beason and Weinstein, 1996; Bergström, 2000; Tzelepis and Skuras, 2004; Howell, 2017; Hu et al., 2019). The second objective this paper aims to accomplish is to explore what role the government subsidies play between technology innovation and corporate sustainability.

Government supports the development of the renewable energy industry through multiple methods, including policy guidance, direct fiscal subsidies, tax incentives, and the establishment of special funds (see **Supplementary Appendix**). In terms of policy guidance, since 2012, the government has attached great importance to the innovation of renewable energy companies and has issued several incentive policies to promote the development of renewable energy companies. In addition to policy guidance, direct financial subsidies have played a major role in alleviating funding difficulties for renewable energy companies and helping to promote products. The government also provides tax incentives in multiple taxes such as value-added tax, income tax, vehicle and vessel tax, and vehicle purchase tax. Besides, the government has established a special fund to support the development of the renewable energy industry. Therefore, investigating whether different types of government subsidies have different impacts on the relationship between technology innovation and corporate sustainability is the third objective this paper intends to accomplish.

The contributions of this paper: First, based on the micro company level, include government subsidies, technology innovation, and corporate sustainability into the same framework, discussing the role of government subsidies between technology innovation and corporate sustainability. Corporate sustainability is measured from two dimensions of financial and SES, which is different from most documents that only measure corporate sustainability from the growth of financial performance. This paper is an expansion for current studies about sustainable development. Second, due to the imbalance of regional social and environmental development, it is found that technology innovation has regional heterogeneity in the promotion of corporate sustainability. Renewable energy companies obtain different types of subsidies, so this paper subdivides government subsidies into government subsidies beforehand (GSB) and government subsidies afterwards (GSA); we find that different subsidies have different impacts on the relationship between technology innovation and corporate sustainability. Based on the study conclusions, we put forward feasible suggestions for the government to formulate and improve precise and effective subsidy policies.

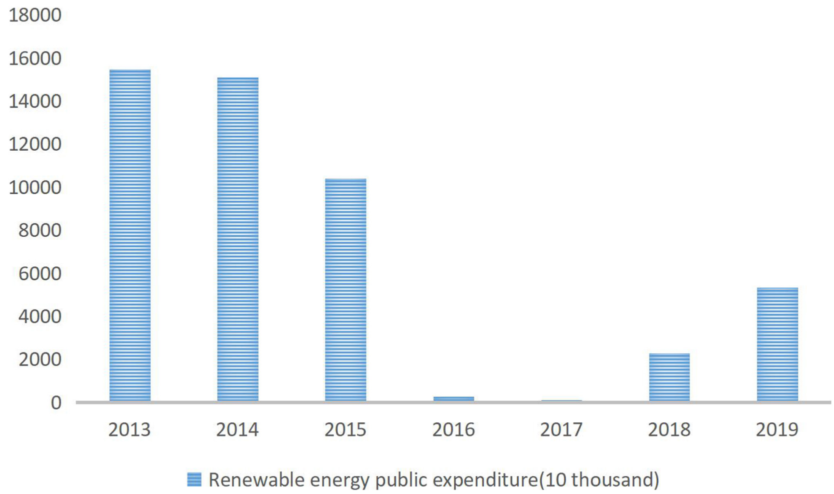

FIGURE 1 | Public budget expenditure for renewable energy industry (unit: 10,000 yuan).

LITERATURE REVIEW

Sustainability

Sustainability has gradually become a new consensus for corporate development, which requires companies to promote corporate economic growth and solve corporate environmental problems by improving resource use efficiency and reducing environmental pollution (Lin and Benjamin, 2017). Regarding the definition of sustainability, the Brundtland Commission (WCED, 1987) emphasized the economic and environmental dimensions of sustainability and defined sustainability as "meeting contemporary needs without compromising the satisfaction of future generations' Need for development." The Triple bottom line proposed by Elkington (1998) also pointed out that broad sustainability includes three dimensions—economy, society, and environment. The Triple bottom line puts forward new requirements for considering the development capabilities of companies, transforming from the pursuit of economic benefits to the common development of economy, society, and environment (Yudi et al., 2019). Environmental sustainability focuses on protecting the natural environment, reducing the consumption of natural resources, and producing environmentally friendly products (Lucas, 2010). Social sustainability emphasizes the improvement of the organizational relationship between human and society and the improvement of human well-being (Guerrero-Villegas et al., 2018). The economic aspect of sustainable development refers to maximizing profits by increasing revenue and reducing costs (Jawad and Mustafa, 2019). It is necessary to take into account the harmony and unity of the environment and society when expanding economic value. Therefore, this paper measures corporate sustainability from FS and SES.

Technology Innovation and Sustainability

Some studies have addressed the question of how technology innovation affects sustainability (see **Table 1**). Most studies suggest that technology innovation has a positive effect on sustainability. Especially for the renewable energy industry, technology innovation not only promotes economic sustainability (Jiang et al., 2020; Yan et al., 2020) but also reduces carbon dioxide emissions and promotes environmental sustainability (Solarin and Bello, 2019; Cheng et al., 2020). On the contrary, some scholars also put forward different opinions on the relationship between technology innovation and corporate sustainability. Bekhet and Latif (2018) believe that although technology innovation does not play a positive role in sustainable economic growth, the interaction between good governance quality and technology innovation will have a significant positive impact on economic sustainability in the long run. Also, some scholars believe that the impact of technology innovation on sustainability depends on the economic level of the region (Anis, 2020).

The Role of Government Subsidies

Government subsidies are regarded as a tool to correct the market failure (Arrow, 1971). However, because of the inefficient subsidies caused by rent-seeking, in many conditions, government subsidies have not achieved the expected results. At present, the relationship between government subsidies and corporate sustainability can be divided into three categories: promotion, inhibition, and no impact. Scholars with the view of promotion believe that government subsidies can have a positive impact on corporate financial performance, market share, and environmental awareness. Soltani-Sobh et al. (2017) consider that the government incentives are positively correlated with the Electric vehicle market share growth in the US. Deng et al. (2020) divide government subsidies into selective subsidies and non-selective subsidies, suggesting that selective subsidies can help companies maintain high performance, while the effectiveness of non-selective subsidies depends on the intensity of regional legal protection and market competition. Besides, some scholars point out that the government will also promote

TABLE 1 | Literature review about technology innovation in the latest years.

Study	Dataset	Model	Variables			Major findings
			Dependent	Independent	Control	
Bekhet and Latif (2018)	Malaysia (1985–2015) Country level Time serious	ARDL; VECM; VAR; DOLS	Real gross domestic product	Technology innovation	Total employment; Electricity consumption; Domestic credit to private sector; Composite measure; Finance Institution; Gross fixed capital formation	There is the negative impact of technology innovation on economic growth; the interaction of technology innovation and governance institution quality has a positive and significant impact on economic growth
Su and An (2018)	China (2009–2015) Province level Panel data	Threshold regression	Sustainable development	Regional technology innovation	The secondary industry as a proportion of the GDP; Investments in industrial pollution treatment as indexes	There is a positive threshold effect between regional technology innovation and regional sustainable development
Lin and Zhu (2019)	China (2000–2015) Province level Panel data	Random-effect model; fixed effect model; Fully-modified OLS model	Per capita CO_2 emissions	Per capita income; Renewable energy technology innovation; Energy structure	Urbanization rate; Industrial structure	Renewable energy technology innovation has a significant negative effect on CO_2 emissions
Lin et al. (2019)	China (2011–2017) Firm level Panel data	GMM regression	Green innovation strategy	Corporate financial performance	Firm size; firm risk; Research and development intensity; Advertising intensity; Slack resources	Green innovation strategy positively affected the corporate financial performance
Solarin and Bello (2019)	U.S. (1974–2016) Country level Time serious	STIRPAT approach	CO_2 emission per capita	Real GDP per capita; Immigrant population; Total spending on research, Development and demonstration in the energy sector or energy innovations	-	Energy innovations significantly improve environmental quality
Yan et al. (2020)	China (1997–2015) Province level Panel data	PLFC model with a fixed-effects estimation method	Green productivity	Technology innovation	Accumulated green productivity level; Per capita GDP; Industrial structure; Energy structure; Foreign trade	The effect of renewable energy technology innovation on green productivity is significant only when the relative income level of a province passes a critical turning point.
Jiang et al. (2020)	China (2009–2016) Province level Panel data	Generalized Method of Moments (GMM) Vector Auto Regression (VAR)	Economic sustainability	Green innovation transformation	R&D expenditure input intensity; Energy consumption	The green innovation transformation, instead of total innovation counts, can reduce energy consumption and benefit economic sustainability
Anis (2020)	75 low-, middle-, and high-income countries (1990–2014) Country level Time serious	VECM model	Gross domestic product ; CO_2 emissions ; Human development index	Technological innovation	-	Technology innovation (TI) contributes simultaneously to the economic, social, and environmental sustainable development only in the case of rich countries; TI only affects the economic and environmental dimensions in the middle-income countries; and no impact is found in the case of low-income countries
Chen et al. (2020)	19 MENA countries (1990–2016) Country level Time serious	The second-generation methodological approaches	Energy efficiency	Technology innovation	Shadow economy; Population; Structural transformation of economy	Technology innovation has a positive impact on energy efficiency
Cheng et al. (2020)	China (2005–2018) Country level Time serious	CCR, FMOLS, and DOLS methods	CO_2 emissions	Technology innovation; FD denotes fiscal decentralization	Economic globalization; Gross domestic product	Strategy of technology innovation is helpful in abating CO_2 emissions in China

companies' emphasis on the environment (Wang and Zhang, 2020). Scholars with the opposite view believe that companies receiving government subsidies may focus more on political gains rather than economic benefits, resulting in excessive production and efficiency losses, and affecting the development of companies (Beason and Weinstein, 1996; Bergström, 2000; Tzelepis and Skuras, 2004; Howell, 2017; Hu et al., 2019). Some scholars believe that government subsidies do not directly affect the sales of companies, but government subsidies make an indirect contribution to company sales by improving technology (Li et al., 2020). Technology comes from innovation, and government subsidies only play a guiding and supporting role, but the endogenous driving force for companies still comes from innovation. However, there is not a consensus on the relationship between government subsidies and technology innovation. Scholars with opposite views believe that government subsidies have a crowding-out effect on technology innovation (Busom, 2000; Liu et al., 2019). Supporters believe that government subsidies can promote the level of innovation (Lin and Luan, 2020; Yu et al., 2020). Other scholars pointed out that different technologies require different types of policy tools, and demand-driven policies may be more effective for renewable companies' technology innovation (Pitelis et al., 2019). In addition, some scholars believe that the effect of government subsidies on technology innovation is non-linear; only at certain intervals can government innovation and non-innovation subsidies play a role in promoting innovation (Liu et al., 2020; Li et al., 2020).

Above all, current studies have focused on the importance of technology innovation for sustainability, but most of the existing studies have focused on sustainability at the macro level and have not reached an agreement about the relationship between technology innovation and sustainability. Besides, although current studies have noticed that government subsidies, as external tools, will affect technology innovation and corporate growth, there is still considerable controversy over the effects of government subsidies. Therefore, based on the micro company perspective, this paper examines the impact of technology innovation on corporate sustainability and explores whether there is regional heterogeneity in the relationship between them. Besides, this paper explores the role of government subsidies in the impact of technology innovation on corporate sustainability and discusses whether different types of subsidies have different effects.

HYPOTHESIS DEVELOPMENT

The Relationship Between Technology Innovation and Corporate Sustainability

The Relationship Between Technology Innovation and FS

The resource-based view (RBV) and the knowledge-based view (KBV) explain why innovation affects corporate FS from the perspective of competitive advantage. RBV points out that companies with scarce resources that are difficult to imitate will gain a stronger competitive advantage and show better and sustainable financial performance (Wernerfelt, 1984; Barney, 1991; Barney, 2001; Kuncoro and Suriani, 2017; Hameed et al., 2020). Inimitable resources come from technology innovation (Bakar and Ahmad, 2010), because technology innovation helps companies develop new products and services, construct the barrier from their competitors, and make companies expand their business scale, then enhance their competitiveness (Ireland et al., 2001; Su and Zhou, 2019). Among all the resources pointed out by RBV, knowledge is the most relevant to the competitiveness of companies (Villasalero, 2017). KBV shows that transforming tacit knowledge into explicit knowledge is the source of sustainable competitive advantage (Yang, 2008, 2012; Jawad and Mustafa, 2019). Technology Innovation contributes to knowledge management (Kamara et al., 2002), which leads to the explicit expression of accumulated knowledge. Therefore, innovation is a key factor for companies to seize the competition and promote corporate financial potential (Patterson, 1998; Veland and Shqipe, 2011; VanderPal, 2015; Zhang et al., 2018). Based on the analysis above, this paper proposes hypothesis 1:

H1: There is a positive relationship between technology innovation and corporate FS.

The Relationship Between Technology Innovation and SES

Due to the reduction of natural resources and the intensification of global warming issues, social and corporate stakeholders are paying more and more attention to corporate environmental and social sustainability (Albort-Morant et al., 2018; Davenport et al., 2019), which is different from only focusing on financial growth. In the face of this revolution, green technology innovation characterized by minimizing impacts on the environment by conserving energy and resources (Lee and Kim, 2011), providing companies with the opportunity to use win-win logic to increase innovation to improve competitiveness (Porter and Van der Linde, 1995; Kong et al., 2016; Ishak et al., 2017; Li et al., 2019). Because producing green products, low resource consumption, high cleanliness, etc. are the characteristics of the renewable energy company, the technology innovation of the renewable company is consistent with the meaning of green technology innovation, which makes positive contributions to the realization of environmental and social sustainable development goals (Xie et al., 2019). So, to sum up, this paper proposes hypothesis 2:

H2: There is a positive relationship between technology innovation and corporate SES.

The Role of Government Subsidies Between Technology Innovation and Corporate Sustainability

Because of the long investment return cycle, competitors' imitation, and uncertainty (Staw and Dutton, 1981; McKinley et al., 2014), under-investment in innovation is obvious in the market (Arrow, 1972). Government subsidies are considered an important tool to solve market failure problems. Subsidies aim to show a signal effect, helping companies relieve financial pressure when doing innovation activities (Yu et al., 2020). However, government subsidies also bring many unexpected negative effects, especially when government subsidies are tremendous. Companies choose rent-seeking rather than innovation to enhance their short-term competitive advantage, excessive subsidies make rent-seeking activity and crowding-out effect more serious, hindering their promotion effect on innovation, which inhibit companies' long-term development (Howell, 2017; Peng and Liu, 2018; Ahn et al., 2020; Guo et al., 2020). Therefore, this paper proposes hypothesis 3:

H3: There is a threshold effect of government subsidies, when government subsidies are greater than the threshold value, the contribution of technology innovation to FS would be weakened.

Based on stakeholder theory, companies must respond to the needs of stakeholders when making decisions to gain a competitive advantage (Roy and Goll, 2014). Therefore, the focus of stakeholders' concerns will affect the operating direction of companies, especially those that have received government subsidies (Deng et al., 2020). With the increasing attention paid to the environment and society, to obtain government subsidies, companies will carry out more innovative activities to take more environmental and social responsibility, and companies that have received subsidies will also actively indicate to stakeholders that they attach importance to SES (Wang and Zhang, 2020). However, government subsidies may also have a crowding-out effect on technology innovation (Busom, 2000: Liu et al., 2019) and excessive government subsidies act as a substitution in the relationship between innovation and SES, thereby inhibiting innovation's promotion to SES. Based on the analysis above, this paper proposes hypothesis 4:

H4a: Government subsidies have a positive moderating effect on the relationship between technology innovation and SES.

H4b: Government subsidies have a negative moderating effect on the relationship between technology innovation and SES.

RESEARCH METHOD

Data

This paper selects the data of China A-share listed companies from 2014 to 2019 in the field of renewable energy. The data of ESG rating and technology innovation comes from the Wind database, the data of government subsidies is collected from the companies' annual reports, and the rest comes from the CSMAR. After excluding samples with ST, ST*, and missing main variables, a panel data of 166 Chinese renewable energy companies is obtained (there are 830 observations) finally.

Variables

In this study, the dependent variables are the FS and SES, and the independent variable is technology innovation. Government subsidies are the threshold variable and the moderating variable. In addition, our study considers some control variables. The selected variables will be discussed separately later, and the definition of each variable is presented in **Table 2**.

Corporate Sustainability

This paper analyzes corporate sustainability from two dimensions: FS and SES. Firstly, for the FS, McKelvie and Wiklund (2010) indicates that companies with different types and companies in different periods show different growth characteristics. Higgins (1981) points out that FS reflects a company's ability to use resources to obtain income. Tibor et al. (2015) and Peng and Liu (2018) define income as entrepreneurial companies' growth capacities. However, revenue only reflects companies' financial performance, not show the dynamic growth of the companies. Pandey (1994) and Zhao and Wijewardanab (2012) explained that in the long run, the company's growth is an increase in company size and activities. Growth means that the company's expansion activities involve sales, profits, and assets. Xu et al. (2020) point out that the FS is the maximum growth rate of operating revenue that can be achieved, and the average sales growth is a recurring indicator of performance

TABLE 2 | Independent variable, dependent variable, moderating (threshold) variable, and control variable definition.

Variable type	Variable name	Variable code	Variable definitions	Data sources
Dependent variable	Financial sustainability	FS	(Total operating income for the current year - Total operating income for last year)/Total operating income for last year	CSMAR
	Social and environmental sustainability	SES	Assign a value of 0 to ratings BBB and below, and 1 to ratings above BBB	Wind
Independent variable	Technology innovation	Inn	Total R&D expenditure/Total operating income	Wind
Moderating or threshold variable	Government subsidies	Gov	Government subsidies recorded in current profit and loss+government subsidies recorded in other income+increase in deferred income in the current financial report decrease in deferred income in the current financial report	Company Annual Report
Control variable	Company size	Size	The company's total operating income takes the logarithm;	CSMAR
	Capital structure	Lev	Debt-to-asset ratio	CSMAR
	Return on assets	ROA	Net income/Average balance of total assets	CSMAR
	Equity concentration	Top1	H index (square of the shareholding ratio of the largest shareholder)	CSMAR
	Company age	Age	Measured as the number of years from registration	CSMAR

because it discloses market acceptance and technical quality (Marino and De Noble, 1997; Utsch and Rauch, 2000), which is also regarded as an important parameter of corporate competitiveness (Bobillo et al., 2006; Ciro et al., 2020). Therefore, this paper selects the growth rate of operating revenue as an indicator of FS.

Sustainability needs to meet multiple aspects simultaneously (Elkington, 1998); FS alone cannot represent corporate sustainability (Gladwin et al., 1995). According to the "Triple bottom line" concept, society and environment are also two important parts of sustainability. So, this paper chooses ESG rating to measure SES. ESG is an important standard for measuring environmental protection and social responsibility of companies. The environmental rating takes into account waste of resources, green products, environmental violations, etc.; social rating is the concern for social contribution and external certification of the new energy company (Nirino et al., 2020). Nollet et al. (2016) believes that ESG rating is one of the best parameters for measuring the environmental, social, and business impact of the companies.

This paper selects Hua Zheng ESG Rating Index in the Wind database to measure the SES. Referring to the study of Zhang and Zhao (2019), we quantify the companies' ESG performance as 0, if its ESG rating is BBB and below, and quantify the remaining companies' ESG performance as 1.

Technology Innovation

Previous studies have used the intensity of R&D investment (Cumming et al., 2016), all intangible assets and capability (Sung, 2019), the proportion of technical staff, design or research, the proportion of sales or profits of new products (Chouaibi, 2020), and the number of patent applications (He et al., 2018; Plank and Doblinger, 2018) to measure technology innovation. It is a kind of strategic behavior that companies increase innovation inputs to raise profit opportunities (Clausen, 2009), and R&D investment can reflect companies' efforts in promoting technology innovation and companies' innovation ability (Hagedoorn and Cloodt, 2003). So, referring to the study of Xu et al. (2020), this paper uses the proportion of R&D expenditure to operating income to measure technology innovation.

Government Subsidies

Government subsidies are often measured by the natural logarithm of the total amount of government subsidies (Wu and Hu, 2020) or public expenditure for encouraging R&D and protection activities for industrial intellectual property (Sung, 2019). Hu et al. (2019) use the government subsidy amount reported under the non-operating income on the Statement of Financial Performance and divide it by the total assets as the indicator. Zhang and Guan (2021) choose the government subsidy amount in the annual report data of listed companies as the indicator. Combining the latest China Accounting Standards for government subsidies in 2017 and the study of Song et al. (2020), this paper uses government subsidies amount in deferred income and current income to measure government subsidies.

Control Variables

This paper selects five control variables based on previous studies: company size, equity concentration, return on total assets (ROA), company age, and capital structure.

The natural logarithm of revenue is used to measure the size of the company. The scale of a company is directly related to finances, and it is usually reflected in total assets, fixed assets, income, and the number of employees (Ahmedova, 2015). Considering that most of the renewable energy companies are in the start-up stage, revenue can more fully reflect the size of the company, so this paper chooses natural logarithm of revenue.

The capital structure is reflected by the debt-to-asset ratio. An increase of debt will aggravate financial risk and worsen capital constraints (Yu et al., 2020), and innovation is a risky activity with a long-lasting cycle (Li et al., 2020), so this paper chooses debt-to-asset ratio to measure the company's risk situation.

ROA refers to the profitability of a company on its total assets. Return on total assets is usually defined as an accounting measure of performance (Waddock and Graves, 1997), which can be used to measure the company's profitability. The most basic requirement of corporate sustainability is continuous profitability, so this paper chooses ROA as one of the control variables.

The H index is used to measure the concentration of equity. The share ratio of major shareholders may affect the way managers use government subsidies. Equity diversification can strengthen management supervision and restrain rent-seeking behavior (Yu et al., 2020). Equity concentration may lead to insufficient technology innovation activities because of "moral hazard" (Lin and Luan, 2020).

The company age. Young companies have additional resource constraints than old companies (Sung, 2019), and older companies have more time to accumulate knowledge and experience to support innovation (Li et al., 2020), so the company age is also an important control variable.

Econometric Model

Effect of Technology Innovation on FS and SES

According to the study of Hu et al. (2019) and Yang et al. (2019), this paper constructs the regression model (1) as below to test the impact of technology innovation on FS. Referring to Ben-Akiva and Lerman (1985), this paper constructs the regression model (2) to test the effect of technology innovation on SES:

$$FS_{i,t} = \alpha + \beta Inn_{i,t-1} + \delta Controls_{i,t} + \mu_i + \vartheta_t + \varepsilon_{i,t} \quad (1)$$

$$SES_{i,t} = \alpha + \beta Inn_{i,t-1} + \delta Controls_{i,t} + \mu_i + \vartheta_t + \varepsilon_{i,t} \quad (2)$$

where i is the firm and t is the year; μ_i is the unobservable firm-specific effect and η_t refers to the unobservable time-specific effect; and β is the coefficients of the effect of technology innovation on FS and SES. $Size$, $Top1$, ROA, Lev, and Age are included in control variables, which represent the heterogeneity of companies. $\varepsilon_{i,t}$ refers to the random error term.

Threshold and Moderating Effect of Government Subsidies

Referring to Qing et al. (2021), existing studies typically add a quadratic term to the model or consider Hansen's static threshold model. Hansen first proposed the threshold model (Hansen, 1999), which was used to describe the characteristics of skip or structural break as for the correlation between different variables. Seo and Shin (2016) proposed the first-difference GMM estimation of the dynamic panel threshold model. On this basis, this paper constructs the regression model (3) to test the threshold effect of government subsidies.

Hansen believes that the explanatory variable or the independent threshold variable can be set as the threshold variable. Therefore, when one of the threshold variables is selected, the other threshold variables could still be used as control variables. So, this paper selects government subsidies as the threshold.

Referring to Hong et al. (2019), Liu and Tsaur (2020), and Yu et al. (2020), this paper adds the interaction between government subsidies and technology innovation to construct the regression model (4) to test the moderating effect of government subsidies:

$$FS_{i,t} = \alpha + \beta_1 Inn_{i,t-1}\left[Gov_{\mathrm{i,t}} \leq c_1\right] + \beta_2 Inn_{i,t-1}\left[Gov_{\mathrm{i,t}} > c_1\right] + \delta Controls_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \quad (3)$$

$$SES_{i,t} = \alpha + \beta_1 Inn_{i,t-1} + \beta_2 Gov_{i,t} + \beta_3 InnGov_{i,t-1} + \delta Controls_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \quad (4)$$

c_1 denotes threshold values of the government subsidies. β_1, β_2 are the coefficients of the effect of technology innovation on FS under the single threshold effect of government subsidies. β_3 indicates the impact of government subsidies on the effects of technology innovation on SES.

EMPIRICAL RESULTS

Descriptive Statistics and Correlation Analysis

The descriptive statistics and correlations of dependent variables, independent variables, moderating (threshold) variable, and control variables are shown in **Tables 3**, **4**, respectively.

TABLE 3 | Descriptive statistics.

Variables	Obs	Mean	Std. dev.	Min	Max
FS	830	0.196	0.359	−0.422	1.811
SES	830	0.436	0.496	0	1
Inn	830	0.045	0.028	0	0.152
Gov (a hundred million)	830	1.502	3.92	0	58.019
Size	830	22.094	1.367	18.993	25.744
Top1	830	0.113	0.095	0.007	0.413
ROA	830	0.029	0.047	−0.165	0.153
Lev	830	0.47	0.17	0.097	0.897
Age	830	18.917	4.791	8	34

The average of FS is 19.6%, the minimum is −42.2%, and the maximum is 181.1%, indicating that most of the sample companies are in the growth stage, but the development gap between companies is large; the average of SES is 0.436, indicating that the overall performance of the sample companies is relatively good in environment and society, and the standard deviation is 0.496, which means that there are differences in SES among different companies; R&D investment accounts for 4.5% of operating income, indicating that the sample companies focus on R&D investment and technology innovation as a whole; the average value of Gov is 1.502, indicating the government's positive attitude toward the development of renewable energy companies, and the standard deviation is 3.92, indicating that government subsidies vary greatly among different companies.

This paper uses the Pearson method to analyze the correlation between variables. The results in **Table 3** show that there is a high correlation between FS, SES, Gov, and Inn, indicating that the variables are statistically correlated. The correlation coefficient between the variables is low (<0.5), and VIF is >1 and <10, indicating that there is no interference of multicollinearity.

Regression Analysis

According to previous study results, technology innovation has a lag effect on companies' development (Yun et al., 2008; Campbell, 2012; Yarden and Caldes, 2013; Xu et al., 2020), so this paper lags the technology innovation variables by 1 year. Referring to the studies of Roberts and Whited (2011); Sudarshan and Todd (2012), and Zhang et al. (2018), this paper avoids the endogenous problem between technology innovation and corporate sustainability through the practice of lagging technology innovation, and it is obvious that the current corporate sustainability has no impact on previous technology innovation. Besides, to eliminate the interference of outliers on the estimation results, this paper winsorizes our variables at the 1st and 99th percentiles.

The Relationship Between Technology Innovation and FS

The result of the Hausman test ($P < 0.0000$) shows that the fixed effects regression model is suitable. The regression analysis results are as follows:

From the regression results of model (1) in **Table 5**, it can be seen that there is a significant positive relationship between Inn_L and FS ($\beta = 6.578, p < 0.01$), which means that technology innovation will promote the company's FS. Therefore, hypothesis 1 is accepted. The reason may be that, on the one hand, the pioneer advantage gained by companies through technology innovation can help the company respond to rapid changes and the heterogeneity of markets (Chouaibi, 2020; Ma et al., 2021); on the other hand, technology innovation can provide organizations with continuous learning ability (Cheng et al., 2014).

The Relationship Between Technology Innovation and SES

Since ESG indicators are dummy variables, this paper uses the logit model to perform regression analysis. According to the regression results of model (2) in **Table 5**, Inn_L can promote

TABLE 4 | Correlations coefficients.

	FS	SES	Inn	Gov	Size	Top1	ROA	Lev	Age
FS	1								
SES	−0.058*	1							
Inn	−0.060*	−0.080**	1						
Gov	−0.068**	0.228***	0.0310	1					
Size	0.00700	0.439***	−0.406***	0.438***	1				
Top1	−0.078**	0.109***	−0.083***	0.053*	0.160***	1			
ROA	0.265***	0.082***	−0.0360	0.00600	0.084***	0.0110	1		
Lev	−0.0440	0.128***	−0.318***	0.151***	0.546***	0.074**	−0.330***	1	
Age	−0.101***	0.149***	−0.134***	0.134***	0.278***	−0.167***	−0.00200	0.211***	1

Standard errors are in parentheses.
****p < 0.01, **p < 0.05, *p <0 .1.*

corporate SES, so hypothesis 2 is accepted. It proves that renewable energy companies' innovation has the characteristics of green technology innovation, which minimizes impacts on the environment by conserving energy and resources (Lee and Kim, 2011), is beneficial to reduce environmental impacts during a product's life cycle (Christensen, 2011), and improves processes to reduce adverse environmental impacts. Renewable energy companies' innovation brings them differentiation advantages (Cheng et al., 2014) and is beneficial to their SES.

TABLE 5 | Regression results.

	(1) FS	(2) SES	(3) FS	(4) SES
Inn_L	6.578***	7.799***		7.284**
	(1.403)	(2.893)		(3.018)
Gov				0.148*
				(0.088)
Inn*Gov				−1.115*
				(0.632)
Size	0.386***	0.825***	0.268***	0.744***
	(0.052)	(0.074)	(0.038)	(0.094)
Top1	−0.081	1.331	0.427	1.406
	(0.659)	(0.865)	(0.496)	(0.858)
ROA	2.527***	2.947*	2.758***	3.248**
	(0.319)	(1.642)	(0.336)	(1.656)
Lev	−0.001		−0.002	
	(0.002)		(0.002)	
0_Inn_L			7.735***	
			(0.889)	
1_Inn_L			3.067***	
			(0.957)	
Age		0.031*		0.029*
		(0.017)		(0.017)
Cons	−8.534***	−19.673***	−6.001***	−17.944***
	(1.151)	(1.686)	(0.844)	(2.106)
Observations	830	830	830	830
R^2	0.312	0.171	0.263	0.174

Standard errors are in parentheses.
****p < 0.01, **p < 0.05, *p < 0.1.*

The Role of Government Subsidies Between Technology Innovation and Corporate Sustainability

Threshold effect of government subsidies between technology innovation and FS

This paper uses government subsidies as the threshold variable. The result in **Table 6** shows that only a single threshold model is significant at the 1% level. Additionally, a small confidence interval indicates that the threshold value is accurate; that is, the effect of Inn_L on FS has a single threshold effect of Gov. The estimated thresholds for Gov is 0.5181, and the 95% confidence interval for threshold values is [0.5066, 0.5193].

According to the regression results of model (3) in **Table 5**, we can find that if Gov exceeds the threshold, the promotion effect of Inn_L weakens. When the Gov is less than the threshold, a 1% increase of Inn_L results in a 7.735% increase in FS at the 1% significance level. When Gov exceeds the threshold, for every 1% increase in Inn_L, FS increases to 3.067% at the 1% significance level. The results show that technology innovation has a significant threshold effect on FS, so hypothesis 3 is accepted.

It means when government subsidies are greater than the threshold value, with the increase of government subsidies, the crowding-out effect emerges (Jiang and Yan, 2018). Excessive government subsidies would be wasted through various rent-seeking approaches (Wu and Hu, 2020), which weakens companies' capability to innovate independently in the long term (Yu et al., 2020), that is, suppresses companies' financial growth.

Moderating effect of government subsidies between technology innovation and SES

According to the regression results of model (4) in **Table 5**, the regression coefficient of the cross term between Gov and

TABLE 6 | Results of the threshold effect test.

Gov	*F*-value	*P*-value	Threshold value	95% confidence interval
Single threshold	30.35***	0.0050	0.6820	[0.6598, 0.6842]
Double threshold	8.34	0.3790	6.2007	[4.2809, 6.2182]

Inn_L is negative ($p < 10\%$), indicating that Gov has a negative moderating effect on the promotion relationship between Inn_L and SES. Thus, hypothesis 4b is accepted.

The result suggests that government subsidies have a crowding-out effect on technology innovation (Liu et al., 2019; Busom, 2000) and excessive government subsidies act as a substitution in the relationship between innovation and SES, inhibiting the positive effect of technology innovation. Companies would choose rent-seeking to achieve short-term benefits (Lee et al., 2014; Du and Mickiewicz, 2016), instead of developing long-term environmental and social projects. Thus hindering the promotion of technology innovation on SES.

Robustness Test

In order to further verify the reliability of the study results and investigate the stability of the model, this paper adjusts the period of the sample, changing the study time to 2014–2018, to conduct a robustness test. The results are as above.

The results of the robustness test in **Table 7** are consistent with previous regression in general, indicating that even if we change the time frame of the data and reduce the sample size, technology innovation still has a positive effect on financial, social, and environmental sustainability. Besides, excessive government subsidies weaken the role of technology innovation in promoting both FS and SES. These indicate that the model in this paper is robust and the study results also have certain reliability.

TABLE 7 | Results of robustness test.

	(1) FS	(2) SES	(3) FS	(4) SES
Inn_L	8.349***	8.88***		11.176***
	(1.544)	(3.062)		(3.364)
Gov				0.336**
				(0.159)
Inn*Gov				−5.6**
				(2.732)
Size	0.514***	0.85***	0.367***	0.779***
	(0.065)	(0.084)	(0.046)	(0.102)
Top1	−0.05	0.64	0.539	0.655
	(0.76)	(0.964)	(0.562)	(0.956)
ROA	2.261***	2.469	2.633***	3.013*
	(0.351)	(1.712)	(0.379)	(1.72)
Lev	−0.002		−0.003	
	(0.003)		(0.002)	
0_Inn_L			8.981***	
			(1.001)	
1_Inn_L			5.641***	
			(1.113)	
Age		0.029		0.029
		(0.019)		(0.019)
Cons	−11.328***	−20.044***	−8.206***	-18.684***
	(1.394)	(1.897)	(0.994)	(2.259)
Observations	664	664	664	664
R^2	0.357	0.169	0.32	0.175

Standard errors are in parentheses.
****p < 0.01, **p < 0.05, *p < 0.1.*

DISCUSSION

Regional Heterogeneity

In order to further study whether the impact of technology innovation on corporate sustainability has regional heterogeneity, and according to the division of regions by the National Bureau of Statistic, we find that the east covers 445 samples, central covers 105 samples, and west covers 80 samples, which means that listed renewable energy companies are mainly located in the east, with a small number of samples in the central and west, and the development level of the central and west is relatively backward compared to the eastern regions, so this paper divides the region into the east and the central & west (C&W).

Grouping regression was carried out according to the region. The results of grouping regression are shown in **Table 8**. The empirical p-values are estimated based on the null hypothesis that the coefficients are equal for the two groups under consideration.

Effect of Technology Innovation on FS Between the East and C&W

According to the regression results of models (1) and (2) in **Table 8**, the coefficients of Inn_L in the two groups are 6.205 and 9.936, which are both significant at the 1% level; that is, Inn_L has a positive effect on FS. However, empirical p-value is 0.1730, suggesting that there is no significant difference in the coefficient of Inn_L between the two groups, which means that there is no difference in the promotion of technology innovation on FS between the east and the C&W.

TABLE 8 | Regional impact of technology innovation on corporate sustainability.

	(1) East_FS	(2) C&W_FS	(3) East_SES	(4) C&W_SES
Inn_L	6.205***	9.936***	10.547**	−14.030
	(5.21)	(4.05)	(2.56)	(−1.54)
Size	0.385***	0.374***	0.876***	1.085***
	(7.31)	(2.81)	(7.87)	(6.01)
Top1	0.326	−0.839	3.126**	−2.106
	(0.60)	(−0.82)	(2.28)	(−1.17)
ROA	2.236***	3.796***	4.109*	−1.719
	(5.52)	(3.93)	(1.67)	(−0.42)
Lev	0.002	−0.004		
	(0.89)	(−1.05)		
Age			0.006	0.064
			(0.26)	(1.33)
cons	−8.781***	−8.291***	−20.517***	−24.640***
	(−7.65)	(−2.80)	(−8.12)	(−6.18)
N	445	185	445	185
Empirical p-values	0.1730		0.004	

Standard errors are in parentheses.
****p < 0.01, **p < 0.05, *p < 0.1.*

The conclusion that the technology innovation of companies in the east and the C&W promotes the FS is consistent with the conclusion of Pandit et al. (2011), and their result shows that activities related to innovation have a positive impact on profits, while controlling the company's leverage and its scale. A possible reason is that the technology innovation of companies can bring about a decrease in production and management costs, thereby increasing corporate profits and improving corporate financial performance. More importantly, Zhu et al. (2014) found that the accumulated technological progress will enhance the core competitiveness of the company, and external investors will be full of confidence in the future development of the company, so that the value of the company will continue to increase.

Effect of Technology Innovation on SES Between the East and C&W

From the regression results of models (3) and (4) in **Table 8**, it can be seen that there is a significant positive relationship between Inn_L and SES (β = 10.547, $p < 0.05$) in the east. However, Inn_L has no significant effect in the C&W. The empirical p-value is 0.004, suggesting that there is a significant difference in the coefficient of Inn_L between the two groups, which means that there is difference in the relationship of technology innovation and SES between the east and C&W.

A possible reason is that there are differences in the regional environmental and social development between the east and the C&W. Yang and Wen (2017) found that the green development efficiency of the east and the C&W presents a serious polarization pattern. Chen and Wang (2018) believed that due to population migration, the C&W are aging faster than the east. The study of Hu et al. (2018) found that the average urban land use efficiency of China is higher in the east than in the C&W under the concept of green development. The quality of industrial development between the east and the west has the biggest difference (Deng and Liu, 2021). The east is no longer in the stage of relying on pollutant emissions to promote economic growth, while the increase in population and resource consumption in the central region leads to more pollutant emissions, and the west region is weak in environmental protection (He and Ran, 2009). With the same technology innovation resources, the contribution value of the economic indicators such as "GDP," "GDP per capita," and "industrial added value" in the northwest is lower than that in the east (Zhu and Zhang, 2005).

Due to the imbalance of regional social and environmental development, there are corresponding differences between eastern and C&W companies in the performance of social responsibility and innovation capabilities. Firstly, there are different degrees of emphasis placed on environmental and social responsibility. The eastern companies have a deeper understanding of the concept of social responsibility and related standards (Deng and He, 2013). Second, there are differences in the practice of company social responsibility, which means that eastern companies are at the highest level in terms of social responsibility for shareholders, employees, and environmental resources and the construction of a social responsibility management system, while company social responsibility in the northwest is the lowest level in China (Dong and Liu, 2017). Third, there are differences in the company's innovation capabilities. There are obvious regional differences in the distribution of corporate innovation capabilities, and it shows the same spatial pattern as China's regional economic development (Wang and Gao, 2017). Thus, there is obvious regional heterogeneity in the impact of company technology innovation on SES. Compared with the C&W, the technology innovation of eastern companies has played a significant role in promoting SES.

The Role of GSB and GSA

According to the "Accounting Standard for Business Enterprises No. 16–Government grants," government subsidies received by companies can be subdivided into government subsidies related to assets and government subsidies related to income. Government subsidies related to assets refer to government subsidies obtained by companies for purchasing and constructing long-term assets. Government subsidies related to income refer to government subsidies other than government subsidies related to assets. Government subsidies related to income can be subdivided into those used to compensate the related costs or losses in the future period and those used to compensate the related costs or losses that have incurred. According to the time when companies receive the government subsidies, this paper defines those compensations for the related costs or losses that the company has incurred as GSA, and other subsidies as GSB. Taking the new energy vehicle industry as an example, subsidies for companies' R&D investment, intellectual property awards, and establishment of R&D bases belong to the GSB. While price subsidies, exemption from purchase tax, and electricity subsidies can be classified as GSA. Referring to the study of Yu et al. (2020), we use the increase in deferred government subsidies in the current financial report to measure GSB and measure GSA as the amount of subsidies recorded in current profit and loss, and in other income after deducting the amortization of deferred income.

The Role of GSB

According to the regression results of model (2) and model (4) in **Table 9**, GSB inhabit the positive relationship between technology innovation and corporate sustainability.

The reason may be that the renewable energy industry is a technology-intensive industry; if companies want to gain a competitive advantage, they need to continue to carry out technology innovation. However, technology innovation requires a large amount of capital investment and has a high degree of uncertainty and spillover effects, which reduces the motivation for corporate innovation to a certain extent. The government needs to give certain subsidies and support before the start of the innovation project, that is, GSB. Because GSB are received before the investment in the project, they created a larger space for rent-seeking (Lee et al., 2014; Du and Mickiewicz, 2016; Wu and Hu, 2020). Therefore, when the threshold for subsidies is low, there are many companies attracted to squeeze into the renewable energy industry, especially large traditional energy companies (Peng and Liu, 2018). These large companies are more likely to receive subsidies due to their political connections, making start-ups that need subsidies for technology innovation unable to receive financial support. On the one hand, the intervention of several traditional energy companies has increased the intensity of competition in the renewable energy industry, and on the other hand, they have distorted the allocation efficiency of subsidies. Under the dual pressures of finance and excessive competition, the innovative motivation of renewable energy companies has weakened, which inhibits corporate sustainability.

The Role of GSA

According to the regression results of the threshold effect test in **Table 10**, only a single threshold model is significant at the 1% level for GSA, while GSB has no threshold effect. The estimated threshold for GSA is 0.4907, and the 95% confidence interval for threshold values is [0.4561, 0.4974]. In **Table 8**, When GSA exceed the threshold, for every 1% increase in technology innovation, the coefficient of financial growth decreases from 7.156 to 2.94%. The regression coefficient of the cross term between GSA and technology innovation is negative in model (3). These indicate that GSA are the main reason for the threshold effect of government subsidies and have a restraining effect on the relationship between technology innovation and corporate sustainability.

GSA aim to make up for the cost of completed projects, but they alleviate the promotion of technology innovation on corporate sustainability. Our results are different from the opinions of some scholars. Some scholars believe that GSA will be more effective than GSB (Peng and Liu, 2018), because GSA have a smaller rent-seeking space. This paper considers that although GSA are intended to help companies to expand market influence, if the actual production and sales capacity of renewable energy companies is not taken into account when formulating subsidy policies, only making the number of driving permits, registration certificates, and license plates reported as a basis for subsidies gives companies room to cheat for subsidies. Taking new energy vehicles as an example, 2013–2015 is a golden period for China to vigorously develop the new energy vehicle industry. The scope and amount of subsidies continue to expand, which provides opportunities for companies to cheat. For example, on September 8, 2016, the Ministry of Finance revealed that five new energy vehicle manufacturers, including Suzhou Jimxi Bus Manufacturing Co., Ltd., intended to defraud the government's subsidies for more than one billion yuan. These companies used licenses without cars, cars without electricity, inconsistent signs, related parties and dealers idle, end-users idle, and other means to defraud government subsidies by inflating production quantity. On the one hand, cheating for subsidies reduces the efficiency of subsidies. Innovative companies that need subsidies fail to obtain funds, which undermines the companies' enthusiasm for innovation. On the other hand, the actual sales situation is not taken into account in making the subsidy standards, falsely reporting their market influence through idle production after production or through expanding production blandly. GSA only play a role in mobilizing the companies' enthusiasm in production, not promoting the enthusiasm for innovation, but have a negative impact on corporate sustainability.

TABLE 9 | Effects of GSA and GSB on corporate sustainability.

	(1) FS(GSA)	(2) FS(GSB)	(3) SES(GSA)	(4) SES(GSB)
Inn_L			9.176***	8.267***
			(2.966)	(3.004)
Gov			0.299**	0.348**
			(0.131)	(0.176)
Inn*Gov			−4.517**	−4.406**
			(2.09)	(2.142)
Size	0.257***	0.2***	0.764***	0.776***
	(0.039)	(0.038)	(0.084)	(0.085)
Top1	0.483	0.561	1.402	1.335
	(0.499)	(0.512)	(0.856)	(0.866)
ROA	2.729***	2.972***	3.374**	3.028*
	(0.339)	(0.345)	(1.65)	(1.643)
Lev	−0.002	−0.003*		
	(0.002)	(0.002)		
0_Inn_L	7.156***	6.064***		
	(0.878)	(0.881)		
1_Inn_L	2.94***	4.491***		
	(0.996)	(1.19)		
Age			0.03*	0.032*
			(0.017)	(0.017)
cons	−5.774***	−4.488***	−18.468***	−18.714***
	(0.847)	(0.838)	(1.901)	(1.917)
Observations	830	830	830	830
R^2	0.254	0.215	0.176	0.174

Standard errors are in parentheses.
****p < 0.01, **p < 0.05, *p < 0.1.*

TABLE 10 | Results of the threshold effect test.

Threshold variables	Single threshold		Threshold value	95% confidence interval
	F-value	*P*-value		
GSA	46.97***	0.0000	0.4907	[0.4561, 0.4974]
GSB	4.62	0.6520	0.6736	[0.6480, 0.6963]

Standard errors are in parentheses.
****p < 0.01, **p < 0.05, *p < 0.1.*

CONCLUSION AND POLICY IMPLICATIONS

Conclusion

This study investigates the impact of technology innovation on corporate financial, social, and environmental sustainability and further investigates the mechanism of government subsidies in the relationship between technology innovation and corporate sustainability. A sample of 830 observations is obtained from the 166 A-share listed companies in the renewable energy industry of China from 2014 to 2019. The hypotheses are tested by the application of the fixed-effect model and the logit model. The following conclusions are drawn:

(1) Technology innovation will promote financial, social, and environmental sustainability.
(2) Technology innovation has a significant role in promoting FS in both the eastern and central and western regions; technology innovation has regional heterogeneity in SES and has a significant role in promoting the eastern and central and western regions.
(3) When the government subsidies are greater than the threshold value, the role of technology innovation in promoting FS is weakened.
(4) Government subsidies play a negative role in the relationship between technology innovation and SES).
(5) The threshold effect of subsidies mainly comes from the GSA, while the moderating effect of government subsidies is caused by both GSA and GSB.

Policy Implications

The objective of this paper is to empirically analyze the impact of technology innovation on corporate sustainability and investigate what role government subsidies play. This paper enriches the theoretical studies about the sustainable development of renewable energy companies. Furthermore, this paper puts forward the following policy implications:

First, refine the subsidy policy to achieve precise subsidies. At present, except for the new energy vehicles industry, most subsidy policies for the renewable energy industry are too broad, only suggesting policy directions without specifying specific implementation measures, so the operability is poor. Future policy formulation can be more precise and strengthen supervision and management during policy implementation.

Second, adjust the directions of subsidies. At present, the GSA and GSB in the renewable energy industry are not effective. Because GSB give space for rent-seeking, the future policies should focus on R&D subsidies and establishing a reasonable technical threshold. Improve market research work, and make technology standards adapt to market development. For GSA, the focus can be shifted to subsidies for supporting facilities and subsidies for consumers, as price subsidies and purchase subsidies may have negative effects such as blind production. Taking the new energy vehicle industry as an example, at present, China's subsidies are mostly concentrated on the promotional subsidies; insufficient charging facilities are another important factor that limits the development of the new energy vehicle market. The government should adjust the directions of subsidies, to improve the market consumers' acceptance of new energy vehicles. Besides, most of the current subsidies focused on companies and pay insufficient attention to consumers. The government can refer to the experience of other countries, such as the U.S. federal government to purchase new energy vehicles to take a slope-back tax credit and the U.S. state governments through electricity tariff relief and driving facilities and other supporting subsidies to reduce the cost of using new energy vehicles. Through subsidies to enable consumers to get real benefits, improve the efficiency of subsidies and expand the market influence of renewable energy companies.

Third, increase the stimulation for R&D. Because innovation is an important driving force to promote corporate sustainability, the government can put forward higher requirements for companies' innovation, from subsidy driven gradually to policy promotion. The Chinese government has issued a number of subsidies to motivate companies to carry out R&D to increase innovation for many years, but the efficiency of subsidies has been undermined by the rent-seeking behavior. How to make companies' innovation from encouraging to compulsory is the core of government policy-making. The Measures for the Parallel Management of Average Fuel Consumption and Points of New Energy Vehicles for Passenger Vehicle Companies, issued in September 2017, form a market-oriented mechanism to promote the coordinated development of energy-saving and new energy vehicles through the establishment of a point trading mechanism, which, to a certain extent, imposes mandatory requirements on the innovation. In the future, technology innovation not only needs to be driven by subsidy policy but also needs to be promoted by reward and punishment measures.

The subsidy policies can only play a role in guiding development; for companies in the context of high-quality development, how to enhance their innovation ability is the first way to achieve sustainable development. In the early stage of the COVID era, China's renewable energy industry faces the dual pressure of subsidy declines and production shutdowns. The production and sales of new energy vehicles fell by about 50%, and a large number of wind power projects planned and under construction were difficult to complete. In the face of emergencies, the government has taken a lot of helping measures for the renewable energy industry, such as extending the subsidies for new energy vehicles for 2 years to 2022. In order to cut off the transmission path of the COVID-19 as far as possible, off-line production activities during the COVID era were strictly managed, and the advantages of automated production and cloud office gradually show out. Digitalization and intelligence are future transformation directions of companies. In the post-COVID era, guiding the renewable energy industry to accelerate the digitalization process and making technology innovation fully include digital transformation can be the focus of policy guidance. Companies should fully grasp the opportunity of intelligent transformation to better achieve corporate sustainability, that is, not only to apply intelligence and digitalization to product innovation, but also to promote it to management and governance innovation. This paper will further explore the relationship among different types of technology innovation, government subsidies, and corporate sustainability in the post-COVID era in the future study.

Our study has insightful results, but it also has some limitations. Due to limitations on data availability, we only collect panel data over a relatively short time period. As a result, we cannot investigate the long-term effects. We will try to integrate the long-term effect of technology innovation in the future.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://www.gtarsc.com/#/index, and Wind dataset.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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The data refers to the National Bureau of Statistics, and it is publicly available.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2021.638459/full#supplementary-material

REFERENCES

Ahmedova, S. (2015). Factors for increasing the competitiveness of small and medium sized enterprises (SMEs) in Bulgaria. *Procedia Soc. Behav. Sci.* 195, 1104–1112. doi: 10.1016/j.sbspro.2015.06.155

Ahn, J. M., Lee, W., and Mortara, L. (2020). Do government R&D subsidies stimulate collaboration initiatives in private firms? *Technol. Forecast. Soc. Change* 151:119840. doi: 10.1016/j.techfore.2019.119840

Akwesi, A.-K. (2019). The resource-based view: a tool of key competency for competitive advantage. *Probl. Perspect. Manag.* 17, 143–152.

Albort-Morant, G., Leal-Rodríguez, A. L., and De Marchi, V. (2018). Absorptive capacity and relationship learning mechanisms as complementary drivers of green innovation performance. *J. Knowl. Manag.* 22, 432–452. doi: 10.1108/JKM-07-2017-0310

Anis, O. (2020). Technological innovation and sustainable development : does the stage of development matter? *Environ. Impact Assessm. Rev.* 83:106398. doi: 10.1016/j.eiar.2020.106398

Arrow, K. J. (1971). "The economic implications of learning by doing," in *Readings in the Theory of Growth*, ed. F. H. Hahn (London: Palgrave Macmillan). doi: 10.1007/978-1-349-15430-2_11

Arrow, K. J. (1972). "Economic welfare and the allocation of resources for invention," in *Readings in Industrial Economics*, ed. C. K. Rowley (London: Palgrave). doi: 10.1007/978-1-349-15486-9_13

Bakar, L. J. A., and Ahmad, H. (2010). Assessing the relationship between firm resources and product innovation performance: a resource−based view. *Bus. Process Manag. J.* 16, 420–435. doi: 10.1108/14637151011049430

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *J. Manag.* 17, 99–120. doi: 10.1177/014920639101700108

Barney, J. B. (2001). Resource-based theories of competitive advantage: a ten-year retrospective on the resource-based view. *J. Manag.* 27, 643–650. doi: 10.1016/S0149-2063(01)00115-5

Batlle, C. (2011). A method for allocating renewable energy source subsidies among final energy consumer. *Ener. Policy* 39, 2586–2595. doi: 10.1016/j.enpol.2011.02.027

Beason, R., and Weinstein, D. (1996). Growth, economies of scale, and targeting in Japan (1955-1990). *Rev. Econ. Statist.* 78, 286–295. doi: 10.2307/2109930

Ben-Akiva, M. E. and Lerman, S. R. (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. Cambridge, MA: MIT Press.

Bekhet, H. A., and Latif, N. W. A. (2018). The impact of technological innovation and governance institution quality on Malaysia's sustainable growth: evidence from a dynamic relationship. *Technol. Soc.* 54, 27–40. doi: 10.1016/j.techsoc.2018.01.014

Bergström, F. (2000). Capital subsidies and the performance of firms. *Small Bus. Econ.* 14, 183–193. doi: 10.1023/A:1008133217594

Bobillo, A. M., Rodriguez Sanz, J. A., and Gaite, F. T. (2006). Innovation investment, competitiveness, and performance in industrial firms. *Thunderb. Int. Bus. Rev.* 48, 867–890. doi: 10.1002/tie.20126

Busom, I. (2000). An empirical evaluation of the effects of R&D subsidies. *Econom. Innovat. N. Technol.* 9, 111–148. doi: 10.1080/10438590000000006

Campbell, M. (2012). What a difference a year makes: time lag effect of information technology investment on firm performance. *J. Organ. Comput. Electron. Commer.* 22, 237–255. doi: 10.1080/10919392.2012.696944

Cancino, C. A., Ariel, I. L. P., Ramaprasad, A., and Syn, T. (2018). Technological innovation for sustainable growth: an ontological perspective. *J. Clean. Product.* 179, 31–41. doi: 10.1016/j.jclepro.2018.01.059

Chen, M., Sinha, A., Hu, K., and Shah, M. I. (2020). Impact of technological innovation on energy efficiency in industry 4.0 era: moderation of shadow economy in sustainable development. *Technol. Forecast. Soc. Change* 164:120521. doi: 10.1016/j.techfore.2020.120521

Chen, R., and Wang, M. (2018). Unbalanced economic development, population migration and regional differences of population aging——based on the research of 287 prefecture-level cities in China. *J. Demogr.* 40, 71–81.

Cheng, C. C. J., Yang, C. -l., and Sheu, C. (2014). The link between eco-innovation and business performance: a taiwanese industry context. *J. Clean. Product.* 64, 81–90. doi: 10.1016/j.jclepro.2013.09.050

Cheng, Y., Awan, U., Ahmad, S., and Tan, Z. (2020). How do technological innovation and fiscal decentralization affect the environment? A story of the fourth industrial revolution and sustainable growth. *Technol. Forecast. Soc. Change* 162:120398. doi: 10.1016/j.techfore.2020.120398

Chouaibi, J. (2020). Innovation and financial performance in manufacturing companies: an empirical study tunisian. *J. Knowl. Econ.* doi: 10.1007/s13132-020-00692-8

Christensen, T. B. (2011). Modularised eco-innovation in the auto industry. *J. Cleaner Product.* 19, 212–220. doi: 10.1016/j.jclepro.2010.09.015

Ciro, T., Matricano, D., Candelo, E., and Sorrentino, M. (2020). Crowdfunded and then? The role of intellectual capital in the growth of equity-crowdfunded companies. *Measur. Bus. Excell.* 24:31. doi: 10.1108/MBE-02-2020-0031

Clausen, T. H. (2009). Do subsidies have positive impacts on R&D and innovation activities at the firm level? *Struct. Change Econ. Dynam.* 20, 239–253. doi: 10.1016/j.strueco.2009.09.004

Cumming, D., Rui, O., and Wu, Y. P. (2016). Political instability, access to private debt, and innovation investment in China. *Emerg. Mark. Rev.* 29, 68–81. doi: 10.1016/j.ememar.2016.08.013

Davenport, M., Delport, M., Blignaut, J. N., Hichert, T., and van der Burgh, G. (2019). Combining theory and wisdom in pragmatic, scenario-based decision support for sustainable development. *J. Environ. Plann. Manag.* 62, 692–716. doi: 10.1080/09640568.2018.1428185

Deng, J., and Liu, R. (2021). Regional differences in the quality of China's industrial development and its distribution dynamic evolution. *Statist. Decis.* 37, 92–96.

Deng, X., Xianyi, L., Schuler, D. A., Huan, L., and Xiaofei, Z. (2020). External corporate social responsibility and labor productivity: a S-curve relationship and the moderating role of internal CSR and government subsidy. *Corpor. Soc. Responsibil. Environ. Manag.* 27, 393–408. doi: 10.1002/csr.1877

Deng, Z., and He, Y. (2013). The difference and improvement of corporate social responsibility: the perspective of regional classification comparison. *Tianjin Soc. Sci.* 5, 97–100.

Diaz Arias, A., and van Beers, C. (2013). Energy subsidies, structure of electricity prices and technological change of energy use. *Ener. Econom.* 40, 495–502. doi: 10.1016/j.eneco.2013.08.002

Dong, S., and Liu, H. (2017). Analysis of the regional differences in the performance of social responsibilities of the enterprises under the state-owned assets supervision and administration commission. *Commer. Account.* 22–24.

Du, J., and Mickiewicz, T. (2016). Subsidies, rent seeking and performance: being young, small or private in China. *J. Bus. Ventur.* 31, 22–38. doi: 10.1016/j.jbusvent.2015.09.001

Elkington, J. (1998). Partnerships from cannibals with forks: the triple bottom line of 21st-century business. *Environ. Qual. Manag.* 8, 37–51. doi: 10.1002/tqem.3310080106

Gladwin, T., Kennelly, J., and Krause, T. (1995). Shifting paradigms for sustainable development: implications for management theory and research. *Acad. Manage. Rev.* 20, 874–907. doi: 10.5465/amr.1995.9512280024

Guerrero-Villegas, J., Sierra-García, L., and Palacios-Florencio, B. (2018). The role of sustainable development and innovation on firm performance. *Corpor. Soc. Responsibil. Environ. Manag.* 25, 1350–1362. doi: 10.1002/csr.1644

Guo, F., Zou, B., Zhang, X., Bo, Q., and Li, K. (2020). Financial slack and firm performance of SMMEs in China: Moderating effects of government subsidies and market-supporting institutions. *Int. J. Product. Econom.* 223:107530. doi: 10.1016/j.ijpe.2019.107530

Hagedoorn, J., and Cloodt, M. (2003). Measuring innovative performance: is there an advantage in using multiple indicators? *Res. Pol.* 32, 1365–1379. doi: 10.1016/S0048-7333(02)00137-3

Hameed, W. U., Nisar, Q. A., and Wu, H.-C. (2020). Relationships between external knowledge, internal innovation, firms' open innovation performance, service innovation and business performance in the Pakistani hotel industry. *Int. J. Hospital. Manag.* 92:102745. doi: 10.1016/j.ijhm.2020.102745

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: estimation, testing, and inference. *J. Econ.* 93, 345–368. doi: 10.1016/S0304-4076(99)00025-1

He, C., and Ran, M. (2009). Environmental pollution and economic growth——a study on regional differences based on inter-provincial panel data. *China Popul. Resourc. Environ.* 19, 56–62.

He, Z.-X., Xu, S.-C., Li, Q.-B., and Zhao, B. (2018). Factors that influence renewable energy technological innovation in China: a dynamic panel approach. *Sustain. Times* 10:124. doi: 10.3390/su10010124

Higgins, R. C. (1981). Sustainable growth under inflation. *Financ. Manage.* 10, 36–40.

Hong, J., She, Y., Wang, S., and Dora, M. (2019). Impact of psychological factors on energy-saving behavior: moderating role of government subsidy policy. *J. Clean. Product.* 232, 154–162. doi: 10.1016/j.jclepro.2019.05.321

Howell, A. (2017). Picking 'winners' in China: do subsidies matter for indigenous innovation and firm productivity? *China Econom. Rev.* 44, 154–165. doi: 10.1016/j.chieco.2017.04.005

Hu, B., Li, J., and Kuang, B. (2018). Evolutionary characteristics and influencing factors of urban land use efficiency differences under the concept of green development. *Econom. Geogr.* 38, 183–189.

Hu, J., Jiang, H., and Holmes, M. (2019). Government subsidies and corporate investment efficiency: Evidence from China. *Emerg. Mark. Rev.* 41:658. doi: 10.1016/j.ememar.2019.100658

Ireland, R. D., Hitt, M. A., Camp, S. M., and Sexton, D. L. (2001). Integrating entrepreneurship and strategic management actions to create firm wealth. *AMP* 15, 49–63. doi: 10.5465/ame.2001.4251393

Ishak, I., Jamaludin, R., and Abu, N. H. (2017). Green technology concept and Implementation: a brief review of current development. *Adv. Sci. Lett.* 23, 8558–8561. doi: 10.1166/asl.2017.9928

Jawad, A., and Mustafa, S. (2019). Impact of knowledge management practices on green innovation and corporate sustainable development: a structural analysis. *J. Clean. Product.* 229, 611–620. doi: 10.1016/j.jclepro.2019.05.024

Jiang, W., and Yan, Z. (2018). The certification effect of R&D subsidies from the central and local governments: evidence from China. *R D Manag.* 8, 615–626. doi: 10.1111/radm.12333

Jiang, Z., Lyu, P., Ye, L., and Zhou, Y. W. (2020). Green innovation transformation, economic sustainability and energy consumption during China's new normal stage. *J. Clean. Product.* 273:123044. doi: 10.1016/j.jclepro.2020.123044

Kamara, J. M., Anumba, C. J., and Carrillo, P. M. (2002). A clever approach to selecting a knowledge management strategy. *Int. J. Proj. Manag.* 20, 205–211. doi: 10.1016/S0263-7863(01)00070-9

Kang, K. N., and Park, H. (2012). Influence of Government R & D support and inter-firm collaborations on innovation in korean biotechnology SMEs. *Technovation* 32, 68–78. doi: 10.1016/j.technovation.2011.08.004

Klewitz, J., and Hansen, E. G. (2014). Sustainability-oriented innovation of SMEs: a systematic review. *J. Clean. Product.* 65, 57–75. doi: 10.1016/j.jclepro.2013.07.017

Kong, T., Feng, T., and Ye, C. (2016). Advanced manufacturing technologies and green innovation: the role of internal environmental collaboration. *Sustainability* 8:1056. doi: 10.3390/su8101056

Kuncoro, W., and Suriani, W. O. (2017). Achieving sustainable competitive advantage through product innovation and market driving. *Asia Pac. Manag. Rev.* 23, 186–192. doi: 10.1016/j.apmrv.2017.07.006

Lee, E., Walker, M., and Zeng, C. (2014). Do Chinese government subsidies affect firm value? *Account. Org. Soc.* 39, 149–169. doi: 10.1016/j.aos.2014.02.002

Lee, K. H., and Kim, J. W. (2011). Integrating suppliers into green product innovation development: an empirical case study in the semiconductor industry. *Bus. Strat. Environ.* 20, 527–538. doi: 10.1002/bse.714

Li, G., Wang, X., Su, S., and Su, Y. (2019). How green technological innovation ability influences enterprise competitiveness. *Technol. Soc.* 59:101136. doi: 10.1016/j.techsoc.2019.04.012

Li, Q., Wang, M., and Xiangli, L. (2020). Do government subsidies promote new-energy firms' innovation? Evidence from dynamic and threshold models. *J. Clean. Product.* 286.

Lim, C. Y., Wang, J., and Cheng (Colin), Z. (2017). China's "Mercantilist" government subsidies, the cost of debt and firm performance. *J. Bank. Finan.* 86, 37–52. doi: 10.1016/j.jbankfin.2017.09.004

Lin, B., and Benjamin, N. I. (2017). Green development determinants in China: a non-radial quantile outlook. *J. Clean. Product.* 162, 764–775. doi: 10.1016/j.jclepro.2017.06.062

Lin, B., and Luan, R. (2020). Do government subsidies promote efficiency in technological innovation of China's photovoltaic enterprises? *J. Clean. Product.* 254:120108. doi: 10.1016/j.jclepro.2020.120108

Lin, B., and Zhu, J. (2019). The role of renewable energy technological innovation on climate change: Empirical evidence from China. *Sci. Total Environ.* 659:449. doi: 10.1016/j.scitotenv.2018.12.449

Lin, W.-L., Cheah, J.-H., Azali, M., Ho, J. A., and Yip, N. (2019). Does firm size matter? Evidence on the impact of the green innovation strategy on corporate financial performance in the automotive sector. *J. Clean. Product.* 229, 974–988. doi: 10.1016/j.jclepro.2019.04.214

Liu, D., Chen, T., Liu, X., and Yu, Y. (2019). Do more subsidies promote greater innovation? Evidence from the Chinese electronic manufacturing industry. *Econom. Model.* 80, 441–452. doi: 10.1016/j.econmod.2018.11.027

Liu, H. T., and Tsaur, R. C. (2020). The theory of reasoned action applied to green smartphones: moderating effect of government subsidies. *Sustainability* 12:5979. doi: 10.3390/su12155979

Liu, Z., Li, X., Peng, X., and Lee, S. (2020). Green or nongreen innovation? Different strategic preferences among subsidized enterprises with different ownership types. *J. Clean. Product.* 245:118786. doi: 10.1016/j.jclepro.2019.118786

Long, J. B. D., and Summers, L. H. (1991). Equipment investment and economic growth. *J. Bradford Longs Work. Pap.* 106, 445–502.

Lucas, M. (2010). Understanding environmental management practices: integrating views from strategic management and ecological economics. *Bus. Strat. Environ.* 19, 543–556. doi: 10.1002/bse.662

Ma, Y., Zhang, Q., and Yin, Q. (2021). Top management team faultlines, green technology innovation and firm financial performance. *J. Environ. Manag.* 285:112095. doi: 10.1016/j.jenvman.2021.112095

Marino, K. E., and De Noble, A. F. (1997). Growth and early returns in technology-based manufacturing ventures. *J. High Technol. Manag. Res.* 8, 225–242. doi: 10.1016/S1047-8310(97)90004-3

McKelvie, A., and Wiklund, J. (2010). Advancing firm growth research: a focus on growth mode instead of growth rate. *Entrep. Theory Pract.* 34, 261–288. doi: 10.1111/j.1540-6520.2010.00375.x

McKinley, W., Scott, L., and Michael, B. (2014). Organizational decline and innovation: turnarounds and downward spirals. *Acad. Manag. Rev.* 39, 88–110. doi: 10.5465/amr.2011.0356

Nirino, N., Santoro, G., Miglietta, N., and Quaglia, R. (2020). Corporate controversies and company's financial performance: exploring the moderating role of ESG practices. *Technol. Forecast. Soc. Change* 162:120341. doi: 10.1016/j.techfore.2020.120341

Nitsch, V. (2009). Die another day: duration in german import trade. *Rev. World Econ.* 145, 133–154. doi: 10.1007/s10290-009-0008-3

Nollet, J., Filis, G., and Mitrokostas, E. (2016). Corporate social responsibility and financial performance: a non-linear and disaggregated approach. *Econ. Model.* 52, 400–407. doi: 10.1016/j.econmod.2015.09.019

Østergaard, P., and Sperling, K. (2014). Towards sustainable energy planning and management. *Int. J. Sustain. Ener. Plann. Manag.* 1, 1–5. doi: 10.5278/ijsepm.2014.1.1

Pandey, I. M. (1994). *Financial Management*, Sixth Revised Edn. Noida: Vikas.

Pandit, S., Charles, E. W., and Zach, T. (2011). The effect of R&D inputs and outputs on the relation between the uncertainty of future operating performance and R&D expenditures. *J. Account. Audit. Finan.* 26:15255.

Patterson, M. L. (1998). From experience: linking product innovation to business growth. *J. Product. Innovat. Manag.* 15, 390–402. doi: 10.1111/1540-5885.1550390

Peng, H., and Liu, Y. (2018). How government subsidies promote the growth of entrepreneurial companies in clean energy industry: an empirical study in China. *J. Clean. Product.* 188, 508–520. doi: 10.1016/j.jclepro.2018.03.126

Pitelis, A., Vasilakos, N., and Chalvatzis, K. (2019). Fostering innovation in renewable energy technologies: choice of policy instruments and effectiveness. *Renew. Ener.* 151, 1163–1172. doi: 10.1016/j.renene.2019.11.100

Plank, J., and Doblinger, C. (2018). The firm-level innovation impact of public R&D funding: evidence from the German renewable energy sector. *Ener. Policy* 113, 430–438. doi: 10.1016/j.enpol.2017.11.031

Porter, M. E., and Van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *J. Econom. Perspect.* 9, 97–118. doi: 10.1257/jep.9.4.97

Qiao, H., and Su, Q. (2020). Impact of government subsidy on the remanufacturing industry. *Waste Manag.* 120, 433–447. doi: 10.1016/j.wasman.2020.10.005

Qing, L., Wang, M., and Xiangli, L. (2021). Do government subsidies promote new-energy firms' innovation? Evidence from dynamic and threshold models. *J. Clean. Product.* 286:124992. doi: 10.1016/j.jclepro.2020.124992

Roberts, M. R., and Whited, T. M. (2011). Endogeneity in empirical corporate finance. *Sim. Sch. Work. Pap.* 11, 11–29. doi: 10.2139/ssrn.1748604

Roy, A., and Goll, I. (2014). Predictors of various facets of sustainability of nations: the role of cultural and economic factors. *Int. Bus. Rev.* 23, 849–861. doi: 10.1016/j.ibusrev.2014.01.003

Saunila, M., Nasiri, M., Ukko, J., and Rantala, T. (2019). Smart technologies and corporate sustainability: the mediation effect of corporate sustainability strategy. *Comput. Indust.* 108, 178–185. doi: 10.1016/j.compind.2019.03.003

Seo, M. H., and Shin, Y. (2016). Dynamic panels with threshold effect and endogeneity. *Economics* 195, 169–186. doi: 10.1016/j.jeconom.2016.03.005

Solarin, S. A., and Bello, M. O. (2019). Energy innovations and environmental sustainability in the U.S.: the role of immigration and economic expansion using a maximum likelihood method. *Sci. Tot. Environ.* 712:135594. doi: 10.1016/j.scitotenv.2019.135594

Soltani-Sobh, A., Heaslip, K., Stevanovic, A., Bosworth, R., and Radivojevic, D. (2017). Analysis of the electric vehicles adoption over the United States. *Transportat. Res. Proc.* 22, 203–212. doi: 10.1016/j.trpro.2017.03.027

Song, J., Zhang, H., and Su, Z. (2020). Does capitalization reflect innovation?–Evidence from Firms receiving R&D subsidy. *Account. Res.* 6, 3–23.

Staw, B. M., and Dutton, S. J. E. (1981). Threat rigidity effects in organizational behavior: a multilevel analysis. *Administr. Q.* 26, 501–524. doi: 10.2307/2392337

Su, X., and Zhou, S. (2019). Ambidextrous innovation and firm competitive position: empirical evidence from listed companies in China. *South China J. Econom.* 38, 52–77.

Su, Y., and An, X. -I. (2018). Application of threshold regression analysis to study the impact of regional technological innovation level on sustainable development. *Renew. Sustain. Ener. Rev.* 89, 27–32. doi: 10.1016/j.rser.2018.03.005

Sudarshan, J., and Todd, T. M. (2012). The role of stock liquidity in executive compensation. *Account. Rev.* 87, 537–563. doi: 10.2308/accr-10204

Sung, B. (2019). Do government subsidies promote firm-level innovation? Evidence from the Korean renewable energy technology industry. *Ener. Policy* 132, 1333–1344. doi: 10.1016/j.enpol.2019.03.009

Tibor, T., Edina, K., and Laurentiu, D. (2015). Risk and growth analysis of small and medium size enterprises between 2010 and 2012. *Proc. Econ. Financ.* 32, 1323–1331. doi: 10.1016/S2212-5671(15)01509-9

Tzelepis, D., and Skuras, D. (2004). The effects of regional capital subsidies on firm performance: an empirical study. *Small Bus. Enterprise Dev.* 11, 121–129. doi: 10.1108/14626000410519155

UNCTAD (2018). *Technology and Innovation Report 2018: Harnessing Frontier Technologies for Sustainable Development*. Geneva: United Nations Publication.

Utsch, A., and Rauch, A. (2000). Innovativeness and initiative as mediators between achievement orientation and venture performance. *Eur. J. Work Organ. Psychol.* 9, 45–62. doi: 10.1080/135943200398058

VanderPal, G. A. (2015). Impact of R&D expenses and corporate financial performance. *J. Account. Finan.* 15, 135–149.

Veland, R., and Shqipe, G. (2011). Theoretical framework of innovation: competitiveness and innovation program in macedonia. *Eur. J. Soc. Sci.* 23, 268–276.

Villasalero, M. (2017). A resource-based analysis of realized knowledge relatedness in diversified firms. *J. Bus. Res.* 71, 114–124. doi: 10.1016/j.jbusres.2016.10.011

Waddock, S. A., and Graves, S. B. (1997). The corporate social performance-financial performance link. *Strateg. Manag. J.* 18, 303–319.

Wang, B., Wang, Q., Wei, Y.-M., and Li, Z.-P. (2018). Role of renewable energy in China's energy security and climate change mitigation: an index decomposition analysis. *Renew. Sustain. Ener. Rev.* 90, 187–194. doi: 10.1016/j.rser.2018.03.012

Wang, P., and Gao, Y. (2017). An empirical study on the differences of regional innovation ability in China–a comment on the influencing factors of regional innovation ability. *J. Nanj. Univ. Technol. (Soc. Sci. Ed.)* 16, 121–128.

Wang, Y., and Zhang, Y. (2020). Do state subsidies increase corporate environmental spending? *Int. Rev. Finan. Anal.* 72:101592. doi: 10.1016/j.irfa.2020.101592

Wang, Y., Zhang, D., Ji, Q., and Shi, X. (2020). Regional renewable energy development in China: a multidimensional assessment. *Renew. Sustain. Ener. Rev.* 124:565.

WCED (1987). *World Commission on Environment and Development. Our Common Future*. New York, NY: Oxford University Press.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strat. Mgmt.* 5, 171–180. doi: 10.1002/smj.4250050207

Wu, H., and Hu, S. (2020). The impact of synergy effect between government subsidies and slack resources on green technology innovation. *J. Clean. Product.* 274:122682. doi: 10.1016/j.jclepro.2020.122682

Xie, X., Huo, J., and Zou, H. (2019). Green process innovation, green product innovation, and corporate financial performance: a content analysis method. *J. Bus. Res.* 101, 697–706. doi: 10.1016/j.jbusres.2019.01.010

Xu, J., Shang, Y., Yu, W., and Liu, F. (2019). Intellectual capital, technological innovation and firm performance: evidence from china's manufacturing sector. *Sustainability* 11:5328. doi: 10.3390/su11195328

Xu, X. L., Shen, T., Zhang, X., and Chen, H. H. (2020). The role of innovation investment and executive incentive on financial sustainability in tech-capital-labor intensive energy company: moderate effect. *Ener. Rep.* 6, 2667–2675. doi: 10.1016/j.egyr.2020.09.011

Yan, Z., Zou, B., Du, K., and Li, K. (2020). Do renewable energy technology innovations promote China's green productivity growth? Fresh evidence from partially linear functional-coefficient models. *Ener. Econom.* 90:104842. doi: 10.1016/j.eneco.2020.104842

Yang, J. (2008). Managing knowledge for quality assurance: an empirical study. *Int. J. Qual. Reliabil. Manag.* 2, 109–124. doi: 10.1108/02656710810846907

Yang, J. (2012). Innovation capability and corporate growth: an empirical investigation in China. *J. Eng. Technol. Manag.* 29, 34–46. doi: 10.1016/j.jengtecman.2011.09.004

Yang, X., He, L., Xia, Y., and Chen, Y. (2019). Effect of government subsidies on renewable energy investments: the threshold effect. *Ener. Policy* 132, 156–166. doi: 10.1016/j.enpol.2019.05.039

Yang, Z., and Wen, C. (2017). Evaluation of China's green development efficiency and regional differences. *Econom. Geogr.* 37, 10–18.

Yarden, Y., and Caldes, C. (2013). Basic cancer research is essential for the success of personalised medicine. *Eur. J. Cancer* 49, 2619–2620. doi: 10.1016/j.ejca.2013.04.020

Yu, F., Wang, L., and Li, X. (2020). The effects of government subsidies on new energy vehicle enterprises: The moderating role of intelligent transformation. *Ener. Policy* 141:111463. doi: 10.1016/j.enpol.2020.111463

Yudi, F., Jabbour, C. J. C., and Wah, W.-X. (2019). Pursuing green growth in technology firms through the connections between environmental innovation and sustainable business performance: does service capability matter? *Resourc. Conserv. Recycl.* 141, 8–20. doi: 10.1016/j.resconrec.2018.09.031

Yun, K., Tung-Yu, T., and Yang-Kuang, O. (2008). "Study of the time lag effect of patent impact on profitability of U.S. Pharmaceutical Industry from innovation to profit," in *Proceedings of the PICMET '08 – 2008 Portland International Conference on Management of Engineering & Technology* (Cape Town), 2588–2596. doi: 10.1109/PICMET.2008.4599887

Zhang, D., Zheng, W., and Ning, L. (2018). Does innovation facilitate firm survival? Evidence from Chinese high-tech firms. *Econom. Model.* 75, 458–468. doi: 10.1016/j.econmod.2018.07.030

Zhang, H., Li, L., Zhou, D., and Zhou, P. (2014). Political connections, government subsidies and firm financial performance: evidence from renewable energy manufacturing in China. *Renew. Ener.* 63, 330–336. doi: 10.1016/j.renene.2013.09.029

Zhang, L., and Zhao, H. (2019). Does corporate environmental, social and corporate governance (ESG) performance affect corporate value?–Based on empirical research of a-share listed companies. *Wuhan Finance* 10, 36–43.

Zhang, Y., and Guan, Y. (2021). The impact of government subsidies on enterprise innovation performance. *Industr. Technol. Econom.* 40, 18–25.

Zhao, B. A., and Wijewardanab, W. P. (2012). Financial leverage, firm growth and financial strength in the listed companies in Sri Lanka. *Proc. Soc. Behav. Sci.* 40, 709–715. doi: 10.1016/j.sbspro.2012.03.253

Zhu, N., Zhu, L., and Kong, Y. (2014). Research on the synergistic influence of technological innovation input and social responsibility on financial performance. *Account. Res.* 2, 57–63.

Zhu, Y., and Zhang, Z. (2005). Study on regional differences of the impact of technological innovation on economic growth. *China Soft Sci.* 11, 92–98.

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Embodied Energy in Export Flows Along Global Value Chain: A Case Study of China's Export Trade

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Energy issues are closely related to the development of human society and economy. Embodied energy is the total direct and indirect energy consumption required for the production of goods and services. In the context of the intensifying development of economic globalization and prosperity of international trade, embodied energy is considered as a better indicator to comprehensively reflect the nature of a country's energy use than the direct energy use. The development of trade in value added (TiVA) accounting and global value chain theory has brought new ideas to embodied energy research. This study applies TiVA accounting to the study of embodied energy and establishes a complete framework to decompose the sources, destinations, and transfer routes of embodied energy in a country's exports, and comprehensively depicts the embodied energy flows in China's exports at the country and sector levels as an instance. The results show that China exports large amounts of embodied domestic energy use, and export is an important factor for the rapid growth of China's energy and emissions. At the country level, the United States and EU28 are traditional major importers of China, and developing countries, such as Brazil, India, and Indonesia, are emerging markets. China's embodied energy flows to different importers vary in terms of trade patterns, flow routes, and the embodied domestic energy intensities. At the sector level, the light industry and the services create more benefits, whereas manufacturing, such as chemicals and metal products, consumes more energy, and there is a mismatch between the main sectors that create economic benefits from exports and the main sectors that consume energy for exports. These results indicate that embodied energy of China's exports has a great impact on global energy consumption and carbon emission, and the optimizing of China's export embodied energy structure is conducive to global energy conservation and emission reduction. This article strongly suggests the importance of the global value chain decomposition framework in embodied energy research.

Keywords: embodied energy, global value chain, export, input-output analysis, trade in value added

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INTRODUCTION

Energy is a basic element of the social economy, and the available energy both limits and governs the structure of human economies (Costanza, 1980). The huge economic growth and human welfare improvements are coupled with ever-increasing energy depletion. The primary world energy consumption rose sharply from 361.52 EJ in 1995 to 583.90 EJ in 2019 (BP, 2019). On the other hand, owing to the rapid development of the global economy and industrialization, the massive emissions resulting from the combustion of fossil energy have become a leading cause of global climate change. Sustainable energy development and combating climate change have become key issues of global concern. Meanwhile, the emerging economic globalization has accelerated the spatial separation of production and consumption in global supply chains, connecting economic development in one country with energy use in another country through good flows in international trade. Such separation no longer limits the energy import (by countries) to the context of direct import of energy products and can also improve the import of energy-intensive intermediate and final products to achieve the goal of reducing domestic energy consumption (Wiedmann et al., 2015). Simultaneously, this kind of spatial separation occurs to carbon emissions related to fossil fuel energy embodied in the products. Such carbon emission flows related to the embodied fossil fuel energy may result in carbon leakage if only the carbon emitted domestically is taken into account, without considering carbon embodied in imported goods and emitted in the exporting countries (Wyckoff and Roop, 1994). And many studies on international trade, embodied energy, and emissions demonstrated that the embodied flows of energy and emissions may cause the consequence of carbon leakage (Mongelli et al., 2006; Lin and Sun, 2010; Cui et al., 2015). With the development of international trade and increasing production globalization, energy flows among countries are becoming increasingly intricate, as are the carbon emissions related to these energy flows. Direct domestic energy consumption can no longer completely delineate the nature of a country's energy use, and therefore, "embodied energy" is considered to be a more appropriate measure. In the context of global action to tackle climate change and carbon emission reduction, trade embodied energy (especially embodied fossil fuel energy) is closely related to the transfer and flows of carbon emissions, and may even cause carbon leakage, which is not conducive to global emission reduction. Therefore, it is of great significance to study the flows of energy embodied in trade, especially fossil fuel energy.

Embodied energy is the total direct and indirect energy consumption required for the production of goods and services (Bullard and Herendeen, 1975). Input-output analysis is the main method used to measure embodied energy. In recent decades, research on embodied energy using input-output analysis has been developed in a spurt with the continuous improvement of input-output technology, along with the growing enrichment of energy statistics in various countries and different input-output databases. The related literature can be divided according to the research scale, including the global level (Bortolamedi, 2015; Chen and Wu, 2017; Jiang et al., 2020), multilateral country level (Wu and Chen, 2019; Zhang et al., 2019), bilateral country level (Yang et al., 2014; Tao et al., 2018), single-country level (Costanza, 1980; Lenzen, 1998; Machado et al., 2001; Lam et al., 2019; Wang and Yang, 2020), region level (Sun et al., 2017; Guo et al., 2020a; Zheng et al., 2020), city level (Chen and Chen, 2015; Guo et al., 2015, 2020b), and sector level (Liu et al., 2012, Liu et al., 2020a,b; Sun et al., 2016; Guo et al., 2019). There are also numerous studies regarding the research of embodied energy of different energy varieties, such as coal (Xia et al., 2017; Wu and Chen, 2018), oil (Tang et al., 2012; Wu and Chen, 2019; Wang and Yang, 2020), natural gas (Kan et al., 2019, 2020), biomass (Ji et al., 2020), and nuclear energy (Cortés-Borda et al., 2015). "Complex network analysis" is also commonly used in embodied energy research (An et al., 2015; Chen and Chen, 2015; Yang et al., 2015; Sun et al., 2016; Chen et al., 2018; Liu et al., 2019; Tang et al., 2019). Chen conducted a comprehensive analysis of the abundance of literature related to embodied energy and concluded that embodied energy can provide a well-integrated perspective on energy consumption and demand, and as embodied energy has been used in academics, issues related to China have been holding a high level of attention (Chen et al., 2019).

China is the largest energy consumer and CO_2 emitter in the world, and its energy issue has attracted worldwide attention. China is also the largest trading country and the primary trading partner of many countries. In recent years, China's huge international trade surplus has received unprecedented attention, and it has become a reason for bilateral trade friction. Compared with imported products from developed countries and regions, China's export products have lower value added and higher energy consumption and emissions per unit export trade volume, which will inevitably lead to the imbalance of energy consumption and emission flows. On the one hand, it has brought great pressure on domestic energy resources and the environment; on the other hand, it has also aroused international concern and even criticism about the growth of China's energy demand and emissions, and various "China threat theories" have emerged in an endless stream. In recent years, with respect to the context of global action to tackle climate change, "China's climate threat theory" is also on the rise. However, regarding the studies on embodied energy, the fact that China is a net exporter of energy contradicts this "threat theory" to some extent in terms of energy use (Tang et al., 2012; Cui et al., 2015; Wu and Chen, 2017; Jiang et al., 2020; Wang and Ge, 2020). Many empirical analyses on carbon emission embodied in China's export also suggested that the scale of carbon emission embodied in China's foreign trade is very large (Shui and Harriss, 2006; Weber et al., 2008; Lin and Sun, 2010; Su and Ang, 2013). A large amount of energy and carbon emissions embodied in China's exports meet the consumption of other countries and regions (especially developed countries), which has changed the pattern of global energy consumption and carbon emissions to a certain extent. The embodied fossil fuel energy in China's exports is not only closely related to embodied carbon emissions, but also an important factor driving China's energy consumption. Studies on the energy (especially fossil fuel energy) embodied in China's exports are significant for China's energy conservation and emission reduction, as well as the global emission reduction and combating climate change. Conversely, previous research on China's embodied energy is mostly limited to the gross value measure at the national, regional, or sector levels, as well as the net energy transfer in China's international or domestic regional trade (Gao et al., 2018; Tang et al., 2019; Guo et al., 2020a; Liu et al., 2020a; Zheng et al., 2020).

Studies on detailed energy flows embodied in China's international trade are as important as the amount of embodied energy in international trade; however, previous studies have seldom depicted the detailed energy flow routes, except for the gross value and the net flow value and directions. In addition, there is still a lack of comprehensive analyses at various levels. Moreover, most of the existing research is based on gross value accounting. Due to the deepening of the international division of labor in production and the in-depth development of intermediate goods trade, intermediate goods may cross borders back and forth. Therefore, the energy embodied in export goods is not limited to domestic sources and can come from foreign countries. Imports may also include the domestic energy that was previously exported. Nevertheless, the analysis based on gross value accounting cannot separate these parts from the total embodied energy. Moreover, previous studies often use the domestic energy use coefficient to replace the coefficients of other countries when it comes to import and export issues and to deduct the embodied energy of imported intermediate products in exports, resulting in large inaccuracies in the results. It is difficult to analyze the source of embodied energy in a country's imports and exports, nor to ascertain the real destinations of the energy embodied in the exported intermediates because of the restrictions on energy data and corresponding input-output data, as well as the limitation of gross value accounting itself. With the advent of trade in value added (TiVA) accounting and the development of the global value chain theory, the sources, destinations, and transfer routes of the value added in international trade can be completely decomposed; these harbor new ideas for embodied energy research.

In 2012, the WTO (World Trade Organization) and OECD (Organization for Economic Co-operation and Development) launched the "Measurement of Trade in Value Added" joint research project. Several international organizations, such as the European Union and United Nations Conference on Trade and Development (UNCTAD) have also conducted statistical studies on TiVA (OECD and WTO, 2011). This work has promoted the mainstreaming of TiVA statistics and made it a permanent part of the official international statistical system. The measurement of the global value chain based on TiVA accounting has been widely adopted. "Global value chain" is also called "vertical specialization," and it has many related labels (such as "value chain cutting," "outsourcing production," "production non-integration," "production fragmentation," "multi-level production," and "product internal specialization") (Hummels et al., 2001). Balassa proposed a kind of continuous production process in which product is divided into a vertical trade chain, which extends to many countries, and the interconnectivity of this production process is gradually enhanced. Each country focuses on a specific stage in the production process and adds value according to its comparative advantage. This global division phenomenon is defined as vertical specialization (Balassa, 1965). However, because of the restrictions on data and calculation methods, the research on vertical specialization remained at the case study level until Hummels defined a narrow concept of vertical specialization and put forward a quantitative index of systematic measurement, which made it possible to measure the global value chain (Hummels et al., 2001). Since then, the methodology has been developed continuously (Koopman et al., 2008, 2010, 2012, 2014; Wang et al., 2009; Daudin et al., 2011; Johnson and Noguera, 2012; Stehrer, 2012; Timmer et al., 2014). Finally, Wang et al. compared the TiVA accounting method (with the gross value accounting system) from the perspective of gross exports and decomposed the total exports into 16 terms (consisting of 12 value added items and 4 double-counting items), thereby, realizing the complete decomposition of gross exports (Wang et al., 2014); the decomposition framework of the global value chain accounting is thus complete.

The TiVA accounting and global value chain decomposition framework have brought new ideas to embodied energy research, and in particular, because of the abundance of the global input-output data, some studies have adopted this measure to analyze embodied energy (Liu et al., 2019, 2020b); however, these analyses were only conducted at the country aggregate level and focused on the construction sector. There is still a lack of detailed analyses of China's export embodied energy flows. In addition, in the process of completing the final decomposition framework, the importance of the forward linkage and backward linkage measures at the sector level has been stressed, owing to the fact that forward linkage focuses on the source sectors that initially consume the energy, whereas the backward linkage focuses on the sectors that finally export products (Wang et al., 2014). However, this difference has not been considered in previous studies at the sector level, and the analysis of embodied energy at the sector level was mostly conducted for a certain sector, with relatively little analysis of the differences between the various sectors. Following the global value chain decomposition framework, this study decomposes a country's gross export into 17 terms and energy embodied in the gross exports into 13 terms (respectively, according to the sources and final destinations of value added and energy consumption). Then, using the decomposed components, this study provides a detailed analysis of China's export embodied energy at both country and sector levels according to the comprehensive aspects of gross value, trade patterns, sources, and destinations. Furthermore, a new indicator of energy intensity is proposed in this study to evaluate the real domestic energy cost of economic benefits in exports. Overall, considering China's exports as an example, this article shows the detailed routes (from sources to the final destinations) to depict the embodied energy flows along the global value chain. On one hand, it is conducive to analyze the impact of China's export embodied energy on global energy consumption; on the other hand, it can describe the flow of energy-related carbon emissions. Moreover, this study is the basis and conducive to describe the real energy transfer between countries, and the research framework of this study is also applicable to the study of embodied carbon emissions and other embodied flows.

The remainder of this article is organized as follows. In section "Methodology and Data," the methodology and data sources are introduced. In section "Empirical Result," the empirical results are analyzed in detail. Section "Discussion and Implications" presents a discussion of the relevant results, and the conclusions and outlooks are presented in section "Conclusion and Outlooks."

METHODOLOGY AND DATA

Methodology

The multi-region input-output (MRIO) analysis is commonly used to measure the embodied resource and environmental flows across regions. Almost all the decomposition methods in the recent vertical specialization and TiVA literature are rooted in the work of Leontief (1936). **Table 1** provides a fundamental framework for the MRIO table. According to the basic input-output model, all gross output of country s must be used as either intermediate goods or final goods at home (or abroad):

$$X^s = A^{ss}X^s + Y^{ss} + \sum_{r \neq s}^{G} A^{sr}X^r + \sum_{r \neq s}^{G} Y^{sr} \tag{1}$$

where X^s (X^r) denotes the gross output of country s (country r), and A^{sr} (A^{ss}) is the direct input coefficient matrix, which gives the intermediate use in country r (country s) of goods produced in country s, and each element of it equals the corresponding intermediate use divide gross input, i.e., $a_{ij} = z_{ij}/\ x_j$. Y^{sr} (Y^{ss}) denotes the final use in country r (country s) of goods produced in country s. It can be expressed in matrix form as follows:

$$\begin{bmatrix} X^s \\ \vdots \\ X^G \end{bmatrix} = \begin{bmatrix} A^{ss} & & A^{sG} \\ \vdots & \ddots & \vdots \\ A^{Gs} & & A^{GG} \end{bmatrix} \begin{bmatrix} X^s \\ \vdots \\ X^G \end{bmatrix} + \begin{bmatrix} Y^{ss} + \sum_{r \neq s}^{G} Y^{sr} \\ \vdots \\ Y^{Gs} + \sum_{r \neq G}^{G-1} Y^{Gr} \end{bmatrix} \tag{2}$$

After rearranging equation (2), we can obtain the following:

$$\begin{bmatrix} X^s \\ \vdots \\ X^G \end{bmatrix} = \begin{bmatrix} I - A^{ss} & \cdots & -A^{sG} \\ \vdots & \ddots & \vdots \\ -A^{Gs} & \cdots & I - A^{GG} \end{bmatrix}^{-1} \begin{bmatrix} Y^{ss} + \sum_{rs}^{G} Y^{sr} \\ \vdots \\ Y^{Gs} + \sum_{rG}^{G-1} Y^{Gr} \end{bmatrix}$$

$$= \begin{bmatrix} B^{ss} & \cdots & B^{sG} \\ \vdots & \ddots & \vdots \\ B^{Gs} & \cdots & B^{GG} \end{bmatrix} \begin{bmatrix} Y^s \\ \vdots \\ Y^G \end{bmatrix} \tag{3}$$

where B^{sr} is the total requirements matrix, which gives the total requirement to produce a unit of gross output of country r needed from country s (similar for B^{ss}, B^{Gs}, B^{sG}, and B^{GG}). Y^s (Y^G) is the gross final goods produced in country s (country G), including domestic use Y^{ss} (Y^{Gs}) and abroad use $\sum_{r \neq s}^{G} Y^{sr}$ ($\sum_{r \neq G}^{G-1} Y^{Gr}$).

Subsequently, we denote the direct energy use coefficient matrix as F, and $F = \begin{bmatrix} F^s & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & F^G \end{bmatrix}$; each submatrix in it is the diagonal matrix of the sectoral direct energy use coefficient. For instance, $F^s = \begin{bmatrix} f_1^s & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & f_N^s \end{bmatrix}$; its elements are denoted by $f_j^s = eu_j^s/x_j^s$. f_j^s is the direct energy use coefficient of sector j in

TABLE 1 | Basic framework of a multi-region input-output table.

Intermediate Input	Country	Sector	Intermediate use: Country s	⋯	Intermediate use: Country G	Final use: Country s	⋯	Final use: Country G	Gross output
			1 ⋯ N		1 ⋯ N				
	Country s	1	Z_{ij}^{ss}	⋯	Z_{ij}^{sG}	Y_i^{ss}	⋯	Y_i^{sG}	X_i^s
		⋮							
		N							
	⋮		⋯	⋱	⋯	⋮	⋱	⋮	⋮
	Country G	1	Z_{ij}^{Gs}	⋯	Z_{ij}^{GG}	Y_i^{Gs}	⋯	Y_i^{GG}	X_i^G
		⋮							
		N							
Value added			V_j^s						
Gross Input			X_j^s						

The subscripts i and j in the table denote the sector number, and i, j = 1, …, N.

country s, and eu_j^s is the direct energy use of sector j in country s. Then, we can obtain the gross direct energy use vector (i.e., $EU = \begin{bmatrix} EU^s \\ \vdots \\ EU^G \end{bmatrix}$; each element represents the gross direct energy use of the corresponding country) as follows:

$$\begin{bmatrix} EU^s \\ \vdots \\ EU^G \end{bmatrix} = \begin{bmatrix} F^s & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & F^G \end{bmatrix} \begin{bmatrix} B^{ss} & \cdots & B^{sG} \\ \vdots & \ddots & \vdots \\ B^{Gs} & \cdots & B^{GG} \end{bmatrix} \begin{bmatrix} Y^s \\ \vdots \\ Y^G \end{bmatrix} \tag{4}$$

The gross exports of country s, E^s, includes the intermediate exports ($\sum_{r \neq s}^{G} A^{sr} X^r$) and final goods exports ($\sum_{r \neq s}^{G} Y^{sr}$), that is, $E^s = \sum_{r \neq s}^{G} A^{sr} X^r + \sum_{r \neq s}^{G} Y^{sr}$. The corresponding energy use embodied in the gross exports of country s ($GEEX^s$) can be denoted as: $GEEX^s = \sum_{r \neq s}^{G} F^s A^{sr} X^r + \sum_{r \neq s}^{G} F^s Y^{sr}$.

As a significant contribution to the global value chain and TiVA accounting, a country's exports to another country are completely decomposed into 16 components (Wang et al., 2014). This study follows the decomposition framework proposed by Wang et al. (2014) and further splits the fifth term of their decomposition framework into two parts according to the final destination, and the process is detailed in **Appendix**. Thus, this study decomposes a country's bilateral exports into 17 terms in line with the sources, absorbed destinations, and flow routes of value added. The final decomposition equation is expressed as follows:

$$\begin{aligned}
E^{sr} = {} & \underbrace{(V^s B^{ss})^{\mathrm{T}} \# Y^{sr}}_{(1)} + \underbrace{(V^s L^{ss})^{\mathrm{T}} \# (A^{sr} B^{rr} Y^{rr})}_{(2)} \\
& + \underbrace{(V^s L^{ss})^{\mathrm{T}} \# \left(A^{sr} \sum_{t \neq s,r}^{G} B^{rt} Y^{tt} \right)}_{(3)} + \underbrace{(V^s L^{ss})^{\mathrm{T}} \# \left(A^{sr} B^{rr} \sum_{t \neq s,r}^{G} Y^{rt} \right)}_{(4)} \\
& + \underbrace{(V^s L^{ss})^{\mathrm{T}} \# \left(A^{sr} \sum_{t \neq s,r}^{G} \sum_{u \neq s,r,t}^{G} B^{rt} Y^{tu} \right)}_{(5)} \\
& + \underbrace{(V^s L^{ss})^{\mathrm{T}} \# \left(A^{sr} \sum_{t \neq s,r}^{G} B^{rt} Y^{tr} \right)}_{(6)} + \underbrace{(V^s L^{ss})^{T} \# (A^{sr} B^{rr} Y^{rs})}_{(7)} \\
& + \underbrace{(V^s L^{ss})^{T} \# \left(A^{sr} \sum_{t \neq s,r}^{G} B^{rt} Y^{ts} \right)}_{(8)} + \underbrace{(V^s L^{ss})^{T} \# (A^{sr} B^{rs} Y^{ss})}_{(9)} \\
& + \underbrace{(V^s L^{ss})^{T} \# \left(A^{sr} \sum_{t \neq s,r}^{G} B^{rs} Y^{st} \right)}_{(10)} + \underbrace{(V^s B^{ss} - V^s L^{ss})^{T} \# (A^{sr} X^r)}_{(11)}
\end{aligned}$$

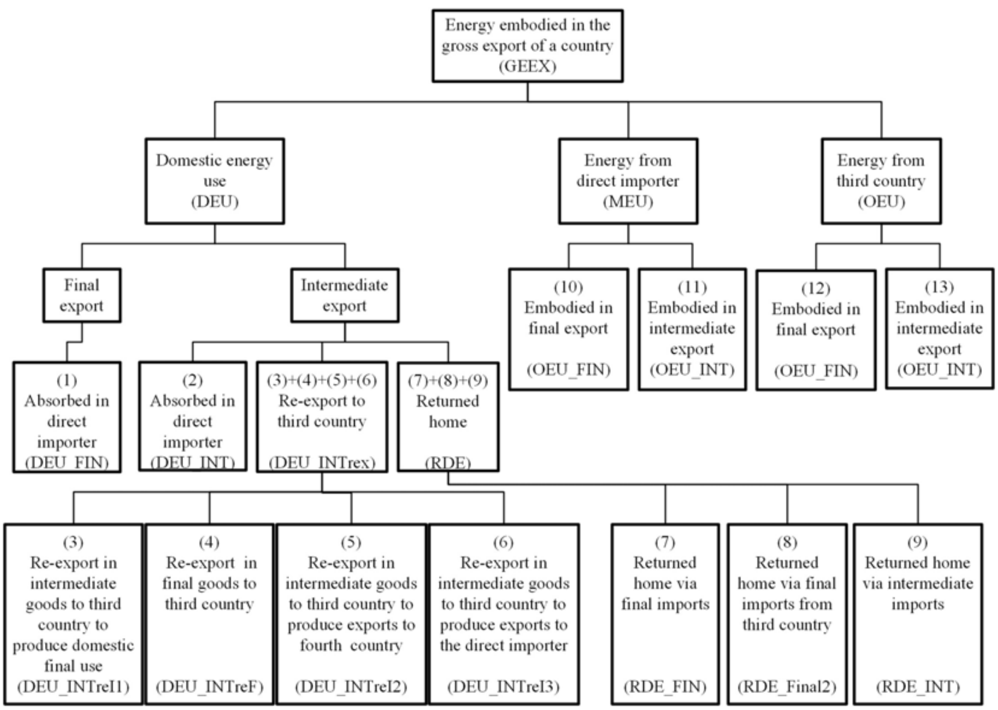

FIGURE 1 | Decomposition framework of gross energy embodied in exports.

$$+\underbrace{(V^rB^{rs})^T\#Y^{sr}}_{(12)}+\underbrace{(V^rB^{rs})^T\#(A^{sr}L^{rr}Y^{rr})}_{(13)}+\underbrace{(V^rB^{rs})^T\#(A^{sr}L^{rr}E^{r*})}_{(14)}$$

$$+\underbrace{\left(\sum_{t\neq s,r}^{G}V^tB^{ts}\right)^T\#Y^{sr}}_{(15)}+\underbrace{\left(\sum_{t\neq s,r}^{G}V^tB^{ts}\right)^T\#(A^{sr}L^{rr}Y^{rr})}_{(16)}$$

$$+\underbrace{\left(\sum_{t\neq s,r}^{G}V^tB^{ts}\right)^T\#(A^{sr}L^{rr}E^{r*})}_{(17)} \quad (5)$$

where E^{sr} is the total exports of country s to country r, and V^s is the value added coefficient diagonal matrix of country s, in which each element v_j^s is the value added coefficient of sector j in country s, and $v_j^s = va_j^s/x_j^s$, va_j^s is the value added of the corresponding sector. L^{ss} is the local Leontief inverse matrix; $L^{ss} = \begin{bmatrix} l_{11}^{ss} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & l_{NN}^{ss} \end{bmatrix} = \begin{bmatrix} 1-a_{11}^{ss} & \cdots & -a_{1N}^{ss} \\ \vdots & \ddots & \vdots \\ -a_{N1}^{ss} & \cdots & 1-a_{NN}^{ss} \end{bmatrix}^{-1}$, and E^{r*} is the gross export of country r. And the meaning and acronym of each term in equation (5) are as follows:

(1) DVA_FIN is the domestic value added in the final exports and absorbed in the direct importer.
(2) DVA_INT is the domestic value added in intermediate exports and absorbed in the direct importer.
(3) DVA_INTrexI1 is the domestic value added in the intermediate exports and re-exported by the direct importer to a third country to produce domestic final use.
(4) DVA_INTrexF is the domestic value added in the intermediate exports and used by the direct importer to produce final goods and used in the third country.
(5) DVA_INTrexI2 is the domestic value added in intermediate exports and used by the direct importer to produce intermediate goods and re-exported to the third country to produce their exports to the fourth country.
(6) DVA_INTrexI3 is the domestic value added in intermediate export and used by the direct importer to produce intermediate goods and re-exported to the third country to produce their exports to the direct importer.
(7) RDV_FIN is the domestic value added in intermediate exports and returns home via final imports.
(8) RDV_Final2 is the domestic value added in intermediate exports and returns home via final imports from the third country.
(9) RDV_INT is the domestic value added in intermediate exports and returns home via intermediate imports.
(10) DDC_FIN is the pure double-counting from domestic source due to final exports production.
(11) DDC_INT is the pure double-counting from domestic source due to intermediate exports production.
(12) MVA_FIN is the value added from the direct importer used in the final exports.
(13) MVA_INT is the value added from the direct importer used in intermediate exports.
(14) MDC is the pure double-counting sourced from the direct importer.
(15) OVA_FIN is the value added from the third country used in the final exports.
(16) OVA_INT is the value added from the third country used in the intermediate exports.
(17) ODC is the pure double-counting sourced from the third country.

Following this decomposition framework, we decompose the gross energy embodied in the exports of country s to country r ($GEEX^{sr}$) into 13 parts as follows:

$$GEEX^{sr} = \underbrace{(F^sB^{ss})^T\#Y^{sr}}_{(1)}+\underbrace{(F^sL^{ss})^T\#(A^{sr}B^{rr}Y^{rr})}_{(2)}$$

$$+\underbrace{(F^sL^{ss})^T\#\left(A^{sr}\sum_{t\neq s,r}^{G}B^{rt}Y^{tt}\right)}_{(3)}+\underbrace{(F^sL^{ss})^T\#\left(A^{sr}B^{rr}\sum_{t\neq s,r}^{G}Y^{rt}\right)}_{(4)}$$

$$+\underbrace{(F^sL^{ss})^T\#\left(A^{sr}\sum_{t\neq s,r}^{G}\sum_{u\neq s,r,t}^{G}B^{rt}Y^{tu}\right)}_{(5)}+\underbrace{(F^sL^{ss})^T\#\left(A^{sr}\sum_{t\neq s,r}^{G}B^{rt}Y^{tr}\right)}_{(6)}$$

$$+\underbrace{(F^sL^{ss})^T\#(A^{sr}B^{rr}Y^{rs})}_{(7)}+\underbrace{(F^sL^{ss})^T\#\left(A^{sr}\sum_{t\neq s,r}^{G}B^{rt}Y^{ts}\right)}_{(8)}$$

$$+\underbrace{(F^sL^{ss})^T\#(A^{sr}B^{rs}Y^{ss})}_{(9)}+\underbrace{(F^rB^{rs})^T\#Y^{sr}}_{(10)}$$

$$+\underbrace{(F^rB^{rs})^T\#(A^{sr}L^{rr}Y^{rr})}_{(11)}+\underbrace{\left(\sum_{t\neq s,r}^{G}F^tB^{ts}\right)^T\#Y^{sr}}_{(12)}$$

$$+\underbrace{\left(\sum_{t\neq s,r}^{G}F^tB^{ts}\right)^T\#(A^{sr}L^{rr}Y^{rr})}_{(13)} \quad (6)$$

The decomposition framework of the embodied energy in exports is presented in **Figure 1**, and the terms in equation (6) correspond to each term in the figure. Thus, we can measure the domestic content of energy and value added embodied in a country's gross exports.

To analyze the real situation of domestic energy use and economic gains, this study defines a new measure of energy intensity (export embodied domestic energy intensity, EMDEI), representing a country's domestic energy consumption for creating a unit of domestic value added through export; the formulas for the country aggregate and bilateral country levels are as follows:

Country aggregate level:

$$EMDEI^{s} = DEU^{s}/DVA^{s} \tag{7}$$

Bilateral country level:

$$EMDEI^{sr} = DEU^{sr}/DVA^{sr} \tag{8}$$

where DEU and DVA are the sums of the first to the ninth term in equations (6) and (5), respectively, denoting the gross value of the domestic content embodied in the country's exports at the corresponding level; the superscript s denotes the exporter and r denotes the direct importer.

As mentioned in the previous section, the exports (accounting based on forward and backward linkages) are equal at the country level but differ at the sector level; this distinction has been disregarded in previous embodied energy studies. A sector's gross export embodied energy (or value added) based on the forward linkage focuses on the source sector, including the energy (or value added) of a given sector and embodied in the gross exports of all sectors in this country, whereas the measure based on backward linkage focuses on the final export sector, including the gross energy (or value added) from all sectors in the country embodied in a given sector's gross exports. For instance, in a two-sector country case, the export value of sector 1 is 60 units and the value of sector 2 is 40 units based on the forward linkage measure, and the values change to 35 and 65 units, respectively, based on the backward linkage measure. The country aggregation is the same (100 units) (An illustration refers to **Supplementary Figure 1**). These two measures are expressed in the following equations:

$$deu^{s}_{i\_fw} = \sum_{j=1}^{N} deu^{s}_{ij}, \quad dva^{s}_{i\_fw} = \sum_{j=1}^{N} dva^{s}_{ij} \tag{9}$$

$$deu^{s}_{j\_bw} = \sum_{i=1}^{N} deu^{s}_{ij}, \quad dva^{s}_{j\_bw} = \sum_{i=1}^{N} dva^{s}_{ij} \tag{10}$$

where deu^{s}_{i} and dva^{s}_{i} are the sector aggregations of the first to ninth terms in equations (6) and (5); "***fw***" and "***bw***" in the subscript represent the forward and backward linkage measures, respectively. The forward linkage measure is the sum across the columns along the row, whereas the backward linkage measure is the sum across the rows along the column. Thus, the EMDEI at the sector level can be calculated as follows:

Forward linkage based:

$$EMDEI^{s}_{i\_fw} = deu^{s}_{i\_fw}/dva^{s}_{i\_fw} \tag{11}$$

Backward linkage based:

$$EMDEI^{s}_{j\_bw} = deu^{s}_{j-bw}/dva^{s}_{j-bw} \tag{12}$$

Data Sources

The MRIO tables used in this study were derived from the world input-output Database (WIOD) (Timmer et al., 2015) and were released in 2016. The series of world input-output tables (WIOTs) cover 28 EU (European Union) countries and 15 other major economies, along with the "rest of the world region" (ROW) for the period 2000-2014 (for specific countries and regions, refer to **Supplementary Table 1**). The corresponding energy data were derived from the Joint Research Center of the European Commission (Corsatea et al., 2019). The Joint research center provides two sets of data, including total energy use and emission-related energy use, and the emission-related energy use data were used in this study. This article decomposes the gross export of China to other countries and regions covered in the WIOT, along with the gross energy embodied in the export for the period 2000–2014. In this study, 18 sectors (merged of the 56 sectors in the original WIOTs) in China were analyzed at the sector aggregate level, the details are listed in **Table 2**.

EMPIRICAL RESULTS

Analysis at Country Aggregate Level

Based on equations (5) and (6), this study decomposes China's exports to the 43 importers covered in the WIOT for the period 2000–2014, and the results at country aggregate level are presented in this section.

The decomposition results of China's gross exports (17 terms) and gross exports embodied energy (13 terms) are shown in the stacked bars in **Figure 2**, along with the domestic value added (DVA) (gross exports embodied domestic energy use,

TABLE 2 | Sectors and numbers.

No.	Sector	No.	Sector
S.01	Agriculture, forestry, fishing, and related service activities	S.10	Manufacture of electrical equipment, and products
S.02	Mining and quarrying	S.11	Manufacture of machinery and equipment n.e.c.
S.03	Manufacture of food products, beverages, and tobacco products	S.12	Manufacture of transport equipment
S.04	Manufacture of textiles, wearing apparel, and leather products	S.13	Other manufacturing
S.05	Manufacture of products of wood and cork	S.14	Electricity, gas, steam, and water supply
S.06	Manufacture of paper, printing, and reproduction	S.15	Construction
S.07	Chemical industry	S.16	Wholesale and retail trade, accommodation, and food service activities
S.08	Manufacture of other non-metallic mineral products	S.17	Transportation, warehousing, postal, and telecommunications
S.09	Manufacture of basic metals and metal products	S.18	Other service actives

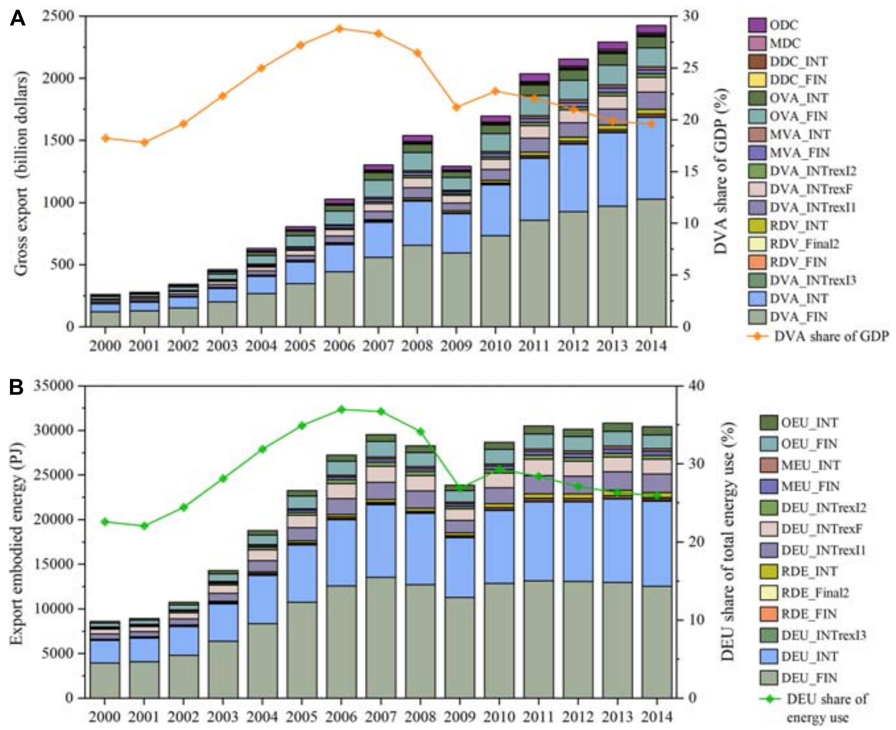

FIGURE 2 | Decomposed terms of gross export and corresponding embodied energy and the domestic content share in total China's GDP and energy use. The graphs are provided for **(A)** gross export and **(B)** gross export embodied energy.

DEU) proportion of China's total GDP (total energy use) shown in the line charts. China's gross export increased from 262 billion dollars in 2000 to 2,425 billion dollars in 2014, with only a slight dip caused by a global recession in 2009. DVA_FIN and DVA_INT (the domestic value added in final exports and intermediate exports and absorbed in the direct importer) dominated the gross exports, DVA_INTrexI1 (the domestic value added in the intermediate exports and re-exported by the direct importer to a third country to produce domestic final use), DVA_INTrexF (the domestic value added in the intermediate exports and used by the direct importer to produce final goods and used in the third country), OVA_FIN (the value added from the third country used in the final exports), and OVA_INT (the value added from the third country used in the intermediate exports) also accounted for significant proportions, along with the growing pure double-accounting part [that included DDC_FIN (the pure double-counting from domestic source due to final exports production), DDC_INT (the pure double-counting from domestic source due to intermediate exports production), MDC (the pure double-counting sourced from the direct importer), and ODC (the pure double-counting sourced from the third country)]. What should be noted is that the pure double counting in the exports is due to the intermediates across borders back and forth in international trade. This part grows as the intermediate trade and processing trade are increasing in recent decades. And the traditional gross value accounting, these double countings are also calculated as part of a country's gross exports, although they do not create any value added (whether domestic or foreign). The DVA proportion of China's total GDP reflects, to some extent, the dependence on the export of China's economic development, which showed an increasing trend before 2007 and a decreasing trend thereafter. The proportion reached a peak of 28.8% in 2006 and stabilized at approximately 20% in 2013 and 2014, equivalent to the level in 2002.

The gross energy use embodied in China's exports (GEEX) showed the same tendency as the gross exports before 2008 and increased from 8,600 PJ in 2,000 to 29,600 PJ in 2007, while showing a different trend since 2008. After the global financial crisis, the GEEX picked up slightly in 2010; after 2011, it stabilized at 30,000 PJ. DEU_FIN and DEU_INT (domestic energy use embodied in the final exports and intermediate exports and absorbed in the direct importer) accounted for over 70% of the GEEX, whereas DEU_INTrexI1 (the domestic energy use embodied in the intermediate exports and re-exported by the direct importer to a third country to produce domestic final use), DEU_INTrexF (the domestic energy use embodied in the intermediate exports and used by the direct importer to produce final goods and used in the third country), OEU_FIN (the energy use from the third country used in the final exports), and OEU_INT (the energy use from the third country used in the intermediate exports) dominated the remainder. The DEU proportion of China's gross energy use showed the same trends as the economic results throughout the study period, peaking in 2006 at 40% and stabilizing in 2013 and 2014 at approximately 26%. The proportion of DEU each year was slightly higher than the corresponding DVA proportion, implying that China's exports are more domestic energy-intensive than its domestic consumed products.

According to the trade pattern, the gross export can be classified as final trade [including DVA_FIN, MVA_FIN (the value added from the direct importer used in the final exports), and OVA_FIN] and intermediate trade [including the remainder 14 terms in equation (5)]. Correspondingly, the GEEX can be divided into GEEFX [gross energy embodied in final exports, including DEU_FIN, MEU_FIN (the energy use from the direct importer used in the final exports), and OEU_FIN] and GEEIX [gross energy embodied in intermediate exports, including the remaining 10 terms in equation (6)]; the decomposition results by trade pattern can be found in **Supplementary Figure 2**. The final trade accounted for more than half of China's total exports, and at the end of the study period, the share decreased to approximately 50%. The GEEFX accounted for over half of the GEEX before 2013, and the GEEIX exceeded 50% in 2013 and 2014.

In terms of the sources, the value added and energy embodied in China's exports can be divided into domestic and foreign contents, namely, DVA and FVA [foreign value added embodied in export, including MVA_FIN, MVA_INT (the value added from the direct importer used in intermediate exports), OVA_FIN, and OVA_INT]; DEU and FEU [foreign energy embodied in exports, including MEU_FIN, MEU_INT (the energy use from the direct importer used in intermediate exports), OEU_FIN, and OEU_INT]; the pure double-counting terms of exports are excluded, and the details can be found in the **Supplementary Figure 3**. Domestic sources dominated throughout the study period, with the DVA accounting for over 80% and DEU accounting for over 90% in most years. The proportion of domestic energy in China's exports was higher than that of the DVA, which indicates that the role of China's exports in creating economic benefits was less than that of stimulating energy consumption. The share of FVA was larger than the share of FEU, implying that China's exports drove more foreign economy compared to its dependence on foreign energy, especially during the period 2002-2008, in which China's exports showed extensive growth.

The EMDEI (export-embodied domestic energy intensity) of China can be calculated using equation (7). In contrast to the commonly used energy intensity in exports (gross energy consumption divided by gross exports), the EMDEI used in this study measures the domestic energy use when creating a unit of domestic value added through exports and is supposed to be a more effective index to evaluate the relationship between energy use and economic growth driven by a country's exports. The results of China's EMDEI for the period 2000-2014 are shown in **Figure 3**. The EMDEI of gross export decreased from 35.8 kJ/dollar in 2000 to 13.4 kJ/dollar in 2014. The energy intensity of the export products was higher than that of products consumed domestically, which further reflected that China's export product structure tended to be highly energy-dependent; although this phenomenon has improved since 2007, the export product structure still needs to be improved. The embodied domestic energy intensity of China's exports has been declining, mainly due to the general improvement in the energy efficiency of domestic production and partly due to the structural optimization of export products. The most striking finding is that China's EMDEI in gross exports continuously declined after 2003, and the EMDEI of the intermediate exports was always higher than that of the final exports, indicating that China needs to pay more energy cost to obtain economic benefits through the export of intermediate goods more than that of final goods.

Analysis at Bilateral Country Level

Analysis at the country aggregate level can only present an overview of energy flows embodied in China's exports. The analysis of the energy embodied in China's exports to different economies can provide further information based on spatial heterogeneity. The distribution of China's GEEX is presented in **Figure 4**, along with the proportions of the energy embodied in the final exports. 28 EU countries covered in the WIOT are analyzed as one region in this study, that is, EU28. According to the figure, the rest of the world (ROW), the United States, EU28, Japan, and Korea were the top five importers of China in terms of the gross export embodied energy, accounting for over 60% of China's GEEX

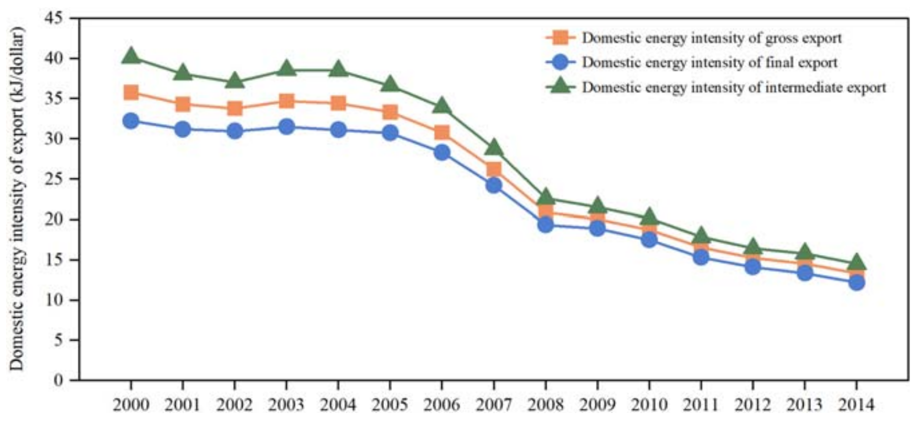

FIGURE 3 | Embodied domestic energy intensity of China's exports.

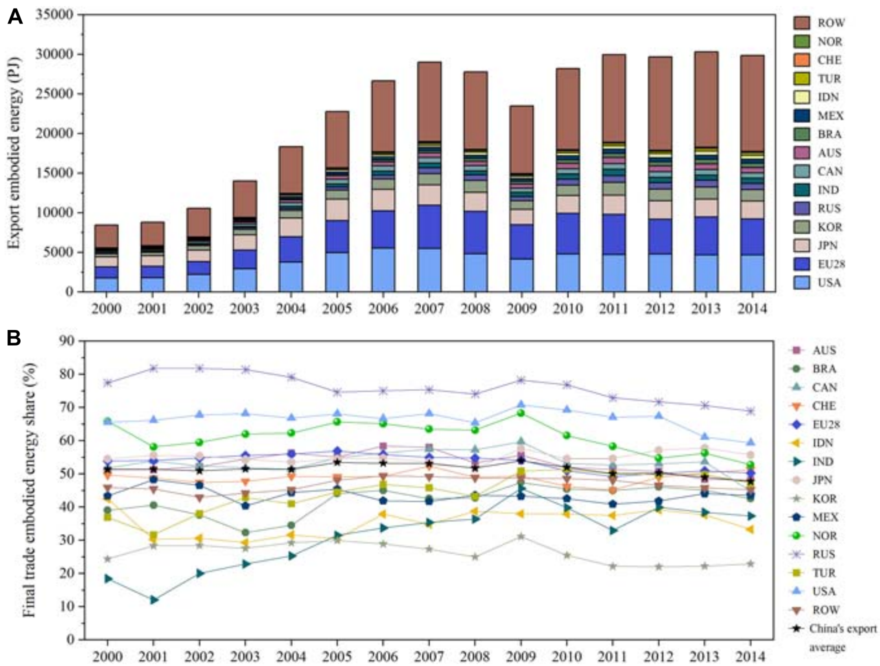

FIGURE 4 | Energy embodied in China's export to each importer and the corresponding proportion of energy embodied in final exports; graphs are provided for **(A)** gross export embodied energy and **(B)** proportion of final export embodied energy.

calculated during the whole study period; the United States is the largest individual importer except for the country groups, such as ROW and EU28. In addition, developing countries, like Brazil, India, and Indonesia, accounted for a growing proportion.

Trade patterns of embodied energy varied widely between the importers of China's exports, and according to **Figure 4**, the GEEFX proportions of the GEEX in China's exports to each importer (hereinafter referred to as "the proportion" in this paragraph) varied significantly. The proportion of China's exports to Russia was the largest, followed by the exports to the United States and Norway. In addition, except for the top three countries, the proportions of exports to Japan, EU28, Australia, and Canada were higher than the proportion of China's aggregate exports. The proportion of exports to India was the lowest before 2004, and since then, South Korea has occupied the last rank. Except for these two importers, the proportions of exports to the Czech Republic, Turkey, Mexico, Brazil, Indonesia, and ROW were lower than the proportion of China's aggregate exports in most years during the study period. To sum up, the embodied energy is exported to developed economies, mainly through final goods, and to developing economies, mainly through intermediates.

The analysis of the GEEX sources can reveal the dependence of China's exports on different energy sources. The GEEX sources of export to the importers are shown in **Figure 5**, and three types of energy sources were analyzed in this study, including domestic energy, energy from the direct importer, and energy from the third-party (energy from all countries and regions except for China and the direct importer). Domestic energy supplied the vast majority of export energy demand, over 87% as calculated, and foreign sources were mainly from a third-party, with a small part also from direct importers themselves. The domestic share was higher in 2000 as a whole and lower in 2007 and 2014. The source mix varied for different importers; the DEU share of exports to the United States was the lowest, whereas the share of exports to Korea was higher than the share of exports to other economies. The DEU share of exports to India ranked third in 2000 and 2005 and was replaced by Mexico in 2010 and 2014. The share of energy from the importer itself was larger in China's exports to Russia and ROW than to other importers, while the share of energy from the third-party in exports to Brazil and the United States was the highest.

The GEEX does not come from one source, and the DEU is not completely absorbed by the direct importers. **Figure 6** shows the destinations where the DEU was finally absorbed, and three types of final destinations were analyzed in this study, including the direct importer, the third-party (energy absorbed in all countries and regions except for China and the direct importer), and returned home (absorbed in China), and the energy absorbed in the former two destinations is the part of domestic energy that is really exported to foreign countries and regions. In general, over 70% of domestic value added was absorbed in the direct importers for export to most countries. The share that is absorbed in direct importer was higher, the corresponding value chain of the export products was shorter. The share of DEU absorbed by the direct importer in exports to the United States was the highest, followed by the export to Russia, Brazil, Australia, and Japan. The share of DEU returned home in exports to Korea was

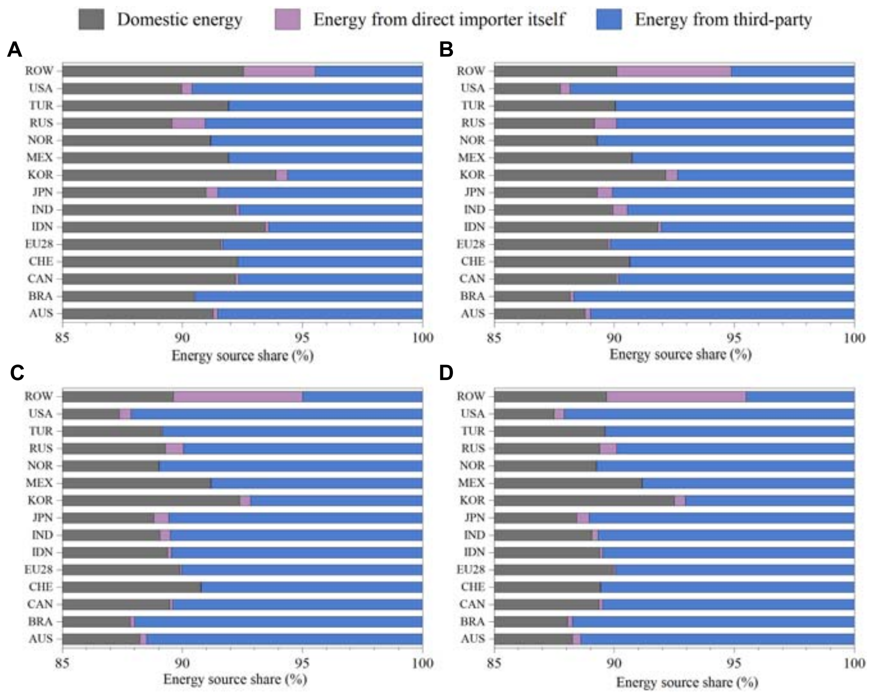

FIGURE 5 | Embodied energy sources of China's export to each importer; graphs are provided for **(A)** 2000, **(B)** 2005, **(C)** 2010, and **(D)** 2014.

evidently higher than those of exports to other importers. The share of DEU absorbed by the third-party in exports to Mexico was the highest, followed by the exports to Korea.

The EMDEI varies among importers, and differences exist in final exports and intermediate exports. The details of EMDEI in the gross exports, final exports, and intermediate exports (to each

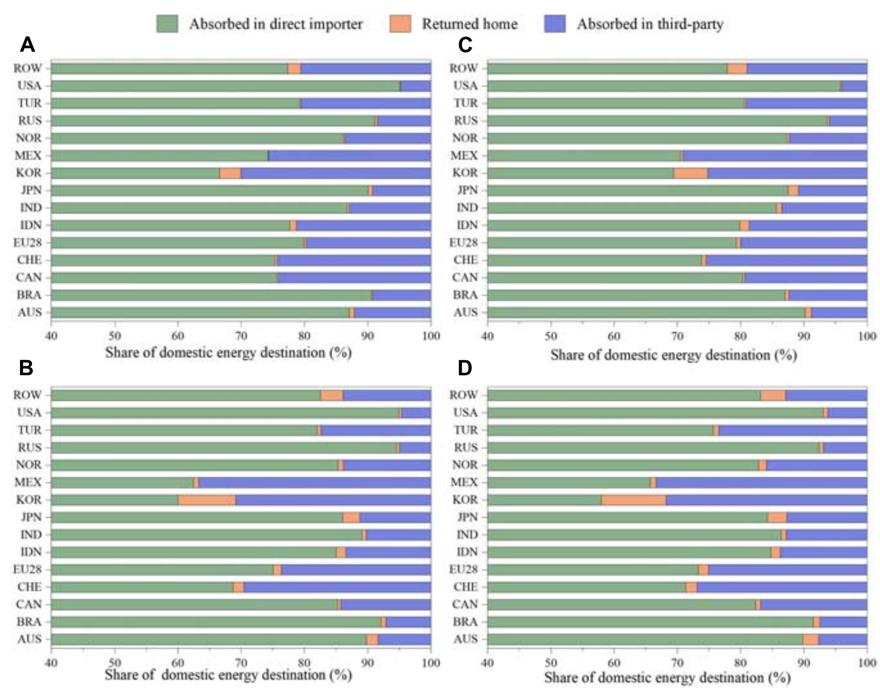

FIGURE 6 | Final destination of embodied domestic energy in China's export to each importer; graphs are provided for **(A)** 2000, **(B)** 2005, **(C)** 2010, and **(D)** 2014.

importer) can be found in **Supplementary Figure 4**. The EMDEI generally showed a significant decline in the gross exports and final exports, and the range of difference among importers in the final export was the smallest, whereas in intermediate exports it was the largest. The EMDEI in the gross exports decreased from 30 kJ/dollar to 48 kJ/dollar to less than 20 kJ/dollar in the exports to all the importers. In 2014, the EMDEI in the gross exports to India was the highest, followed by the EMDEI in the gross exports to Korea and Turkey; the EMDEI in gross exports to Russia was the lowest, followed by the EMDEI in the gross exports to ROW, Norway, the Czech Republic, and EU28. The EMDEI in the final exports decreased from 27 kJ/dollar to 38 kJ/dollar to less than 15 kJ/dollar in exports to all the importers. In 2014, the EMDEI in the final exports to Mexico was the highest, followed by the EMDEI in the final exports to Turkey, India, Brazil, Australia, EU28, and the United States, and the EMDEI in final export to Russia was the lowest, followed by the EMDEI in the final exports to ROW, the Czech Republic, Korea, Japan, and Norway. For EMDEI in intermediate exports, the value varied in a wide range among economies, and the value in the intermediate exports to India (in 2001 and 2002) and Korea were largest, whereas the value in the intermediate exports to Russia was lower than that in the intermediate exports to other economies. In 2014, the EMDEI in the intermediate exports to Korea was much higher than that of others, whereas in the intermediate exports to Russia it was the lowest, followed by the United States, Norway, and Japan. Except for Korea, both China's intermediate and final exports to developing economies have higher export-embodied domestic energy intensities, while its exports to developed economies have lower embodied domestic energy intensities. However, the domestic energy intensity of China's intermediate and final export to the United States varies highly; the final export to the United States has a higher domestic energy intensity than the final export of other countries. However, in the case of intermediate export, the United States has a lower domestic energy intensity than the intermediate export of other countries; this is because the final products that the United States imports from China are mainly clothing, textiles, and other manufacturing products having a high energy intensity, whereas the intermediate imports include services having a low energy intensity.

Analysis at Sector Aggregate Level

Analysis at the sector level can provide further information about the energy flows embodied in China's exports according to sector heterogeneity. In this study, we have segregated the decomposition results based on equations (5) and (6) according to 18 sectors, and the results at the sector aggregate level are presented in this section. As mentioned in the previous section, the analysis at the sector level shows a distinction between the forward and backward linkage measures. The forward linkage measure focuses on the source sector, including the energy (or value added) from this sector, and is embodied in the gross exports of other sectors, whereas the backward linkage measure focuses on the export sector, including all the energy (or value added) from other sectors, and is embodied in this given sector's gross exports.

The domestic value added and energy embodied in each sector's gross exports are shown in **Figure 7**. The sector mix differed widely between the forward and backward linkage measures. As for DVA (the embodied domestic value added) based on the forward linkage measure, the top three sectors were S.18 (other service activities), S.16 (wholesale and retail trade, accommodation, and food service activities), and S.10 (manufacture of electrical equipment and products); S.10, S.04 (manufacture of textiles, wearing apparel, and leather products), and S.16 (wholesale and retail trade, accommodation, and food service activities) were the top three sectors based on the backward linkage measure. For DEU (the gross embodied domestic energy) based on the forward linkage measure, S.14 (electricity, gas, steam, and water supply) was undisputedly the largest, followed by S.09 (Manufacture of basic metals and metal products) and S.07 (chemical industry), whereas the top three sectors based on the backward linkage measure were S.10, S.09, and S.07. Except for that S.10 ranks top three in terms of both its contribution to DVA and DEU based on the two measures; there is a mismatch between the main sectors that create the economic benefits from the exports and the main sectors that consume energy for the exports. In general, the light industry and the services create more benefits, whereas manufacturing, such as chemicals and metal products, consumes more energy.

The export patterns of the sectors differ greatly, and **Figure 8** presents the GEEFX (energy use embodied in gross final exports) proportion of the GEEX (energy use embodied in gross exports) in each sector (hereinafter referred to as "the proportion" in this section) based on the backward linkage and forward linkage measures. When using the forward linkage measure, the proportions of the sectors can be divided into four grades: the first grade includes S.13 (other manufacturing) and S.04 (manufacture of textiles, wearing apparel, and leather products), of which the proportions were much higher than other sectors (over 75%), implying that the energy in these sectors was almost exported embodied in the final goods; the second grade includes S.03 (manufacture of food products, beverages, and tobacco products), S.10 (manufacture of electrical equipment and products), S.01 (agriculture, forestry, fishing, and related service activities), S.11 (manufacture of machinery and equipment n.e.c), and S.12 (manufacture of transport equipment), of which the proportions ranged between 55% and 70%; the third grade includes S.05 (manufacture of products of wood and cork), S.14 (electricity, gas, steam, and water supply), S.16 (wholesale and retail trade, accommodation, and food service activities), S.06 (manufacture of article, printing, and reproduction), S.18 (other service activities), S.07 (chemical industry), S17 (transportation, warehousing, postal, and telecommunications), S.09 (manufacture of basic metals and metal products), S.02 (mining and quarrying) after 2003, and S.08 (manufacture of other non-metallic mineral products) before 2010, of which the proportions ranged between 40% and 55%; and the last grade included S.15 (construction), S.02 before 2003 and S.08 after 2010, of which the proportions were lower than 40%. The situation differed when using the backward linkage measure, and the proportions of sectors can be clearly divided into three grades: the first grade includes S.13, S.03, and S.04, of

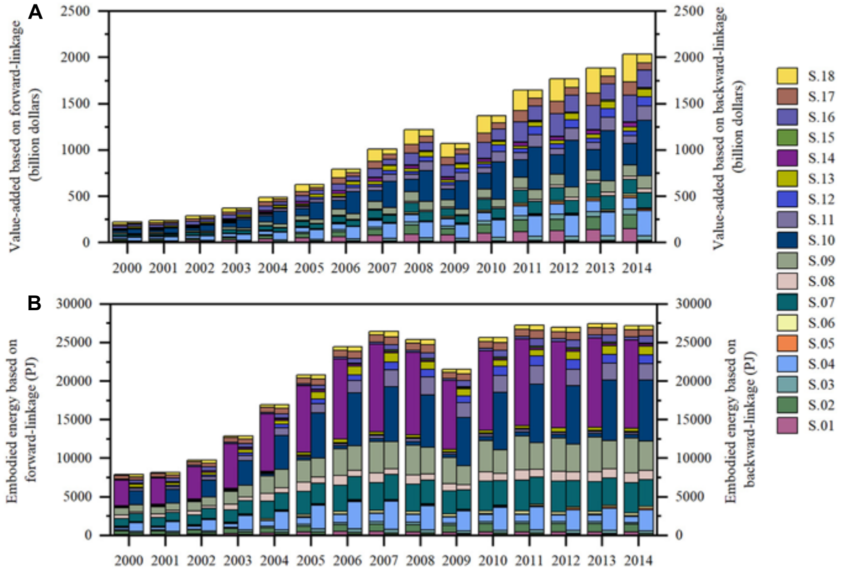

FIGURE 7 | Export embodied domestic value added and domestic energy at sector aggregate level based on forward and backward linkages; graphs are provided for **(A)** domestic value added embodied in each sector's export and **(B)** domestic energy embodied in each sector's export.

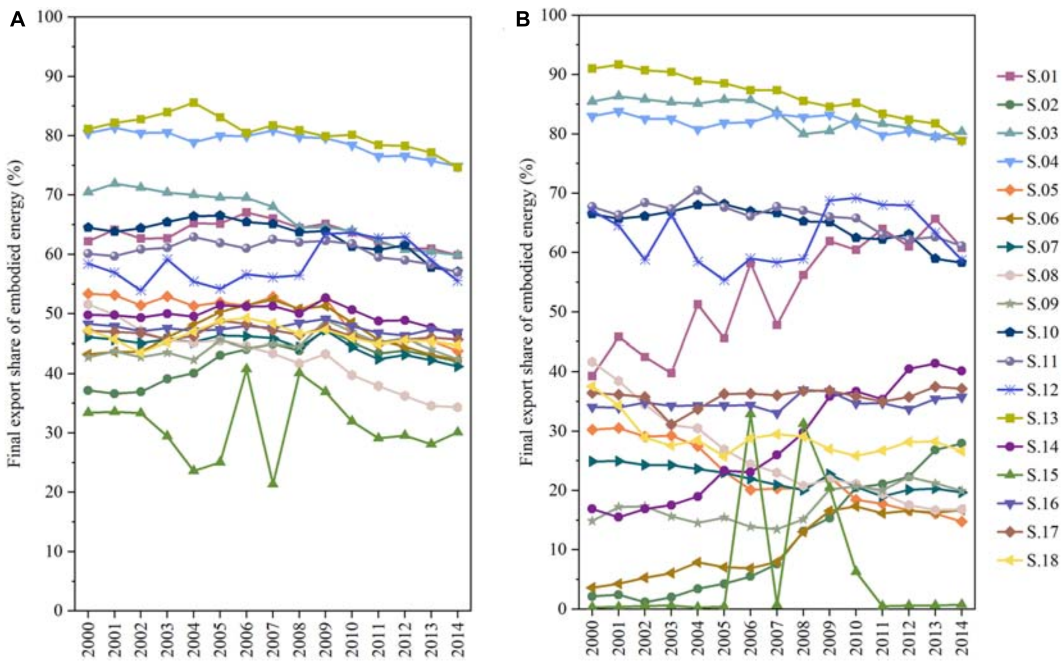

FIGURE 8 | Share of final export embodied energy in the sector's gross export embodied energy; graphs are provided for **(A)** forward linkage and **(B)** backward linkage.

which the proportions were higher than 80%, implying that the energy exported through these sectors almost embodied in the final goods; the second grade includes S.11, S.10, S.12, and S.01 for most years, of which the proportions were higher than 50%; the third grade includes the other sectors, of which the proportions were almost lower than 40%, and the proportion of construction sector (S.15) in this grade was approximately 0 for most years because this sector scarcely directly exported products.

Figure 9 shows the sources of the GEEX in each sector. The domestic source generally dominated each sector's GEEX, followed by the energy from the third-party, and the share of energy from the direct importer was the least. Based on the forward linkage measure, the sector ranks by domestic source

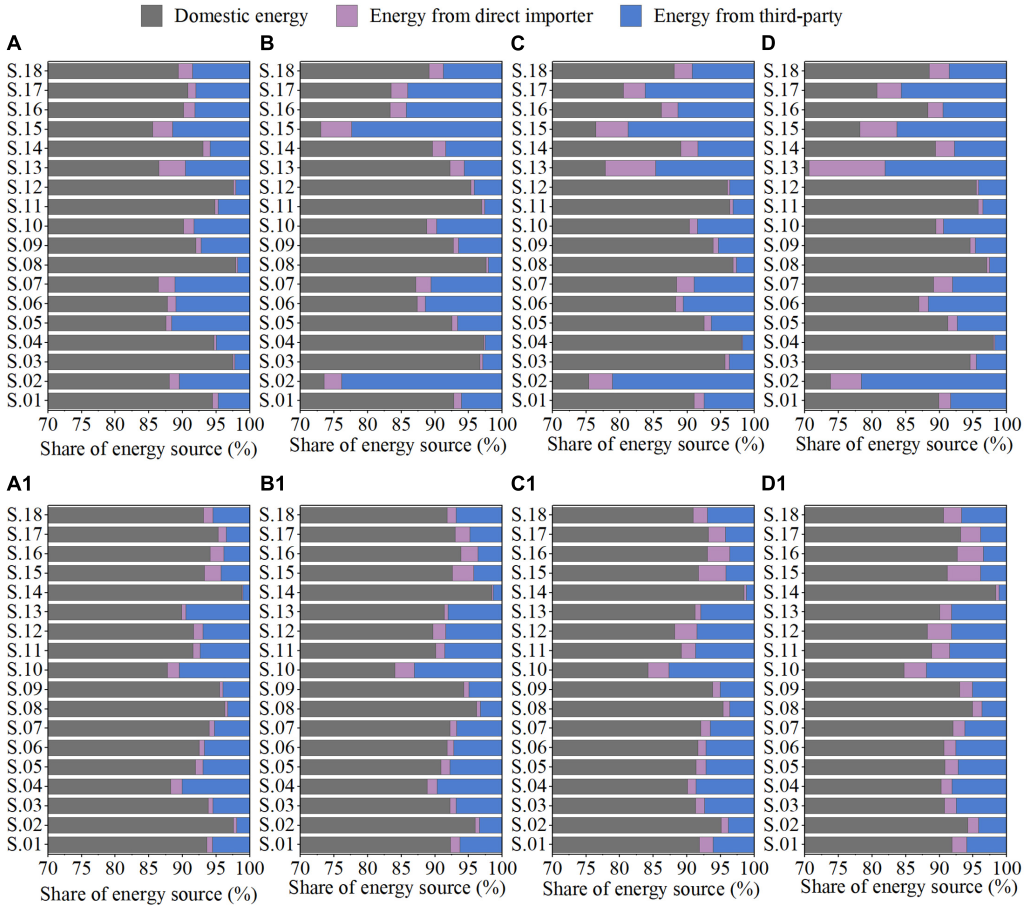

FIGURE 9 | Embodied energy source of each sector's export; graphs are provided for forward linkage-based measure in **(A)** 2000, **(B)** 2005, **(C)** 2010, and **(D)** 2014 and backward linkage-based measure in **(A1)** 2000, **(B1)** 2005, **(C1)** 2010, and **(D1)** 2014.

share differed in various years; for example, the domestic energy share of S.02 (mining and quarrying) and S.15 (construction) ranked as the lowest two in 2005 and 2010, respectively, whereas S.13 (other manufacturing) had the lowest domestic source share in 2014. However, when using the backward linkage measure, the sector ranks of the domestic source share were relatively stable, and S.14 (electricity, gas, steam, and water supply), S.02, S.08 (manufacture of other non-metallic mineral products), and S.09 (manufacture of basic metals and metal products) ranked in the top four, and S.10 (manufacture of electrical equipment and products) occupied the bottom position.

Figure 10 presents the share of destinations where the DEU of each sector is finally absorbed. Based on the forward linkage measure, over 75% of the DEU in each sector was absorbed by the direct importers, and the proportions in S.13 (other manufacturing), S.04 (manufacture of textiles, wearing apparel, and leather products), S.03 (manufacture of food products, beverages, and tobacco products), and S.01 (agriculture, forestry, fishing, and related service activities) ranked in the top four. In general, the share that finally returned home grew over time. The share that was finally absorbed by the third-party was higher in S.02 (mining and quarrying), S.07 (chemical industry), and S.09 (manufacture of basic metals and metal products) than in other sectors. When using the backward linkage measure, the share of DEU that was absorbed by the direct importer in S.13, S.03, S.04, and S.01 ranked in the top four, similar to the results obtained using the forward linkage measure; the shares in S.02 and S.09 ranked the lowest in 2000 and 2005, whereas S.07 took the place of S.09 in 2010 and 2014. The share that finally returned home also grew over time in most of the sectors, and this share in S.02, S.07, and S.09 was relatively larger than in other sectors. The share that was finally absorbed by the third-party in S.02, S.07, and S.09 ranked in the top three, whereas the share in S.03, S.04, and S.13 ranked in the bottom three.

The sector EMDEI measures the domestic energy use for creating a unit of domestic value added through exports, that is, the energy cost of economic income derived from the exports for each sector, and the result is shown in **Figure 11**. Moreover, the forward linkage-based EMDEI of a sector actually means the energy use in this sector for the country to create a unit domestic value added through exports. Based on this measure, the EMDEI of S.14 (electricity, gas, steam, and water supply) was much higher than the value of other sectors, and the value in 2014 was approximately 230 kJ/dollar, equivalent to 40% of

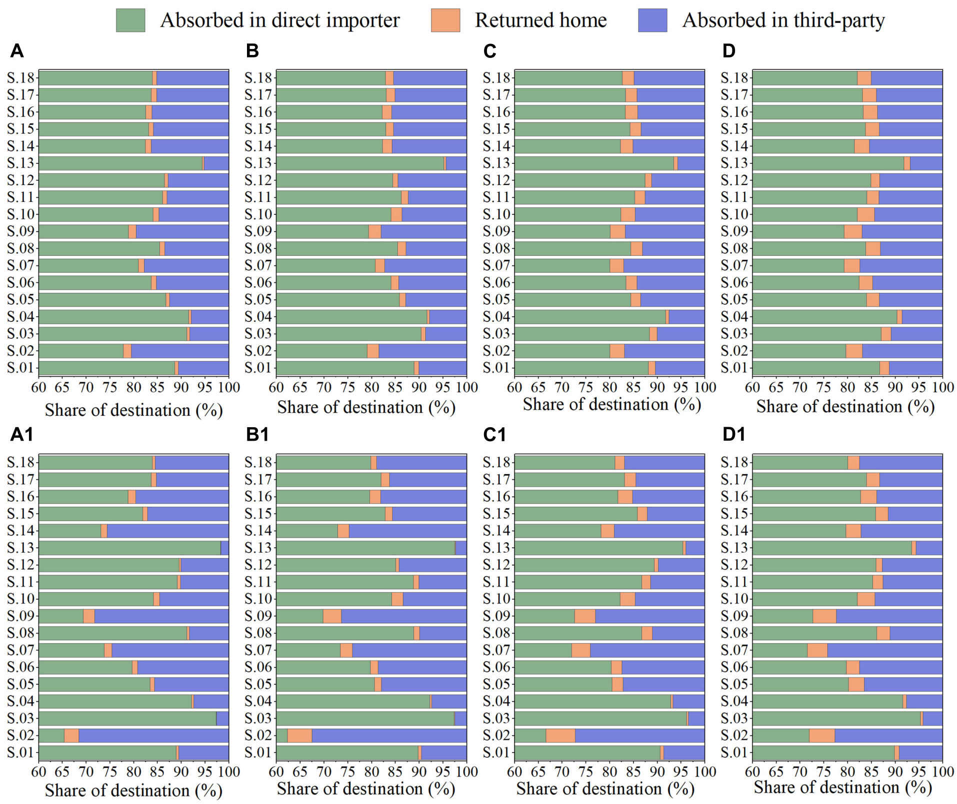

FIGURE 10 | Embodied domestic energy destination of each sector's export; graphs are provided for forward linkage-based measure in **(A)** 2000, **(B)** 2005, **(C)** 2010, and **(D)** 2014 and backward linkage-based measure in **(A1)** 2000, **(B1)** 2005, **(C1)** 2010, and **(D1)** 2014.

the value in 2000. The EMDEI of S.08 (manufacture of other non-metallic mineral products) ranked second, declining from 102 kJ/dollar in 2000 to 40 kJ/dollar in 2014, and different from the tortuous downward trend of other sectors, the value of this sector smoothly ascended to the peak in 2004 to later decline. The EMDEIs of S.09 (manufacture of basic metals and metal products) and S.07 (chemical industry) ranked third and fourth, respectively, and that of S.06 (manufacture of article, printing, and reproduction) stably ranked fifth after 2005. In 2014, except for the top five sectors, S.13 (other manufacturing) had the highest value, followed by S.02 (mining and quarrying), S.04 (manufacture of textiles, wearing apparel, and leather products), and S.05 (manufacture of products of wood and cork). The value of S.16 (wholesale and retail trade, accommodation, and food service activities) was the lowest, followed by those of S.15 (construction) and S.10 (manufacture of electrical equipment and products).

The backward linkage-based EMDEI of each sector calculates the energy use to create a unit domestic value added in the whole country through exports in this sector. Based on this measure, the EMDEI of S.14 was much higher than the value of other sectors, but much lower than the value based on the forward linkage measure. The EMDEIs of S.08, S.09, and S.07 ranked second, third, and fourth, respectively, the same as the forward linkage-based measure, and the EMDEIs of other sectors showed a downward trend and were generally higher than those based on the forward linkage measure. In 2014, except for the mentioned top four sectors, the EMDEI of S.06 was the highest, followed by that of S.02 and S.15, whereas the value of S.16 was the lowest, followed by that of S.18 (other service activities), S.01 (agriculture, forestry, fishing, and related service activities), and S.03 (manufacture of food products, beverages, and tobacco products). In addition, the EMDEIs of the chemical industry and metal and non-metallic equipment manufacturing industries were the highest (based on the forward and backward-linkage measures), implying that these sectors need to pay the greatest cost of energy when China creates domestic economic benefits through exports. The costs of energy were also higher for these sectors to create economic income through exports than as compared to other sectors. Therefore, improving the export structure and reduce the proportion of these sectors' products in total exports, as well as fundamentally improving the technical level of these sectors and promote their energy efficiency in production are conducive for China's energy conservation.

Analysis at Sector-Country Level

The results at the country aggregate and bilateral country levels are presented in the previous subsections, along with the results obtained at the sector aggregate level. **Figure 12** shows the energy flows embodied in China's export at the sector-country level in 2000 and 2014. In each chord diagram, the nodes in

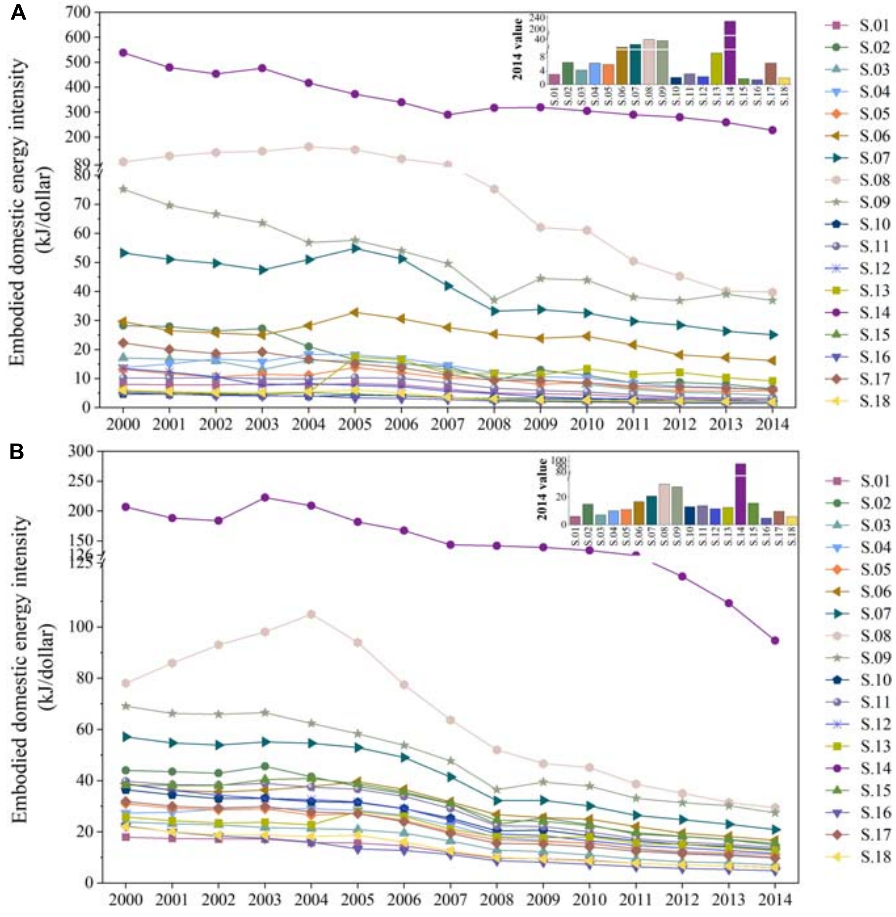

FIGURE 11 | Export embodied domestic energy intensity of each sector; the graphs are provided for **(A)** forward-linkage based measure and **(B)** backward-linkage based measure.

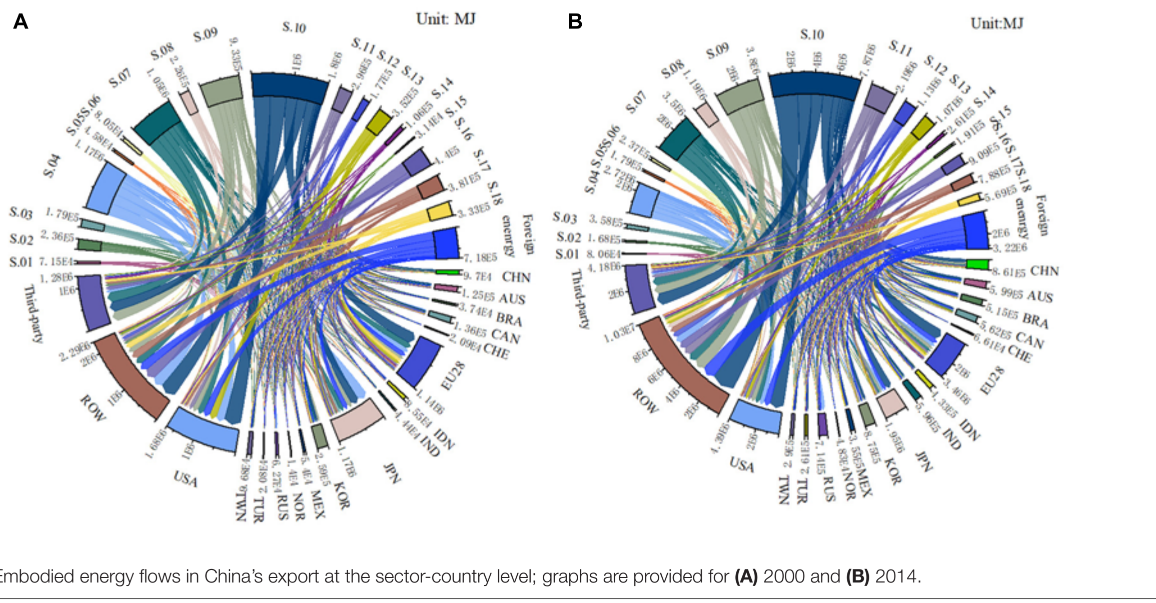

FIGURE 12 | Embodied energy flows in China's export at the sector-country level; graphs are provided for **(A)** 2000 and **(B)** 2014.

the upper half (proceeding clockwise from "S.01" to "S.18") represent the DEU in each sector's export (based on backward linkage measure), and "Foreign energy" represents the foreign energy embodied in China's export; these nodes are source nodes, representing the energy sources of China's GEEX (energy embodied in gross exports). The nodes proceeding clockwise from "CHN" to "Third-party" in the lower half represent the destinations where the embodied energy is finally absorbed. The destination node of "CHN" represents the DEU (domestic energy embodied in exports) that is exported at first and finally returns home and is absorbed by China; the node of "Third-party" represents the gross value of the DEU that was absorbed by the third-party. The lines from the source nodes to the destination nodes represent the scales of the embodied energy flows.

As shown in **Figure 12**, the details of the results over these two years vary significantly; a few examples are given below. Comparing the results of 2014 to 2000, the scale of China's GEEX increased, and the foreign energy share also slightly increased. The share of the DEU that returned home also increased significantly; the main sources were S.09 (manufacture of basic metals and metal products) and S.10 (manufacture of electrical equipment and products). The sector share decreased evidently in S.01 (agriculture, forestry, fishing, and related service activities), S.02 (mining and quarrying), S.03 (manufacture of food products, beverages, and tobacco products), S.04 (manufacture of textiles, wearing apparel, and leather products), S.16 (wholesale and retail trade, accommodation, and food service activities), S.17 (transportation, warehousing, postal, and telecommunications), and S.18 (other service activities), while increased obviously in S.08 (manufacture of other non-metallic mineral products), S.09, S.10, S.11 (manufacture of machinery and equipment n.e.c), and S.12 (manufacture of transport equipment). The destinations of sectors also varied, and some sectors showed their unique distribution of destinations, while for other sectors, the distribution of importers was ranked by their gross import volume from China. For instance, the GEEX of S.13 (other manufacturing) was mainly absorbed by the United States and EU28, while the ROW was China's largest importer in 2000. The share of S.13 to ROW increased evidently. In general, the GEEX was mainly absorbed by the EU28, ROW, and third-party in both years.

Overall, the United States and EU28 have been China's largest energy importers, except for the ROW and Japan (whose share fell sharply in 2014). Therefore, this study further analyzes these two key importers more specifically. The detailed energy flows embodied in China's export to the United States in 2014 are shown in **Figure 13**, and the energy flows embodied in China's exports to the United States in 2000 and exports to EU28 in 2000 and 2014 can be found in **Supplementary Figures 5–7**.

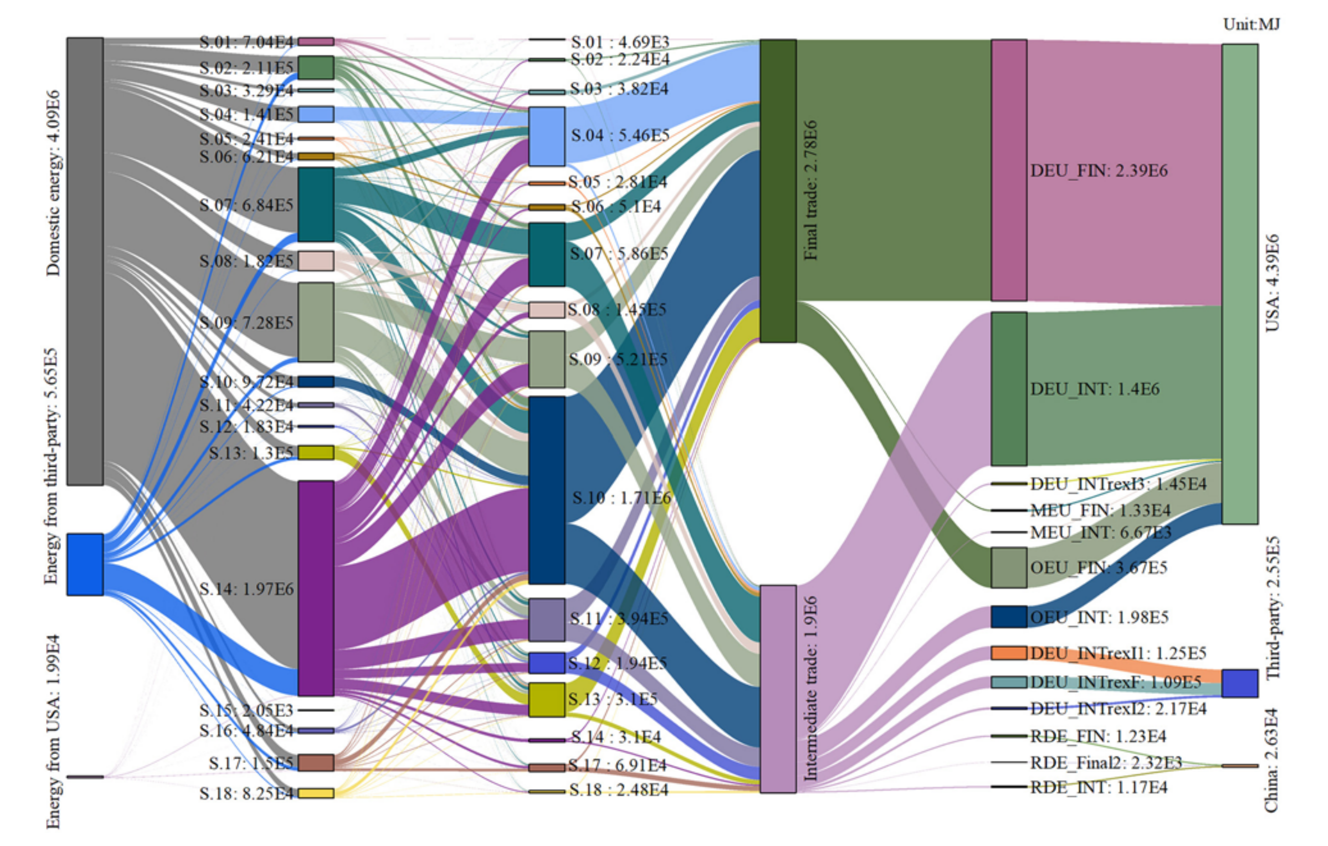

FIGURE 13 | Energy flows embodied in China's export to the United States in 2014.

As shown in **Figure 13**, from left to right, the first column represents t, which is the total energy embodied in China's export to the United States in 2014 from different sources, including domestic energy (that is, from China), energy from third-party (that is from other countries and regions except for China and the United States), and energy from the United States itself. The second column represents the forward linkage sectors that initially consume domestic energy (or foreign energy in intermediates) to produce products. The line between domestic energy and each sector is the domestic energy directly used for each sector's production, while the other two sources are the foreign intermediate goods directly used for each sector's production. The third column represents the backward linkage sectors that finally export products to the United States, and the line from the second column to the third column is the flow of the total energy embodied in China's exports to the United States in the domestic value chain stage. The fourth column shows the export patterns, that is, the energy embodied in the final products and embodied in the intermediate products. The fifth column contains 13 parts, which are the 13 terms in GEEX decomposition framework of this article, and represents the transfer routes of the embodied energy flows. The last column represents the final destination where the embodied energy of China's exports is finally absorbed, including energy that is absorbed in the United States, energy that is absorbed by third parties (other countries and regions except for China and the United States), and energy that returns to China and is absorbed.

Comparing the results of exports to the United States for the year 2014 (referring to **Figure 13**) with that of 2000 (referring to **Supplementary Figure 5**), the overall size of the embodied energy flows increased by a factor of 1.5, whereas the share of domestic sources decreased slightly and the share of third-party sources increased. The sector mix based on both the forward and backward linkages changed in a way. The top five source sectors were S.14 (electricity, gas, steam, and water supply), S.07 (chemical industry), S.09 (manufacture of basic metals and metal products), S.08 (manufacture of other non-metallic mineral products), and S.02 (mining and quarrying) in 2000, while changed slightly to S.14, S.09, S.07, S.02, and S.08 in 2014. The top five export sectors were S10 (manufacture of electrical equipment and products), S.04 (manufacture of textiles, wearing apparel, and leather products), S.13 (other manufacturing), S.07, and S.09 in 2000, while S.10, S.07, S.04, S.09, and S.11 (manufacture of machinery and equipment n.e.c) ranked in the top five in 2014. In addition, no energy was exported to the United States through S.15 (construction) and S.16 (wholesale and retail trade, accommodation, and food service activities). Furthermore, the share of energy embodied in the intermediate exports increased obviously in 2014. As for the final destination, the share of domestic energy absorbed by the United States decreased slightly, whereas that of the other two increased slightly.

At the sector level, the structures of energy source sectors and export sectors were relatively different. In 2014, as for the source sector, S.14 (electricity, gas, steam, and water supply), S.09 (manufacture of basic metals and metal products), and S.07 (chemical industry) contributed the most, whereas S.10 (manufacture of electrical equipment and products), S.07, and S.04 (manufacture of textiles, wearing apparel, and leather products) exported the most. There were also significant differences in the transfer between the forward and backward sectors. For example, the energy used in S.04 was mainly exported to the United States through S.04 itself, but the energy used in S.14 was mainly exported through other sectors. In addition, the energy used in S.15 (construction) and S.16 (wholesale and retail trade, accommodation, and food service activities) was exclusively exported to the United States through other sectors. Trade patterns also differed among the sectors, as the exports of S.04, S.10, and S.13 (other manufacturing) were mainly through final goods while intermediate export was the main way for the export of S.07, S.12 (manufacture of transport equipment), and S.17 (transportation, warehousing, postal, and telecommunications).

Comparing the results of exports to the EU28 for the year 2014 (referring to **Supplementary Figure 7**) with those obtained for 2000 (referring to **Supplementary Figure 6**), it can be found that the overall scale of the embodied energy flows increased by 2.4 times, whereas the share of domestic source decreased, and the share of the third-party source and energy from EU28 itself both increased. There were no significant changes in the source sector mix, except for an obvious increase in S.13 (other manufacturing) and a decrease in S.08 (manufacture of other non-metallic mineral products) and S.17 (transportation, warehousing, postal, and telecommunications). The top five export sectors were S.10 (manufacture of electrical equipment and products), S.07 (chemical industry), S.04 (manufacture of textiles, wearing apparel, and leather products), S.09 (manufacture of basic metals and metal products), and S.18 (other service activities) in 2000, but changed to S.10, S.07, S.09, S.04, and S.11 (manufacture of machinery and equipment n.e.c) in 2014. The share of the energy embodied in the final exports increased obviously, whereas that of the intermediate exports decreased. As for the final destination, the share of the domestic energy that was absorbed by the EU28 decreased evidently, and the shares that returned home and was finally absorbed by the third-party both increased.

In 2014, as for the source sectors, S.14 (electricity, gas, steam, and water supply), S.09 (manufacture of basic metals and metal products), and S.07 (chemical industry) contributed the most, while S.10 (manufacture of electrical equipment and products), S.07, and S.09 exported the most as the backward sectors. Notably, the embodied energy flows of China's exports to EU28 differed considerably from those of China's exports to the United States in various details. For instance, the source sector structures in both cases were similar; although the backward sector mix was similar in 2014, it differed widely in 2000. S.18 (other service activities) accounted for a significant share of the gross embodied energy flows from China to EU28 as a backward sector, sourcing from S.14 and S.18 itself, while the embodied energy of China's exports to the United States seldom flows through S.18 directly. Furthermore, there were some energy flows exported to EU28 through S.15 (construction) and S.16 (wholesale and retail trade, accommodation, and food service activities) despite a decrease in the share in 2014, whereas in the case of United States, there was no direct export through these two sectors. Another difference is the trade pattern of S.10 (in the case of EU28), the export pattern of S.10 was represented by a 50/50 split between the final and intermediate exports in 2014. Additionally, the share of intermediate exports in 2014 increased evidently compared with the share in 2000, which is inconsistent with the evolution of the export trade pattern distribution of China's total exports to EU28. However, in the case of exports to the United States, the evolution of the export trade pattern of S.10 was consistent with the trend of China's total exports to the United States, showing the trend of an increase in the intermediate export exports.

DISCUSSION AND IMPLICATIONS

At the country aggregate level, China exported a large amount of embodied energy, while other countries avoid a large amount of domestic energy use by consuming China's products. Since the energy data used in this study are emission-related energy use, it suggests that China also exported large amounts of carbon emissions to meet the demand for other countries and regions, which shows that China's exports have changed the global energy consumption and carbon emission pattern to a certain extent. Taking both the embodied energy and the economy into consideration, the role of exports in China's economic development and energy consumption showed an initial rise followed by a decline, while peaking in 2006. Moreover, according to the decomposition of China's gross exports, there is a growing share of pure double countings, which cannot be recognized and excluded in the traditional gross value accounting and lead to an overestimation of the gross exports volume. Thus, the TiVA accounting and global value-chain theory used in this study do perform better in international trade analysis. The share of domestic energy in the two patterns of trade, that is, the final exports and intermediate exports, was similar to the trade pattern share of value added. Each of these two export routes accounted for approximately half of the gross value of the exports, which was inconsistent with the trend that the share of intermediate trade was in a rapid expansion globally, due to China's downstream position in the global value chain and its participation in global production through the processing and assembly of supplied materials. The ratio of domestic content in gross exports indicates the ability to create value added per unit of energy consumption. The ratio rising means that there are some local market advantages, such as a low cost of transportation or low cost of high-skilled labor (Liu et al., 2020a). The ratio of domestic content in China's gross export showed a decreasing trend before 2007 and an increasing trend thereafter, reflecting the growing competitiveness of China's exports in the later study period. The higher the proportion of domestic components of embodied energy, on the one hand, it can be considered that exports are more dependent on domestic energy supply, or that the domestic self-sufficiency rate of export embodied energy is relatively high. But from another point of view, about 90% of the fossil energy embodied in China's exports is supplied domestically, indicating that China mainly acts as a supplier of fossil energy in its export production and its participation in the global value chain. The energy intensity of the export products was higher than that of products consumed domestically, which further reflected that China's export product structure tended to be highly energy-dependent; the domestic energy intensity of the intermediate exports was higher than that of the final exports, indicating that China needs to pay more energy cost to obtain economic benefits through the export of intermediate goods more than that of final goods. This result suggests that China's participation in global production is more inclined towards high-energy consumption, even upstream of the production chain, and is more inclined to be an energy supplier with high-energy consumption and low income, rather than to be in the research and development stage of low-energy consumption and high income. Previous literature has shown that China's energy intensity and carbon intensity are higher than those of many developed countries. Developed countries imported products with high energy intensity and carbon intensity from China to reduce their domestic energy use and carbon emissions and to reach their carbon emission reduction targets. However, from a global point of view, the imbalances of energy and carbon intensities between China and developed countries may lead to a growth of global carbon emissions, which increases the risk of global carbon leakage. Thus, optimizing the energy structure and declining the energy intensity of China's exports are conducive to energy conservation and emission reduction in China and the whole world.

At the bilateral country level, the United States and EU28 are the top two importers, and the shares of Brazil, India, and Indonesia are also increasing. The embodied energy is exported to developed economies mainly through final goods, and to developing economies mainly through intermediates. Russia is a special case because China's exports to Russia are mainly concentrated in the fields of clothing, instruments, mechanical and electrical transport equipment, raw materials, chemical products, and agricultural products; these are mainly final goods. Compared with China's exports to other importers, China's export structure to South Korea is more in favor of energy-intensive intermediates. The exports to Korea are mainly concentrated in low-end mechanical and electrical products, base metals, and chemical products, and the export structures can be further improved. The embodied domestic energy intensities of China's intermediate exports differ significantly among importers, whereas the energy intensities of the final exports differ slightly, which is due to the greater difference in the importer distribution of China's intermediate exports. Except for Korea, both China's intermediate and final exports to developing economies, such as Mexico, India, Indonesia, and Turkey, have higher export-embodied domestic energy intensities, while its exports to developed economies, such as Norway, Japan, EU28, and the Czech Republic have lower embodied domestic energy intensities. Therefore, the international trade between China and emerging markets needs to be emphasized and embodied flows of fossil fuel energy and carbon emissions in these trades may be an increasingly important factor of global emission reduction.

At the sector aggregate level, there is a big difference based on the forward and backward linkage measures, whether for embodied value added analysis or embodied energy analysis. In general, the light industries and the services create more benefits, whereas manufacturing sectors, such as chemicals and metal products, consume more energy. There is a mismatch between the main sectors that create the economic benefits from the exports and the main sectors that consume energy for the exports. In fact, the transfer process between the forward-linkage sectors and backward-linkage sectors of energy flows is the energy transfer process in domestic value chains. The imbalances between the forward linkage and backward linkage measures are the effects of domestic value chains. Thus, the differences between the forward and backward linkage measures at the sector level deserve more attention. S.14 (electricity, gas, steam, and water supply) is the upstream sector of the production chain, and most of the energy embodied in exports is initially consumed in this sector. The energy in S.15 (construction) is almost exported embodied in the export of other sectors, and thus is easily neglected in the research of energy export. The construction sector is a special sector that needs attention in the study of export embodied energy. The domestic energy embodied in the exports of S.02 (mining and quarrying), S.07 (chemical industry), and S.09 (manufacture of basic metals and metal products) are more often absorbed by the third-party than the domestic energy embodied in other sectors' exports, because the production chains related to these sectors are longer, and thus, it is easier for these sectors to participate in global production. Therefore, enhancing the competitiveness of these sectors in global trade and promoting the energy efficiency of their productions are conducive to improving China's position in the global value chain and achieve the country's goal of energy reduction. The EMDEI of S.14 is significantly higher than that of other industries, and the energy consumption of this sector is mainly due to the production of electricity; therefore, optimizing the power supply structure of China may effectively improve China's export embodied energy intensity, and is conducive to China's energy conservation and emission reduction. In addition, the EMDEIs of the chemical industry and metal and non-metallic equipment manufacturing industries are the highest (based on the forward and backward-linkage measures), implying that these sectors need to pay the greatest cost of energy when China creates domestic economic benefits through exports. Additionally, the costs of energy are also higher for these sectors to create economic income through exports than as compared to other sectors. Therefore, improving the export structure and reducing the proportion of these sectors' products in total exports, as well as fundamentally improving the technical level of these sectors and promoting their energy efficiency in production are conducive to China's energy reservation and emission reduction, as well as to the global emission reduction.

At the sector-country level, the domestic energy embodied in some sectors showed a unique distribution of destinations, although, for many sectors, the distribution of importers was ranked by their total import volume from China. In addition, the energy source and export sectors have extremely different structures, and the energy flows from the source sector to the export sector reflect the embodied energy transfer routes in the domestic supply chain. The embodied energy flows of China's exports to the EU28 are relatively different from those in exports to the United States. Although EU28 and the United States are both major importers of China, the flow routes of the export embodied energy vary significantly, and even in their domestic value chain stage, the flow routes between the source and export sectors are different.

CONCLUSION AND OUTLOOKS

This study presents a detailed analysis of the energy embodied in China's exports at the country aggregate, bilateral country, sector aggregate, and sector-country levels in terms of the gross value, trade patterns, energy sources, and domestic energy destinations. The export embodied domestic energy intensity is calculated to show the energy cost required to create a unit domestic value added through exports. The major conclusions are as follows.

(1) In terms of total volume, China's export embodied energy is very large, and the domestic energy use proportion of China's gross energy use was high (although declining after 2006, but still at 26% at the end of the study period), and to a certain extent, China's embodied fossil fuel energy exports have changed the pattern of world energy consumption, as well as the carbon emission. This finding well confirms China's unique position as a "world processing plant" in international trade, and proves that export is an important factor that cannot be ignored to promote the rapid growth of China's energy and emissions. Optimizing the energy structure of China's exports is conducive to energy conservation and emission reduction in China and the whole world.
(2) The proportion of domestic energy in China's exports was higher than that of the domestic value added; China's exports in creating economic benefits were less than that of stimulating energy consumption. The energy intensity of the export products was higher than that of products consumed domestically, and China's export structure is still characterized by high-energy consumption and needs to be continuously optimized. China's participation in global production is more inclined to high-energy consumption, even in the upstream of the production chain, and is more in the initial energy-input stage of high-energy consumption and low-income than in the research and development stage of low-energy consumption and high-income. Optimizing the structure of export products in China, can not only improve China's position in the global production chain, and enhance its competitiveness in high-end industries with low energy intensity, but is also conducive to global energy reservation and emission reduction.

(3) At the country level, the United States and EU28 are traditional major importers of China, and developing countries, such as Brazil, India, and Indonesia, are emerging markets. Embodied energy exported to developed importers is mainly through final goods, and to developing regions, mainly through intermediates. In general, the domestic energy cost per unit of economic income (through exports) to developed countries is lower than that of exports to developing countries. Therefore, the international trade between China and emerging markets needs to be emphasized, and embodied flows of fossil fuel energy and carbon emissions in these trades may be an increasingly important factor of global emission reduction.
(4) At the sector level, the light industry and the services create more benefits, whereas manufacturing, such as chemicals and metal products, consumes more energy, and there is a mismatch between the main sectors that create economic benefits from exports and the main sectors that consume energy for exports. The differences between the forward and backward linkage measures at the sector level require more attention. The sectors of electrical equipment manufacturing and products, mining and quarrying, chemical industry, manufacture of basic metals and metal products, and construction sector are the key sectors that need more attention in the study of export embodied energy. The costs of domestic energy to benefit from the exports of chemical, metal, and non-metal equipment manufacturing sectors are the highest among all sectors, and China should not only improve the export structure and reduce the proportion of products from these sectors in total exports but also fundamentally improve the technical level of these sectors and promote their energy efficiencies.
(5) The domestic energy embodied in some sectors showed a unique distribution of destinations. There is a large gap in the flow routes of the energy embodied in China's exports to different importers, and even in their domestic value chain stages, the flow routes between the domestic sectors are different. Therefore, it is of great significance and importance to conduct detailed studies on the sources, destinations, and transfer routes of energy flows embodied in China's international trade from the perspectives of the trade-in value added method and the global value chain.

This article provides a basic framework for the study of embodied flows based on the global value chain theory and trade in value added accounting. As a stage achievement, this article makes a detailed analysis of the embodied energy flows of China's exports. The main deficiency of this article lies in the lag of the research period caused by data limitation. The world input-output tables have a strong lag and cannot reflect the latest information, and it is necessary to improve the timeliness of research. Besides, this study can be further deepened, such as switching importers and exporters, in order to analyze the net energy transfer in bilateral trade. Moreover, the research framework of this article is also applicable to the study of carbon emissions embodied in international trade and has an important reference role for the flow and transfer of carbon emissions embodied in international trade.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

BZ, SB, and YN made substantial contributions to the conception of the work, and to its drafting and/or critical revision, and approved for publication. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2021.649163/full#supplementary-material

REFERENCES

An, Q., An, H., Wang, L., Gao, X., and Lv, N. (2015). Analysis of embodied exergy flow between Chinese industries based on network theory. *Ecol. Model.* 318, 26–35. doi: 10.1016/j.ecolmodel.2015.01.020

Balassa, B. (1965). Trade liberalisation and "revealed" comparative advantage. *Manchester Sch.* 33, 99–123. doi: 10.1111/j.1467-9957.1965.tb00050.x

Bortolamedi, M. (2015). Accounting for hidden energy dependency: the impact of energy embodied in traded goods on cross-country energy security assessments. *Energy* 93, 1361–1372. doi: 10.1016/j.energy.2015.09.127

BP (2019). *Statistical Review of World Energy*. Available online at: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html (accessed December 19, 2020)

Bullard, C. W., and Herendeen, R. A. (1975). The energy cost of goods and services. *Energy Policy* 3, 268–278. doi: 10.1016/0301-4215(75)90035-X

Chen, B., Li, J. S., Wu, X. F., Han, M. Y., Zeng, L., Li, Z., et al. (2018). Global energy flows embodied in international trade: a combination of environmentally extended input-output analysis and complex network analysis. *Appl. Energy* 210, 98–107. doi: 10.1016/j.apenergy.2017.10.113

Chen, G. Q., and Wu, X. F. (2017). Energy overview for globalized world economy: source, supply chain and sink. *Renew. Sustain. Energy Rev.* 69, 735–749. doi: 10.1016/j.rser.2016.11.151

Chen, J., Zhou, W., and Yang, H. (2019). Is embodied energy a better starting point for solving energy security issues?–based on an overview of embodied Energy-Related research. *Sustainability* 11:4260. doi: 10.3390/su11164260

Chen, S., and Chen, B. (2015). Urban energy consumption: different insights from energy flow analysis, input-output analysis and ecological network analysis. *Appl. Energy* 138, 99–107. doi: 10.1016/j.apenergy.2014.10.055

Corsatea, T. D., Lindner, S., Arto, I., Román, M. V., Rueda-Cantuche, J. M., Velázquez Afonso, A., et al. (2019). *World Input-Output Database Environmental Accounts. no. 1831-9424*. Luxembourg: Publications Office of the European Union.

Cortés-Borda, D., Guillén-Gosálbez, G., and Jiménez, L. (2015). Assessment of nuclear energy embodied in international trade following a world multi-regional input-output approach. *Energy* 91, 91–101. doi: 10.1016/j.energy.2015.07.117

Costanza, R. (1980). Embodied energy and economic valuation. *Science* 210, 1219–1224. doi: 10.1126/science.210.4475.1219

Cui, L., Peng, P., and Zhu, L. (2015). Embodied energy, export policy adjustment and China's sustainable development: a multi-regional input-output analysis. *Energy* 82, 457–467. doi: 10.1016/j.energy.2015.01.056

Daudin, G., Rifflart, C., and Schweisguth, D. (2011). Who produces for whom in the world economy? *Can. J. Econ.* 44, 1403–1437. doi: 10.1111/j.1540-5982.2011.01679.x

Gao, C., Su, B., Sun, M., Zhang, X., and Zhang, Z. (2018). Interprovincial transfer of embodied primary energy in China: a complex network approach. *Appl. Energy* 215, 792–807. doi: 10.1016/j.apenergy.2018.02.075

Guo, S., Han, M., Yang, Y., and Di, H. (2020a). Embodied energy flows in China's economic zones: Jing-Jin-Ji, Yangtze-River-Delta and Pearl-River-Delta. *J. Clean. Prod.* 268:121710. doi: 10.1016/j.jclepro.2020.121710

Guo, S., Li, Y., Hu, Y., Xue, F., Chen, B., and Chen, Z. (2020b). Embodied energy in service industry in global cities: a study of six Asian cities. *Land Use Policy* 91:104264. doi: 10.1016/j.landusepol.2019.104264

Guo, S., Shen, G., Yang, J., Sun, B., and Xue, F. (2015). Embodied energy of service trading in Hong Kong. *Smart Sustain. Built Environ.* 4, 234–248. doi: 10.1108/SASBE-08-2014-0046

Guo, S., Zheng, S., Hu, Y., Hong, J., Wu, X., and Tang, M. (2019). Embodied energy use in the global construction industry. *Appl. Energy* 256:113838. doi: 10.1016/j.apenergy.2019.113838

Hummels, D., Ishii, J., and Yi, K. M. (2001). The nature and growth of vertical specialization in world trade. *J. Int. Econ.* 54, 75–96. doi: 10.1016/s0022-1996(00)00093-3

Ji, X., Liu, Y., Meng, J., and Wu, X. (2020). Global supply chain of biomass use and the shift of environmental welfare from primary exploiters to final consumers. *Appl. Energy* 276:115484. doi: 10.1016/j.apenergy.2020.115484

Jiang, L., He, S., Tian, X., Zhang, B., and Zhou, H. (2020). Energy use embodied in international trade of 39 countries: spatial transfer patterns and driving factors. *Energy* 195:116988. doi: 10.1016/j.energy.2020.116988

Johnson, R. C., and Noguera, G. (2012). Accounting for intermediates: production sharing and trade in value added. *J. Int. Econ.* 86, 224–236. doi: 10.1016/j.jinteco.2011.10.003

Kan, S., Chen, B., Meng, J., and Chen, G. (2020). An extended overview of natural gas use embodied in world economy and supply chains: policy implications from a time series analysis. *Energy Policy* 137:111068. doi: 10.1016/j.enpol.2019.111068

Kan, S. Y., Chen, B., Wu, X. F., Chen, Z. M., and Chen, G. Q. (2019). Natural gas overview for world economy: from primary supply to final demand via global supply chains. *Energy Policy* 124, 215–225. doi: 10.1016/j.enpol.2018.10.002

Koopman, R., Powers, W., Wang, Z., and Wei, S. (2010). *Giving Credit Where Credit is Due: Tracing Value Added in Global Value Chains. NBER Working Paper 16426*. Cambridge, MA: National Bureau of Economic Research, doi: 10.3386/w16426

Koopman, R., Wang, Z., and Wei, S. (2008). *How Much of Chinese Exports is Really Made in China? Assessing Domestic Value-Added When Processing Trade is Pervasive. NBER Working Paper 14109*. Cambridge, MA: National Bureau of Economic Research, doi: 10.3386/w14109

Koopman, R., Wang, Z., and Wei, S. (2012). Estimating domestic content in exports when processing trade is pervasive. *J. Dev. Econ.* 99, 178–189. doi: 10.1016/j.jdeveco.2011.12.004

Koopman, R., Wang, Z., and Wei, S. (2014). Tracing Value-Added and double counting in gross exports. *Am. Econ. Rev.* 104, 459–494. doi: 10.1257/aer.104.2.459

Lam, K. L., Kenway, S. J., Lane, J. L., Islam, K. M. N., and Bes De Berc, R. (2019). Energy intensity and embodied energy flow in Australia: an input-output analysis. *J. Clean. Prod.* 226, 357–368. doi: 10.1016/j.jclepro.2019.03.322

Lenzen, M. (1998). Primary energy and greenhouse gases embodied in Australian final consumption: an input-output analysis. *Energy Policy* 26, 495–506. doi: 10.1016/S0301-4215(98)00012-3

Leontief, W. (1936). Quantitative input and output relations in the economic system of the United States. *Rev. Econ. Stat.* 18, 105–125. doi: 10.2307/1927837

Lin, B., and Sun, C. (2010). Evaluating carbon dioxide emissions in international trade of China. *Energy Policy* 38, 613–621. doi: 10.1016/j.enpol.2009.10.014

Liu, B., Zhang, L., Liu, C., Wang, D., Sun, J., Luther, M., et al. (2019). Measuring energy poverty based on energy embodied in exports of vertical specialisation trade in the construction sector. *Energy Build.* 196, 157–168. doi: 10.1016/j.enbuild.2019.05.022

Liu, B., Zhang, L., Sun, J., Wang, D., Liu, C., Luther, M., et al. (2020a). Analysis and comparison of embodied energies in gross exports of the constrcution sector by means of their value-added origins. *Energy* 191:116546. doi: 10.1016/j.energy.2019.116546

Liu, B., Zhang, L., Sun, J., Wang, D., Liu, C., Luther, M., et al. (2020b). Composition of energy outflows embodied in the gross exports of the construction sector. *J. Clean. Prod.* 248:119296. doi: 10.1016/j.jclepro.2019.119296

Liu, Z., Geng, Y., Lindner, S., Zhao, H., Fujita, T., and Guan, D. (2012). Embodied energy use in China's industrial sectors. *Energy Policy* 49, 751–758. doi: 10.1016/j.enpol.2012.07.016

Machado, G., Schaeffer, R., and Worrell, E. (2001). Energy and carbon embodied in the international trade of Brazil: an input-output approach. *Ecol. Econ.* 39, 409–424. doi: 10.1016/s0921-8009(01)00230-0

Mongelli, I., Tassielli, G., and Notarnicola, B. (2006). Global warming agreements, international trade and energy/carbon embodiments: an input–output approach to the Italian case. *Energy Policy* 34, 88–100. doi: 10.1016/j.enpol.2004.06.004

OECD and WTO (2011). *Trade in Value-Added: Concept, Methodologies and Challenges (Joint OECD-WTO note)*. Available online at: http://www.oecd.org/sti/ind/49894138.pdf (accessed December 19, 2020)

Shui, B., and Harriss, R. (2006). The role of CO2 embodiment in US–China trade. *Energy Policy* 34, 4063–4068. doi: 10.1016/j.enpol.2005.09.010

Stehrer, R. (2012). *Trade in Value Added and the Value Added in Trade. WIIW Working Paper 81*. Available online at: https://wiiw.ac.at/trade-in-value-added-and-the-valued-added-in-trade-dlp-2620.pdf (accessed December 19, 2020).

Su, B., and Ang, B. (2013). Input–output analysis of CO2 emissions embodied in trade: competitive versus non-competitive imports. *Energy Policy* 56, 83–87. doi: 10.1016/j.enpol.2013.01.041

Sun, X., An, H., Gao, X., Jia, X., and Liu, X. (2016). Indirect energy flow between industrial sectors in China: a complex network approach. *Energy* 94, 195–205. doi: 10.1016/j.energy.2015.10.102

Sun, X., Li, J., Qiao, H., and Zhang, B. (2017). Energy implications of China's regional development: new insights from multi-regional input-output analysis. *Appl. Energy* 196, 118–131. doi: 10.1016/j.apenergy.2016.12.088

Tang, M., Hong, J., Liu, G., and Shen, G. Q. (2019). Exploring energy flows embodied in China's economy from the regional and sectoral perspectives via combination of multi-regional input-output analysis and a complex network approach. *Energy* 170, 1191–1201. doi: 10.1016/j.energy.2018.12.164

Tang, X., Zhang, B., Feng, L., Snowden, S., and Höök, M. (2012). Net oil exports embodied in China's international trade: an input-output analysis. *Energy* 48, 464–471. doi: 10.1016/j.energy.2012.10.010

Tao, F., Xu, Z., Duncan, A., Xia, X., Wu, X., and Li, J. (2018). Driving forces of energy embodied in China-EU manufacturing trade from 1995 to 2011. *Resour. Conserv. Recycl.* 136, 324–334. doi: 10.1016/j.resconrec.2018.04.021

Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R., and de Vries, G. J. (2015). An illustrated user guide to the world Input-Output database: the case of global automotive production. *Rev. Int. Econ.* 23, 575–605. doi: 10.1111/roie.12178

Timmer, M. P., Erumban, A. A., Los, B., Stehrer, R., and de Vries, G. J. (2014). Slicing up global value chains. *J. Econ. Perspect.* 28, 99–118. doi: 10.1257/jep.28.2.99

Wang, Q., and Ge, S. (2020). Uncovering the effects of external demand on China's coal consumption: a global input-output analysis. *J. Clean. Prod.* 245:118877. doi: 10.1016/j.jclepro.2019.118877

Wang, Q., and Yang, X. (2020). German's oil footprint: an input-output and structural decomposition analysis. *J. Clean. Prod.* 242:118246. doi: 10.1016/j.jclepro.2019.118246

Wang, Z., Powers, W., and Wei, S. (2009). *Value Chains in East Asian Production Networks – An International Input-Output Model Based Analysis. USTIC Working Paper*. Available online at: https://www.usitc.gov/publications/332/EC200910C.pdf (accessed December 19, 2020)

Wang, Z., Wei, S., and Zhu, K. (2014). *Quantifying International Production Sharing at the Bilateral and Sector Level. NBER Working Paper 19677*. Cambridge, MA: National Bureau of Economic Research, doi: 10.3386/w19677

Weber, C., Peters, G., Guan, D., and Hubacek, K. (2008). The contribution of Chinese exports to climate change. *Energy Policy* 36, 3572–3577. doi: 10.1016/j.enpol.2008.06.009

Wiedmann, T. O., Schandl, H., Lenzen, M., Moran, D., Suh, S., West, J., et al. (2015). The material footprint of nations. *Proc. Natl. Acad. Sci. U.S.A.* 112, 6271–6276. doi: 10.1073/pnas.1220362110

Wu, X. F., and Chen, G. Q. (2017). Global primary energy use associated with production, consumption and international trade. *Energy Policy* 111, 85–94. doi: 10.1016/j.enpol.2017.09.024

Wu, X. F., and Chen, G. Q. (2018). Coal use embodied in globalized world economy: from source to sink through supply chain. *Renew. Sustain. Energy Rev.* 81, 978–993. doi: 10.1016/j.rser.2017.08.018

Wu, X. F., and Chen, G. Q. (2019). Global overview of crude oil use: from source to sink through inter-regional trade. *Energy Policy* 128, 476–486. doi: 10.1016/j.enpol.2019.01.022

Wyckoff, A., and Roop, J. (1994). The embodiment of carbon in imports of manufactured products: implications for international agreements on greenhouse gas emissions. *Energy Policy* 22, 187–194. doi: 10.1016/0301-4215(94)90158-9

Xia, X., Chen, B., Wu, X., Hu, Y., Liu, D., and Hu, C. (2017). Coal use for world economy: provision and transfer network by multi-region input-output analysis. *J. Clean. Prod.* 143, 125–144. doi: 10.1016/j.jclepro.2016.12.142

Yang, R., Long, R., Yue, T., and Shi, H. (2014). Calculation of embodied energy in Sino-USA trade: 1997-2011. *Energy Policy* 72, 110–119. doi: 10.1016/j.enpol.2014.04.024

Yang, Y., Poon, J., Liu, Y., and Bagchi-Sen, S. (2015). Small and flat worlds: a complex network analysis of international trade in crude oil. *Energy* 93, 534–543. doi: 10.1016/j.energy.2015.09.079

Zhang, Z., Xi, L., Su, B., Zhao, Y., Song, W., Liu, Y., et al. (2019). Energy, CO2 emissions, and value added flows embodied in the international trade of the BRICS group: a comprehensive assessment. *Renew. Sustain. Energy Rev.* 116:109432. doi: 10.1016/j.rser.2019.109432

Zheng, H., Li, A., Meng, F., and Liu, G. (2020). Energy flows embodied in China's interregional trade: case study of Hebei Province. *Ecol. Model.* 428:109061. doi: 10.1016/j.ecolmodel.2020.109061

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APPENDIX

In Wang et al. (2014), the gross exports of country s to country r were decomposed into 16 terms using equation (A1):

$$
\begin{aligned}
E^{sr} = {} & \underbrace{(V^s B^{ss})^{\mathrm{T}} \# Y^{sr}}_{(T1)} + \underbrace{(V^s L^{ss})^{\mathrm{T}} \# (A^{sr} B^{rr} Y^{rr})}_{(T2)} \\
& + \underbrace{(V^s L^{ss})^{T} \# \left(A^{sr} \sum_{t \neq s,r}^{G} B^{rt} Y^{tt} \right)}_{(T3)} + \underbrace{(V^s L^{ss})^{T} \# \left(A^{sr} B^{rr} \sum_{t \neq s,r}^{G} Y^{rt} \right)}_{(T4)} \\
& + \underbrace{(V^s L^{ss})^{\mathrm{T}} \# \left(A^{sr} \sum_{t \neq s,r}^{G} \sum_{u \neq s,t}^{G} B^{rt} Y^{tu} \right)}_{(T5)} + \underbrace{(V^s L^{ss})^{\mathrm{T}} \# (A^{sr} B^{rr} Y^{rs})}_{(T6)} \\
& + \underbrace{(V^s L^{ss})^{\mathrm{T}} \# \left(A^{sr} \sum_{t \neq s,r}^{G} B^{rt} Y^{ts} \right)}_{(T7)} + \underbrace{(V^s L^{ss})^{\mathrm{T}} \# (A^{sr} B^{rs} Y^{ss})}_{(T8)} \\
& + \underbrace{(V^s L^{ss})^{T} \# \left(A^{sr} \sum_{t \neq s,r}^{G} B^{rs} Y^{st} \right)}_{(T9)} + \underbrace{(V^s B^{ss} - V^s L^{ss})^{T} \# (A^{sr} X^{r})}_{(T10)} \\
& + \underbrace{(V^r B^{rs})^{T} \# Y^{sr}}_{(T11)} + \underbrace{(V^r B^{rs})^{T} \# (A^{sr} L^{rr} Y^{rr})}_{(T12)} \\
& + \underbrace{(V^r B^{rs})^{T} \# (A^{sr} L^{rr} E^{r*})}_{(T13)} + \underbrace{\left(\sum_{t \neq s,r}^{G} V^t B^{ts} \right)^{T} \# Y^{sr}}_{(T14)} \\
& + \underbrace{\left(\sum_{t \neq s,r}^{G} V^{\mathrm{T}} B^{ts} \right)^{\mathrm{T}} \# (A^{sr} L^{rr} Y^{rr})}_{(T15)} + \underbrace{\left(\sum_{t \neq s,r}^{G} V^{\mathrm{T}} B^{ts} \right)^{\mathrm{T}} \# (A^{sr} L^{rr} E^{r*})}_{(T16)}
\end{aligned}
\tag{A1}
$$

where E^{sr} is the total exports of country s to country r, and V^s is the value added coefficient diagonal matrix of country s, in which each element v_j^s is the value added coefficient of sector j in country s (similar for V^r and V^{T}). L^{ss} is the local Leontief inverse matrix. E^{r^*} is the gross export of country r. The meaning and acronym of each term in equation (A1) are as follows:

(T1) is the domestic value added in the final exports and absorbed in the direct importer.
(T2) is the domestic value added in intermediate exports and absorbed in the direct importer.
(T3) is the domestic value added in the intermediate exports and re-exported by the direct importer to a third country to produce domestic final use.
(T4) is the domestic value added in the intermediate exports and used by the direct importer to produce final goods and used in the third country.
(T5) is the domestic value added in intermediate exports and used by the direct importer to produce intermediate goods and re-exported to the third country to produce their exports to other countries (except for the original exporter, country s).
(T6) is the domestic value added in intermediate exports and returns home via final imports from country r.
(T7) is the domestic value added in intermediate exports and returns home via final imports from the third country.
(T8) is the domestic value added in intermediate exports and returns home via intermediate imports.
(T9) is the pure double-counting from domestic source due to final exports production.
(T10) is the pure double-counting from domestic source due to intermediate exports production.
(T11) is the value added from the direct importer used in the final exports.

(T12) is the value added from the direct importer used in intermediate exports.
(T13) is the pure double-counting sourced from the direct importer.
(T14) is the value added from the third country used in the final exports.
(T15) is the value added from the third country used in the intermediate exports.
(T16) is the pure double-counting sourced from the third country.

What should be noted in this decomposition framework is that, in the fifth terms (T5), only export from the third country (country *t*) to the original exporter (country *s*) are excluded from country *t*'s total export. However, there is still a part of exports are consumed by country *r*, and related value added from country'*s* embodied in this part of exports are absorbed in country *r*, and it should be split from (T5). In the formula, when $u = r$, $(T5)' = (V^s L^{ss})^{\mathrm{T}}\#(A^{sr} \sum_{t \neq s,r}^{G} B^{rt} Y^{tr})$, represents the domestic value added in intermediate export and is used by the direct importer to produce intermediate goods and re-exported to the third country to produce their exports back to the direct importer. From the perspective of the final absorbed destination of the domestic value added embodied in country *s*, this part should be calculated separately, since it represents the domestic value added of the exporter, country *s*, and is absorbed in the direct importer, country *r*, through the third country, country *t*. This transfer route is different from other flows. Thus, in this study, the fifth term (T5) in Wang et al. (2014) is divided according to the final absorbed destination. Namely, we divided (T5) into two parts, *ur* in one part and $u = r$ in the other as follows:

$$(T5) = (V^s L^{ss})^{\mathrm{T}}\# \left(A^{sr} \sum_{t \neq s,r}^{G} \sum_{ut \neq s,t,r}^{G} B^{rt} Y^{tu} \right) = (V^s L^{ss})^{\mathrm{T}}\# \left(A^{sr} \sum_{t \neq s,r}^{G} B^{rt} Y^{tr} \right) \tag{A2}$$

Thus, this article decomposes the gross exports of a country into 17 terms according to the original sources, final destinations, and transfer routes of the value added embodied in the exports.

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Carbon Emissions in the Xinjiang Production and Construction Corps and Driving Factors

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Xinjiang production and Construction Corps (XPCC) is an important provincial administration in China and vigorously promotes the construction of industrialization. However, there has been little research on its emissions. This study first established the 1998-2018 XPCC subsectoral carbon emission inventory based on the Intergovernmental Panel on Climate Change (IPCC) carbon emission inventory method and adopted the logarithmic mean Divisia indexmethod (LMDI) model to analyze the driving factors. The results revealed that from 1998 to 2018, the total carbon emissions in the XPCC increased from 6.11 Mt CO_2 in 1998 to 115.71 Mt CO_2 in 2018. For the energy structure, raw coal, coke and industrial processes were the main contributors to carbon emissions. For industrial structure, the main emission sectors were the production and supply of electric power, steam and hot water, petroleum processing and coking, raw chemical materials and chemical products, and smelting and pressing of nonferrous metals. In addition, the economic effect was the leading factor promoting the growth of the corps carbon emissions, followed by technical and population effects. The energy structure effect was the only factor yielding a low emission reduction degree. This research provides policy recommendations for the XPCC to formulate effective carbon emission reduction measures, which is conducive to the construction of a low-carbon society. Moreover, it is of guiding significance for the development of carbon emission reduction actions for the enterprises under the corps and provides a reference value for other provincial regions.

Keywords: XPCC, carbon emissions, economic effect, technical effect, population effect, energy structure effect

INTRODUCTION

Carbon emissions are the most important factor causing climate change Liu et al. (2019), Wang et al. (2020), and the burning of fossil fuels and industrial processes are the main sources of global carbon emissions (Habert et al., 2020; Zhang et al., 2020; Wang et al., 2021). As the world's largest carbon emitter Janssens-Maenhout et al. (2019), Yang et al. (2020), the Chinese government proposed its nationally determined contribution target in the Paris Agreement signed in 2016 Zhang (2017) and promised to reach peak carbon emissions by 2030, while the carbon emissions per unit of the gross domestic product (GDP) in 2030 would be reduced by 60–65% based on the rate in 2005. To achieve this goal, China has implemented many active countermeasures Shan et al. (2020), including starting the construction of a national carbon emission trading market in 2017 Weng and Xu (2018) and enshrining ecological civilization in the constitution in 2018, which provided an impetus and guarantee for ecological and environmental legal system construction in China (Li et al., 2019). Although China achieved the goal of reducing its carbon emission intensity by 40–45% in 2005 Liu et al. (2017), future emission reduction efforts still face many challenges (Luo et al., 2020; Wang et al., 2021).

Regional carbon emission accounting is the basis for the allocation of emission reduction responsibilities, definition of emission reduction targets, and measurement of emission reduction results (Franzen and Mader, 2018; Wei et al., 2020b). At present, many scholars have performed carbon emission accounting work at municipal Cai et al. (2019), provincial Liu et al. (2016) or national CO_2 emission levels (Davis and Caldeira, 2010; Zhang et al., 2020; Wei et al., 2020c). Furthermore, the Tapio model Wang and Jiang (2019), Wang and Su (2019) and the two-layer logarithmic mean Divisia index (LMDI) Jiang et al. (2017), Gu et al. (2019), Wang et al. (2019) decomposition method have been applied to analyze the decoupling relationship Wei et al. (2020a) and influencing factors of energy consumption-related carbon emissions (Xie et al., 2019). However, as the regions of which are distributed in the administrative regions of Xinjiang are relatively scattered, the existing carbon emission accounting research has neglected a distinct administrative area called the Xinjiang Production and Construction Corps (XPCC) McMillen (1981), which has led to carbon emission accounting gaps regarding the XPCC.

The XPCC was established in 1954 and is an extremely unique provincial administration in China. The corps integrates agriculture, industry, transportation, construction, and commerce (Guo, 2015). It plays an important role in developing border affairs and maintaining unity, especially in regard to the economic aspect, and it has also made irreplaceable contributions to the development of China (McMillen, 1981). By 2018, the XPCC GDP reached RMB 25.15 million. The XPCC now contains a population of more than 3.1 million people, and it has an extensive area covering 70,600 square kilometers. In 2018, the carbon emissions in the XPCC amounted to 115 Mt, equivalent to that in Venezuela (123.7 Mt), which ranked 38th in the world in terms of carbon emissions. The carbon emissions per capita of the XPCC reached 37.3 t, which followed that of the United Arab Emirates (38.8 t) and exceeded that of Kuwait (35.0 t) (BP, 2019). Therefore, all the above evidence demonstrate that the carbon emissions in the XPCC administrative area have a nonnegligible contribution to the carbon emissions in China. Starting by processing agricultural and sideline products on the basis of developing agriculture, the Corps developed modern industry and gradually formed a multisector industrial system with light and textile industries as the main part and supplemented by iron and steel, coal, building materials, electricity, chemicals and machinery industries. Therefore (The State Council Information Office of the People's Republic of China, 2014), it is of great research importance to establish a separate carbon emission inventory of the corps to calculate and analyze its carbon emissions, further analyze the carbon emission trend in the administrative area of the XPCC and examine the factors affecting its carbon emission changes for the corps to respond to the national call to achieve the set emission reduction targets as soon as possible.

This study bridges the gaps in carbon emission accounting in regard to the XPCC. First, we compile the 1998-2018 carbon emission inventory of the XPCC by applying the Intergovernmental Panel on Climate Change (IPCC) carbon emission inventory method and analyze the change trends of various carbon emission indicators in the XPCC, such as the total carbon emissions, per capita emissions, and carbon emission intensity. Then, we adopt the LMDI model to decompose the carbon emissions of energy consumption and examine the contribution of the influencing factors of carbon emissions. This study provides an important scientific basis for research on the green development of the regional economy and low-carbon energy development strategies and aims to provide directions and policy recommendations for the XPCC to establish effective carbon emission reduction policies and build a low-carbon society. It is of guiding importance for the development of carbon emission reduction measures for enterprises under the jurisdiction of the corps and provides a reference value for other provincial regions.

METHODS AND DATA SOURCES

Establishment of the Carbon Emission Inventory

The calculation method of the carbon emission inventory in this study is based on the approach provided by the IPCC for the calculation of greenhouse gas emissions. Our carbon emission inventory is constructed in two parts: energy-related carbon emissions and industrial process-related carbon emissions.

Energy-Related Sectoral Approach to Emissions

Energy-related carbon emissions represent the carbon emitted during the burning of fossil fuels. We adopt a sectoral method to calculate the carbon emissions by determining the emissions in various sectors due to fossil fuel combustion (Shan et al., 2018). The type of fossil fuel is represented by i, and each department is represented by j. The carbon emission accounting **Eq. 1** is expressed as follows:

$$CE_{ij} = AD_{ij} \times NCV_i \times CC_i \times O_{ij} \times 44/12 \tag{1}$$

where CE_{ij} are the carbon emissions generated by the combustion of fossil fuel i in sector j, in Mt CO_2; AD_{ij} is the fossil fuel consumption of the corresponding fossil fuel type and department, in ton; NCV_i is the net calorific value produced by the combustion of fuel i, in pJ/(10^4 tons or 10^8 m^3); CC_i are the fossil fuel i carbon emissions per net calorific value, in ton C/TJ; O_{ij} is the oxidation ratio during the burning of fossil fuels; and 44/12 is the molar mass ratio between CO_2 and C.

The following assumptions are made in the calculations in this paper: 1) The total energy consumption is represented by the energy consumption of the industrial enterprises above a designated size. 2) The fuel and energy losses during transportation are negligible. 3) In the calculation, only the carbon emissions within the boundaries of the administrative region of the XPCC are considered, and the emissions caused by the consumption of imported electricity and heat energy from outside the boundaries are not included. 4) It is assumed that the emission factor of the same fuel remains constant under the different combustion conditions in the various sectors.

Due to the lack of XPCC energy consumption data for farming, forestry, animal husbandry and fishery, construction, and wholesale, retail trade and catering services, we apply the method of multiplying the industrial output value by the carbon emission factor of the industry to calculate its emissions (the calculation method is expressed in **Eq. 2**, and the following assumptions are made for the calculation of the carbon emission factors of the above three industries: 1) The output value of the three industries of agriculture, forestry, animal husbandry & fishery; construction; and wholesale, retail trade & catering services in the XPCC is assumed. The carbon emission ratio of the industry, i.e., the carbon emission factor, is consistent with that of Xinjiang. 2) The energy consumption ratios of the three major industries of farming, forestry, animal husbandry & fishery; construction; and wholesale, retail trade & catering services are assumed to be consistent with those of Xinjiang. 3) The energy consumption ratios of the three major industries in Xinjiang of farming, forestry, animal husbandry and fishery, construction, and wholesale, retail trade and catering services are assumed to remain basically unchanged from 1998 to 2018.

The calculation methods for the carbon emissions of farming, forestry, animal husbandry and fishery, construction, and wholesale, retail trade and catering services are as follows:

$$CE_n = M_n \times CC_n \tag{2}$$

where CE_n are the carbon emissions in industry n (farming, forestry, animal husbandry and fishery, construction, and wholesale, retail trade and catering services) in Mt CO_2; M_n are the annual output value data in industry n; and CC_n is the carbon emission factor of industry n (Shan et al., 2016).

Process-Related Sectoral Approach to Emissions

Process-related carbon emissions refer to the carbon produced by physical and chemical reactions during the production process. Since the carbon emissions generated during cement production in China account for approximately 75% of the total industrial process-related carbon emissions, we assume that the ratio of the carbon emissions from the industrial processes related to cement production to the total industrial carbon emissions in the XPCC is consistent with that in China. Therefore, we only need to calculate the carbon emissions from the cement production process and multiply it with a proportional coefficient to obtain the industrial process-related carbon emissions in the XPCC. The calculation **Eq. 3** is as follows:

$$CE_p = AD_p \times CC_p \div \lambda \tag{3}$$

where CE_p is the total amount of process-related carbon emissions within the boundaries of the administrative region of the XPCC, in Mt CO_2; AD_p is the cement production volume related to carbon emission accounting within the boundaries of the administrative region of the XPCC, in ton; CC_p is the emission factor of cement production, which is 0.2906 t CO_2/(t km^3), obtained from Liu et al. Zhu et al. (2015); and λ is the proportional coefficient between the carbon emissions from the cement production process and the carbon emissions from the total industrial process, which is 0.75.

Logarithmic Mean Divisia Index Method

A decomposition model is established to analyze the driving factors of the changes in the carbon emissions in the XPCC from 1998 to 2018 based on the LMDI approach (B.W. Ang, 2015), and the following decomposition model is established:

$$CO_2 = \frac{CO_2}{PE} \times \frac{PE}{GDP} \times \frac{GDP}{POP} \times POP \tag{4}$$

where CO_2 is the carbon emissions, PE is the total energy consumption, GDP is the gross domestic product, and POP is the total population.

The carbon emission change decomposition in the XPCC over a year is given by:

$$C = \sum_{i=1}^{17} C_i = \sum_{i=1}^{17} \frac{C_i}{E_i} \times \frac{E_i}{Y_i} \times \frac{Y_i}{P_i} \times P_i = \sum_{i=1}^{17} ES_i \times T_i \times A_i \times P_i \tag{5}$$

where C_i is the amount of carbon emissions of energy type i, E_i is the consumption of energy type i producing the carbon emissions, Y_i is the gross national product of the XPCC in a given year, and P_i is the total population of the XPCC in that year. Pi is also called the population effect. Assuming that the carbon emission factors of the various fossil fuels remain constant, the ratio of the carbon emissions to the energy consumption is ES_i, which represents the energy structure effect. Similarly, T_i is the ratio of the energy consumption to the GDP, representing the technical effect, and A_i is the ratio of the gross national product to the total population, which represents the economic effect.

According to the LMDI method, the general equation for the carbon emission changes in the XPCC is described by the additive decomposition method as:

$$\Delta C = C^T - C^t = \Delta C_{ES} + \Delta C_T + \Delta C_A + \Delta C_P \tag{6}$$

where ΔC is the change in carbon emissions from year t to year T, ΔC_{ES}, ΔC_T, ΔC_A, and ΔC_P are the impact changes in the ES, T, A, and *P* indicators, respectively, based on the carbon emission

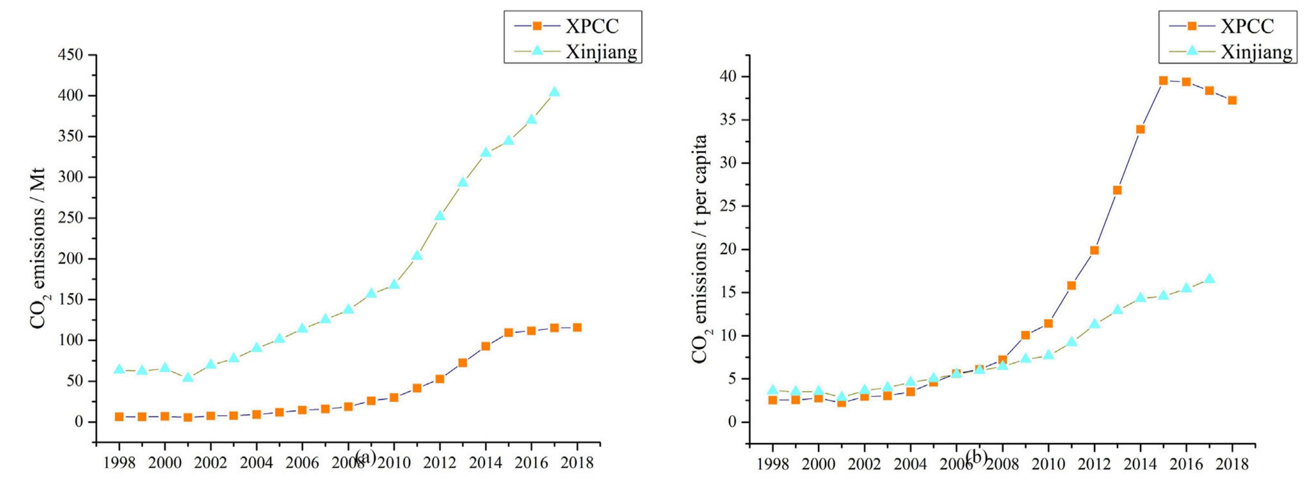

FIGURE 1 | The carbon emissions in XPCC and Xinjiang from 1998 to 2018 **(A)** Change in trend of the total carbon emissions in XPCC and Xinjiang from 1998 to 2018, **(B)** change in trend of the carbon emissions per capita share of the XPCC and Xinjiang from 1998 to 2018.

changes from year t to T, ΔC_{ES} is the carbon emission effect of the energy structure, ΔC_T is the carbon emission effect of the energy intensity, ΔC_A is the carbon emission effect of the economic development level, and ΔC_P is the carbon emission effect of the population size.

ΔC_{ES}, ΔC_T, ΔC_A and ΔC_P are calculated as follows:

$$\Delta C_{ES} = \sum_{i=1}^{17} \frac{C_i^T - C_i^t}{\ln\left(C_i^T/C_i^t\right)} \ln\left(\frac{ES_i^T}{ES_i^t}\right) \tag{7}$$

$$\Delta C_T = \sum_{i=1}^{17} \frac{C_i^T - C_i^t}{\ln\left(C_i^T/C_i^t\right)} \ln\left(\frac{T_i^T}{T_i^t}\right) \tag{8}$$

$$\Delta C_A = \sum_{i=1}^{17} \frac{C_i^T - C_i^t}{\ln\left(C_i^T/C_i^t\right)} \ln\left(\frac{A_i^T}{A_i^t}\right) \tag{9}$$

$$\Delta C_P = \sum_{i=1}^{17} \frac{C_i^T - C_i^t}{\ln\left(C_i^T/C_i^t\right)} \ln\left(\frac{P_i^T}{P_i^t}\right) \tag{10}$$

where T and t are the previous and base years, respectively. Let $W_i = \frac{C_i^T - C_i^t}{\ln(C_i^T/C_i^t)}$, and the contribution value of each factor can be obtained as follows, $\Delta C_{ES} = \sum_{i=1}^{17} W_i \ln \frac{ES_i^T}{ES_i^t}$, $\Delta C_T = \sum_{i=1}^{17} W_i \ln \frac{T_i^T}{T_i^t}$, $\Delta C_A = \sum_{i=1}^{17} W_i \ln \frac{A_i^T}{A_i^t}$, and $\Delta C_P = \sum_{i=1}^{17} W_i \ln \frac{P_i^T}{P_i^t}$.

Data Sources

In this study, the subsectoral fossil fuel consumption and cement production of the XPCC, as well as the output values of farming, forestry, animal husbandry and fishery, construction, and wholesale, retail trade and catering services, are obtained from the 1998-2018 Statistical Yearbook of the Xinjiang Production and Construction Corps (Statistical Bureau of Xinjiang production and Construction Corps scoNBos, 1998-2018). The data on the net calorific value, oxidation efficiency and carbon content of the various fuels originate from the research of (Shan et al., 2018).

RESULTS

Temporal Evolution Characteristics of the Carbon Emissions in the Xinjiang Production and Construction Corps from 1998 to 2018

The administrative area of the XPCC is located in the Xinjiang Uyghur Autonomous Region, and the XPCC is under the dual jurisdiction of the Chinese Central Government and the Xinjiang Uyghur Autonomous Region Government. The corps and the autonomous region exhibit similar industrial structures and resource types. Therefore, this study analyzes the temporal evolution characteristics of crop carbon emissions by comparing them to those in the Xinjiang Uyghur Autonomous Region.

As shown in **Figure 1A** and **Supplementary Table SA1**, from 1998 to 2018, the total carbon emissions in the XPCC increased approximately 18 times (from 6.11 Mt CO_2 in 1998 to 115.71 Mt CO_2 in 2018). The total carbon emissions in the XPCC slowly increased from 1998 to 2008 (the average annual growth rate of the total carbon emissions from 1998 to 2008 was 11.77%) and even declined in 2001, decreasing to 5.48 Mt CO_2, which was the lowest value in twenty years. Similar to the XPCC, the lowest value of the carbon emissions in Xinjiang during this period also occurred in 2001, at 53.50 Mt CO_2 (Shan et al., 2018; Shan et al., 2020). During the period from 2008 to 2015, the XPCC total carbon emissions increased at a fast pace, and the average growth rate increased to 28.81%. The last period is from 2015 to 2018, and in contrast to the continued rapid growth of Xinjiang, the carbon emissions in the XPCC suddenly transitioned from rapid growth to slow growth after a turning point was reached in 2015, and the average annual growth rate of the corps carbon emissions also decreased from 28.81% to 1.89%.

Figure 1B and **Supplementary Table SA2** shows the change in trend of the per capita carbon emissions in XPCC and Xinjiang from 1998 to 2018. **Figure 1B** reveals that from 1998 to 2008, the per capita carbon emissions and growth trend in the XPCC were

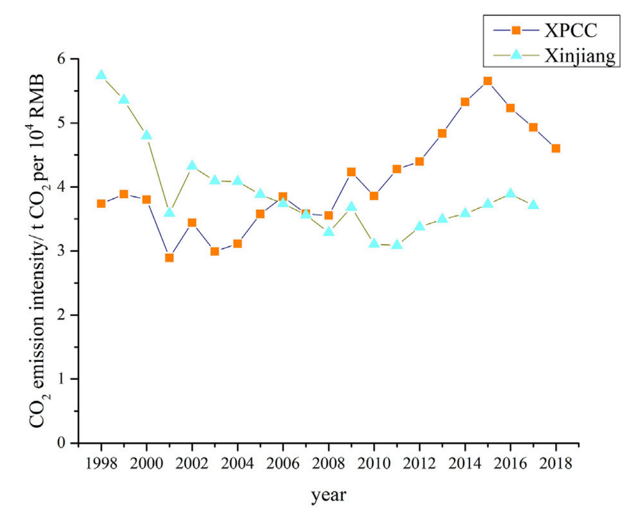

FIGURE 2 | The change in the carbon emission intensity of XPCC and Xinjiang from 1998 to 2018.

basically consistent with those in the Xinjiang region (Shan et al., 2018). However, from 2008 to 2018, there was a substantial difference in the per capita share of the two regions. After 2008, the per capita share of the carbon emissions in Xinjiang was the same as that from 1998 to 2008, and it exhibited a gradual growth trend (Shan et al., 2020). The growth remained very stable without major fluctuations. However, the XPCC experienced two periods of change, namely, the rapid growth stage from 2008 to 2015 and the decline stage from 2015 to 2018, while the population of the corps maintained slow and balanced growth during the observation period from 1998 to 2018. Therefore, in the XPCC, the per capita share of the carbon emissions was basically consistent with the change in trend of the total carbon emissions, and the per capita share amplified the effect of the changes in the XPCC carbon emission trend.

In addition, we also analyze and compare the carbon emission intensity and trend in the XPCC and Xinjiang from 1998 to 2018 (as shown in **Figure 2** and **Supplementary Table SA3**). The change in trend of the XPCC carbon emission intensity from 1998 to 2018 can also be divided into three stages, namely, 1998-2001 showed a downward trend, 2001-2015 exhibited an overall upward trend, and 2015-2018 revealed a downward trend, with normal fluctuations within a small range during this period.

Changes in the Carbon Emission Structure of the Xinjiang Production and Construction Corps from 1998 to 2018

The XPCC carbon emission inventory was constructed in two parts: energy- and process-related (cement) carbon emissions. When calculating the fossil energy-related carbon emissions in the XPCC, this paper applied a fossil fuel classification that was consistent with that of the China Emission Accounts and Datasets (CEADs) carbon emission inventory Shan et al. (2017), including raw coal, washed coal, other washed coal, briquettes, coke, coke oven gas, other gases, other coking products, crude oil, gasoline, diesel, kerosene, fuel oil, liquefied natural gas, refinery gas, other petroleum products, and natural gas, for a total of 17 kinds of fossil fuels. And the industrial process-related carbon emissions largely originated from the cement production process. We calculated the percentage of the total carbon emissions resulting from the consumption of the various energy sources (including the carbon emissions related to industrial processes) in the XPCC from 1998 to 2018 (**Figure 3**). The results reveal that raw coal (689.27 Mt CO_2) is always the largest contributor to carbon emissions, accounting for the majority of the total carbon emissions at 78.68%, and the proportion of its energy emissions has steadily increased. However, the growth rate of its carbon emissions slightly decreased after 2015. Coke (55.54 Mt CO_2) and washed coal (17.10 Mt CO_2), accounting for the second and fifth highest emissions, respectively, reached their peak in 2015, changing from an increasing trend to a decreasing trend. The carbon emissions of petroleum and gasoline have gradually changed, and both have begun to exhibit a downward trend after 2016. The proportion of the carbon emissions related to industrial processes ranks third at 51.06 Mt CO_2.

Figure 3 and **Supplementary Table SA4** shows a chart of the carbon emission against energy structure in the XPCC from 1998 to 2018. We find that the change in trend of the carbon emissions from coal, accounting for the largest proportion of the total emissions, is basically consistent with the change in trend of the total carbon emissions. This indicates that the emissions produced by raw coal largely determine the change in trend of the total carbon emissions. Therefore, controlling the carbon emissions at the source should start with controlling the carbon emissions produced by raw coal.

Figure 4 and **Supplementary Table SA5** shows the carbon emission against industrial structure in the XPCC from 1998 to 2018. From 1998 to 2018, the main emission sectors were the sectors of the production and supply of electric power, steam and hot water, petroleum processing and coking, raw chemical materials and chemical products, and smelting and pressing of nonferrous metals. Among these sectors, the production and supply of electric power, steam and hot water industry always contributed the most to the corps carbon emissions, and the carbon emissions generated by this industry increased year by year, reaching a maximum value in 2018 (46.81 Mt CO_2). The petroleum processing and coking industry, the second largest contributor to carbon emissions, started later. It began to generate carbon emissions in 2004 and then rapidly grew, reaching a peak in 2016 (25.36 Mt CO_2). The smelting and pressing of the nonferrous metals sector only started producing a notable emission effect in 2012 and then continuously exhibited a growth trend until 2018.

Driving Factors of the Changes in Carbon Emissions in the Xinjiang Production and 293 Construction Corps

We applied the LMDI method to calculate the individual effects of the various influencing factors of the carbon emissions in the XPCC from 1998 to 2018. The decomposition results are summarized in **Figure 5** and **Supplementary Table SA6**.

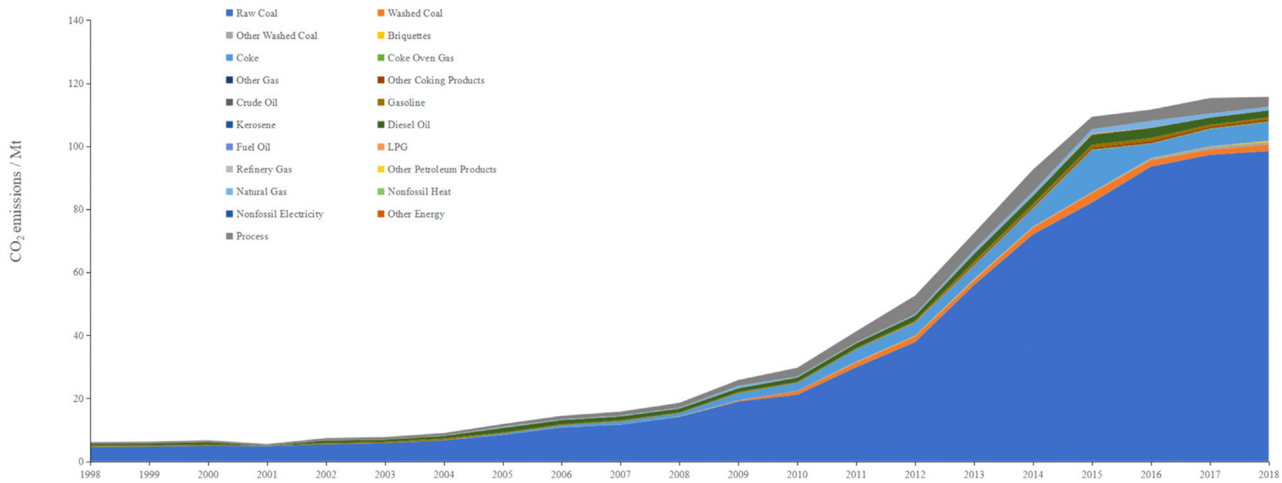

FIGURE 3 | Carbon emission against energy structure in the XPCC from 1998 to 2018.

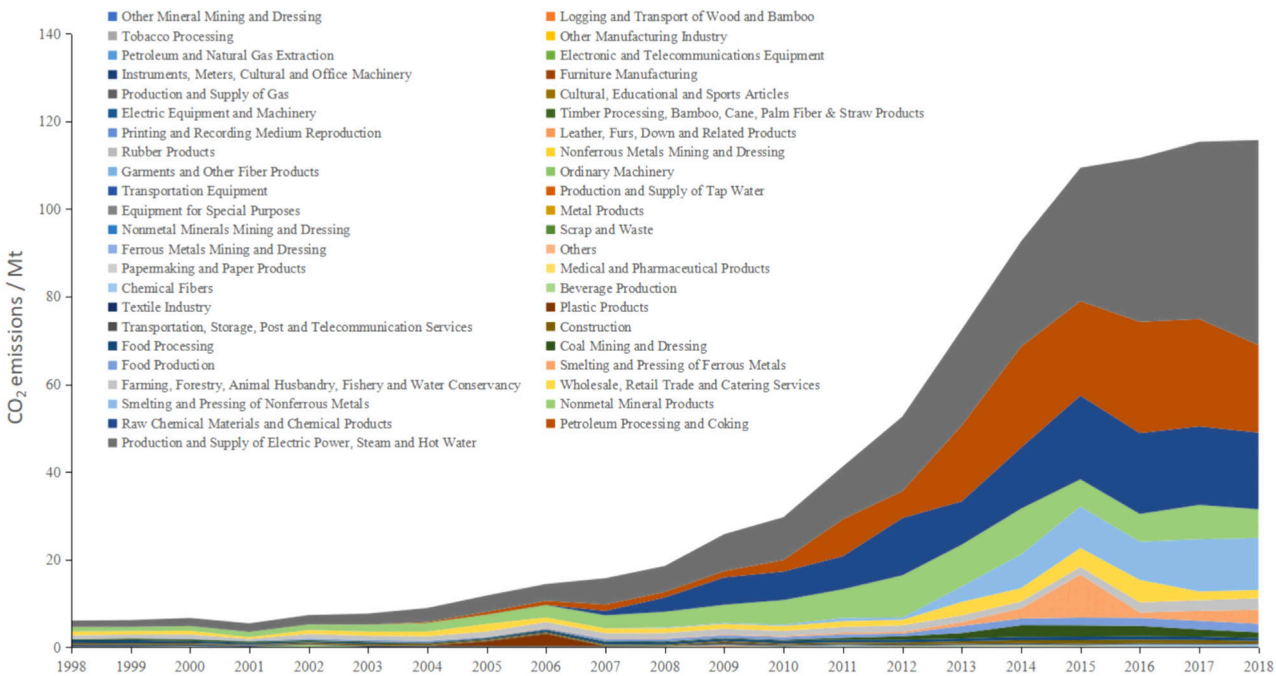

FIGURE 4 | Carbon emission against industrial structure in the XPCC from 1998–2018. Driving factors of the changes in carbon emissions in the Xinjiang Production and Construction Corps.

Supplementary Table SA6 indicates that the average annual growth of the total effect from 1998 to 2018 amounted to 5,479,900 tons. Moreover, the energy structure effect accounted for 159,800 tons of the emission reduction effects, which provided a contribution rate of -2.92% to the total effect. In terms of the technical effect, it yielded an increase of 1.5804 million tons, providing a 28.84% contribution rate. In terms of the economic effect, economic development produced a discharge increase effect of 3.1574 million tons, thereby yielding a contribution rate of 57.62%. In terms of the population effect, continuous population growth resulted in a total emission increase of 901,800 tons, providing a 16.46% contribution rate.

DISCUSSION

Since the central government resumed the formation of the corps at the end of 1981, the XPCC started a second venture, vigorously

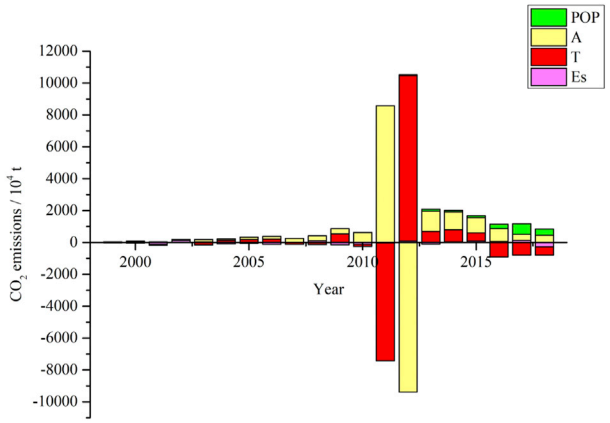

FIGURE 5 | Decomposition results of the carbon emission driving factors in the XPCC. Note: POP represents the population effect, A represents the economic effect, T represents the technical effect, and ES represents the energy structure effect.

promoted urbanization, new-type industrialization and agricultural modernization, and continuously improved its economic development level. The total production value of the corps increased from 6.550 billion yuan in 1981 to 16.349 billion yuan in 1998 and reached 251.516 billion yuan in 2018 (Statistical Bureau of Xinjiang production and Construction Corps, 1998–2018). Economic development was accompanied by a surge in carbon emissions. Moreover, the change in trend of the total carbon emissions in the XPCC was similar to that in Xinjiang, both showing an upward trend. The average carbon emission growth rate in Xinjiang was slightly higher than the XPCC carbon emission growth rate, and the XPCC total carbon emission growth rate first increased and then decreased. In terms of the per capita carbon emissions, Xinjiang consistently showed an increasing trend, and the XPCC change trend first gradually increased, rapidly increased and then decreased. The time node of the XPCC separation time period is consistent with that of the total emissions, which intuitively reflects that the implemented environmental protection policy is of great importance to slowing down the growth of carbon emissions.

Therefore, according to the changes in the growth rate of the total carbon emissions and the growth rate of the per capita carbon emissions, we roughly divide the annual carbon emissions in the XPCC from 1998 to 2018 into the following three stages:

The first stage extended from 1998 to 2008, during which the corps total carbon emissions increased at a moderate rate of 11.77%. During this period, the carbon emission intensity in the XPCC constantly fluctuated, and 2001 was the turning point of the first stage. After 2001, with the development of thermal power, copper nickel ore, PVC and other industrial systems, the XPCC carbon emission-related fuel structure considerably shifted to a high-emission fuel-dependent fuel structure. For example, the growth rate of raw coal usage increased from −2.80% during the 2000–2001 period to 12.60% during the 2001–2002 period. Besides, the growth rate of diesel usage increased from −32.10% to 30.70% (Statistical Bureau of Xinjiang production and Construction Corps, 1998–2018). Coke generated almost no energy emissions before 2004, but its emissions gradually increased after 2004. The two major industries, namely, petroleum processing & coking industry and raw chemical materials & chemical products industry, produced the second and third highest total carbon emissions. Therefore, the reduction in the various types of high-emission sectors during this stage also led to low total emissions. According to the LMDI analysis results, during this period, only the energy structure effect yielded a reduction effect, contributing 7.78 Mt to the observed carbon reduction. The economic effect bore most of the increase in emissions, and its contribution to the total impact reached as high as 96%. From 2001 to 2005, China implemented the 10th Five-Year Plan. The Western Development Project was the strategic focus of the 10th Five-Year Plan (Yang et al., 2018). Its successful implementation greatly promoted the economic growth of the western region. This is also the main reason why the economic effect accounted for such a large proportion of the carbon emissions from 1998 to 2008 (Zhang et al., 2019). During the 10th Five-Year Plan period, the Party Central Committee proposed the strategy of establishing a scientific outlook on the development and construction of a harmonious society (Zhuo and Deng, 2020). Moreover, the 11th Five-Year Plan further strengthened environmental protection and vigorously encouraged the development of a circular economy, and it established an assessment system and an energy conservation, consumption reduction and pollution reduction system (Chen et al., 2021; Feng et al., 2021). The emission reduction effect in the XPCC during this period demonstrated the effectiveness of the above environmental protection policies. In addition, the fluctuating carbon emission intensity also revealed a balance between the effect of economic growth and the emission reduction effect of environmental protection policies (He et al., 2018).

The second stage was the period from 2008 to 2015, during which the carbon emissions exhibited a rapid growth trend, with an average annual growth rate of 28.81%. Since 2008, several major high-emission industrial sectors started showing obvious growth trends, and the types of energy generating high carbon emissions increased. Moreover, both the XPCC emission intensity and its GDP continuously increased. According to the LMDI decomposition analysis results, the XPCC energy structure effect during this period still generated emission reduction effects (21.32 Mt CO_2), but the difference from the previous stage was that the technical effect during the second stage replaced the economic effect and became the main contributor promoting carbon emissions. The technical effect contributed 58.53% to the total effect, while the economic effect, as the second largest contributor, caused a 38.22% increase in emissions. This result demonstrates that the XPCC economic growth and technological backwardness between 2008 and 2015 were the main reasons for the rapid growth of its carbon emissions.

The third stage lasted from 2015 to 2018. The XPCC carbon emissions were still on the rise, but the growth rate had decreased to 1.89%. During this period, the XPCC carbon emission intensity changed in 2015, from an increasing trend to a decreasing trend. The high-emission energy and industry sectors peaked in 2015, such as coke and smelting and pressing ferrous metals. According to the LMDI analysis results, the technical effect was transformed into a reduction effect during the third stage, providing a large contribution of −354.88% to the total carbon reduction. This result was directly linked to the rapid development of science and technology during this stage, while 2015 represented the demarcation point between the latter two stages, and it was also a year when China strongly promoted environmental protection and emphasized ecological development (Fang et al., 2020). In the Paris Agreement signed in 2015, China solemnly pledged to strive to achieve the maximum total carbon emission goals by 2030 (Isabel Hilton, 2014). To achieve this emission reduction target, on January 1, 2015, a new environmental protection law, regarded as the most stringent in history, was formally implemented in China (Chang et al., 2020). In addition, the Central Committee of the Communist Party of China and the State Council issued the Overall Plan for Ecological Civilization System Reform. The first environmental protection reform involved the implementation of vertical management. XPCC also put forward specific implementation suggestions on strengthening the construction of ecological civilization, such as XPCC's 13th Five-Year Plan for energy conservation and emission reduction. China has paid increasing attention to environmental protection and ecological development Andersson (2018), Gu et al. (2020), and governments at all levels across China have actively responded to the call. Among them, the output value growth rate of several high-emission departments of the XPCC also notably decreased. For example, the output value of the major emission sectors of smelting and pressing of ferrous metals, coal mining and dressing, smelting and pressing of nonferrous metals, raw chemical materials and chemical products, and food processing decreased 87.24%, 8.11%, 5.63%, 3.56%, and 3.02%, respectively, from 2015- 2016 (Statistical Bureau of Xinjiang production and Construction Corps, 1998–2018). The obvious decline in the growth rate of the output value of the above high-emission sectors directly indicated that the national environmental protection policy played a good role in reducing emissions in the administrative area of the XPCC. The above also demonstrates that environmental protection policies can achieve specified emission reduction targets by optimizing the energy industry structure and appropriately adjusting the development frequency of high-emission sectors.

After applying the LMDI method to decompose the influencing factors of the carbon emissions, we find that the impact of the energy structure effect of the XPCC on its carbon emissions fluctuated around zero from 1998 to 2018. The energy structure is determined by the region's resource talent and proportion of clean energy. The coal resources in the administrative area of the XPCC are relatively abundant. However, the use of clean energy is low and not stable enough, and there is no complete utilization system, which leads to large fluctuations in the effect of the energy structure and uncertain results. Although the energy structure effect only contributes −2.92% to carbon emissions, accounting for a small share, it is feasible to realize emission reduction *via* energy structure improvement based on the observation and analysis results from 1998 to 2018. Much room remains for the development of the use of clean energy, which is also an important direction to optimize the energy structure in the future. The average performance of the technical effect is 1.5804 million tons, and the overall impact is an emission increase, with a large contribution to carbon emissions. This can be reduced by improving the energy use efficiency, which is an important reference factor for effective emission reduction (Wei et al., 2021). Technology is directly linked to the carbon emission intensity, which suppresses carbon emissions by improving the production capacity and equipment efficiency to achieve an effective use of energy (Chen et al., 2020). The contribution of the economic effect to emission reduction is as high as 57.62%, which is the main driving factor of the increase in carbon emissions (Dong et al., 2020). The development of a green economy makes it possible to achieve a balance between carbon emissions and economic growth, which could effectively guarantee continuous GDP growth and appropriately suppress the impact of the economic effect on carbon emissions (Qian et al., 2021). The population effect on the growth of carbon emissions remains relatively stable every year, and the contribution value is relatively low. The average value of the total effect in the carbon emission analysis over the past two decades is 5,479,900 tons, indicating that the overall effect of these four effects still promotes carbon emission growth. The main reason is that the economic effect has a large positive contribution. Therefore, future emission reduction measured in the XPCC could be implemented through the following two methods: one method is to reduce economic effect promotion, and emission reduction may be rationally planned through reducing the energy demand in economic production (Quan et al., 2020); the second approach is to increase the inhibitory effect of the energy structure, strengthen the construction of key energy-saving projects, and vigorously develop the circular economy and environmental protection industries, while much room remains for green economic development.

This study still has certain limitations. For example, although we conducted a detailed analysis of the corps carbon emissions from 1998 to 2018, the types of LMDI decomposition factors were relatively few and not sufficiently comprehensive. We did not consider the amount of carbon emissions transferred among the various XPCC industrial sectors or between the XPCC and other regions. Therefore, related follow-up research should focus on these points to further improve the accuracy and comprehensiveness.

CONCLUSION

As the only provincial administration in China under the dual leadership of the Central Government and the Xinjiang Uyghur Autonomous Region, the XPCC ran the first batch of industrial, traffic, construction and commercial enterprises in Xinjiang, laying the modern industrial foundation of Xinjiang. However, almost no previous research has focused on carbon emissions in the administrative area of the corps. Therefore, this article first compiled the carbon emission inventory of the XPCC from 1998 to 2018. The calculation method is consistent with that of the CEADs. The LMDI model is adopted to decompose the driving factors of carbon emissions in the corps. The following conclusions are drawn: From 1998 to 2018, the total carbon emissions in the XPCC exhibit an upward trend, and the growth rate of the total carbon emissions first increases and then decreases. We divide the carbon emission changes in the

XPCC from 1998 to 2018 for analysis purposes: the first stage extends from 1998 to 2008, and only the energy structure effect yields a reduction effect, while the economic effect bears most of the increase in emissions. The carbon emission intensity constantly fluctuates during this stage, which reflects the mutual restriction between the economic effect of the economic growth caused by the Western Development Program on the carbon emissions and the emission reduction effects of the energy structure produced by the implemented environmental protection policies. The second stage lasts from 2008 to 2015. During this stage, the total carbon emissions rapidly increase. The technical and economic effects mainly contribute to carbon emission growth, indicating that XPCC economic growth and technological backwardness are the reasons for the rapid increase in carbon emissions. The third stage is the period from 2015 to 2018. The total carbon emissions of the corps gradually increase. The reason is that since 2015, China has increased its emission reduction efforts to development Strategy for Ecological Civilization as well as achieve the set Paris Agreement emission targets. Environmental protection policies could achieve the specified emission reduction targets by optimizing the energy industry structure and appropriately adjusting the development frequency of high-emission sectors.

The analysis in this paper clearly shows that every implementation of a national environmental protection policy imposes a major reduction effect on the carbon emissions in the XPCC. This indicates that the government departments of the XPCC demonstrate a strong ability to implement central commands. Therefore, in terms of environmental protection and emission reduction, the local government can appropriately formulate certain emission reduction policies based on local characteristics and design carbon emission reduction policies according to local conditions. Areas with power production and supply as the main sector should pay attention to the technology upgrading and emission transformation of the power sector. Areas with sector raw chemical materials and chemical products and sector lighting and pressing of nonferrous metals should pay more attention to the formulation of emission standards and pollution prevention and treatment within the sector to reduce carbon emissions from the source of emissions. It is necessary to consider the actual local basis and actual status of carbon emissions, as well as the XPCC local economic development focus. It is also vital to improve the execution capabilities of lower-level government departments in regard to the implementation of policies. The measures proposed above could effectively improve the efficiency of carbon emission reduction. Moreover, we find that in terms of the administrative region of the XPCC from 1998 to 2018, the technical effect results in the second largest increase in the total effect over the past 2 decades. This result shows that the XPCC extremely lacks carbon emission reduction technology, and it also implies that the corps has much room for technological development. In the XPCC, it is expected that the technical effect could be changed from the second largest emission increase factor to the leading emission reduction factor by achieving technological progress. The energy structure effect is the only factor achieving an emission reduction effect in the XPCC, but its emission reduction effect is insignificant. At present, the energy consumption of the corps mainly involves fossil energy based on coal. In fact, the energy structure should be appropriately optimized, such as the development of clean energy and the appropriate reduction in energy use with high carbon emission factors. We suggest that the corps shares the pressure of energy use with energy sources exhibiting a low carbon emission factor as much as possible without affecting economic development. The improvement of the energy structure is an important direction for future emission reduction. The economic effect is the leading factor of the increase in emissions. Carbon emissions are an inevitable price in the process of economic development. On the one hand, it is essential to maintain economic growth, and on the other hand, it is necessary to achieve the goal of reducing emissions. Emission reduction should not undermine economic growth. Therefore, to achieve an effective balance between economic growth and emission reduction policy implementation, the focus of economic development should be appropriately adjusted according to production and life needs to reduce carbon emissions, and emission reduction targets should be scientifically and rationally adjusted according to the actual local development conditions. In this way, the orderly advancement of emission reduction and sustained economic growth can be realized.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: www.xjbt.gov.cn https://www.nature.com/articles/sdata2017201/.

AUTHOR CONTRIBUTIONS

MW: Software, Writing-Review and Editing. Methodology. Formal analysis, LF: Data curation, Writing-Original Draft, Writing-Review and Editing, Methodology, Software. PZ: Methodology, Writing-Review and Editing. GC: Writing-Review and Editing. HL: Writing-Review and Editing. JC: Methodology, Data curation. XL: Methodology, Data curation. WW: Writing-Review and Editing, Supervision, Funding acquisition.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2021.627149/full#supplementary-material

REFERENCES

Andersson, F. N. G. (2018). International Trade and Carbon Emissions: The Role of Chinese Institutional and Policy Reforms. *J. Environ. Manage.* 205, 29–39. doi:10.1016/j.jenvman.2017.09.052

B. W. Ang. (2015). LMDI Decomposition Approach: A Guide for Implementation. *Energ. Pol.* 86, 233–238.

BP Statistical Review of World Energy (2019). Global—By Country and Region, Annual Data Since 1952.

Cai, B., Cui, C., Zhang, D., Cao, L., and Dai, C. (2019). China City-Level Greenhouse Gas Emissions Inventory in 2015 and Uncertainty Analysis. *Appl. Energ.* 253. doi:10.1016/j.apenergy.2019.113579

Chang, Y., Wang, C., Khan, M. I., and Wang, N. (2020). The Legal System for Environmental protection during Exploration and Exploitation of marine mineral Resources in China. *Resour. Pol.* 67. doi:10.1016/j.resourpol.2020.101670

Chen, H., Guo, W., Feng, X., Wei, W., Liu, H., Feng, Y., et al. (2021). The Impact of Low-Carbon City Pilot Policy on the Total Factor Productivity of Listed Enterprises in China. *Resour. Conservation Recycling* 169, 105457. doi:10.1016/j.resconrec.2021.105457

Chen, S., Shi, A., and Wang, X. (2020). Carbon Emission Curbing Effects and Influencing Mechanisms of China's Emission Trading Scheme: The Mediating Roles of Technique Effect, Composition Effect and Allocation Effect. *J. Clean. Prod.* 264. doi:10.1016/j.jclepro.2020.121700

Davis, S. J., and Caldeira, K. (2010). Consumption-based Accounting of CO_2 Emissions. *Proc. Natl. Acad. Sci.* 107, 5687.

Dong, B., Ma, X., Zhang, Z., Zhang, H., Chen, R., Song, Y., et al. (2020). Carbon Emissions, the Industrial Structure and Economic Growth: Evidence from Heterogeneous Industries in China. *Environ. Pollut.* 262, 114322. doi:10.1016/j.envpol.2020.114322

Fang, G., Lu, L., Tian, L., He, Y., and Bai, Y. (2020). Can China Achieve the Energy-Saving and Emission Reducing Objectives during the "13th Five-Year-Plan"? -- A Systematic Evolutionary Analysis. *J. Clean. Prod.* 262, 121256. doi:10.1016/j.jclepro.2020.121256

Feng, Y., Chen, H., Chen, Z., Wang, Y., and Wei, W. (2021). Has Environmental Information Disclosure Eased the Economic Inhibition of Air Pollution? *J. Clean. Prod.* 284, 125412. doi:10.1016/j.jclepro.2020.125412

Franzen, A., and Mader, S. (2018). Consumption-based versus Production-Based Accounting of CO2 Emissions: Is There Evidence for Carbon Leakage? *Environ. Sci. Pol.* 84, 34–40. doi:10.1016/j.envsci.2018.02.009

Gu, S., Fu, B., Thriveni, T., Fujita, T., and Ahn, J. W. (2019). Coupled LMDI and System Dynamics Model for Estimating Urban CO2 Emission Mitigation Potential in Shanghai, China. *J. Clean. Prod.* 240, 118034. doi:10.1016/j.jclepro.2019.118034

Gu, Y., Wu, Y., Liu, J., Xu, M., and Zuo, T. (2020). Ecological Civilization and Government Administrative System Reform in China. *Resour. Conservation Recycling* 155, 104654. doi:10.1016/j.resconrec.2019.104654

Guo, R. (2015). "Chinese-style Development in Xinjiang," in *China's Spatial (Dis) integration*. Editor R. Guo (United Kingdom, Chandos Publishing), 15–41. doi:10.1016/b978-0-08-100387-9.00002-6

Habert, G., Miller, S. A., John, V. M., Provis, J. L., Favier, A., Horvath, A., et al. (2020). Environmental Impacts and Decarbonization Strategies in the Cement and concrete Industries. *Nature Reviews Earth & Environment*.

He, L., Wu, M., Wang, D., and Zhong, Z. (2018). A Study of the Influence of Regional Environmental Expenditure on Air Quality in China: the Effectiveness of Environmental Policy. *Environ. Sci. Pollut. Res.* 25, 7454–7468. doi:10.1007/s11356-017-1033-8

Isabel Hilton, O. K. (2014). The Paris Agreement: China's 'New Normal' Role in International Climate Negotiations. *Clim. Pol.* 17, 48–58.

Janssens-Maenhout, G., Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Dentener, F., et al. (2019). EDGAR v4.3.2 Global Atlas of the Three Major Greenhouse Gas Emissions for the Period 1970-2012. *Earth Syst. Sci. Data* 11, 959–1002. doi:10.5194/essd-11-959-2019

Jiang, J., Ye, B., Xie, D., and Tang, J. (2017). Provincial-level Carbon Emission Drivers and Emission Reduction Strategies in China: Combining Multi-Layer LMDI Decomposition with Hierarchical Clustering. *J. Clean. Prod.* 169, 178–190. doi:10.1016/j.jclepro.2017.03.189

Li, X., Yang, X., Wei, Q., and Zhang, B. (2019). Authoritarian Environmentalism and Environmental Policy Implementation in China. *Resour. Conservation Recycling* 145, 86–93. doi:10.1016/j.resconrec.2019.02.011

Liu, B., Shi, J., Wang, H., Su, X., and Zhou, P. (2019). Driving Factors of Carbon Emissions in China: A Joint Decomposition Approach Based on Meta-Frontier. *Appl. Energ.* 256, 113986. doi:10.1016/j.apenergy.2019.113986

Liu, Q., Zhang, W., Yao, M., and Yuan, J. (2017). Carbon Emissions Performance Regulation for China's Top Generation Groups by 2020: Too Challenging to Realize?. *Resour. Conservation Recycling* 122, 326–334. doi:10.1016/j.resconrec.2017.03.008

Liu, Z., Davis, S. J., Feng, K., Hubacek, K., Liang, S., Anadon, L. D., et al. (2016). Targeted Opportunities to Address the Climate-Trade Dilemma in China. *Nat. Clim Change* 6, 201–206. doi:10.1038/nclimate2800

Luo, F., Guo, Y., Yao, M., Cai, W., Wang, M., and Wei, W. (2020). Carbon Emissions and Driving Forces of China's Power Sector: Input-Output Model Based on the Disaggregated Power Sector. *J. Clean. Prod.* 268, 121925. doi:10.1016/j.jclepro.2020.121925

McMillen, D. H. (1981). Xinjiang and the Production and Construction Corps: A Han Organisation in a Non-han Region. *Aust. J. Chin. Aff.* 6, 65–96. doi:10.2307/2159052

Qian, H., Xu, S., Cao, J., Ren, F., Wei, W., Meng, J., et al. (2021). Air Pollution Reduction and Climate Co-benefits in China's Industries. *Nat. Sustain.* 4, 417–425. doi:10.1038/s41893-020-00669-0

Quan, C., Cheng, X., Yu, S., and Ye, X. (2020). Analysis on the Influencing Factors of Carbon Emission in China's Logistics Industry Based on LMDI Method. *Sci. Total Environ.* 734. doi:10.1016/j.scitotenv.2020.138473

Shan, Y., Guan, D., Zheng, H., Ou, J., Li, Y., Meng, J., et al. (2018). China CO2 Emission Accounts 1997–2015. *Scientific Data* 5, 170201. doi:10.1038/sdata.2017.201

Shan, Y., Huang, Q., Guan, D., and Hubacek, K. (2020). China CO2 Emission Accounts 2016–2017. *Scientific Data* 7, 54. doi:10.1038/s41597-020-0393-y

Shan, Y., Guan, D., Liu, J., Mi, Z., Liu, Z., Liu, J., et al. (2017). Methodology and Applications of City Level CO 2 Emission Accounts in China. *J. Clean. Prod.* 161, 1215–1225. doi:10.1016/j.jclepro.2017.06.075

Shan, Y., Liu, J., Liu, Z., Xu, X., Shao, S., Wang, P., et al. (2016). New Provincial CO2 Emission Inventories in China Based on Apparent Energy Consumption Data and Updated Emission Factors. *Appl. Energ.* 184, 742–750. doi:10.1016/j.apenergy.2016.03.073

Shan, Y., Huang, Q., Guan, D., and Hubacek, K.(2020). China CO2 Emission Accounts 2016–2017. *Scientific Data* 7, 54.

Statistical Bureau of Xinjiang production and Construction Corps scoNBos (1998-2018). *Statistical Yearbook of Xinjiang Production and Construction Corps*. Beijing: China Statistics Press.

The State Council Information Office of the People's Republic of China (2014). The History and development of Xinjiang production and Construction Corps. People's daily. October 6,008.

Wang, M., Yao, M., Wang, S., Qian, H., Zhang, P., Wang, Y., et al. (2021). Study of the Emissions and Spatial Distributions of Various Power-Generation Technologies in China. *J. Environ. Manage.* 278, 111401. doi:10.1016/j.jenvman.2020.111401

Wang, Q., and Jiang, R. (2019). Is China's Economic Growth Decoupled from Carbon Emissions? *J. Clean. Prod.* 225, 1194–1208. doi:10.1016/j.jclepro.2019.03.301

Wang, Q., and Su, M. (2019). The Effects of Urbanization and Industrialization on Decoupling Economic Growth from Carbon Emission - A Case Study of China. *Sust. Cities Soc.* 51, 101758. doi:10.1016/j.scs.2019.101758

Wang, Y., Zhao, J., Li, Z., Liu, X., and Zhou, J. (2019). Study on Decoupling Effect and Driving Factors of Carbon Emission and Economic Growth in Northeast China. *Environ. Sci. Tech.* 42, 190–196.

Wang, Y., Yang, H., and Sun, R. (2020). Effectiveness of China's Provincial Industrial Carbon Emission Reduction and Optimization of Carbon Emission Reduction Paths in "lagging Regions": Efficiency-Cost Analysis. *J. Environ. Manage.* 275, 111221. doi:10.1016/j.jenvman.2020.111221

Wang, Z., Zhao, N., Wei, W., and Zhang, Q. (2021a). A Differentiated Energy Kuznets Curve: Evidence from Mainland China. *Energy* 214, 118942. doi:10.1016/j.energy.2020.118942

Wei, W., Cai, W., Guo, Y., Bai, C., and Yang, L. (2020a). Decoupling Relationship between Energy Consumption and Economic Growth in China's Provinces from the Perspective of Resource Security. *Resour. Pol.* 68, 101693. doi:10.1016/j.resourpol.2020.101693

Wei, W., Hao, S., Yao, M., Chen, W., Wang, S., Wang, Z., et al. (2020b). Unbalanced Economic Benefits and the Electricity-Related Carbon Emissions Embodied in China's Interprovincial Trade. *J. Environ. Manage.* 263, 110390. doi:10.1016/j.jenvman.2020.110390

Wei, W., Li, J., Chen, B., Wang, M., Zhang, P., Guan, D., et al. (2021). Embodied Greenhouse Gas Emissions from Building China's Large-Scale Power Transmission Infrastructure. *Nat. Sustain*. doi:10.1038/s41893-021-00704-8

Wei, W., Zhang, P., Yao, M., Xue, M., Miao, J., Liu, B., et al. (2020c). Multi-scope Electricity-Related Carbon Emissions Accounting: a Case Study of Shanghai. *J. Clean. Prod.* 252, 119789. doi:10.1016/j.jclepro.2019.119789

Weng, Q., and Xu, H. (2018). A Review of China's Carbon Trading Market. *Renew. Sust. Energ. Rev.* 91, 613–619. doi:10.1016/j.rser.2018.04.026

Xie, P., Gao, S., and Sun, F. (2019). An Analysis of the Decoupling Relationship between CO2 Emission in Power Industry and GDP in China Based on LMDI Method. *J. Clean. Prod.* 211, 598–606. doi:10.1016/j.jclepro.2018.11.212

Yang, F., Yang, M., Xue, B., and Luo, Q. (2018). The Effects of China's Western Development Strategy Implementation on Local Ecological Economic Performance. *J. Clean. Prod.* 202, 925–933. doi:10.1016/j.jclepro.2018.08.203

Yang, Y., Qu, S., Cai, B., Liang, S., Wang, Z., Wang, J., et al. (2020). Mapping Global Carbon Footprint in China. *Nat. Commun.* 11, 2237. doi:10.1038/s41467-020-15883-9

Zhang, C., Zhou, B., and Wang, Q. (2019). Effect of China's Western Development Strategy on Carbon Intensity. *J. Clean. Prod.* 215, 1170–1179. doi:10.1016/j.jclepro.2019.01.136

Zhang, P., Cai, W., Yao, M., Wang, Z., Yang, L., and Wei, W. (2020a). Urban Carbon Emissions Associated with Electricity Consumption in Beijing and the Driving Factors. *Appl. Energ.* 275, 115425. doi:10.1016/j.apenergy.2020.115425

Zhang, Y., Wang, W., Liang, L., Wang, D., Cui, X., and Wei, W. (2020b). Spatial-temporal Pattern Evolution and Driving Factors of China's Energy Efficiency under Low-Carbon Economy. *Sci. Total Environ.* 739, 140197. doi:10.1016/j.scitotenv.2020.140197

Zhang, Z. (2017). Are China's Climate Commitments in a post-Paris Agreement Sufficiently Ambitious? *Wires Clim. Change* 8, e443. doi:10.1002/wcc.443

Zhu, L., Dabo, G., Wei, W, Steven, J. D, Philippe, C., Jin, B., et al. (2015). Reduced Carbon Emission Estimates from Fossil Fuel Combustion and Cement Production in China. *Nature* 524, 335–338.

Zhuo, C., and Deng, F. (2020). How Does China's Western Development Strategy Affect Regional green Economic Efficiency? *Sci. Total Environ.* 707, 135939–135939.14. doi:10.1016/j.scitotenv.2019.1359391

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