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Towards 2030: sustainable development goal 9: industry, innovation and infrastructure. A sociological perspective

Edited by
Andrzej Klimczuk, Grzegorz Piotr Gawron,
Magdalena Klimczuk-Kochańska and Piotr Toczyski

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Towards 2030: sustainable development goal 9: industry, innovation and infrastructure. A sociological perspective

Topic editors
Andrzej Klimczuk — Warsaw School of Economics, Poland
Grzegorz Piotr Gawron — University of Silesia in Katowice, Poland
Magdalena Klimczuk-Kochańska — University of Warsaw, Poland
Piotr Toczyski — The Maria Grzegorzewska University, Poland

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EDITED AND REVIEWED BY
Juan Diego Ibáñez-Álamo,
University of Granada, Spain

*CORRESPONDENCE
Andrzej Klimczuk
klimczukandrzej@gmail.com

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Editorial: Towards 2030: sustainable development goal 9: industry, innovation and infrastructure. A sociological perspective

Andrzej Klimczuk[1]*, Grzegorz Piotr Gawron[2], Magdalena Klimczuk-Kochańska[3] and Piotr Toczyski[4]

[1]Department of Social Policy, Collegium of Socio-Economics, SGH Warsaw School of Economics, Warsaw, Poland, [2]Institute of Sociology, Faculty of Social Sciences, University of Silesia in Katowice, Katowice, Poland, [3]Faculty of Management, University of Warsaw, Warsaw, Poland, [4]Media and Communication Department, Institute of Philosophy and Sociology, The Maria Grzegorzewska University, Warsaw, Poland

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SDG9, environmental regulation, industrial policies, innovation, sustainable industrial development, technology transfer

Editorial on the Research Topic
Towards 2030: sustainable development goal 9: industry, innovation and infrastructure. A sociological perspective

Overview

This Research Topic explores the ninth Sustainable Development Goal (SDG), which aims to build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation, particularly in the context of post-COVID-19 pandemic recovery. The pandemic significantly impacted the manufacturing sector, leading to a global production drop, job losses, and disrupted supply chains, with less technology-intensive industries taking longer to regain ground. Despite these challenges, the United Nations highlights opportunities to enhance industrialization and technology distribution, emphasizing, among other things, the need to expand mobile broadband networks, increase research and development investment, and improve rural road connectivity.

The Research Topic "*Towards 2030: sustainable development goal 9: industry, innovation and infrastructure. A sociological perspective*" was edited in cooperation with two journals: "Frontiers in Sociology" and "Frontiers in Ecology and Evolution." The presented Research Topic includes eight original research articles of prepared in total by 30 authors who deal with subjects covering issues such as green development, environmental regulation, carbon reduction, institutional development, digital economy, innovation, and technology transfer. The articles comprising this Research Topic are organized according to three themes.

Theme I: selected challenges of the inclusive and sustainable industrialization

The team of Cao et al. analyzed Chinese firms that are internationalizing rapidly, challenging mainstream theories of corporate growth. Using data from Chinese industrial enterprises, the study examines the relationship between exports and innovation through a recombinatory framework integrating resource-based and institution-based views. Findings reveal a *U*-shaped relationship between exports and innovation, influenced by provincial institutional factors, with higher institutional development levels reversing this relationship, offering significant insights for managing export-driven innovation. Moreover, Zhang and Wang present a study that provides evidence for another *U*-shaped relationship in the industrial sector. The authors argue that environmental information disclosure is crucial for promoting carbon neutrality and sustainable development amidst economic growth and environmental degradation. Using data from Chinese A-share listed companies, their study finds a *U*-shaped relationship between environmental information disclosure and corporate sustainable growth, initially decreasing but then increasing, mediated by innovation inputs. The association of these factors is influenced by firm size and equity incentives, which are more pronounced in non-state enterprises than state-owned ones.

Theme II: regulation and measures supporting innovation

The following section covers studies that further examine environment-related innovations in industrial development. Chen et al. examine the impact of environmental regulation on industrial green development in China, using data from 30 provinces between 2006 and 2018. Employing various empirical models, their research reveals that the environmental regulation index significantly promotes green development, with specific regulations influencing technological progress and fiscal decentralization. Peng and Zhang continue to discuss the regulatory conditions in studying industry-university-research cooperation (IURC). According to the authors, IURC is a strategic measure to boost the international competitiveness of China's high-tech manufacturing (HTM) sector, but its links to environmental efficiency (EE) are underexplored. The presented investigation uses advanced models to analyze the impact of IURC on HTM's EE, revealing that, while IURC has a significant negative direct effect, it positively influences EE indirectly through research and development investment. The findings underline the urgent need to improve EE in China's HTM industry, especially in central and western regions, by promoting IURC and increasing investment in environmental technology. Finally, Zhou and Peng present the results of the study regarding the promotion of technology transfer. The authors argue that this is a crucial strategy for enhancing industrial innovation in China. Yet, its impact on the green innovation efficiency (GIE) of the high-tech industry (HTI) remains under-researched. The article presents a three-stage network data envelopment analysis (NDEA) model and regression models to evaluate the effects of domestic technology acquisition (DTA) and foreign technology introduction (FTI) on GIE, finding that DTA significantly boosts GIE. At the same time, FTI has a positive but not statistically significant impact. These insights highlight the need for tailored technology transfer policies to improve green innovation across different provinces in China's HTI.

Theme III: regional and local conditions for green development

The last part of this Research Topic is opened with the study by Liu et al., which focused on the integrated development of industries in China that increasingly focus on achieving carbon neutrality. Analyzing data from 30 Chinese provinces, this study reveals that collaborative agglomeration between productive service and manufacturing industries significantly improves regional green development efficiency, with technological innovation playing a key mediating role. Additionally, the research identifies a non-linear relationship and regional heterogeneity in the impact, leading to policy recommendations for enhancing industrial synergy, promoting technological innovation, and boosting regional green productivity. Ma et al. show another example related to challenges in green development. Integrating digital technology and China's national carbon neutrality strategy can reduce urban carbon emission intensity (CEI). Analysis of data from 110 cities in the Yangtze River Economic Belt (YREB) shows that the development of the digital economy lowers CEI by promoting industrial structure optimization and green technology innovation and exerts a positive spatial spillover effect on surrounding cities. The final chapter of this section by Shen et al. continues on these Research Topics. The authors argue that promoting digital technology is crucial for addressing global climate change and achieving carbon neutrality goals. An econometric analysis of Chinese cities from 2006 to 2020 indicates that digital technology significantly reduces carbon emission intensity and improves carbon emission efficiency through green technological innovation and reduced energy intensity. The study highlights the role of digital technology in accelerating knowledge transfer and creating spillover effects that aid in carbon emission reductions, thus supporting the green transformation of the economy and society.

Conclusion

The research results contained in the articles in this Research Topic allow for the proposal of at least five directions for further research. These are (1) social and cultural aspects of innovation regulation and technology transfer (see UNCTAD, 2014; OECD, 2021); (2) multi-level, cross-sectoral, and multi-sectoral cooperation of various stakeholders in the development of sustainable industry, innovation, and infrastructure (see Arbeiter and Bučar, 2021); (3) regional and local bottom-up solutions in the fields of green development, their scalability, feedbacks from environmental change, degrowth, and community resilience (see Marradi and Mulder, 2022); (4) advances in the access of various industries to digital infrastructures, information, and communications technologies as well as artificial intelligence solutions (see Diodato et al., 2022; ECLAC, 2021); and (5) new ideas for support of SDGs in the fields of technological policy, industrial policy, and innovation policy such as the mission-oriented innovation and industry 5.0 concept (see UNCTAD, 2017; Dixson-Decleve et al., 2022).

Author contributions

AK: Conceptualization, Investigation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing. GG: Supervision, Validation, Writing – review & editing. MK-K: Supervision, Validation, Writing – review & editing. PT: Supervision, Validation, Writing – review & editing.

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Conflict of interest

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The U-Shaped Effect and Its Reversal Mechanism of Export and Innovation—Evidence From Chinese Industrial Enterprises

Xin Cao[1,2†], Peng Li[3†], Limin Fan[3], Yuan Jiang[1,4] and Xiaozhi Huang[3]**

[1] School of Economics, Guangxi University, Nanning, China, [2] School of Economics and Trade, Guangxi University of Finance and Economics, Nanning, China, [3] School of Business Administration, Guangxi University, Nanning, China, [4] School of Finance and Public Administration, Guangxi University of Finance and Economics, Nanning, China

Chinese firms are advancing their internationalization process at a surprisingly rapid pace, which is at odds with the descriptions of mainstream theories of corporate internationalization, such as the internalization theory and the eclectic theory of international production. In this context, a large number of existing literatures have examined the learning-by-export effect but have not agreed on its advantages. In the framework of recombinatory view of innovation, we integrate the resource-based view and the institution-based view, taking Chinese industrial enterprises as the research object, taking the export intensity and the output value of new products as the main indicators. We using the fixed effect model based on the Chinese Industrial Enterprise Database construction with China's Marketization Index. Then this study aims to examine the relationship between exports and innovation. Research results show a non-linear effect, that is U-shaped relationship between exports and innovation; furthermore, the relationships are influenced by institutional factors at the provincial level. The institutional development level is a reverse mechanism of relationship between exports and innovation; when the institutional development level is higher, the relationship between exports and innovation has an inverted U shape. The findings enhance the understanding of export innovation from the perspective of resources and institutions, and export enterprise innovation management can benefit from its significant insights.

Keywords: exports, innovation, institutional development, U-shaped effect, reversal mechanism

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Magdalena Klimczuk-Kochańska,
University of Warsaw, Poland

Reviewed by:
Fei Fan,
Wuhan University, China
Jaan Masso,
University of Tartu, Estonia

****Correspondence:***
Yuan Jiang
jiangyuanyuan722@qq.com
Xiaozhi Huang
hxiaozhi@mail3.sysu.edu.cn

† These authors share first authorship

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INTRODUCTION

As an effective means of organizational learning, exporting provides companies with the opportunity to acquire knowledge from other places (Xie and Li, 2018; Dangelo et al., 2020). This phenomenon of acquiring knowledge from exports is called "learning by exporting" (Wang and Ma, 2018; Ipek, 2019; Dangelo et al., 2020), which means that exporters have access to advanced foreign knowledge, which, if effectively absorbed, will greatly enhance the innovation capabilities of firms (Golovko and Valentini, 2011; Love and Manez, 2019; Dangelo et al., 2020). However, compared with enterprises in developed markets, Chinese exporters, as enterprises in emerging markets, face two deficiencies in converting information advantages into innovation advantages (Xie and Li, 2018). On the one hand, companies often lack resources such as strong technological capabilities, excellent absorptive capacity and close relationships with customers, which makes it difficult for companies to rely on their proprietary advantages to advance their internationalization process (Li et al., 2010; Smith, 2014; Wang et al., 2018). On the other hand, companies usually also face adverse effects such as source country disadvantage or latecomer disadvantage (Wei et al., 2016; Wang et al., 2018). Even so, Chinese firms are advancing their internationalization process at a surprisingly rapid pace, which is at odds with the descriptions of mainstream theories of corporate internationalization, such as the internalization theory and the eclectic theory of international production (Kim et al., 2020). This apparent difference has been considered one of the "big questions" in recent years in the study of corporate internationalization (Buckley et al., 2017).

To theoretically explain the phenomenon that firms are able to grow in international markets despite the lack of proprietary advantages of the firm, the literature discusses it from the perspective of the resource-based view (Barney, 1991) or the institutional-based view (Peng et al., 2008). The literature based on the resource-based view perspective follows the logic of the prevailing theory and analyzes the sources of the firm's proprietary advantage at the micro level (Chen et al., 2016); however, because the perspective assumes institutional homogeneity, this may obscure the understanding of how institutions help or hinder innovation in exporting firms (Corredoira and Mcdermott, 2014). The institutional-based view provides a theoretical perspective for discussing the role of institutions in corporate export learning at the macro level (Xie and Li, 2018).

However, the resource-based and institutional-based views still fall short in independently explaining the following two issues: (1) At the micro level, How does export affect innovation? (2) At the macro level, does the level of institutional development facilitate or hinder innovation by exporters? This study aims to integrate the resource-based view and the institutional-based view based on the framework of recombinatory view of innovation to investigate the above two issues.

The recombinatory view of innovation considers that the forces of both the novelty from acquiring knowledge and the cost of recombining this knowledge influence the effectiveness of innovation (Davis and Eisenhardt, 2011; Balachandran and Hernandez, 2018). This extends the application of resource and institutional perspectives to the study of export innovation in emerging market firms. On the one hand, in the recombinatory view of innovation, resources are not simply used to promote innovation by increasing the export intensity of firms. The linear relationship between higher firm export intensity and better innovation performance does not simply apply to the emerging market environment. Since innovation is influenced by both knowledge acquisition and knowledge recombination factors, this study finds a non-linear effect, that is U-shaped relationship between firm export intensity and innovation. On the one hand, since institutions will also act on both knowledge acquisition and knowledge recombination, the level of institutional development does not simply facilitate or hinder innovation in emerging market exporters either. This study finds a reversal mechanism in the relationship between export intensity and innovation, which will be able to reverse the U-shaped relationship between export intensity and innovation when the level of institutional development is high. The above findings extend previous work in the literature on learning through exporting by showing that the effectiveness of learning through exporting can be influenced not only by factors internal to the firm but also by external macrolevel institutional factors.

LITERATURE REVIEW

Export and Learning

Knowledge is regarded as a valuable resource in both domestic and international markets, therefore, learning has become a crucial issue in the international business environment (Evangelista and Mac, 2016; Ipek, 2019). In this context, export is defined as a learning process. In this process, the enterprises collect information about the export environment timely and accurately (Brouthers et al., 2009). By contacting the export market, enterprises can accelerate the accumulation of market information and technical knowledge (Salomon and Shaver, 2005), so as to enhance the effect of export learning (Love and Ganotakis, 2013). Enterprises often obtain more technology and knowledge in the international market through export than in the domestic market, thus forming information arbitrage (Kogut, 1989), this is the basic mechanism for transforming tangible goods into intangible knowledge (Xie and Li, 2018).

The accumulation of market and technical knowledge often promotes the performance of export enterprises. Early empirical research on export learning at the enterprise level mainly focused on finding the causal relationship between export and enterprise productivity (Wagner, 2007). From the perspective of international trade theory, these studies found that the performance of export enterprises was better than that of non-export enterprises (Bernard and Jensen, 1999). Theoretically, there are two mechanisms to explain the relationship between export and performance. One is self-selection effect (Melitz, 2003), that is, only those enterprises with high productivity will choose to export (Bernard et al., 1995; Bernard and Jensen, 1999; Van Biesebroeck, 2005). The other is the export learning effect. Many empirical studies have tested these two effects, among which the self-selection effect is supported by a large amount of evidence (Eaton et al., 2004; Yang and Mallick, 2010) however, the results of export learning effect are inconsistent. Some studies have found evidence of the effect of export learning (Sun and Hong, 2011; Mallick and Yang, 2013), However, some studies have not found that exports have a significant impact on enterprise productivity (Sharma and Mishra, 2011; Luong, 2013). In order to solve the above disputes, the existing literature has made efforts in two aspects. On the one hand, it is committed to explaining the mechanism of export learning effect, on the other hand, it is committed to shifting the focus of research from the impact of exports on productivity to the impact of innovation (Chittoor et al., 2015; Xie and Li, 2018).

At the enterprise level, the research on export and innovation found that enterprises in developed markets and emerging markets are likely to benefit from export learning (Li et al., 2010; Bratti and Felice, 2012; Xie and Li, 2018). Compared with foreign direct investment and other ways to achieve internationalization, exports involve relatively few commitments, risks and management skills (Cassiman and Golovko, 2011). Therefore, export is usually the first step for emerging market enterprises seeking international sales (Luo and Tung, 2007). Learning income from export is one of the policies that many emerging market governments encourage exports, including the establishment of export processing zones, export tax incentives, export quality inspection and other policies (Xie and Li, 2018). In emerging markets, there are many ways to learn through exports. For example, in order to ensure the quality and performance of imported goods, foreign importers may transfer extensive knowledge about production technology, quality and cost control measures, customer needs, and even competitive product information (Wu et al., 2007). However, emerging market enterprises may not benefit as much from exports as developed market enterprises (Navasaleman, 2011).

Resources and Institutions

Two main viewpoints help to explain the relationship between export and innovation. The resource-based view mainly focuses on the internal operation of export enterprises and the specific attributes of companies (Sousa et al., 2008). The institutional-based view emphasizes the influence of the institutional environment from which export enterprises come (Peng et al., 2008). In the research based on the resource-based view, the classic view is that those enterprises with specific resources and capabilities usually have competitive advantages (Sousa et al., 2008; Chen et al., 2016). These documents implicitly assume that the market environment and institutional environment faced by export enterprises are homogeneous, stable and consistent (Peng et al., 2008). The stronger the ability of the enterprise, the better the export performance. Most of these studies are carried out in the environment of developed markets, and the institution is only used as a background factor. Therefore, enterprise scale, enterprise capability and experience have become the key factors to determine export performance (Majocchi et al., 2005; Pla-Barber and Alegre, 2007).

The institutional-based view follows the definition of institution in New Institutional Economics and holds that institution is the constraint designed by human beings and shaping interpersonal interaction (North, 1990). Institution is the structure and activity of regulation, norm and cognition, which can provide stability and significance for social behavior (Scott, 1995). The institutional-based view divides the institution into formal institution and informal institution, and regards culture as a part of informal institution (Peng et al., 2008). Institutions have a great impact on people's behavior, as well as the strategy and performance of organizations (DiMaggio and Powell, 1983).

Compared with the resource-based view, which takes the institution as the background condition, the basic idea of the institutional-based view comes from the thinking that the institution determines what enterprises can do in the process of formulating and implementing strategies and building competitive advantage (Peng et al., 2008). The institutional-based view transforms the emphasis on more detailed description of culture and institution in the literature (Leung et al., 2005) into a clear strategic focus of enterprises, that is, to discuss how the institution affects the enterprise strategy and performance (Peng et al., 2008). The institutional-based view focuses on the relevant research of emerging markets and emphasizes that there are great differences in the institutional framework between emerging markets and developed markets. Therefore, in addition to resources and other factors, we should pay more attention to the impact of institutional differences on enterprise strategies (Chacar and Vissa, 2005; Peng et al., 2008).

The Recombinatory View of Innovation

Many scholars regard innovation as a new combination of existing knowledge (Cohen and Malerba, 2001; Fleming, 2001), this conceptual view holds that innovation is not only the search for new knowledge, but also an effort to combine the old and new components in a novel way (Fleming, 2001). Enterprises with multiple knowledge sources may obtain more different inputs and reorganize them to obtain more effective opportunities to improve innovation, so as to carry out high-quality and valuable innovation (Wang et al., 2011). Therefore, innovation is regarded as a process of reorganization, through this reorganization, enterprises find novel knowledge and integrate it in an original way (Davis and Eisenhardt, 2011). The novelty of knowledge acquisition and the cost of integration affect the process of reorganization (Balachandran and Hernandez, 2018), On the one hand, the diversity and non-redundancy of knowledge acquired through external connections will have a positive impact on innovation (Srivastava and Gnyawali, 2011), on the other hand, this knowledge needs to be reorganized in some original way. Since it is not easy to reinterpret these knowledge and integrate these different ideas, the integration of knowledge may be costly (Kogut and Zander, 1993; Szulanski, 1996). The result of innovation will be determined by the net effect between the two forces (Balachandran and Hernandez, 2018).

For emerging market export enterprises, the first step is to obtain overseas knowledge through export (Bratti and Felice, 2012; Alcacer and Oxley, 2014), the second step is to deal with knowledge acquired through exports, which may involve extensive adaptation and combine it with relevant local knowledge (Corredoira and Mcdermott, 2014). The resources and institutions play a role in both steps. On the one hand, according to the eclectic theory of international production, the export intensity of enterprises is affected by the ability of enterprises. The stronger the ability of enterprises, the higher the export intensity (Sousa et al., 2008). On the other hand, local institutions are an important source of local knowledge (Corredoira and Mcdermott, 2014), it affects the combination of external knowledge and local knowledge, which has an impact on the process of knowledge reorganization (Xie and Li, 2018).

Summary

The above literature provides a solid theoretical basis for this study. First of all, exports have created channels to learn from overseas, but how to apply this knowledge to innovation is a complex matter. A survey of this process may help explain how some emerging market companies earn more from exports than others. Secondly, the resource-based view and institutional-based view provide different research perspectives for analyzing the relationship between enterprise export and innovation, the combination of the two will provide richer explanatory power for the study of the relationship between enterprise export and innovation. Finally, by dividing the forces affecting innovation into two aspects, the recombinatory view of innovation expands the perspective of analysis and provides an analytical framework for the integration of resource-based view and institutional-based view.

RESEARCH HYPOTHESIS

The Impact of Exports on Innovation

Exporting is one of the important channels for firms to internationalize (Wang and Ma, 2018), and exporting firms are usually exposed to new technologies and market knowledge from abroad that is more available than at home, which allows for information arbitrage (Kogut, 1989), and the accumulation of diverse knowledge about markets and technologies tends to promote the innovative performance of exporting firms (Xie and Li, 2018). The resource-based view emphasizes that the more capable a firm is, the more it tends to export and the stronger is its performance (Sousa et al., 2008; Chen et al., 2016). Most of these studies were undertaken in developed market environments, so it can be implicitly assumed that the institutional environment faced by exporting firms is to some extent homogeneous, stable and consistent and that the factors determining firms' export strategies are firm size, firm technology and capabilities, rather than the institutional environment faced by firms (Majocchi et al., 2005; Pla-Barber and Alegre, 2007). Therefore, based on the resource-based view, the relationship between exports and innovation is more inclined to be seen as linear, and empirical studies provide evidence for a linear relationship between exports and innovation (Ellis et al., 2011).

However, when the recombinatory view of innovation is introduced into the export-innovation relationship, the impact of exporting on innovation is determined by two forces: The knowledge acquired through exporting and the cost of recombining this knowledge, and the net effect of both forces determines the performance of exporting (Balachandran and Hernandez, 2018). In this view, the impact of exports on innovation should be more complex, and the linear relationship of the previous literature would be difficult to effectively describe the relationship between exports and innovation; therefore, the recombinatory view of innovation implies the possibility of a non-linear relationship between exports and innovation.

The recombinatory view of innovation argues that firms with multiple sources of knowledge may have access to more diverse inputs and that recombining them can give them more effective opportunities for high-quality and valuable innovation (Faems et al., 2010; Wang et al., 2011). Access to a variety of knowledge resources creates a diverse knowledge base internally, but new knowledge may be useless if the company fails to integrate it with its own knowledge (Savino et al., 2017). Thus, effective integration of domestic and foreign knowledge is a key mechanism that influences firm innovation (Corredoira and Mcdermott, 2014), and the presence of this mechanism may make the relationship between exporting and innovation exhibit a non-linear relationship. Several empirical studies also provide evidence for a non-linear relationship between exports and firm performance (Chiao et al., 2006; Corredoira and Mcdermott, 2014; Wang and Ma, 2018).

Specifically, on the relationship between exports and innovation, the literature based on the recombinatory view of innovation argues that while exports create avenues for learning from abroad, how to apply this knowledge to innovation is a complex matter (Xie and Li, 2018). The net effect of exports on innovation is likely to be negative if firms do not have the necessary technological capabilities, absorptive capacity and domestic resources to take full advantage of foreign spillover benefits or to meet the demand for more advanced products abroad (Smith, 2014). This result suggests that firm innovation may decline even if export intensity is increased if firms have insufficient capabilities; an increase in export intensity will benefit firm innovation only if firms have strong capabilities.

Synthesizing the above analysis, we infer a U-shaped relationship between exports and innovation and propose the following hypothesis.

H1:There is a U-shaped relationship between corporate exports and innovation.

The Influence of the Institutions

Institutions influence to some extent the resource environment of the economy and thus the resources and capabilities of the firms embedded in that environment (Jackson and Deeg, 2008). The research literature on emerging markets argues that firms' export strategies are largely related to the institutional environment and that when the institutional environment changes, firms' strategies change accordingly (Xie and Li, 2018). In fact, changes in the institutional environment can either improve or impair performance, and such changes may be reflected in multiple dimensions and by various indicators (Sousa et al., 2008; Chen et al., 2016). When progress is made in any or all of the dimensions, it is reasonable to assume that the institutional environment is improving (Wang and Ma, 2018). The literature usually considers institutions as resources and as the main determinants of transaction costs (Jackson and Deeg, 2008), and these roles of institutions influence the relationship between export and innovation by affecting the forces of both knowledge acquisition and costs of the restructuring process (Xie and Li, 2018).

Institution and Innovation Recombining Costs

Institutional improvements affect the relationship between exports and innovation by reducing the cost of recombining. According to the basic view of transaction cost economics, transaction costs tend to discourage the trading and restructuring of knowledge (Williamson, 1975). In the institutional environment of the home country, knowledge search, contracting and monitoring can be costly in the absence of a well-established market intermediary (Xie and Li, 2018). Therefore, according to the recombinatory view of innovation, the institutional environment will facilitate the transfer and reorganization of knowledge by reducing the transaction costs of knowledge (Jackson and Deeg, 2008; Xie and Li, 2018).

When there is a lack of specialized intermediaries, such as brokers, law firms, accounting firms, consulting firms, and industry associations in the home country's institutional environment, this institutional void could greatly affect the capital, factor and product markets of emerging economies (Khanna and Palepu, 2010). It will then be expensive and sometimes impossible to find potential counterparties, to smoothly and efficiently enter into contracts and to execute signed contracts. This is particularly difficult when there is knowledge involved in the transaction. Intermediaries are often required to play a pricing, trust-building and recognition role in such transactions. Although informal systems such as relationships may sometimes replace market intermediaries, they are usually less efficient in facilitating transactions between unfamiliar parties (Peng, 2003).

When the institutional environment in the home country is improved, effective market intermediaries are expected to improve the innovation ability of export enterprises more than non-export enterprises by facilitating knowledge flows, intermediating between buyers and sellers of knowledge, and providing complementary expertise and resources to reduce interaction costs (Kostinets, 2014). Market intermediaries can significantly reduce the transaction costs involved in sourcing from multiple knowledge sources, seeking and helping exporters with adaptation and restructuring efforts, which will help exporters build on knowledge acquired through exports as well as on innovative knowledge acquired locally (Xie and Li, 2018).

Institution and Knowledge Acquisition

Through the above analysis, it can be found that institutional improvements will be able to positively influence the relationship between exports and innovation. However, the institutions influence on the export-innovation relationship by reducing transaction costs is only one aspect of the institutional influence effect; on the other hand, institutions will also influence the export-innovation relationship by affecting exporters' access to knowledge. In this aspect of knowledge acquisition, institutions will have a reverse impact on exporting firms for the following reasons.

First, if the institutional environment in the home country is improved, more firms will enter the market due to reduced trade frictions and government restrictions, leading to more intense market competition (Hermelo and Vassolo, 2010). Those exporters pursuing an expansionary strategy may find the domestic market more attractive and thus further increase their capabilities in the domestic market (Wang and Ma, 2018). Under such conditions, institutional improvements reduce the positive component of the innovation-influencing power of innovation restructuring by making it less attractive to acquire knowledge abroad and thus will probably attenuate the positive innovation-influencing effect of firms' export intensity.

Second, when institutional improvements make the home country's market more open, the information advantage of exporters may be offset by alternative access to overseas knowledge. Foreign direct investment (FDI) enterprises may come with their products and investments, and they bring overseas knowledge that can be shared with local partners or counterparties. Even local firms that are not directly related to multinational firms benefit from the demonstration effect and the unconscious knowledge spillover that results from the movement of people. In addition, all firms in a more open institutional environment would have better opportunities to seek knowledge abroad by importing technology and capital goods or even by investing abroad (Luo and Tung, 2007; Khanna and Palepu, 2010), which would reduce the effect of firms that acquire knowledge through exports.

Third, according to the description of the Uppsala model, the internationalization process of firms follows a gradual development phase of exports, overseas sales, and FDI, in which empirical market knowledge is an important driving force (Johanson and Vahlne, 2009; Wu, 2019). Thus, institutional improvements are likely to change the means of acquiring knowledge by inducing firms to shift from exports to FDI, which is a possible reason for a reduction in the export learning effect (Genin et al., 2020; Kim et al., 2020; Yang et al., 2020). Overall, the available literature provides evidence that when home country institutions are improved, firms will likely no longer simply rely on exports for innovation (Wang et al., 2020).

In summary, although institutions play an influential role in both aspects of the restructuring process, the reduction in transaction costs may hardly offset the reduction in the information advantage that firms obtain through exporting. On the one hand, when firms shift from exports to FDI, this can result in higher costs in the economy (Witt and Lewin, 2007), which will partially offset the positive effects of lower transaction costs. On the other hand, as the system improves, domestic competition also increases, placing higher demands on firms to innovate (Wang and Ma, 2018), which will partially offset the positive effects of lower transaction costs. Therefore, we expect that the improvement of the system will create an inversion mechanism that will reverse the effect of exports on innovation from the original U-shaped effect to an inverted U-shaped effect. To this end, the following hypothesis is proposed.

H2:There is a reversal mechanism in the U-shaped relationship between exports and innovation. Specifically, as institutions continue to improve, the U-shaped relationship between exports and innovation will continue to smooth out until an inversion occurs, where the impact of exports on innovation shifts to an inverted U-shaped effect in a higher institutional development environment relative to a lower institutional development environment.

Conceptual Model

Through the above analysis, we know that export creates a channel for learning from overseas, but how to apply this knowledge to innovation is a complex task. A survey of this process may help explain how emerging market companies benefit from exports. The recombinatory view of innovation holds that the acquisition of knowledge and the cost of recombining this knowledge affect innovation, We use this logic as the basis for building a conceptual model, By using the recombinatory view of innovation, this paper integrates the resource-based view and the institution-based view into a framework to analyze the relationship between export and innovation. According to the resource-based view, export is conducive to the acquisition of knowledge, so export can promote innovation. However, the reorganization of new knowledge will also incur costs, therefore, we believe that the impact of exports on innovation is non-linear and there is a U-shaped effect. Based on the institution-based view and the recombinatory view of innovation, institutions have an impact on both the acquisition of knowledge and the cost of reorganization, we infer that the level of institutional development may reverse the U-shaped effect of exports on innovation. To sum up, we build the following conceptual model, as shown in **Figure 1**.

RESEARCH METHODS

Data Source

The research data for this paper are obtained from the China Industrial Enterprise Database published by the National Bureau of Statistics of China, and the China Marketization Index published by the National Economic Research Institute, and the two databases are combined. First, the Chinese Industrial Enterprise Database records all state-owned and industrial enterprises with main business revenue above 5 million RMB, and this paper uses the sample from 2000 to 2013 and is organized according to the literature (Nie et al., 2012; Tian and Yu, 2013; Li et al., 2018). Second, the China Marketization Index is organized into a provincial panel data format according to the total index, spanning the period 2000–2013. Since the calculation method of this index was adjusted after 2008, to reconcile the differences of the market-based index before and after 2008, the study of Bai and Liu (2018) was referred to and controlled by setting dummy variables. Finally, the China Industrial Enterprise Database was matched with the China Marketization Index by the name of the province (municipalities and autonomous regions) where the enterprises were located and merged into the data analyzed for the paper. Since some records in the China Industrial Enterprise Database were missing the names of provinces (municipalities and autonomous regions), these records with missing values were deleted in the merging process, and the final merged data had a total of 648,936 records, spanning the period 2004–2013.

Variable Measurement

The dependent variable was firm innovation. The value of change in firm innovation was calculated as the dependent variable, calculated as the current value of new product output minus the new product output of the year prior to the firm's initial export (Wang and Ma, 2018). The calculation formula is:

$$\text{cinno} = \text{xcpcz} - \text{inno0}$$

where "cinno" is the enterprise innovation, "xcpcz" is the current new product output value, and "inno0" is the new product output value of the year before the enterprise's initial export.

The independent variable is export intensity. Export intensity is calculated by dividing the value of export deliveries by the value of industrial sales output. The calculation formula is:

$$\text{EI} = \text{ckjhz}/\text{gyxscz}$$

where "EI" is export intensity, "ckjhz" is export delivery value, and "gyxscz" is industrial sales value. In the specific analysis, the lagged one-period value of "EI" and "EI_lag1" is generated as the independent variable.

The moderating variable is institutional change. Using the total China Marketization Index, institutional change is identified at the provincial level. The rate of institutional change at the provincial level is calculated using 3 years as a window period. Calculated by subtracting the marketability index of the current period from the marketability index of the two lagged periods and dividing by the marketability index of the two lagged periods (Wang and Ma, 2018) The calculation formula is:

$$\text{rmar\_c} = (\text{marketind} - \text{mar\_lag2})/\text{mar\_lag2}$$

where "rmar_c" is the regime change, "marketind" is the current period total marketind index, and "mar_lag2" is the two-period lagged term of the current period total marketind index.

Control variables. This paper also controls for firm size, firm age, industry growth rate, and industry competition (Wang and Ma, 2018; Xie and Li, 2018). where "firmsize" is firm size, calculated using the logarithm of total assets. "Firmage" is firm age, calculated using the annual variable minus start-up time. "Ind_growth" is the industry growth rate, calculated using the average sales growth rates of firms in the same industry. "HHI" is industry competition, calculated using the Herfindahl-Hirschman Index. The calculation formula is:

$$\boldsymbol{HHI_{ikt-1}} = \sum_{i=1}^{n_{kt-1}} \left(\boldsymbol{sales_{ikt-1}}/\sum_{j=1}^{n_{kt-1}} \boldsymbol{sales_{jkt-1}}\right)^2$$

where "i" and j" denote companies, "k" denotes industries, and "sales" are company sales.

Model Setting and Analysis Methods

Model Setting

To analyze the impact of exports on firm innovation and the moderating role of institutional change, the following analytical model was constructed:

$$\boldsymbol{cinno_{it}} = \boldsymbol{c} + \boldsymbol{\alpha_1 EI_{it-1}} + \boldsymbol{\alpha_2 EI^2_{it-1}} + \boldsymbol{\beta D} + \boldsymbol{\mu_{it}} \tag{1}$$

$$\begin{aligned}\boldsymbol{cinno_{it}} = {} & \boldsymbol{c\alpha_1 EI_{it-1}} + \boldsymbol{\alpha_2 EI^2_{it-1}} + \boldsymbol{\alpha_3 rmar\_c_i} + \boldsymbol{\alpha_4 EI_{it-1}} \\ & \times \boldsymbol{rmar\_c_i} + \boldsymbol{\alpha_5 EI^2_{it-1}} \times \boldsymbol{rmar\_c_i} + \boldsymbol{\beta D} + \boldsymbol{\mu_{it}}\end{aligned} \tag{2}$$

Among them, model (1) is the benchmark model to test the U-shaped relationship between exports and firm innovation, and model (2) is the benchmark model to test the moderating role of institutional development. $\text{cinno}_{\text{it}}$is the enterprise innovation

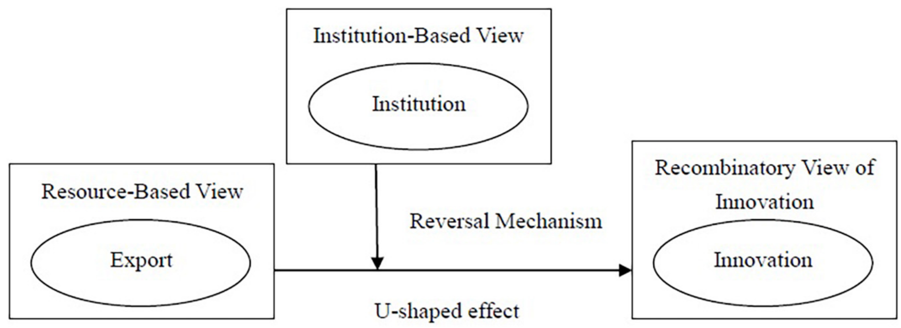

FIGURE 1 | Conceptual model.

change value in the current period, EI_{it-1} is the lagged period value of enterprise export intensity, EI_{it-1}^2 is the squared term of the lagged period of enterprise export intensity, rmar_c_i is the institutional change value of the province where the enterprise is located, and "D" is the set of control variables.

Analysis Method

In this paper, we estimate model (1) and model (2) using a fixed effects model with panel data, which can effectively mitigate the endogeneity problem due to omitted variables by using panel data. Since export and innovation may also have two-way causality, which will also bring endogeneity, this paper alleviates the endogeneity brought by two-way causality in two ways. First, in the baseline model analysis, the independent variables of model (1) and model (2) are the one-period lag of export intensity; second, in the robustness analysis, by setting the second-period lag of export intensity as the instrumental variable, the regression using the instrumental variables method is performed as a robustness test to demonstrate the empirical evidence after mitigating the two-way causality.

Regarding the U-shaped relationship, according to Lind and Mehlum (2010) and Haans et al. (2016) the U (inverted U) relationship was tested in three steps. Taking model (1) as an example for illustration; in the first step,α_2 must be significant and is determined by the sign of whether it has a U or inverted U shape. In the second step, the slope of the curve must be steep and significant at the two endpoints of the curve within the range of values of the independent variable. Taking the U-shaped curve as an example, the slope of the curve should be significantly negative when the independent variable takes the minimum value and significantly positive when the independent variable takes the maximum value. In the third step, the inflection point of the curve must lie within the range of values of the independent variable.

Regarding the test for the moderating effect of the U-shaped relationship, referring to the study by Haans et al. (2016), a judgment is made in two ways; on the one hand, it is necessary to test whether the inflection point of the curve is shifted to the left or to the right. The calculation formula is:

$$\frac{\alpha_1\alpha_5-\alpha_2\alpha_3}{2(\alpha_2\alpha_5 * \mathrm{rmar\_}c)^2} \quad (3)$$

If the sign of formula (3) is positive, it is shifted right, and if the sign is negative, it is shifted left. On the other hand, it is necessary to check whether the shape of the curve is steeper or flatter. Steeper denotes a positive sign of α_5, and flatter denotes a negative sign of α_5, or even a reversal of the curve shape occurs (Haans et al., 2016). In the analysis process, a 1% winsorize was applied to all variables to remove the effect of outliers. The analysis software was stata15.

RESULTS AND DISCUSSION

Results of the Benchmark Model Analysis

Tables 1, **2** report information on the correlation coefficients, means, and standard deviations of the main variables in the model. **Table 3** reports the results of the analysis of the relationship between exports and innovation and the moderating role of institutional development. In the analysis in **Table 3**, records with zero export intensity were removed from the sample to clearly demonstrate the relationship between exports and innovation; therefore, all results reported in **Table 3** are for exporting firms. In the robustness analysis, we add records with zero export intensity back into the sample to demonstrate the robustness of the results.

Model ① adds only control variables. Model ② adds a first-order term with a one-period lag of export intensity and a squared term based on model ① and does not observe a significant U-shaped relationship between exports and innovation ($\alpha_2 = 110.0, p = 0.166$). In model ③, controlling for time fixed effects, the results show that the coefficient of the squared term of export intensity is positive and significant ($\alpha_2 = 342.4, p < 0.01$). This result satisfies the first step in testing for a U-shaped effect, as suggested by Lind and Mehlum (2010), and later by Haans et al. (2016). In the second and third steps, we applied the utest command in stata to check (Lind and Mehlum, 2010; Pollok et al., 2019). The test results of the U-shaped effect show that the slope of the curve is negative and significant at the left end where the exit strength takes the minimum value(slope $= -6878.69, p < 0.01$)and positive and significant

TABLE 1 | Table of correlation coefficients of variables.

	Cinno	EI	EI squ	rmar c	Firmsize	Firmage	Ind growth	HHI
Cinno	1							
EI	–0.0362*	1						
EI squ	–0.0448*	0.9766*	1					
rmar c	–0.00340	0.0073*	0.0066*	1				
Firmsize	0.3286*	–0.1861*	–0.2038*	–0.00210	1			
Firmage	0.1012*	–0.1570*	–0.1521*	0.00220	0.2594*	1		
Ind growth	0.0229*	–0.0152*	–0.0170*	0.1955*	0.0572*	–0.0174*	1	
HHI	0.0564*	–0.1417*	–0.1386*	0.0452*	0.0860*	0.0371*	0.0382*	1

*$p < 0.05$.

at the right end where the exit strength takes the maximum value (slope $= 6890.426, p < 0.01$). The 95% confidence interval for the inflection point value is (9.2786296; 11.60694), which is within the range of values taken for the exit intensity after tailing (0, 20.10667). Therefore, both the second and third steps are also satisfied. The "utest" command also gives the significance level of the overall test for the U-shaped effect, and the results show that the U-shaped effect is significant ($p < 0.01$). H1 is supported.

Models ④-⑥ report the results of the moderating effect of institutional development. The results of model ④ show that the coefficient of the interaction term between the squared term of export intensity and institutional development is negative and significant at the level of 0.1 ($\alpha_5 = -193997.1, p = 0.062$), indicating the presence of the moderating effect of institutional development. Further analysis shows that when the regime moves from a lower to a higher level, the sign of the result calculated according to equation (3) is negative and the point of inflection of the curve shifts to the left; the sign of $\alpha_5$is negative, the curve form is gradually flattened, and finally the inversion of the form occurs, reversing from a U-shaped relationship to an inverted U-shaped relationship. **Figure 2** shows the results of inflection point movement and curve inversion. When institutional development is at a low level, there is a U-shaped relationship between export intensity and enterprise innovation. When the institutional development is at a high level, the relationship between export intensity and enterprise innovation has reversed, from the U-shaped relationship to the inverted U-shaped relationship. Model ⑤ controls for time-fixed effects, and the results are consistent with model ④. Model ⑥ controls for the effect of inconsistent marketization index indicators around 2008 and still finds an inverse effect of institutional development on the U-shaped effect. H2 is supported.

TABLE 2 | Table of descriptive statistical indicators of variables.

Variable	Mean	Sd	Min	Max
Cinno	8,229	42,071	–35,000	330,000
EI	0.470	0.420	0	1
EI squ	0.400	0.420	0	1
rmar c	–0.0600	0.170	–0.730	0.860
Firmsize	10.39	1.530	7.490	14.88
Firmage	9.720	8.410	1	51
Ind growth	0.260	0.240	–0.130	1.820
HHI	0.0200	0.0400	0	0.230

Robustness Tests

Analysis of Instrumental Variables

Table 4 reports the results of the analysis of the instrumental variables, which are export intensity lagged by two periods. Among them, model ①include exporters and non-exporters, and model② include exporters only. Bout of model ① and model ②are 2SLS, the results show that the coefficient of the squared export intensity term is positive and significant ($\alpha_2 = 90227.1, p < 0.05$)in model ①; and the coefficient of the squared export intensity term is positive and significant ($\alpha_2 = 140528.1, p < 0.01$)in model ②. The above models were tested by utest order, and the U-shaped effects of model ①was significant at the level of 0.1($p = 0.0625$); the U-shaped effects of model ② was significant ($p < 0.01$). It shows that the analysis using the instrumental variables approach is still able to observe a significant U-shaped effect between exports and innovation.

Add Control Variables

This paper mainly examines the relationship between export and innovation, and analyzes how the provincial level institution affects the relationship between export and innovation. In fact, in addition to institutional factors, there are other factors at the provincial level that may affect the innovation of enterprises, Therefore, in the robustness analysis, we further controlled some factors to check the robustness of the main results. **Table 5** reports the results of adding control variables in the U-shaped relationship between exports and innovation. Among them, model ① further controls enterprise R & D (rdf), national capital (nationcap), and foreign capital (foreigncap) at the enterprise level. Model ② controls whether it is a state-owned enterprise (stateowned) or a foreign-owned enterprise (foreignowned) on the basis of model ①. Model ③ further controls the per capita GDP(Gdpper), total provincial assets (totalassset) and total investment (totalinv) at the provincial level. It can be seen from the results that the U-shaped effect of export is significant in the three models, indicating that the U-shaped effect of export on innovation is robust.

TABLE 3 | Results of the analysis of the relationship between exports and innovation and the moderating role of institutional development.

	①	②	③	④	⑤	⑥
	Cinno	**Cinno**	**Cinno**	**Cinno**	**Cinno**	**Cinno**
Firmsize	23113.6***	23869.7***	19949.4***	23691.7***	22133.4***	23693.8***
	(6.51)	(6.43)	(6.61)	(5.59)	(5.51)	(5.59)
Firmage	1759.7	1587.5	1175.5	1875.1	1737.3	1875.5
	(1.54)	(1.65)	(1.12)	(1.31)	(1.18)	(1.31)
Ind_growth	–3.012	–2.509	–3.479	–18.90	–24.82	–18.72
	(–0.48)	(–0.26)	(–0.40)	(–0.80)	(–1.06)	(–0.80)
HHI	60170.2*	57044.4	61681.2	111123.0	108236.7	111251.8
	(2.24)	(1.51)	(1.61)	(1.68)	(1.64)	(1.68)
EI_lag1		–2333.5	–6878.7**	7138.9	8166.6	7141.6
		(–1.50)	(–2.96)	(0.52)	(0.60)	(0.52)
EI_lag1_squ		110.0	342.4**	–2921.8	–3183.3	–3127.2
		(1.39)	(2.84)	(–0.21)	(–0.23)	(–0.22)
Time-fixed effects			Control		Control	
rmar_c				–70950.3	–54857.1	–70923.4
				(–1.87)	(–1.06)	(–1.86)
EI_l_rmarc				277235.4*	275792.7*	277131.1*
				(1.99)	(1.98)	(1.99)
EI_l_squ_rmarc				–193997.1	–192209.7	–194460.5
				(–1.85)	(–1.84)	(–1.86)
EI_l_squ_rmarcD						3803.9
						(0.27)
_cons	–236070.4***	–242366.3***	–202989.7***	–246240.5***	–237996.7***	–246264.0***
	(–6.23)	(–6.04)	(–5.84)	(–4.88)	(–4.67)	(–4.88)
N	42,644	39,391	39,391	22,580	22,580	22,580
r^2	0.00499	0.00455	0.00528	0.00645	0.00707	0.00645
r^2_a	0.00489	0.00440	0.00506	0.00606	0.00654	0.00601
F	11.93	9.520	8.418	4.008	4.640	3.660

*t statistics in parentheses, *p < 0.05, **p < 0.01, ***p < 0.001.*

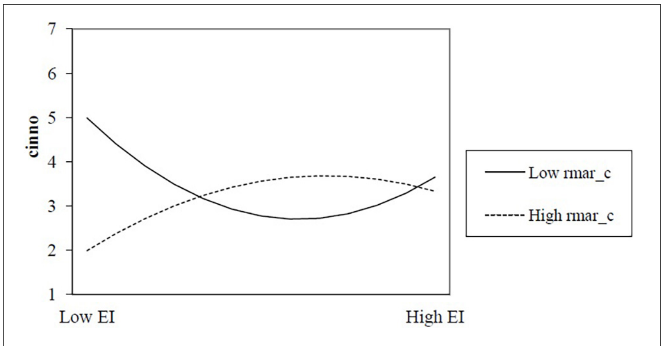

FIGURE 2 | Reversal mechanism of institutional development level.

U-Shaped Relationship Test Including Non-exporting Firms

In the analysis of the benchmark model, we only analyzed the data of exporting enterprises and did not include the enterprises with zero export intensity in the analysis. In the robustness analysis, we included the enterprises with zero export intensity in the sample and analyzed the data containing exporting and non-exporting enterprises, and the results are shown in **Table 6**. In model ②, the coefficient of the squared term of export intensity is positive and significant ($\alpha_2 = 23.44, p < 0.05$), and the utest test results show that the U-shaped relationship between exports and innovation is significant ($p < 0.05$). Model ③ controls for time fixed effects, and the results show that the coefficient of the squared term of export intensity is positive and significant ($\alpha_2 = 52.35, p < 0.01$), and the utest test shows that the U-shaped relationship between exports and innovation is significant ($p < 0.01$).

Subsample Observation of the Reversal of the U-Shaped Effect

In the analysis of the benchmark model, an inversion mechanism is found in the relationship between exports and innovation, where exports and innovation show a U-shaped relationship when institutional development is at a low level and reverse to an inverted U-shaped relationship when institutional development is at a high level. To further observe the reversal mechanism of the U-shaped effect, in the robustness analysis, we observe the performance of the export-innovation relationship by splitting the sample. We calculate the mean and standard deviation of the marketability index by taking the subsample with the

TABLE 4 | Results of instrumental variables analysis.

	Including non-exporting enterprises	Only exporters are included
	①	②
	Cinno	Cinno
EI_lag1	−66836.8	−118663.2**
	(−1.53)	(−2.81)
EI_lag1_squ	90227.1*	140528.1**
	(2.00)	(3.28)
Firmsize	47343.6***	54478.9***
	(5.30)	(5.29)
Firmage	−114.0	840.2
	(−0.20)	(0.96)
Ind_growth	−37.43	−20.19
	(−1.69)	(−0.42)
HHI	4208.6	67681.3
	(0.13)	(1.27)
_cons	−473347.2***	−554908.4***
	(−5.53)	(−5.49)
N	31,842	18,512
r^2	0.0174	0.0300
r^2_a	0.0172	0.0297

*t statistics in parentheses, *p < 0.05, **p < 0.01, ***p < 0.001.*

TABLE 5 | The results of U-shaped relationship between export and innovation with added control variables.

	①	②	③
	Cinno	**Cinno**	**Cinno**
EI_lag1	−4226.1*	−4231.3*	−4405.1*
	(−2.15)	(−2.15)	(−2.16)
EI_lag1_squ	41.96*	42.01*	43.75*
	(2.04)	(2.04)	(2.05)
Firmsize	16116.6***	16134.5***	16135.5***
	(5.76)	(5.75)	(5.65)
Firmage	736.1	745.1	742.8
	(1.22)	(1.23)	(1.23)
Ind_growth	2.818	2.962	3.963
	(0.39)	(0.42)	(0.58)
HHI	13164.2	13682.6	13687.6
	(0.50)	(0.52)	(0.52)
rdf	−4.739	−4.739	−4.739
	(−1.22)	(−1.22)	(−1.22)
Nationcap	0.152	0.153	0.153
	(1.20)	(1.20)	(1.20)
Foreigncap	0.0524	0.0520	0.0522
	(0.11)	(0.11)	(0.11)
Time-fixed effects	Control	Control	Control
Stateowned		−14844.9	−14912.8
		(−0.79)	(−0.79)
Foreignowned		3641.4	3613.1
		(0.70)	(0.69)
Gdpper			0.0431
			(0.13)
Totalassset			0.183
			(0.93)
Totalinv			1.663
			(0.34)
_cons	−158531.3***	−159051.5***	−166876.3***
	(−5.28)	(−5.32)	(−5.00)
N	59,641	59,641	59,641
r^2	0.0476	0.0476	0.0476
r^2_a	0.0474	0.0474	0.0474
F	6.342	5.485	5.593

*t statistics in parentheses, *p < 0.05, ***p < 0.001.*

marketability index less than the mean minus one standard deviation as the low institutional development group and the subsample with the marketability index greater than the mean plus one standard deviation as the high institutional development group. The relationship between exports and innovation is observed separately in the sample of the two groups, and since the missing values of firm innovation are higher in the group with a low level of institutional development, we report the results of the analysis only for the group with a high level of institutional development. The results in **Table 7** show that the coefficient of the squared export intensity term is negative and significant at the level of 0.1 when the sample includes exporters and non-exporters; the results of the utest test show that exports show an inverted U-shaped relationship with innovation, which is significant at the level of 0.1 ($p < 0.1$). The coefficient of the squared export intensity term is negative and significant ($p < 0.05$) when the sample includes only exporting firms; the utest test shows an inverted U-shaped relationship between exports and innovation, which is significant ($p < 0.05$). It shows that when looking only at the part of the sample with a higher level of institutional development, it is still possible to find a reversal of the export-innovation relationship, from the original U-shaped relationship to an inverted U-shaped relationship.

Discussion

This paper discusses the relationship between export and innovation of emerging market enterprises. The basic logical starting point is that compared with non-export emerging market enterprises, emerging market export enterprises have advantages in information arbitrage (Xie and Li, 2018). Emerging market export enterprises expect to transfer advanced technology from abroad through export to avoid high-cost and high-risk R&D (Fagerberg and Godinho, 2005). However, although some emerging market export enterprises have actively participated in the fierce international market competition, their innovation performance still lags behind the market leaders (Navasaleman, 2011).

First, along the basic logic of the resource-based view, the stronger the ability of export enterprises, the higher the export intensity and the better the innovation performance. The test of H1 in this paper extends this logic. Our empirical results show that there is a U-shaped relationship between export intensity and innovation. It is not that the higher the intensity of exports, the higher the performance of innovation. In emerging markets, the relationship between exports and innovation is not

TABLE 6 | Results of the U-shaped relationship test including non-exporting firms.

	①	②	③
	Cinno	Cinno	Cinno
Firmsize	17567.2***	18752.6***	16224.2***
	(5.65)	(5.60)	(5.09)
Firmage	1062.7	1077.1*	734.4
	(1.84)	(2.15)	(1.35)
Ind_growth	2.455	4.175	4.405
	(0.50)	(0.67)	(0.66)
HHI	11552.4	–4072.2	300.7
	(0.53)	(–0.14)	(0.01)
EI_lag1		–2415.5*	–5182.8**
		(–2.38)	(–3.05)
EI_lag1_squ		23.44*	52.35**
		(2.18)	(3.01)
Time-fixed effects			Control
_cons	–174271.6***	–185511.0***	–161909.9***
	(–5.30)	(–5.26)	(–4.84)
N	65,916	59,641	59,641
r^2	0.00131	0.00148	0.00177
r^2_a	0.00125	0.00138	0.00162
F	9.110	6.980	5.396

*t statistics in parentheses, *p < 0.05, **p < 0.01, ***p < 0.001.*

TABLE 7 | Results of the sub-sample analysis of the reversal mechanism of the U-shaped effect.

	①Including non-exporting enterprises	②Only exporters are included
	Cinno	Cinno
EI_lag1	12448.0	24246.9*
	(1.32)	(2.23)
EI_lag1_squ	–16636.5	–28369.7*
	(–1.65)	(–2.35)
Firmsize	14930.7***	20700.7***
	(4.44)	(3.85)
Firmage	1211.1	393.6
	(1.35)	(0.98)
Ind_growth	439.7	2836.9
	(0.76)	(1.49)
HHI	70251.2	143850.0
	(1.08)	(1.15)
_cons	–139765.4***	–206473.4***
	(–4.32)	(–3.68)
N	28,143	20,969
r^2	0.00587	0.00671
r^2_a	0.00566	0.00642
F	4.161	3.378

*t statistics in parentheses, *p < 0.05, ***p < 0.001.*

a simple linear relationship, this result is different from the linear relationship found by research based on developed markets. We introduce the recombinatory view of innovation into the analysis to explain the differences in the relationship between export and innovation observed in emerging and developed markets. The recombinatory view of innovation suggests the existence of two forces that affect the performance of innovation: The novelty of acquiring knowledge through exporting and the cost of recombining knowledge (Davis and Eisenhardt, 2011). Since the exports of developed market firms are based on the firm's proprietary advantages (Dunning, 2001), these firms have the ability to acquire new knowledge and the resources to reorganize it (Smith, 2014). In contrast, emerging market exporters are at a disadvantage in terms of resources and capabilities (Wang et al., 2018), and if firms' capabilities are insufficient, even if these firms enhance their export intensity, they do not have advantages in terms of acquiring new knowledge and reducing recombining costs, and exporting does not lead to an increase in innovation. Only when firms have certain capabilities can they build a knowledge base through exporting and be able to reduce the cost of reorganizing knowledge. Thus, in our data, a U-shaped relationship between exporting and innovation is observed.

Second, by introducing the institution-based view, we argue that appropriate institutional arrangements are important if firms want to increase their innovation capacity through exports. Modern technological updates require new and fundamental changes in the institution (Fagerberg and Godinho, 2005). We measure the development of the system in terms of changes in China's Marketization Index at the provincial level, and in this perspective, observe a very interesting change in the relationship between exports and innovation. The evidence provided in test H2 suggests that institutional development at the provincial level is a reversal mechanism that affects the relationship between firm exports and innovation. When the regime changes more slowly, the relationship between exports and innovation is U-shaped; however, when the regime changes more or faster, the relationship between exports and innovation will reverse, from a U-shaped relationship to an inverted U-shape. This result suggests that in regions where the institution is developing faster, firms can no longer rely on exports alone to meet the requirements of innovation, when outward investment may be a more desirable form of internationalization. The results show that the improvement of the institution will have a positive impact on the relationship between export and innovation. However, the impact of institutions on the relationship between exports and innovation by reducing transaction costs is only one aspect of the impact of institutions. On the other hand, the institution will also affect the relationship between export and innovation by affecting the acquisition of knowledge by export enterprises. Although the institution has an impact on both aspects of the reorganization process, the reduction of transaction costs may be difficult to offset the reduction of information advantages obtained by enterprises through exports. On the one hand, when enterprises shift from export to foreign direct investment, it will cause higher costs in economy (Witt and Lewin, 2007), this will partially offset the positive effect of reducing transaction costs. On the other hand, with the improvement of the institution, domestic competition also increases, which puts forward higher requirements for enterprise innovation (Wang and Ma, 2018), this will also partially offset the positive effect of reducing transaction costs. Therefore, the improvement of the institution has formed a reversal mechanism, reversing the impact of exports on innovation from the original U-shaped effect to the inverted U-shaped effect.

CONCLUSION AND IMPLICATIONS

Conclusion

This paper discusses the relationship between firm exports and innovation based on the resource-based view and the institutional-based view, which correspond to two types of factors affecting export learning, with the resource-based view focusing on the internal factors of firms and the institutional-based view focusing on the external institutional environment of firms. We integrate the resource-based view with the institutional-based view by applying the recombinatory view of innovation, which views innovation as an original combination of existing knowledge. The basic idea is that the outcome of exported on innovation depends on two forces, one being the knowledge acquired by the firm through exporting and the other being the cost of recombining that knowledge, with both resource and institutional factors influencing both forces and the net effect of both forces determining the effectiveness of innovation. Therefore, we believe that there is a non-linear influence between export and innovation, and the institution moderate this non-linear relationship. We tested the above basic hypotheses at the firm level using data from the Chinese Industrial Enterprise Database, and through empirical analysis, the following conclusions were obtained: (1) There is a U-shaped relationship between enterprise exports and innovation. When the export intensity of enterprises is at a low level, exports negatively affect enterprise innovation; when the export intensity of enterprises is at a high level, exports positively affect enterprise innovation. (2) There is a reversal mechanism in the U-shaped relationship between firm exports and innovation, and the level of institutional development can reverse the relationship between exports and innovation. When the level of institutional development is low, there is a U-shaped relationship between firm exports and innovation; when the level of institutional development is high, the relationship between firm exports and innovation reverses and transforms into an inverted U-shaped relationship.

Theoretical Contributions

In an emerging market environment such as China, we use the recombinatory view of innovation to integrate the resource-based view with the institutional-based view to discuss the factors that influence the relationship between firm exports and innovation. According to the resource-based view, the stronger the firm's capabilities, the higher the firm's export intensity and the better the performance of the exporting firm will be. Based on this underlying logic, we tested the impact of firms' export intensity on innovation and found a U-shaped relationship between export intensity and innovation. The institutional-based view discusses the impact of the firm's external institutional environment on corporate strategy, and based on this perspective, we examine the moderating effect of the level of institutional development on the export-innovation relationship at the provincial level and find that there is an inversion mechanism in the U-shaped relationship between export intensity and innovation, with the level of institutional development being able to invert the U-shaped relationship between exports and innovation. These findings enhance our understanding of the relationship between firm exports and innovation and make the incremental contribution to the existing literature in two ways.

(1) By introducing the recombinatory view of innovation into the analysis of the export-innovation relationship, we provide a plausible explanation for the finding of a U-shaped relationship between firm exports and innovation, which makes an incremental contribution to the literature on the application of the resource-based view to explain the firm learning effect at the micro level. In a developed market environment, where there is a reasonable assumption to view the institutional environment as homogeneous and stable, the resource-based view provides a clear explanatory logic for the export-innovation relationship, and since the institution serves only as a background, it is very clear that the factors influencing the export-innovation relationship originate from heterogeneous resources and capabilities within the firm. However, in an emerging market environment, exporters often do not have the above resource advantages. Therefore, even if the discussion is conducted at the micro level, relying only on the resource-based view will hardly provide a reasonable explanation for the relationship between firm exports and innovation. We enter the recombinatory view of innovation into the analysis and argue that the forces of both exported acquired knowledge and the cost of reorganizing knowledge determine the effectiveness of innovation. By introducing this perspective, a plausible explanation for the U-shaped relationship between exports and innovation is provided, thus enhancing the understanding of the relationship between exports and innovation.

(2) The institution-based view can provide a multilevel perspective to explain the relationship between firm exports and innovation at the macro level. By combining the recombinatory view of innovation with the institution-based view, we infer that there is a reversal mechanism for the U-shaped relationship between firm exports and innovation, and we check this inference using data from the Chinese Industrial Enterprise Database and China's Marketization Index and find that the level of institutional development can reverse the U-shaped relationship between exports and innovation. This finding makes an incremental contribution to the literature that applies the institution-based view to explain the learning effect of firms' exports. The basic idea of the institution-based view is that institutions influence the strategy and performance of firms. Based on this view, we can infer that institutions will affect the relationship between firm exports and innovation. However, when the relationship between exports and innovation is U-shaped, the role of institutions has not yet been explained by sound theoretical explanations or by empirical evidence. By combining the recombinatory view of innovation with the institution-based view, we find that institutions influence both the acquisition of exported knowledge and the cost of knowledge recombination, providing a plausible theoretical perspective to explain changes in the relationship between exports and innovation. Empirically, we

find that the level of institutional development at the provincial level can invert the U-shaped relationship between exports and innovation, which also provides new empirical evidence on how institutions actually affect the relationship between exports and innovation.

Management Implications

The findings of this paper also have implications for business managers. First, exporting does not naturally lead to an increase in innovation capacity. Our research has led firm managers to recognize that there are two forces that affect the export learning effect of a firm: one is the knowledge acquired through exports, and the other is the cost of restructuring this knowledge. Enterprises wanting to turn the information advantage brought by exports into innovation advantages need to work on both access to knowledge and the cost of restructuring knowledge. For enterprises, on the one hand, they can learn and accumulate knowledge through export. On the other hand, they should also stimulate their ability of independent innovation through export. Second, a company's strategy should shift as the institutions evolve. Our results show that the relationship between exports and innovation is reversed at different levels of institutional development, a result that prompts managers of firms to pay attention to the role of the institutional environment external to the firm in influencing the firm's strategy. Enterprises need to timely evaluate the institutional development level of the place where they are located. For example, enterprises can hire professional consulting institutions or use the official data of the National Commerce Department to study and judge the institutional situation faced by enterprises in order to develop corresponding innovation strategies. Finally, for the internationalization strategy of enterprises, exporting is not the only way to enhance corporate innovation; when the level of institutional development changes, establishing overseas sales companies and foreign direct investment may be a more appropriate way to internationalize.

Limitations and Future Research Directions

There are also limitations to our study. First, we argue, based on the logic of the resource-based view, that the higher the capacity of the firm is, the stronger the export intensity. Based on this, we hypothesized a U-shaped relationship between export intensity and innovation, checked this hypothesis using data from the Chinese Industrial Enterprise Database and found a U-shaped relationship between export intensity and innovation. However, the relationship between firm capabilities and export intensity has not been tested in this paper, and future research could further examine the relationship between firm capabilities, resources, etc. and firm exports. Second, we hypothesize that the level of institutional development is the inversion mechanism of the U-shaped relationship between exports and innovation, and we test this hypothesis at the provincial level using combined data from the Chinese Industrial Enterprise Database and China's Marketization Index. However, in dealing with China's Marketization Index, we only used the aggregate index and did not examine the impact of differences in institutional development across dimensions. Future research could theoretically discuss the role of the impact of different dimensions of institutions and test this using dimensional indicators of the marketization index. Third, China's Industrial Enterprise database only provides the output value of new products, which limits our measurement of enterprise innovation. Future research can consider using patent data to measure enterprise innovation. Finally, the data analyzed in this paper are up to 2013, and although the Chinese Industrial Enterprise Database provides a large sample of studies for this paper, we have not yet observed the effect of institutional development on the export-innovation relationship after 2013. Because of the preliminary evidence already provided in this study, future studies may choose to use data from public companies to observe the latest changes.

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

XC and PL contributed to conceptualization, formal analysis, funding acquisition, methodology, and writing—original draft preparation. LF contributed to data curation and formal analysis. YJ contributed to data curation, formal analysis, and writing—original draft preparation. XH contributed to conceptualization, formal analysis, funding acquisition, investigation, and writing—original draft preparation. All authors contributed to the article and approved the submitted version.

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EDITED BY
Piotr Toczyski,
The Maria Grzegorzewska University, Poland

REVIEWED BY
Haitao Wu,
Beijing Institute of Technology, China
Yufeng Chen,
Zhejiang Gongshang University, China

*CORRESPONDENCE
Hao Huang
huanghao2156@hust.edu.cn

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The impact of environmental regulation on China's industrial green development and its heterogeneity

Huangxin Chen[1], Yuping Yang[1], Mengting Yang[1] and Hao Huang[2]*

[1]School of Economics, Fujian Normal University, Fuzhou, China, [2]School of Management, Huazhong University of Science and Technology, Wuhan, China

The research analyzes the impact of environmental regulation on industrial green development using panel data from 30 provinces in China from 2006 to 2018. We employ the Super-slack-based measuring (SBM) model to measure the level of domestic industrial green development and use the ordinary panel model, the panel threshold model, and the spatial panel model for empirical estimation. The results reveal that the environmental regulation index plays a significant role in promoting such development. Environmental regulation index, command-and-control environmental regulation, market-incentive environmental regulation, and public-participation environmental regulation all have only a single threshold of technological progress and fiscal decentralization. Further analysis shows that China's industrial green development presents obvious spatial agglomeration characteristics, and there is a significantly positive spatial correlation between different environmental regulation indicators and industrial green development. Our findings provide useful policy recommendations for promoting industrial green development in China.

KEYWORDS

environmental regulation, industrial green development, technological progress, fiscal decentralization, heterogeneity

Introduction

China's industrial development process in recent years has been accelerating, and great achievements have been made. In 2020 its total industrial output value was 31.3 trillion yuan, or an increase of nearly 90% over 2010. However, for a long time, domestic industrial development has been excessively dependent on the input of resources and energy factors, emphasizing the expansion of output scale. Although this extensive development pattern has promoted rapid economic development, it has also led to serious environmental pollution problems (Zhu et al., 2019; Chen et al., 2020a,b;

Zhao et al., 2022a,b). In 2019 China's industry consumed about 66% of its energy and generated more than 85% of sulfur dioxide and dust. It can be seen that the realization of industrial growth is accompanied by huge environmental costs, and the deepening of its industrialization undoubtedly brings new challenges to the construction of ecological civilization.

The ninth sustainable development goal in the 2030 Agenda for Sustainable Development issued by the United Nations, which is to "Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation," points out the direction and presents arduous tasks for the future industrial development of countries. In fact, the China government attaches great importance to resource and environmental pollution issues and is committed to promoting sustainable industrial development. The country has proposed five development concepts of innovation, coordination, greenness, openness, and sharing and has issued a series of relevant laws and regulations to support industrial green development. In addition, the goal of peak carbon emissions by 2030 and achieving carbon neutrality by 2060 has also strengthened China's industrial commitment to green and low-carbon development (Zhao et al., 2022c,d). In this context, the domestic industry urgently needs to transform to green production, reduce excessive resource consumption and pollutant emissions, and contribute to global pollution control and the realization of sustainable development goals (Yang et al., 2022; Zhang et al., 2022). However, effectively coordinating the relationship between industrial development and environmental protection is a major problem to be solved urgently.

Due to the negative externality of environmental pollution, it is difficult to achieve effective regulation of pollution emissions only based on spontaneous market regulation (Sun et al., 2021; Chen et al., 2022). Therefore, government intervention in pollution control and environmental protection is particularly important (Wang and Liu, 2019). Environmental regulation, as the main policy tool for the government to prevent pollution emissions, is of great significance to realize sustainable development of economy and environment (Ma and Xu, 2022). On the one hand, the implementation of environmental regulations will increase the production cost of enterprises by levying pollutant discharge fees, prompting enterprises to reduce the use of high-polluting production factors and adopt clean energy, thus achieving the goal of reducing pollution emissions (Zhang et al., 2019). On the other hand, environmental regulation will promote enterprises to carry out technological research and development and improve the level of green technology and production efficiency (Porter and Van der Linde, 1995). In addition, strict environmental regulations will not only squeeze the profit space of highly polluting enterprises and force them to withdraw from the market, but also strengthen the development of environmentally friendly enterprises and contribute to the upgrading of industrial structure. Most scholars point out that environmental regulation has been effective in improving energy efficiency and addressing the externalities of environmental pollution (Mandal, 2010; Neves et al., 2020; Chen et al., 2022).

The Chinese government in recent years has issued a series of environmental regulatory measures aimed at reducing industrial pollution emissions and achieving sustainable development through environmental regulation (Zhang et al., 2019). However, it can be found that China's environmental quality seems to continue to deteriorate, and industrial emissions are still the main cause of environmental problems. Moreover, through in-depth research, especially after the green paradox theory was put forward, scholars are questioning the necessity and effectiveness of environmental regulation at improving environmental quality (Sinn, 2008; Van der Werf and Di Maria, 2012). Due to the imbalance of its industrial development, there are great differences in the degree of pollution emissions, which in turn result in different effects of environmental policies. In addition, the implementation of environmental regulation policies may also lead to the relocation of industries in different regions, further complicating the industrial pollution situation in China. So can environmental regulation effectively promote China's industrial green transformation? This question has not been adequately answered. Therefore, it is necessary to clearly identify the role and influence mechanism of environmental regulation in industrial green transformation, which is of great significance for China to take further policy measures to promote industrial green transformation.

At present, scholars have conducted extensive discussions on environmental issues and provided useful evidence. However, the existing research still has the following shortcomings. First, there is no consensus on the impact of environmental regulation on environmental performance, and the existing literature on environmental performance focuses on the fields of agriculture and manufacturing (Chen et al., 2021; Chen and Zhu, 2022). There is still a lack of research on green development in the industrial sector. The development of industry is an important factor leading to environmental problems, so it is necessary to expand research on the industrial field. Second, although relevant literatures have investigated the nonlinear characteristics of environmental regulation on green innovation and pollution emission (Chen et al., 2019; Song et al., 2020), these studies seldom consider the interference of external factors and cannot identify the inflection point values. The influence of environmental regulation on industrial green development is a dynamic and complex process, which is restricted by technical conditions and institutional environment. This makes it possible that the effect has threshold characteristics. Third, most studies assume that regions are independent of each other, while ignoring the spatial correlation between economic variables in different regions, making it difficult to comprehensively analyze the spatial effect of environmental regulation on industrial green development.

We therefore adopt the threshold model and spatial econometric model to explore the relationship between environmental regulation and industrial green development in China. The main contributions of this study can be summarized as follows. First, we subdivide the types of environmental regulations, and deeply explore the differences in the impact of various environmental regulations on industrial green development, so as to provide useful supplements to existing research. Second, our study takes technological progress and fiscal decentralization as threshold variables to analyze the nonlinear effects of different types of environmental regulations on industrial green development. Third, considering the spatial dependence characteristics of regional industrial green development, this study further examines the spatial effects of different types of environmental regulations on industrial green development, thus providing a reference for the government to effectively implement joint governance policies for regional pollution.

The remaining contents of this study are arranged as follows. The second part reviews the relevant literature. The third part involves model setting, variable measurement and data description. The fourth part analyzes the empirical results. The fifth part summarizes the research results and puts forward policy suggestions. The sixth part is to clarify the limitations of the research and future research directions.

Literature review

Existing research views on the relationship between environmental regulation and environmental performance have not yet reached a consensus, but mainly offer three viewpoints.

First, most studies in the literature have noted that environmental regulation has a positive effect on environmental performance. Shapiro and Walker (2018) pointed out that environmental regulation promotes the adoption of emission reduction technologies, which is the main reason to explain the reduction of manufacturing pollution emissions. Hashmi and Alam (2019) examined the impact of environmental technologies and regulations on carbon emissions, and found that environmental regulations were more effective in reducing carbon dioxide emissions than environmental technologies, with a 1% increase in per capita environmental taxation and a 0.03% reduction in carbon dioxide emissions. Ulucak et al. (2020) took Brazil, India, China, Russia, and South Africa as research objects, and confirmed the positive role of environmental regulations in mitigating carbon emissions – that is, current environmental regulations are effective in achieving pollution reduction goals in these countries. Sun et al. (2021) recognized that environmental regulation not only increases the number of innovative products in high-tech industries, but also helps to improve the quality of innovative products, thus achieving a win-win situation for economic development and environmental governance. Cai et al. (2020) clarified that direct environmental regulation significantly stimulates green technology innovation in heavily polluting industries, and this impact is heterogeneous – that is, direct environmental regulation has a more obvious effect on green technology innovation of state-owned listed companies in heavy pollution industries and technology-capital-intensive industries.

You et al. (2019) concluded that without the influence of the government's political system, environmental regulation can significantly facilitate the ecological investment and ecological planning innovation of industrial enterprises, which add great significance to the sustainable development of China's economy. Liao and Shi (2018) discussed the positive effect between public appeal and green investment and showed that public appeal encourages local governments to adopt stricter environmental regulation measures, which are conducive to guiding enterprises to increase the research and development of clean technologies and green products. Wang et al. (2021) found that formal environmental regulation alleviates local air pollution by transferring polluting industries, while informal environmental regulation indirectly suppresses air pollution by improving formal environmental regulation measures. Wang et al. (2022) showed that all three types of environmental regulations have effectively contributed to the upgrading of China's industrial structure, among which the market-incentivized environmental regulation has a more significant role in promoting the industrial structure. Yu and Wang (2021) suggested that environmental regulation policy accelerates the change of regional industrial structure, and the legislative supervision and economic incentive of environmental regulation play a stronger role in explaining the upgrading of industrial structure.

Second, some studies have also suggested that environmental regulation may negatively affect environmental performance. The enhancement of environmental regulation increases the production cost of enterprises, which may eventually inhibit the upgrading of industrial structure (Jaffe and Palmer, 1997; Wang et al., 2022). Millimet et al. (2009) explored the economic impact of environmental regulation on different aspects of the market structure and acknowledged that environmental regulation increases enterprises' production cost, thus squeezing their profit margins and reducing their production efficiency. This will affect the entry and exit behavior of enterprises and ultimately have a negative impact on the industrial structure. Sinn (2008) noted that if fossil fuel suppliers feel a potential threat from the gradual implementation of national environmental policies, then they will extract fossil fuel reserves at a faster rate, thereby accelerating global warming. Van der Werf and Di Maria (2012) showed that imperfect environmental policies may give rise to the "green paradox" – that is, the well-intended policies encourage resource owners to increase resource extraction due to insufficient subsidies for alternative energy sources and a lag in implementation, resulting in an increase in current pollution emissions rather than a decrease.

He et al. (2022) pointed out that under the influence of fiscal decentralization, in order to maximize their own interests, local governments engage in "race to the bottom" when formulating and implementing environmental regulation policies, which is not conducive to reducing agricultural carbon emission intensity. Zhang et al. (2021) noticed that local governments in China have diversified competitive behaviors in the implementation of environmental regulations, which lead to the transfer of pollution to nearby areas and increase local carbon dioxide emissions. Moreover, this study also proves that China's current environmental regulation is still in the stage of "green paradox". Millimet and Roy (2016) emphasized that due to the differences in environmental standards between different regions, polluting enterprises move from areas with strict environmental requirements to areas with lax environmental regulations, leading to continuous deterioration of environmental quality in the transferred areas. Kheder and Zugravu (2012) provided evidence for the pollution haven hypothesis by analyzing the impact of environmental regulations on the site selection of French manufacturing firms. They argued that manufacturing in France is more likely to locate in other countries with looser environmental regulations, making them potentially pollution havens. The effect of environmental regulation is also disturbed by external factors. You et al. (2019) believed under the influence of the fiscal decentralization system and political promotion championships that environmental regulation has a significant inhibitory effect on ecological innovation, ecological planning innovation, and ecological investment.

Third, different from the above two viewpoints, some studies pointed out that the relationship between environmental regulation and environmental performance is uncertain or exhibits nonlinear characteristics. Hao et al. (2018) mentioned that the current environmental regulation methods implemented in China have not achieved the expected results and proved that environmental regulation is only effective in curbing pollution emissions when foreign direct investment is controlled. Ren et al. (2018) used the STIRPAT model to examine the impact of environmental regulation on eco-efficiency and found heterogeneity in the influence of different types of environmental regulation on eco-efficiency. Xie et al. (2017) proved a non-linear relationship between command-and-control and market-based environmental regulations and green productivity, and the growth effect of green productivity driven by market-based environmental regulation is much stronger than that of command- and-control regulation. Du et al. (2021) believed that when the level of economic development is low, environmental regulation has no significant impact on the upgrading of industrial structure and also inhibits green technology innovation. Only when the level of economic development is relatively high will environmental regulation significantly promote green technology innovation and industrial structure upgrading, thereby accelerating the process of economic green transformation (Chen et al., 2020a,b; Zou et al., 2022).

The research of Song et al. (2020) confirmed the U-shaped relationship between environmental regulation and green product innovation. As the intensity of environmental regulation increases, its effect on green product innovation shifts from inhibition to promotion. Zhang et al. (2020) believed that environmental regulation has a non-linear impact on carbon emissions. The improvement of environmental regulation makes the reduction effect of the total amount and intensity of carbon emissions more obvious, and foreign direct investment under the constraints of environmental regulation also inhibits carbon emissions. Chen et al. (2019) noted that environmental regulation and industrial structure have obvious non-linear effects on carbon dioxide emissions – that is, the impact of environmental regulation on carbon emissions changes with the rationalization of industrial structure. Wu et al. (2020a) confirmed a U-shape relationship between environmental regulation and green total factor energy efficiency, which means that the expansion of environmental governance decentralization has effectively improved local governments' autonomous choices for pollution control. Chen and Qian (2020) found that various types of marine environmental regulation have a positive U-shape relationship with the upgrading of the manufacturing industry structure and the transfer of polluting industries, in which the inflection point of industrial structure upgrading occurs later than the transfer of polluting industries.

Materials and methods

Model setting

Baseline regression model

Considering the volatility of green development level, this study draws on the research of Li and Wu (2017), and firstly constructs an ordinary panel data model to explore the impact of environmental regulations on the level of industrial green development as follows.

$$y_{it} = \beta_0 + \mu_i + \lambda_t + x_{it}'\beta_1 + k_{it}'\beta_2 + \varepsilon_{it}, \tag{1}$$

where i denotes province and t denotes year; y_{it} denotes industrial green development level; x_{it} denotes environmental regulation; k_{it} denotes a series of control variables; β_1 and β_2 denotes regression coefficients of core explanatory variables and control variables, respectively; μ_i and λ_t denotes individual effects and time effects, respectively; and ε_{it} is a random disturbance term.

Threshold regression model

As the impact of environmental regulation on industrial green development is a complex and dynamic process, which is easily disturbed by external factors such as technologies and policies. On the one hand, most scholars have confirmed that technological progress is a key link in achieving green development (Kang et al., 2018; Xie et al., 2020), and the effects of environmental regulation are closely related to the level of green technologies in enterprises (Ren and Ji, 2021). Therefore, it is necessary to analyze the role of technological progress in the impact of environmental regulation on industrial green development. On the other hand, the impact of environmental regulation on environmental quality is inseparable from institutional constraints (Chen and Chang, 2020; Wu et al., 2020b). Wu et al. (2020a) believe that the effect of environmental regulation on energy efficiency is closely related to environmental decentralization, and there are significant differences in the role of different types of environmental management decentralization. It can be seen that environmental regulation may have threshold characteristics in the process of acting on industrial green development. When technological progress or fiscal decentralization are on both sides of the threshold, the effect may jump or even reverse.

Therefore, we refer to the research of Wang and Shao (2019) and Wu et al. (2020a) to analyze the nonlinear characteristics of environmental regulation affecting industrial green development from the perspective of technological progress and fiscal decentralization. On this basis, drawing on relevant studies by Hansen (2000), the following threshold regression model is constructed.

$$\begin{aligned} y_{it} = {} & \beta_0 + \mu_i + \lambda_t + x'_{it}\beta_{11} \cdot I\left(q_{it} \leq \gamma_1\right) + x'_{it}\beta_{12} \cdot I \\ & \left(\gamma_1 < q_{it} \leq \gamma_2\right) + \cdots + x'_{it}\beta_{1n+1} \cdot I\left(q_{it} > \gamma_n\right) + k'_{it}\beta_2 \\ & + \varepsilon_{it} \end{aligned} \tag{2}$$

where $I(\cdot)$ denotes the indicator function; q_{it} denotes the threshold variable; and γ_i denotes the threshold value.

Spatial econometric model

The panel model constructed above assumes that regions are independent of each other, while in fact any economic variable in one region is often influenced by neighboring regions. Spatial autocorrelation is a common phenomenon in ecological data that affects the estimation and inference of statistical models (Legendre, 1993; Kissling and Carl, 2008). Hu and Wang (2020) emphasized that environmental regulation and environmental performance have obvious spatial attributes, and the results that ignore spatial correlation may be biased. Some scholars have conducted a spatial econometric analysis of the relationship between environmental regulation and pollution emissions, indirectly confirming the existence of this spatial correlation (Feng et al., 2020; Liu et al., 2022). Therefore, we further construct a spatial panel model to investigate the spatial effect of environmental regulation on industrial green development. The spatial correlation test is a prerequisite for spatial model regression. Referring to the study of Feng et al. (2020), we select global *Moran's I* index to test whether the impact of heterogeneous environmental regulation on industrial green development is spatially dependent. The specific formula is as follows.

$$Moran's\ I = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{s^2 \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}} \tag{3}$$

$$s^2 = \frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})^2,$$

where y_i and y_j are the variable values of province i and province j, respectively; N represents the total number of regions; $\bar{y}$ represents the sample mean; and w_{ij} is the adjacency space weight matrix. The values of *Moran's I* index range from [−1, 1], indicating positive spatial correlation when it is greater than 0, negative spatial correlation when it is less than 0, and no spatial correlation when it is equal to 0.

The commonly used spatial econometric models mainly include the spatial lag model (SAR), spatial error model (SEM), and spatial Durbin model (SDM). Since SDM is the most general and widely used form, we adopt SDM for empirical testing based on the research of LeSage and Pace (2009). The specific form is as follows.

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + x'_{it}\beta + \sum_{j=1}^{N} w_{ij} x'_{jt}\delta + \mu_i + \lambda_t + \varepsilon_{it}, \tag{4}$$

where $\sum_{j=1}^{N} w_{ij}x_{jt}\delta$ denotes the spatial lagged explanatory variables of neighboring regions; N denotes the total number of regions; ρ denotes the spatial autoregressive coefficients; β and δ denote the parameters to be estimated; and other variables have the same meanings as above.

Variable description

Calculation of industrial green development level

Given that data envelopment analysis (DEA) can deal with multiple input and multiple output problems, this study uses a Super-slack-based measuring model (Super-SBM model) model containing undesirable outputs to measure the industrial green development level by referring to the relevant research of Tone (2002). The specific form is as follows.

$$\rho^* = \min \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}}{x_{i0}}}{\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{\bar{y}}{y_{r0}}+\sum_{q=1}^{s_2}\frac{\bar{z}}{z_{q0}}\right)} \tag{5}$$

$$s.t.\begin{cases}\bar{x} \geq \sum_{j\neq 1\neq 0}^{n}\lambda_j x_{ij}\\ \bar{y} = \sum_{j\neq 1\neq 0}^{n}\lambda_j y_{ij}\\ \bar{z} = \sum_{j\neq 1\neq 0}^{n}\lambda_j z_{ij}\\ \lambda > 0, j = 1, 2, \ldots, n, and\, j \neq 0\\ \bar{x} \geq x_{i0}\\ \bar{y} \geq y_{r0}\\ \bar{z} \geq z_{q0}\\ i = 1, 2, \ldots, m; r = 1, 2, \ldots, s; q = 1, 2, \ldots, k\end{cases},$$

where ρ^* denotes the efficiency value; n denotes the number of decision units; m, s_1, and s_2 denote the number of input, desirable output, and undesirable output indicators, respectively; x_{ij}, y_{ij}, and z_{ij} denote the input, desirable output, and undesirable output variables of the evaluated units, respectively; and $\bar{x}$, $\bar{y}$, and $\bar{z}$ denote the slack variables of input, desirable output, and undesirable output, respectively.

Combining with related studies, we choose capital stock, total number of employees at the end of the year, and total energy consumption as input indicators, industrial value added as desirable output, and industrial wastewater emissions, industrial solid waste emissions, industrial sulfur dioxide emissions, and industrial carbon dioxide emissions as undesirable outputs.

Calculation of environmental regulation

According to the different subjects of implementing environmental regulation policies, environmental regulation is subdivided into command-and-control environmental regulation (*ERC*), market-incentive environmental regulation (*ERM*), and public-participation environmental regulation (*ERP*). Among them, the command-and-control environmental regulation is measured by the amount of completed investment in industrial pollution control, the market-incentive environmental regulation is represented by pollutant discharge fees and environmental taxes, and the public-participation environmental regulation is measured by the number of proposals made by the National People's Congress. On this basis, the overall environmental regulation index (*ER*) is obtained by using the entropy method and taken as a proxy variable for environmental regulation. A higher value of environmental regulation index means a higher intensity of environmental regulation.

Control variables

The control variables selected in this study include the following. Total actual utilized foreign investment is chosen to measure the foreign direct investment (*FDI*), so as to examine the influence of foreign investment on the level of industrial green development. Referring to the work of Shan and Zhang (2018), the coordination coefficient between industry and employment structure is measured as a proxy variable of industrial coordination degree (*IC*), and the indicators used involve the ratio of the added value of the tertiary industry to the total output value, as well as the proportional relationship between the employment of the tertiary industry and the total employment. Energy structure (*ES*) is captured by the share of coal consumption in total energy consumption. The comprehensive utilization rate of industrial solid waste is taken to measure the resource recycling level of industrial enterprises (*RC*). The ratio of total urban population at the end of the year to land area is selected to evaluate population density (*PD*). Technological progress (*TI*) is measured by the number of patent applications in the region. Fiscal decentralization (*FD*) is measured by the ratio of per capita local fiscal expenditure to per capita central fiscal expenditure.

Data sources

Considering data availability, this study selects panel data of 30 provinces in China from 2006 to 2018 (These provinces refer to provincial administrative units, including provinces, municipalities and ethnic minority autonomous regions, Tibet, Taiwan, Hong Kong, and Macao are not included in the scope of this analysis). The data of each indicator are obtained from China Statistical Yearbook, China Industrial Economic Statistical Yearbook, China Environmental Statistical Yearbook, China Energy Statistical Yearbook, the statistical yearbooks of each province, and the EPS database. To alleviate and eliminate the possible heteroscedasticity without changing the time-varying characteristics of the original data, we perform logarithmic processing on all variables. The descriptive statistical results of variables appear in **Table 1**.

Empirical results and analysis

Baseline regression results

The random effects model and fixed effects model are respectively used for the empirical test, and **Table 2** lists the results. From the results of the Hausman test, the P-statistic values are 0.6861 and 0.1061, respectively, indicating that the research model does not reject the original hypothesis of using random effects. Therefore, we focus on the estimation results of the random effects model.

TABLE 1 Descriptive statistics of variables.

Variable	N	Mean	Standard deviation	Min	Max
ln *IGTFP*	390	−1.2145	0.7976	−3.4336	0.15192
ln *ER*	390	9.2624	1.0683	0.0000	10.9749
ln *ERC*	390	11.8425	0.9810	8.1783	14.1636
ln *ERM*	390	10.6416	0.9481	7.4951	12.5312
ln *ERP*	390	4.8999	1.0711	0.0000	7.0867
ln *FDI*	390	5.2904	1.6354	−1.2203	7.7219
ln *IC*	390	−0.1996	0.1489	−0.7337	−0.0008
ln *ES*	390	−0.4805	0.4752	−3.6082	0.5485
ln *RC*	390	−0.4569	0.3086	−1.3707	−0.0017
ln *PD*	390	5.4799	1.2936	2.0660	8.3157
ln *TI*	390	10.0300	1.5852	5.7838	13.5846
ln *FD*	390	0.1667	0.3875	−0.5317	1.3103

Before the inclusion of control variables, the coefficients for the effect of environmental regulation on industrial green development in model (1) and model (2) are 0.1850 and 0.1926, respectively, and both are significant at the 1% level. This indicates that environmental regulation has a significant contribution to industrial green development when the influence of other factors is not considered, and every 1% increase in environmental regulation causes at least a 0.1850% increase in industrial green development. From the regression results of model (3) and model (4), after adding the control variables, the coefficients of environmental regulation on industrial green development become 0.0840 and 0.0844, and both of them pass the 5% significance level test – that is, every 1% increase in environmental regulation raises the level of industrial green development by at least 0.0840%. Although the influence coefficient of environmental regulation decrease, its significant contribution does not change. When the intensity of environmental regulation is strengthened, industrial enterprises face considerable environmental penalty costs, which motivate them to increase investment in energy-saving equipment and clean technology R&D, thus promoting industry's green development. As we know, the formulation and implementation of environmental regulation have a cost effect, which may squeeze out the funds needed for R&D by industrial enterprises. At the same time, there is also an innovation compensation effect, which forces enterprises to improve resource utilization and expected output through technological innovation. Therefore, the effect of environmental regulation is the result of the game of two opposing forces. From the baseline regression results, it is clear that the innovation compensation effect of environmental regulation is greater than the compliance cost effect, thereby significantly promoting China's industrial green development.

In terms of the control variables, the coefficient of industrial coordination is significantly positive at the 5% level, suggesting that the higher the industrial coordination is, the more conducive it is to the industrial green development. This is because a reasonable industrial structure and employment structure help optimize factor allocation and promote green development efficiency through the technological linkage between industries (Zhao et al., 2016). The coefficient of resource recycling is significantly positive at the 5% level, which indicates that the improvement of resource recycling efficiency is conducive to reducing undesired outputs such as industrial waste and convert them into desired outputs, which in turn promote the development of industrial green transformation. This is also an important reason for the long-term implementation of circular economy development in China. The coefficient of technological progress is also significantly positive, meaning that technological progress contributes to industrial green development. As the core driving force of industrial transformation and upgrading, technological progress implies the transformation of traditional

TABLE 2 Results of the impact of environmental regulation on industrial green development.

Variable	RE model (1)	FE model (2)	RE model (3)	FE model (4)
ln *ER*	0.1850*** (0.0562)	0.1926*** (0.0637)	0.0840** (0.0368)	0.0844** (0.0361)
ln *PD*			−0.1036 (0.0865)	0.9922 (1.0001)
ln *IC*			1.6380** (0.7136)	1.9826** (0.7468)
ln *RC*			0.3790** (0.1680)	0.4073** (0.1811)
ln *FDI*			−0.0198 (0.0667)	0.0028 (0.0676)
ln *TI*			0.1842*** (0.0611)	0.1369* (0.0690)
ln *FD*			0.2212 (0.4219)	−0.2391 (0.4833)
ln *ES*			−0.2926 (0.3040)	−0.2784 (0.3974)
Constant	−2.9284*** (0.5373)	−2.9986*** (0.5902)	−2.8445*** (0.9993)	−8.3339 (5.2753)
Hausman	0.75 [0.6861]		14.48 [0.1061]	
N	390	390	390	390
R^2	0.0732	0.0732	0.2963	0.306

***, **, and * Represent significance at the 1, 5, and 10% levels, respectively. The value in ( ) is the standard error; the value in [ ] is the probability of accepting the null hypothesis.

production methods and the improvement of enterprise production efficiency, thus promoting the green transformation and development of the entire industry. In addition, the effects of fiscal decentralization, population density, foreign direct investment, and energy structure on industrial green development fail to pass the significance test.

Robustness test

To verify the robustness of the above findings, this study re-tests the research model by subdividing regions and environmental regulation indicators. The results appear in Tables 3, 4. Table 3 reports the results of the subregional robustness test. On the one hand, due to the regional differences in China's economic development level and resource endowment, we divide China into the eastern regions and the central and western regions, and examine the impact of environmental regulations on industrial green development in different regions. On the other hand, we calculate the average value of industrial added value in each province during the sample period, and divide the sample data into strong industrial provinces and weak industrial provinces according to the median. From the regression results of models (1)–(4) in Table 3, environmental regulation has shown a significant role in promoting industrial green development in different regions, which means that the above findings are robust.

Table 4 reports the robustness test results of the sub-indicators and replacement methods. On the one hand, environmental regulation is subdivided into command-and-control environmental regulation, market-incentive environmental regulation, and public-participation environmental regulation. We then examine the impact of the three types of environmental regulations on industrial green development. The results of models (1)–(3) in Table 4 show that the coefficients of all three types of environmental regulations are significantly positive at least at the 5% level – that is, they all significantly contribute to industrial green development. This finding is consistent with the baseline regression.

On the other hand, considering the possible endogeneity issue, the two-stage least squares regression is performed by selecting one lag period (Z_1) and two lag periods (Z_2) of the core explanatory variables as instrumental variables. Table 4's models (4)–(7) report the relevant regression results. From the results of the first stage, the instrumental variables highly correlate with the endogenous variables, and environmental regulation shows a tendency to strengthen from year to year. From the results of the second stage, the values of KP rk LM-statistic are 81.410 and 67.988, respectively, and the P-values of the LM test are both 0.0000, which reject the original hypothesis and indicate that the choice of instrumental variables is reasonable. The values of KP rk wald F-statistic are 348.156 and 174.573, respectively, which are much larger than the empirical statistics value of 10, indicating that both Z_1 and Z_2 pass the weak instrumental variable test. Therefore, it can be considered that the selection of the two instrumental variables satisfies the necessary conditions. Specifically, the coefficients of the two instrumental variables are 0.1186 and 0.2607, respectively, and are significant at least at the 10% level, which means that environmental regulation still significantly promotes industrial green development after replacing the regression method. The above results once again confirm the robustness of the findings herein.

Threshold test

We further select technological progress and fiscal decentralization as threshold variables and apply a panel threshold model to explore the nonlinear characteristics of heterogeneous environmental regulations affecting industrial green development. The premise for conducting the threshold model test is that a threshold effect must exist. Therefore, this study uses the bootstrap self-sampling method to examine the significance level and the specific threshold value of the threshold effect.

Threshold effect of technological progress

Table 5 reports the results of the threshold effect of technological progress for each variable. From the environmental regulation index, the F-statistic for its single threshold of technological progress is significant, while the F-statistic for the double threshold is not significant, indicating that there is only a single technological progress threshold for the impact of environmental regulation on industrial green development with a threshold value of 8.7494. From the perspective of the three types of environmental regulation, the single technological progress thresholds of command-and-control environmental regulation, market-incentive environmental regulation, and public-participation environmental regulation all exist, and none of them pass the double-threshold test. The single threshold values are 8.7494, 8.7494, and 10.9373, respectively. It can be seen that the technological progress threshold values of command-and-control environmental regulation and market-incentive environmental regulation are the same as that of the environmental regulation index, while the threshold value of public-participation environmental regulation is higher. Possible explanations for this result are as follows. Currently, environmental regulation is dominated by command-and-control environmental regulation and market-incentive environmental regulation, while public-participation environmental regulation shows a great difference from the other two kinds of environmental regulation. Thus, the impact of technological progress is inconsistent.

On the basis of the above analysis, the threshold model regression is performed for a single threshold of technological

TABLE 3 Regional robustness test results.

Variable	Regional location		Industrial development level	
	(1) Eastern	(2) Central and western	(3) Weak industry	(4) Strong industry
ln *ER*	0.1767* (0.0994)	0.0449** (0.0215)	0.0580* (0.0332)	0.2272** (0.0903)
ln *PD*	0.0591 (0.3520)	−0.0911 (0.1100)	−0.1678 (0.1657)	0.0551 (0.2201)
ln *IC*	7.7773*** (2.9406)	1.9425*** (0.4129)	0.8570 (1.0183)	2.4291 (1.4848)
ln *RC*	−0.5288* (0.3076)	0.5785*** (0.1568)	0.5324*** (0.1674)	0.1036 (0.2211)
ln *FDI*	−0.1783 (0.1475)	−0.0390 (0.0705)	0.0402 (0.0829)	−0.0852 (0.0930)
ln *TI*	−0.1225 (0.1444)	0.2119*** (0.0582)	0.2970** (0.1166)	0.0836 (0.0759)
ln *FD*	0.0579 (0.8319)	0.0193 (0.4321)	0.4623 (0.5030)	−0.3113 (0.5338)
ln *ES*	−1.1073*** (0.1183)	0.5095* (0.2681)	−0.3110 (0.2878)	0.0169 (0.2962)
Constant	−0.9983 (2.8981)	−2.1303*** (0.6765)	−3.7764*** (1.2345)	−3.5675 (2.3021)
N	143	247	195	195
R^2	0.4096	0.4230	0.4050	0.1869

***, **, and * Represent significance at the 1, 5, and 10% levels, respectively. The value in ( ) is the standard error.

TABLE 4 Robustness test results of sub-indicators and replacement methods.

Variable	Variable division			Instrumental variable method (2SLS)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		ln *IGTFP*		ln *ER*	ln *IGTFP*	ln *ER*	ln *IGTFP*
ln *ERC*	0.1156*** (0.0388)						
ln *ERM*		0.2061** (0.0875)					
ln *ERP*			0.1095*** (0.0355)				
Z_1				0.8051*** (0.0431)			
Z_2						0.7079*** (0.0536)	
ln *ER*					0.1186*** (0.0412)		0.2607* (0.1392)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−3.2874*** (0.9878)	−3.9507*** (1.3862)	−2.5135*** (0.8707)	1.1440*** (0.3114)	−3.8423*** (0.8988)	1.7131*** (0.4836)	-3.3010*** (0.9694)
KP rk LM-statistic				81.410		67.988	
LM *P*-value				0.0000		0.0000	
KP rk Wald *F*-statistic				348.156		174.573	
N	390	390	390	358	358	328	328
R^2	0.2997	0.3126	0.2979	0.6772	0.1838	0.6403	0.1706

***, **, and * Represent significance at the 1, 5, and 10% levels, respectively. The value in ( ) is the standard error.

progress, and the results are in Table 6. Table 6's model (1) presents the technological progress threshold effect of the environmental regulation index. When the technological progress is in the low threshold range, the effect of environmental regulation on industrial green development is small, and its value is only 0.0679. When technological progress continues to rise to the high threshold range, the regression coefficient of environmental regulation on industrial green development increases significantly to 0.1183. The reason is that the implementation of environmental regulations squeezes out the R&D investment of industrial enterprises, while technological innovation is characterized by high investment cost, long cycle time and high risk. When the level of technological progress is low, most enterprises can only manage from the pollution side of things due to constraints of capital and technology. Although the total amount of industrial pollution emissions is controlled to a certain extent, the technological progress of the whole industry is hindered, resulting in

TABLE 5 Test of the threshold effect of technological progress.

Variable	Threshold type	Threshold value	*F*-value	*P*-value	95% confidence interval
ln *ER*	Single	8.7494	24.17	0.0340	[8.6513, 8.7622]
	Double	10.9373	10.14	0.4180	[10.8725, 10.9558]
ln *ERC*	Single	8.7494	22.94	0.0620	[8.6513, 8.7622]
	Double	10.9373	10.73	0.4180	[10.8725, 10.9558]
ln *ERM*	Single	8.7494	20.45	0.0610	[8.6513, 8.7622]
	Double	10.9373	9.84	0.3620	[10.8675, 10.9558]
ln *ERP*	Single	10.9373	23.62	0.0460	[10.8831, 10.9558]
	Double	9.8447	14.24	0.1990	[9.6993, 9.8569]

TABLE 6 Regression results of the technological progress threshold model.

Variable		Threshold variable: technological progress			
		(1)	(2)	(3)	(4)
ln *ER*	ln *TI* < 8.7494	0.0679* (0.0375)			
	ln *TI* > 8.7494	0.1183*** (0.0361)			
ln *ERC*	ln *TI* < 8.7494		0.1058*** (0.0374)		
	ln *TI* > 8.7494		0.1436*** (0.0388)		
ln *ERM*	ln *TI* < 8.7494			0.2223*** (0.0609)	
	ln *TI* > 8.7494			0.2615*** (0.0590)	
ln *ERP*	ln *TI* < 10.9373				0.1129*** (0.0331)
	ln *TI* > 10.9373				0.0430 (0.0418)
Control variable		Yes	Yes	Yes	Yes
Constant		−9.7770* (5.0932)	−10.0450* (5.1673)	−9.8051** (4.7331)	−9.7598** (4.6096)
N		390	390	390	390
R^2		0.3472	0.3477	0.3560	0.3472

***, **, and * Represent significance at the 1, 5, and 10% levels, respectively. The value in ( ) is the standard error.

a slow process of industrial green development. When technological progress reaches a high level, the implementation of environmental regulations encourages enterprises to shift from pollution-end governance to production-end governance – that is, to reduce undesired output by using clean technologies and energy-saving equipment, thereby vigorously promoting industrial green development.

Models (2)–(4) report the threshold effects of technological progress for three types of environmental regulations. Command-and-control environmental regulation and market-incentive environmental regulation have an upward jump after crossing the threshold value. In other words, when the level of technological progress changes from low to high, the promotion effect of environmental regulation on industrial green development is enhanced, but the reasons for the improvement of the two effects are not completely consistent. Among them, the command-and-control environmental regulation restrains the enterprises' pollution emissions by issuing punitive and preventive regulation, which leads to an excessive cost burden placed on enterprises and limits technological progress and industrial green development. Only when the level of technological progress is raised to a certain level can environmental regulation promote the green production process of enterprises and thus improve the quality of production and industrial green development (Shen et al., 2018).

Market-incentive environmental regulation is, to the contrary, more flexible, and industrial enterprises have greater autonomy of choose. When the level of technological progress is low, the cost of pollution emission can be compensated by market means such as subsidies and deposit-return systems, so as to promote industrial green development. At higher levels of technological progress, high-tech enterprises profit from environmental regulation policies through the emissions trading market, and small- and medium-sized enterprises (SMEs) can also imitate and learn green technology processes at a lower cost, speeding up the green development of the entire industry (Wang and Xu, 2015). It is noteworthy that public-participation environmental regulation plays a significant facilitating role only when technological progress is in the low threshold range, and its effect becomes less significant as technological progress increases. One possible reason is that in the low-tech stage, the pollution emissions of enterprises are relatively greater, causing certain damage to the life safety of surrounding residents. At this stage, the polluting behavior of enterprises is more likely to be detected by the public, and they will get punished. Therefore, public-participation environmental regulation has a significantly positive effect on industrial green development. With the continuous advancement of technology, the total amount of pollution emissions decreases, and the harm to the public is alleviated. Thus, the role of public participation in environmental supervision gradually decreases at this time.

Threshold effect of fiscal decentralization

Table 7 displays the results of the fiscal decentralization threshold effect for each variable. In terms of the environmental regulation index, it has only a single fiscal decentralization threshold with a threshold value of 0.1017.[1] From the three types of environmental regulation, the single threshold of fiscal decentralization exists for command-and-control environmental regulation, market-incentive environmental regulation, and public-participation environmental regulation. All have a threshold value of 0.1017, but none of them pass the double threshold test. It can be seen that the threshold value of fiscal decentralization is the same for both the environmental regulation index and different types of environmental regulation, indicating that various environmental regulation instruments reflect fiscal decentralization to a similar extent.

We further conduct a threshold model regression on the single threshold of fiscal decentralization, and the results are in Table 8. Model (1) in the table reports the fiscal decentralization threshold effect of the environmental regulation index. When the level of fiscal decentralization is below the threshold, the promotion effect of environmental regulation on industrial green development is not significant. After the fiscal decentralization crosses the threshold value, environmental regulation significantly promotes industrial green development. At this point, a 1% increase in the environmental regulation index raises the level of industrial green development by 0.0855%. This is because the expansion of fiscal decentralization helps to improve public sector efficiency and promotes government attention to environmental governance issues, which in turn increase green total factor productivity (Adam et al., 2014; Ma et al., 2021; Shi et al., 2022). When the level of fiscal decentralization is low, local governments have less autonomy to promote industrial green development through proactive environmental management. Conversely, when the level of fiscal decentralization rises to a certain level, local governments are able to improve the efficiency of environmental regulation tools based on their own information advantages to stimulate the introduction of technology and green development of enterprises.

Models (2)–(4) show the threshold effects of fiscal decentralization for three types of environmental regulations. Similar to the technological progress threshold, command-and-control environmental regulation and market-incentive environmental regulation jump upward after crossing the threshold - that is, as the degree of fiscal decentralization increases from the low threshold range to the high threshold range, the role of environmental regulation in promoting industrial green development is enhanced. This indicates that fiscal decentralization influences both command-and-control environmental regulation with technical coercion and market-incentive environmental regulation with market flexibility. Appropriate fiscal decentralization effectively mobilizes the enthusiasm of local governments and provides more innovations in public services, which guarantee the smooth implementation of environmental regulations and improve the quality of industrial green development.

The role of public-participation environmental regulation by contrast is not significant at lower levels of fiscal decentralization and only exerts a significant positive effect in the high fiscal decentralization threshold interval. The reason may be that when the degree of fiscal decentralization is low, the local government lacks enthusiasm and initiative and ignores the local public-participation environmental regulation. As a result, the environmental problems as reflected by the public cannot be solved in time, and the role of environmental regulation is not obvious. As the degree of decentralization increases, local governments have certain discretionary power, and the public has more opportunities to directly participate in local governments' decisions on key environmental projects, so as to better take a positive role of environmental regulation on industrial green development.

Analysis of spatial effects

Too strict environmental regulation may restrict economic development, while too loose environmental regulation may turn the local area into a polluting paradise. Therefore, when local governments formulate and implement environmental regulation policies, there is often strategic interaction between regions (Zhang, 2016), which makes the impact of environmental regulation have a spatial effect. This study further incorporates spatial factors into the empirical analysis framework and uses a spatial panel model to focus on the spatial effects of heterogeneous environmental regulations on industrial green development.

Spatial autocorrelation test

Before conducting the spatial model regression, the spatial correlation of variables needs to be examined. Table 9 reports

1 Due to the logarithmic processing of fiscal decentralization, its level has a negative value, but it does not affect the conclusions of the empirical analysis.

TABLE 7 Test of the threshold effect of fiscal decentralization.

Variable	Threshold type	Threshold value	*F*-value	*P*-value	95% confidence interval
ln *ER*	Single	0.1017	22.42	0.0200	[0.0877, 0.1091]
	Double	−0.4200	13.06	0.3340	[−0.4512, −0.4159]
ln *ERC*	Single	0.1017	27.21	0.0120	[0.0877, 0.1091]
	Double	−0.4200	11.87	0.2970	[−0.4512, −0.4159]
ln *ERM*	Single	0.1017	28.17	0.0010	[0.0926, 0.1091]
	Double	−0.2443	6.50	0.7660	[−0.2657, −0.2310]
ln *ERP*	Single	0.1017	23.75	0.0190	[0.0877, 0.1091]
	Double	−0.4200	12.85	0.2450	[−0.4463, −0.4159]

TABLE 8 Regression results of the fiscal decentralization threshold model.

Variable		Threshold variable: fiscal decentralization			
		(1)	(2)	(3)	(4)
ln *ER*	ln *FD* < 0.1017	0.0110 (0.0392)			
	ln *FD* > 0.1017	0.0855** (0.0379)			
ln *ERC*	ln *FD* < 0.1017		0.0757* (0.0404)		
	ln *FD* > 0.1017		0.1405*** (0.0440)		
ln *ERM*	ln *FD* < 0.1017			0.2592*** (0.0599)	
	ln *FD* > 0.1017			0.3307*** (0.0681)	
ln *ERP*	ln *FD* < 0.1017				−0.0064 (0.0506)
	ln *FD* > 0.1017				0.1274*** (0.0364)
Control Variable		Yes	Yes	Yes	Yes
Constant		−7.5318 (5.2398)	−7.4321 (5.1863)	−8.0208 (4.8197)	−7.7482 (5.0670)
N		390	390	390	390
R^2		0.3446	0.3546	0.3683	0.3488

***, **, and * Represent significance at the 1, 5 and 10% levels, respectively. The value in ( ) is the standard error.

TABLE 9 Univariate *Moran's I* index of the industrial green development level.

Year	*Moran's I*	*Z*-value	*P*-value	Year	*Moran's I*	*Z*-value	*P*-value
2006	0.318	2.874	0.002	2013	0.486	4.278	0.000
2007	0.394	3.624	0.000	2014	0.533	4.608	0.000
2008	0.330	3.111	0.001	2015	0.587	4.962	0.000
2009	0.191	1.887	0.030	2016	0.417	3.667	0.000
2010	0.224	2.189	0.014	2017	0.307	2.838	0.002
2011	0.064	0.866	0.193	2018	0.111	1.169	0.121
2012	0.364	3.350	0.000				

the results of the global *Moran's I* index test for the level of industrial green development. The results in the table show that the univariate *Moran's I* index of industrial green development is positive and passes the 5% significance test except for 2011 and 2018. Overall, the level of industrial green development in China has a strong positive spatial correlation, and industrial green development among adjacent provinces presents an obvious spatial clustering and dependence characteristics.

Since this part explores the spatial influence of environmental regulation on industrial green development, it is necessary to further investigate the spatial correlation between the two – that is, to measure the bivariate global *Moran's I* index. **Figure 1** portrays the bivariate *Moran's I* index of environmental regulation and industrial green development. As a whole, *Moran's I* index for different environmental regulation indicators and its index for industrial green development are positive and significant. Although the spatial correlation between environmental regulation and industrial green development fluctuates in different years, it does not change the positive spatial correlation between them. In conclusion, both univariate and bivariate global *Moran's I* indices indicate that environmental regulation and industrial green development are

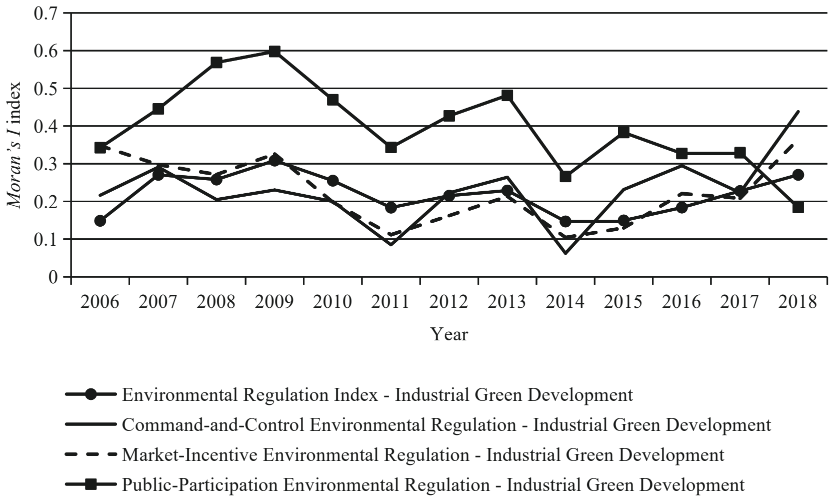

FIGURE 1
Bivariate *Moran's I* index of heterogeneous environmental regulation and industrial green development.

influenced by spatial factors. Therefore, it is necessary to use spatial econometric methods for an in-depth discussion.

Selection and regression of spatial econometric model

Before model estimation, the spatial econometric model needs to be identified and tested, and Table 10 lists the results. On the one hand, the LM test is used to explore whether a SAR or a SEM should be selected. From the results of the LM test and the robust LM test, the null hypothesis of no spatial lag or spatial error is rejected at the 1% level for the environmental regulation index and the three types of environmental regulation instruments, meaning that a spatial model needs to be selected for regression. On the other hand, we also examine which spatial model should be chosen specifically. Both the LR test and the Wald test pass the 1% significance test, indicating that SDM cannot be simplified into SAR or SEM. In addition, the Hausman test results both reject the null hypothesis of using random effects. Therefore, we choose the fixed-effect SDM to explore the spatial effect of heterogeneous environmental regulations on industrial green development.

Table 11 shows the regression results of SDM. In terms of the lagged term spatial coefficient (rho), the estimated coefficients of the environmental regulation index and three types of environmental regulation are all significant at the 10% level, suggesting a strong spatial spillover effect of industrial green development, which again confirms the conclusion drawn from the spatial correlation test. In terms of the main effect of environmental regulation, the estimated coefficients of the environmental regulation index and the three types of environmental regulations are all smaller than the coefficient values when spatial factors are not considered, representing that the promotion of environmental regulation is affected by the combined force of environmental regulation in the entire region. The actual effect of environmental regulation does not fully meet the expectation due to the superposition of many influencing factors, such as inter-regional environmental regulation strategy interaction and spatial clustering of industrial green development. Hence, the use of environmental regulation instruments should be scientifically combined from the regional level rather than limited to the local area. At the same time, the coefficients of environmental regulation index, market-incentive environmental regulation, and public-participation environmental regulation are significantly positive after considering the spatial factor, while the coefficient of command-and-control environmental regulation does not pass the significance level test, which proves that there may be competition to the bottom in the formulation of environmental regulation policies by local governments in order to develop the regional economy, leading to the failure of environmental regulation.

To examine the marginal effects of heterogeneous environmental regulations on industrial green development, the spatial effects need to be decomposed, and the results are reported in Table 12. The three effect coefficients of environmental regulation index, market-incentive environmental regulation, and public-participation environmental regulation are significantly positive, and the indirect and total effects of command-and-control environmental regulation are significantly positive, while the direct effect is not significant. This means that market-incentive environmental regulation and public-participation environmental regulation are beneficial to industrial green development of local and neighboring provinces, while command-and-control environmental regulation mainly is manifested in promoting industrial green development in

TABLE 10 Identification test of the spatial model.

Content		ln *ER*		ln *ERC*		ln *ERM*		ln *ERP*	
		χ^2	*P*-value	χ^2	*P*-value	χ^2	*P*-value	χ^2	*P*-value
Test of SEM and SLM	LM-lag	94.586	0.000	90.091	0.000	90.650	0.000	73.599	0.000
	R-LM-lag	22.144	0.000	22.955	0.000	22.646	0.000	12.702	0.000
	LM-error	79.266	0.000	72.331	0.000	73.019	0.000	72.692	0.000
	R-LM-error	6.823	0.009	5.195	0.023	5.014	0.025	11.794	0.001
Simplified test for SDM	LR-lag	35.46	0.000	41.51	0.000	33.15	0.000	39.45	0.000
	Wald-lag	36.76	0.000	43.13	0.000	34.39	0.000	40.98	0.000
	LR-error	38.22	0.000	44.97	0.000	38.97	0.000	42.46	0.000
	Wald-error	35.02	0.000	40.15	0.000	36.01	0.000	39.54	0.000
Hausman		29.01	0.0344	28.31	0.0414	41.55	0.0008	29.24	0.0324

TABLE 11 The results of the spatial Durbin model.

Variable	(1)	(2)	(3)	(4)
ln *ER*	0.0614** (0.0279)			
ln *ERC*		0.0030 (0.0385)		
ln *ERM*			0.1596** (0.0653)	
ln *ERP*				0.0906** (0.0317)
W * ln *ER*	0.0793* (0.0476)			
W * ln *ERC*		0.1989*** (0.0626)		
W * ln *ERM*			0.1421 (0.0991)	
W * ln *ERP*				0.1206** (0.0534)
Control variable	Yes	Yes	Yes	Yes
Rho	0.4622*** (0.0511)	0.4365*** (0.0532)	0.4678*** (0.0503)	0.4493*** (0.0518)
sigma2_e	0.1194*** (0.0087)	0.1192*** (0.0086)	0.1176*** (0.0085)	0.1184*** (0.0086)
Log-likelihood	−150.2593	−148.6266	−147.5437	−147.9745
Observations	390	390	390	390
R^2	0.3899	0.4108	0.3823	0.4087

***, **, and * Represent significance at the 1, 5, and 10% levels, respectively. The value in ( ) is the standard error. sigma2_e is the within-group standard deviation.

TABLE 12 Decomposition results of spatial effects.

Variable	Direct effect	Indirect effect	Total effect
ln *ER*	0.0781** (0.0307)	0.1945** (0.0825)	0.2726*** (0.0993)
ln *ERC*	0.0307 (0.0399)	0.3394*** (0.0932)	0.3701*** (0.1066)
ln *ERM*	0.1943*** (0.0668)	0.3965** (0.1584)	0.5908*** (0.1765)
ln *ERP*	0.1141*** (0.0352)	0.2814*** (0.0920)	0.3955*** (0.1131)
Control variable	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes

***, **, and * Represent significance at the 1, 5, and 10% levels, respectively. The value in ( ) is the standard error.

neighboring provinces. In recent years, with the gradual improvement of an environmental performance assessment system, inter-provincial environmental regulation competition behavior has improved and formed a "ruler effect" (Zhang et al., 2010). As a result, the environmental regulations in adjacent areas have a certain similarity, and the increase in the intensity of environmental regulation in one place will inevitably lead to the corresponding adjustment of environmental regulations in adjacent areas, thereby driving industry's green development. The direct effect of command-and-control environmental regulation is not significant, which also indicates that the current environmental regulation tools characterized by government coercion measures are not effective means to promote industrial green development. It is often better to make full use of diversified tools such as market-incentive environmental regulation and public-participation environmental regulation.

Conclusion and policy recommendations

In the context of the increasingly severe industrial pollution problem, this study aims to explore the relationship between environmental regulation and industrial green development, to provide a theoretical basis for further identifying the effectiveness of environmental regulation, and to make up for the lack of research on industrial green development, so as to find a sustainable development path that balances industrial development and environmental protection.

Therefore, based on panel data of 30 provinces in China from 2006 to 2018, this study constructs a panel threshold model to empirically test the nonlinear characteristics of different types of environmental regulations on industrial green development from the perspective of technological progress and fiscal decentralization. We further use the spatial panel model to analyze the spatial effects of different environmental regulations on industrial green development. The main conclusions of this study are as follows: (1) The environmental regulation index has a significant role in promoting industrial green development. For every 1% increase in the intensity of environmental regulation, the level of industrial green development rises by at least 0.0840%. (2) Environmental regulation index, command-and-control environmental regulation, market-incentive environmental regulation, and public-participation environmental regulation all have only a single threshold of technological progress and fiscal decentralization. (3) There is a significantly positive spatial correlation between different environmental regulation indicators and industrial green development. (4) The results of spatial effect analysis show that, except for command-and-control environmental regulation, the environmental regulation index and the other two types of environmental regulation have significantly positive impacts on industrial green development.

Based on the above research conclusions, we propose the following policy recommendations: (1) Since different types of environmental regulations have different impacts on industrial green development, it is necessary to use heterogeneous environmental regulation tools flexibly. For enterprises with serious industrial pollution, local governments should mainly adopt command-and-control environmental regulations and strictly supervise the pollution discharge behavior of enterprises. At the same time, the government needs to fully stimulate the vitality of market-incentive environmental regulation such as carbon emissions trading and constantly improve their trading market and systems. It should build a channel for public participation in environmental regulation and expand the coverage of education and publicity. (2) When technological progress crosses the threshold, the positive role of environmental regulation in promoting industrial green development is greatly enhanced, which means that local governments should further improve the technological innovation capabilities of industrial enterprises. The government must encourage industrial enterprises to step up R&D of clean technologies through tax incentives and financial subsidies and introduce foreign advanced environmental protection technologies to promote the upgrading of industrial enterprises. In addition, great importance must be attached to the patent protection of clean technology innovation and process efficiency improvement, providing institutional guarantee for enterprises to carry out technological R&D activities. (3) Since fiscal decentralization plays an important role in the process of environmental regulation promoting green industrial development, it is necessary to appropriately decentralize the government's environmental governance power. The central government should further expand the authority of such departments in personnel arrangement and use of environmental governance funds to ensure the smooth implementation of environmental management power. At the same time, the proportion of environmental governance in the assessment of local governments must be strengthened, so as to encourage local governments to focus on improving environmental issues. (4) The spatial dependence of environmental problems should not be ignored, and the government needs to pay attention to the joint prevention and control of regional pollution. Local governments should improve the inter-regional cooperation mechanisms and establish regional sharing models of green technologies to jointly promote the coordinated management of environmental pollution.

Limitations and future research directions

Although we have expanded the related research from both theoretical and practical aspects, there are still the following shortcomings. First, our research focuses on provincial administrative units and fails to cover data on prefecture-level cities and enterprises. Subsequent research should further analyze the data of prefecture-level cities or enterprises, and conduct detailed research according to the industrial layout of urban agglomerations and the nature of enterprises. Second, this study lacks an examination of different types of industries. Future research should divide specific industries and further investigate the role of factor allocation ratios between different industries in the impact of environmental regulation on industrial green development. Third, we only test the influence of technological progress and fiscal decentralization, while the green development effect of environmental regulation may also be affected by other factors, especially the role of government behavior and its results. Subsequent research should be expanded from other perspectives such as government competition, market segmentation, and factor distortion.

Data availability statement

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

Author contributions

YY and HC: conceptualization and writing–original draft preparation, review and editing. HC: methodology, project administration, funding acquisition, and formal analysis. YY: software and resources. HC, YY, and HH: validation and data curation. MY: investigation. YY and HH: visualization. HH: supervision. All authors have read and agreed to the published version of the manuscript.

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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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EDITED BY
Magdalena Klimczuk-Kochańska,
University of Warsaw, Poland

REVIEWED BY
Dilawar Khan,
Kohat University of Science and Technology, Pakistan
Ning Ma,
Hainan College of Economics and Business, China
Yuan Xu,
Dalian Maritime University, China

*CORRESPONDENCE
Xichun Zhang
ciennazhang@163.com

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Does industry-university-research cooperation promote the environmental efficiency of China's high-tech manufacturing?

Feng Peng[1] and Xichun Zhang[2]*

[1]School of Economics and Management, China Three Gorges University, Yichang, China, [2]School of Business Administration, Zhongnan University of Economics and Law, Wuhan, China

As one of the important strategic measures to increase the international competitiveness of high-tech manufacturing (HTM), industry-university-research cooperation (IURC) has received increasing attention in China. However, there is little literature to explore the links between IURC and the environmental efficiency (EE) of HTM. To incorporate a variety of environmental pollution indicators into the efficiency analysis framework and reduce the adverse effects of random errors on the estimation results, this article combined the projection pursuit model with the stochastic frontier analysis (SFA) method and proposed a translog stochastic frontier model considering undesirable outputs to analyze the multiple impacts of IURC on the EE of HTM. The results show that IURC has both a significant negative direct effect and a significant positive indirect effect on HTM's EE. Although IURC cannot directly promote EE, it has a positive impact on EE of HTM through its complementary effect with research and development (R&D) investment. The results also confirm that the average EE of the whole country is only 0.346, while that of the eastern area is 0.595, and that of the central and western areas are 0.199 and 0.171, respectively. Therefore, it is particularly urgent to improve the EE of China's HTM industry through a variety of measures, such as promoting IURC and increasing R&D investment in environmental technology. This study not only provides an improved SFA method for measuring EE, but also deepens research on the mechanism of the impact of IURC on HTM's EE.

KEYWORDS
environmental efficiency, industry-university-research cooperation (IURC), high-tech manufacturing, stochastic frontier analysis, undesirable outputs, research and development investment, projection pursuit model

1. Introduction

Since the 1990s, China's high-tech manufacturing (HTM) has experienced rapid development. It is not only among the top 10 in the world in terms of industrial output but also has global competitiveness in such high-tech fields as aerospace, high-speed rail, and communications equipment manufacturing. However, due to the neglect of environmental efficiency (EE), China's HTM does not present the characteristics of high added value and low pollution, and environmental pollution incidents are frequently reported in the press (Wu Q. et al., 2022). Furthermore, in the increasingly ecologically fragile eastern region, environmental regulation has caused many HTM enterprises to transfer their highly polluting processing and manufacturing links to the central and western regions, intensifying people's concern that these regions will become "pollution refuges" (Peng et al., 2018). Therefore, how to improve EE has become an important practical problem for the sustainable development of Chinese HTM.

Developing technologies to reduce environmental pollution is an expensive, complex, and highly uncertain task (Oke, 2013; Rabal-Conesa et al., 2022). Usually, it is difficult for enterprises to deal with the pressure of controlling environmental pollution only through internal research and development (R&D) (Chang et al., 2022). Enterprises can and should use external knowledge to improve their technical capabilities and solve environmental pollution problems (Hu et al., 2017). The ability to acquire knowledge from the outside has been proved to be a key factor to enhance the competitiveness of enterprises (Leiponen and Helfat, 2010). Compared with traditional innovation, environmental innovation needs more external knowledge (Aldieri et al., 2020). Enterprises compensate for the lack of the necessary technical capacity, especially knowledge related to the environment, through cooperation with external organizations to implement environmental innovation activities (Diez-Martinez et al., 2022). In the process of realizing the green development of the manufacturing industry, developing countries usually actively acquire external technology to improve their level of environmental technology (Hou et al., 2017). The main ways to acquire external knowledge usually include the introduction of foreign technologies and industry-university-research cooperation (IURC) (Xu et al., 2022).

With the strengthening of technology export control from developed countries to China in the high-tech field, it has become increasingly difficult for China to obtain foreign technology transfer (Kwan, 2020). In this context, China has not only continued to increase investments in green technology R&D. At the same time, it actively accelerates IURC to promote the sustainable development of its manufacturing industry. The Chinese government has not only formulated a series of laws and regulations to promote IURC, but also strengthened its support for IURC in terms of resources and technology (Yao et al., 2021). However, there is still a lack of research on whether these efforts have contributed to the EE of China's HTM. We attempt to reveal the relevance of IURC and EE in China's HTM. Research on this issue will help clarify the current situation of EE in China's HTM and offer a foundation for accelerating its green development.

This study contributes to existing research in three aspects. First, the research on EE of China's industrial sector usually focuses on pollution-intensive industries, with a relatively lack of research on HTM. Moreover, DEA is more common in the method. This article uses the stochastic frontier analysis (SFA) method to measure the EE of China's HTM. Second, little research examines the links between IURC and the EE of Chinese HTM. This article not only examines the direct action of IURC on the EE of HTM, but also analyzes the reciprocal action of IURC and R&D investment and their indirect effect on EE. Thus, it deepens the research on the mechanism of the effect of IURC on EE. Finally, this study combines the projection pursuit (PP) model with SFA and incorporates both desirable and undesirable outputs into the analysis framework for EE, providing an improved SFA method to measure EE. Compared to the commonly used DEA model, this method avoids the error of estimation results because it considers the influence of random factors when EE is analyzed.

The next section is the literature review. Section 3 is the Materials and methods. We combine the PP model and the SFA model to propose an SFA method considering environmental pollution. Section 4 is the Results and discussion. We present the results of the SFA method and discuss the links and differences between this study and previous studies. The last section is the Conclusion and policy implications.

2. Literature review

The related research can be divided into two parts: the estimation of EE and the impact of IURC on EE.

2.1. The estimation of EE

With the rapid growth in economic output, the environmental pollution problem of China's industries is becoming more apparent. This makes its EE has been widely concerned. Much research has examined the EE of China's industries. Chen and Jia (2017) applied the SBM to calculate the EE of Chinese industry. Shao and Wang (2016) used the Malmquist-Luenberger productivity index to evaluate the EE of China's non-ferrous metal manufacturing industry. Wu et al. (2014) utilized DEA to evaluate the EE of Chinese interprovincial industries from 2007 to 2011. Wang et al. (2019) used the SFA method to estimate the EE of China's coal industry. Some scholars revealed regional differences in the EE of China's industries (Fei et al., 2020). An et al. (2020) found that industrial EE in East China was more efficient.

More research has analyzed the differences in EE in different types of Chinese industries. Xiao et al. (2018) examined the EE of 31 industries and found that the EE of most industries showed an upward trend. Among these literatures, studies on China's manufacturing industry are the most abundant. Xie et al. (2016) evaluated the EE of Chinese manufacturing industries and confirmed that EE in most manufacturing industries was low. Qu et al. (2017) found that the EE of the manufacturing industry steadily increased between 2003 and 2011. There are also some studies that compare and analyze differences in EE between subsectors of the manufacturing industry (Yuan et al., 2017; Kang et al., 2018). Xie et al. (2017) found that the EE of HTM was higher than that of the traditional manufacturing industry. Zhang et al. (2022) confirmed that the EE of China's HTM grew faster than that of other manufacturing industries between 2004 and 2017.

DEA and SFA are two common methods to calculate the EE of industrial sector (Khan et al., 2021; Rasheed et al., 2022). The former is often used to evaluate the relative efficiency of similar decision-making units with multi-input and multi-output, and it does not need to assume the form of production function. However, this method is difficult to deal with the measurement error of the data (Li and Tao, 2017). The latter not only allows for the selection of the best form of function (Khan et al., 2022), but also considers the interference of random error and statistical noise (Bibi et al., 2020). In addition, compared with the former, the latter can analyze the influencing factors of EE at the same time when estimating EE (Sun et al., 2019). However, the existing literature usually uses DEA method to evaluate the EE of China's industrial sector, while the literature using SFA method is relatively few. In addition, there is little literature to evaluate the EE of China's HTM, especially the use of the SFA method.

2.2. The impact of IURC on EE

Industry-university-research cooperation refers to collaborative technological innovation and commercialization of enterprises, universities, and scientific research institutions (Bai et al., 2020; Song et al., 2020). External knowledge from universities and scientific research institutions is considered to have a positive influence on environmental innovation (De Marchi and Grandinetti, 2013). On the one hand, enterprises can obtain the external knowledge needed to protect the environment from universities and research institutions. Through contact and interaction with academic departments, enterprises can acquire the technical knowledge needed for their product or process innovation to supplement or replace expensive R&D work (Caloghirou et al., 2004). Enterprises enhance their environmental technology capabilities through cooperation with universities and research institutions (Wang et al., 2012). On the other hand, IURC can achieve the coordination of technology, finance, and human capital, thus stimulating the vitality of environmental technological innovation (Yang et al., 2021).

In emerging economies, however, the opportunities for companies to acquire knowledge from domestic universities and research institutions may be short-lived. Because competitors can easily identify, acquire, or copy this knowledge (Kafouros and Forsans, 2012). In addition, enterprises that focus on IURC may not be able to acquire cutting-edge environmental knowledge, which is usually developed by enterprises in developed economies (Hou et al., 2017).

Furthermore, successful environmental innovation requires enterprises to have the corresponding absorptive capacity to transform external knowledge into their own skills (Ben Arfi et al., 2018). Internal R&D promotes the replication of knowledge and helps enterprises benefit from external knowledge (Kafouros and Buckley, 2008). When enterprises invest in R&D, they not only create new knowledge, but also improve their absorptive capacity (Cohen and Levinthal, 1990). The improvement of absorptive capacity helps enterprises to acquire external knowledge and carry out environmental innovation (Rabal-Conesa et al., 2022). The combination of external knowledge acquisition and internal R&D can enable enterprises to effectively carry out internal R&D activities and benefit from knowledge complementarity (Lokshin et al., 2008).

Although the research literature on the EE of the manufacturing industry is becoming more and more abundant, the research on evaluating the EE of China's HTM is still relatively lacking. In addition, with the intensification of global competition in HTM, China regards IURC as an important way to enhance the international competitiveness of its HTM. However, there is also a lack of in-depth research on whether IURC can promote the EE of China's HTM. Second, the existing literature usually uses a two-stage method (such as DEA-Tobit) to study China's industrial EE (Wang et al., 2017; Peng et al., 2022). This method does not separate random factors when analyzing the factors influencing EE, which may lead to errors in the estimates. Therefore, this article combines the PP model with the SFA method, puts forward a translog stochastic frontier model considering undesirable outputs, and analyses the direct and indirect effects of IURC on EE, to clarify the mechanism of IURC on the EE of HTM.

3. Materials and methods

3.1. Analysis framework

The production system creates value by converting inputs into outputs. Inputs are usually factors of production such as capital and labor. Outputs include not only desirable outputs such as output value, but also undesirable outputs such as wastewater and waste gas, etc. EE can be understood as the ratio of outputs to inputs in the production system (Song et al., 2012). For the given inputs, the more desirable (or less undesirable) outputs provided by the production system, the higher its EE.

The impact of IURC on industrial EE is multiple (see **Figure 1**). First, IURC has a direct effect on industrial EE. This effect can be positive or negative. Second, IURC has an indirect effect on industrial EE, and it has an indirect impact on industrial EE through its complementary effect with R&D investment.

3.2. Model

Due to the ability to incorporate both desirable and undesirable outputs into the efficiency analysis framework, DEA has become one of the common methods for evaluating industrial EE (Li et al., 2013; Song et al., 2018). However, the purpose of this article is not only to measure the EE of HTM, but also to analyze the effect of IURC on EE. To reduce the error in the estimation results caused by random factors, the SFA method was chosen in this study.

The analysis of industrial EE should consider not only desirable outputs but also undesirable outputs. The traditional SFA method is usually difficult to deal with this kind of efficiency analysis of multiple outputs. Therefore, using the PP model (Yu and Lu, 2018), we transform multiple output indexes (multidimensional data) into a compositive output index, that is, multidimensional data into one-dimensional data. Then, on this basis, the stochastic frontier model was established (Sun and Huang, 2020; Zhang and Chen, 2021).

3.2.1. PP model

Projection pursuit is a statistical method to analyze high-dimensional and non-normal data. At the same time, this method has the characteristics of robustness, anti-interference, and high precision (Ouyang et al., 2021).

The steps to establish the PP model are as follows (Wu S. et al., 2022):

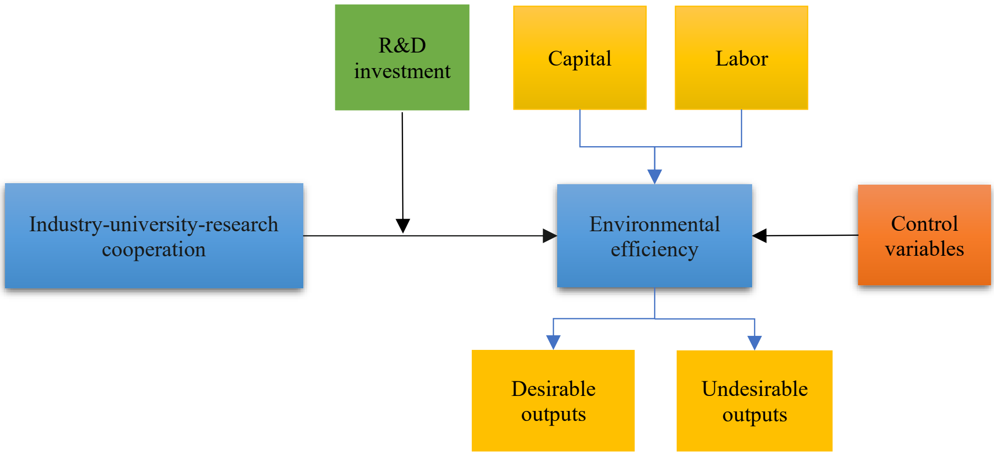

FIGURE 1
Research framework.

① Data normalization.

Let the set of HTM output indexes be $\{x^*(i,j) \mid i = 1, 2, \cdots, m; ; j = 1, 2, \cdots, n\}$, where $x^*(i,j)$ is the j-th output index of the i-th province. To unify the range of index values, the output indicators are normalized as follows:

For the positive index,

$$x(i,j) = \frac{x^*(i,j)}{x_{max}(j)} \tag{1}$$

For the negative index,

$$x(i,j) = \frac{x_{min}(j)}{x^*(i,j)} \tag{2}$$

here $x(i,j)$ is the normalized value of the output index set, $x_{max}(j)$ and $x_{min}(j)$ are the maximum and minimum values of the j-th index in the index set, respectively.

② Construct the projection objective function.

After determining the projection direction $p = \{p_1, p_2, \cdots, p_n\}$, the n-dimensional data $\{x(i,j) \mid j = 1, 2, \cdots, n\}$ is converted into a one-dimensional projection value $z(i)$:

$$z(i) = \sum_{j=1}^{n} p(j)x(i,j),\ i = 1, 2, \cdots, m. \tag{3}$$

where $p(j)$ is a unit vector.

Next, the projection objective function is constructed:

$$Q(a) = S_z D_z \tag{4}$$

where S_z and D_z are the standard deviation and local density of $z(i)$, respectively.

$$S_z = \sqrt{\frac{\sum_{i=1}^{m}(z(i) - E(z))^2}{m-1}} \tag{5}$$

$$D_z = \sum_{i=1}^{m}\sum_{j=1}^{m}(R - r(i,j)) \times u(R - r(i,j)) \tag{6}$$

here $E(z)$ is the mean value of $z(i)$ and R is the window radius; $r(i,j) = |z(i) - z(j)|$; and $u(a)$ is a unit step function, $u(a) = 1$ when $a \geq 0$, $u(a) = 0$ when $a < 0$.

③ Optimize the projection objective function.

The value of $Q(a)$ depends on the projection direction. Solve the following objective function to obtain the best projection direction.

$$\begin{cases} \max & Q(a) = S_z D_z \\ s.t. & \sum_{j=1}^{n} a^2(j) = 1 \end{cases} \tag{7}$$

For this non-linear optimization problem, the accelerated genetic algorithm can be used to solve the maximum problem.

④ Calculate the comprehensive index of the outputs.

After determining the optimal projection direction p^*, p^*, and $x(i,j)$ are brought into the Equation 4 to obtain the projection value $z^*(i)$.

3.2.2. SFA model

Commonly used stochastic frontier models include the Cobb–Douglas production frontier and the translog production frontier. The Cobb–Douglas production frontier model can be set as follows (Battese and Coelli, 1995):

$$lnY_{it} = \beta_0 + \beta_1 t + \beta_2 lnK_{it} + \beta_3 lnL_{it} + (V_{it} - U_{it}) \tag{8}$$

here Y_{it} is the output of the i-th observed value in period t. K_{it} and L_{it} are the capital input and labor input of the i-th observation in period t, respectively. β_1, β_2, and β_3 are parameters to be estimated. V_{it} is a random variable with normal distribution $N(0, \sigma_V^2)$. U_{it} is a non-negative random variable used to explain production inefficiency, which follows the normal distribution $N(m_{it}, \sigma_U^2)$ censored at 0, independent of V_{it}. Where $m_{it} = z_{it}\delta$, z_{it} is a vector that may affect EE, and δ is the parameter vector to be estimated.

Compared with the Cobb–Douglas production function, the translog production function considers substitution effects and interactions between input factors and is more flexible in form (Sun and Huang, 2020; Zhang and Chen, 2021). Therefore, the stochastic frontier model of the translog production function was used to explore the impact of IURC on the EE of the HTM. The translog production frontier model can be set as (Bibi et al., 2020):

$$
\begin{aligned}
lnY_{it} = {} & \beta_0 + \beta_1 t + \beta_2 lnK_{it} + \beta_3 lnL_{it} + 0.5\beta_4 t^2 + 0.5\beta_5 \left(lnK_{it}\right)^2 \\
& + 0.5\beta_6 \, lnL_{it}{}^2 + \beta_7 tlnK_{it} + \beta_8 tlnL_{it} + \beta_9 lnK_{it} lnL_{it} \\
& + (V_{it} - U_{it})
\end{aligned}
\tag{9}
$$

The inefficiency model may be expressed as:

$$
m_{it} = \delta_0 + \delta_1 IURC_{it} + \delta_2 RD_{it} + \omega\Phi \tag{10}
$$

where $IURC_{it}$ represents IURC, RD_{it} represents R&D investment. Φ is the vector of control variables, and ω is the vector of parameters.

Equation 10 does not consider the links between IURC and R&D investment and its impact on EE. In fact, R&D can not only produce more environmentally friendly technologies (Song et al., 2019), but also enhance the absorptive capacity of enterprises to external technologies (Aldieri et al., 2018). The interaction between R&D investment and external technology can be expressed by their product (Danquah, 2018; Barasa et al., 2019). Therefore, to explore the effect of IURC on EE more accurately, this study added an interaction term between IURC and R&D investment and further set the inefficiency model as follows:

$$
m_{it} = \delta_0 + \delta_1 IURC_{it} + \delta_2 RD_{it} + \delta_3 IURC_{it} \times RD_{it} + \omega\Phi \tag{11}
$$

here δ_3 represents the interaction effect between IURC and R&D investment. If δ_3 is significantly positive, it indicates that there is a substitution effect between IURC and R&D investment, which leads to inefficiency of environmental technology. If δ_3 is significantly negative, it indicates that there is a complementary effect between IURC and R&D investment, thus reducing the inefficiency of environmental technology (and improving EE).

To determine whether the stochastic frontier production model is applicable, a common method is to test the hypothesis of the variation coefficient γ (Battese and Coelli, 1995).

$$
\gamma = \frac{\sigma_U^2}{\sigma_U^2 + \sigma_V^2} \tag{12}
$$

If γ is significantly different from 0, it indicates that the stochastic frontier production function is more suitable. The closer γ is to 1, the deviation comes mainly from the inefficiency effect, and it is more appropriate to adopt the stochastic frontier model.

3.3. Variables and data

3.3.1. Input-output index

Production inputs include labor and capital. Labor was reckoned by employment in HTM (Peng et al., 2018). Capital was calculated using the perpetual inventory method (PIM) (Chen et al., 2018). Take the total output value and the output value of new products as desirable output indicators (Peng et al., 2022). Due to the availability of HTM environmental pollution data, sulfur dioxide emissions and industrial wastewater emissions were selected as undesirable output indicators in this study (Chen et al., 2021). The PP model was used to transform the four outputs into a compositive output index (CY).

3.3.2. Explanatory variables

Explanatory variables include IURC and R&D investment (RD).

The funds obtained from enterprises, universities, and scientific research institutions can measure the degree of IURC (Zhang and Sun, 2022). Therefore, we measure IURC by the expenditure of enterprises to purchase domestic technology.

According to the technology purchase expenditure and the RD expenditure, the PIM was used to estimate the knowledge stock of IURC and R&D investment (Coe et al., 2009; Shahabadi et al., 2018). To attenuate heteroscedasticity in the regression model, we used the logarithm of the technological knowledge stock to represent IURC, and the logarithm of the R&D knowledge stock to represent RD.

3.3.3. Control variables

Existing studies have identified the factors that influence industrial EE (Chen et al., 2020; Ma et al., 2022). These factors include foreign direct investment (FDI), R&D investment, and human capital (Tao et al., 2012; Lu and Pang, 2017; Chen et al., 2022). Chen et al. (2020) verified that R&D and human capital have a positive influence on China's industrial EE. Ma et al. (2022) found that human capital and FDI are positively correlated with China's industrial EE. Some studies point out that since China's manufacturing industry has undergone drastic structural changes during market-oriented reform, the degree of marketization plays an important role in explaining the efficiency change and technology gap of China's manufacturing industry (Walheer and He, 2020). In addition, enterprise scale may also be an important factor affecting industrial EE (Wang et al., 2017).

Some literatures have further empirically tested the role of these factors in China's HTM (Peng et al., 2022). Related studies show that in addition to IURC and RD, marketization level (MAR), enterprise size (ES), human capital (HC), government support (GS), FDI, and regional factors may also be important factors affecting the EE of HTM. Therefore, these variables were selected as control variables.

Degree of marketization (MAR): the share of private firms in HTM's production value is used to represent MAR (Wang et al., 2021).

Enterprise scale (ES): The logarithm value of the average production value of the enterprises in HTM is used to represent ES (Li et al., 2018).

Human capital (HC): It is expressed as the proportion of HTM's employees in the local population (Wang and Zhao, 2021).

Government support (GS): GS is represented by the proportion of government funds in R&D funds (Li and Zeng, 2020).

Foreign direct investment: It is measured by the percentage of foreign-funded enterprises in HTM (Wei and Liu, 2006).

Location factor: The National Bureau of Statistics divides China into eastern, central, and western regions. Different regions have different environmental policies. The eastern region is relatively strict, while the central region is relatively loose. In this article, EAST is used to represent the dummy variable in the eastern region, and CEN is used to represent the dummy variable in the central region.

The panel data of the HTM from 2006 to 2017 in 28 provinces in China (with seriously missing data in other provinces) were selected for empirical analysis. We have clarified the abbreviations and descriptions of all variables in Table 1. The descriptive statistics of the variables are shown in Table 2. The data is obtained from the EPS data platform.

The correlation matrix in Table 3 examines the relationship between variables. Both IURC and RD are significantly positively correlated with CY, and all control variables are also significantly correlated with CY.

TABLE 2 Descriptive statistical results.

Variable	Mean	SD	Min	Max
K	125.585	160.713	2.598	1,258.418
L	40.547	72.706	0.474	389.417
CY	0.095	0.171	0.008	1.403
IURC	−1.959	1.342	−5.514	2.009
RD	1.280	1.806	−3.947	5.593
MAR	79.308	17.180	0.000	100.000
ES	−1.651	0.725	−3.369	−0.178
HC	0.733	0.836	0.054	3.627
GS	12.195	11.075	0.675	54.465
FDI	12.238	11.102	0.000	53.521
EAST	0.393	0.489	0.000	1.000
CEN	0.286	0.452	0.000	1.000

4. Results and discussion

4.1. Compositive output index

When the PP model is used for solving the projection index function, an accelerating genetic algorithm was used to better obtain the optimal solution (Wang and Zhan, 2019). We used MATLAB software to obtain the compositive output index of HTM, as shown in Table 4.

Table 4 shows that the comprehensive output index of HTM in all provinces showed an increasing trend from 2006 to 2017. On the one hand, it is due to the growth of the output value of HTM in each province. On the other hand, it benefits from strengthening environmental regulation in China. Guangdong, Jiangsu, and Shanghai have the highest comprehensive output index, these provinces are economically developed, their HTM output is higher, and these provinces have more strict controls on environmental pollution. The lowest comprehensive output index is Guizhou, Inner Mongolia, and Heilongjiang. The economy of these provinces is relatively backward, and the development of their HTM is relatively slow. Therefore, the comprehensive output index can accurately reflect the actual output level of HTM.

4.2. Estimation results of stochastic frontier model

When using Equation 9 to analyze the impact of IURC on the EE of China's HTM, it is necessary to determine the form of the frontier production function. That is, Cobb–Douglas production frontier or translog production frontier, which production function is better? We make our choices through LR tests (see Table 5). The results show that translog production frontier is more suitable than Cobb–Douglas production frontier.

To test whether IURC can promote the EE of China's HTM, this article uses the stepwise regression method to introduce control variables in turn (see Table 6). The variation coefficients of the four models are all greater than 0.95 and are significant at a 1% significance level, showing that the stochastic frontier model is more reasonable than the traditional production function. At the same time, the test results also show that the translog production function has good applicability to the sample data.

TABLE 1 The description of variables.

Variables	Abbreviation	Description	Unit
Comprehensive output	CY	The projection pursuit model was used for calculation	Index
Capital input	K	Estimated using the perpetual inventory method	10^9 RMB
Labor input	L	The average number of employees	10^4 people
Industry-university-research cooperation	IURC	The logarithm of technological knowledge stock	10^9 RMB
R&D investment	RD	The logarithm of R&D knowledge stock	10^9 RMB
Degree of marketization	MAR	The proportion of output value of non-state-owned enterprises	%
Enterprise scale	ES	The logarithm value of the average output value of enterprises	10^9 RMB
Human capital	HC	The proportion of employees in the HTM in the local population	%
Government support	GS	The proportion of government funds in R&D funds	%
Foreign direct investment	FDI	The proportion of the number of foreign-funded enterprises	%
Eastern region	EAST	The dummy variable in the eastern region	–
Central region	CEN	The dummy variable in the central region	–

TABLE 3 Correlation matrix of variables.

	CY	K	L	IURC	RD	MAR	ES	HC	GS	FDI	EAST	CEN
CY	1.000											
K	0.696***	1.000										
L	0.922***	0.638***	1.000									
IURC	0.535***	0.593***	0.554***	1.000								
RD	0.587***	0.631***	0.611***	0.789***	1.000							
MAR	0.306***	0.310***	0.300***	0.281***	0.126	1.000						
ES	0.449***	0.498***	0.387***	0.582***	0.650***	0.408***	1.000					
HC	0.819***	0.581***	0.849***	0.634***	0.717***	0.383***	0.601***	1.000				
GS	−0.269***	−0.231***	−0.266***	−0.153	−0.021	−0.690***	−0.253***	−0.267***	1.000			
FDI	0.313***	0.185**	0.313***	0.418***	0.445***	0.252***	0.477***	0.680***	−0.176*	1.000		
EAST	0.429***	0.281***	0.418***	0.477***	0.518***	0.325***	0.430***	0.604***	−0.256***	0.735***	1.000	
CEN	−0.222***	0.003	−0.170	−0.049	−0.124	−0.013	−0.237***	−0.264***	0.102	−0.352***	−0.509***	1.000

The symbols *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

TABLE 4 Compositive output index.

Province	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	0.069	0.117	0.105	0.112	0.111	0.113	0.113	0.131	0.148	0.140	0.156	0.165
Tianjin	0.081	0.074	0.066	0.068	0.074	0.077	0.106	0.146	0.154	0.165	0.152	0.116
Hebei	0.009	0.010	0.011	0.013	0.015	0.017	0.021	0.025	0.030	0.038	0.041	0.038
Shanxi	0.017	0.017	0.017	0.017	0.017	0.019	0.018	0.019	0.021	0.023	0.024	0.028
Inner Mongolia	0.017	0.016	0.015	0.013	0.012	0.012	0.015	0.015	0.016	0.017	0.021	0.025
Liaoning	0.019	0.023	0.026	0.026	0.031	0.036	0.039	0.042	0.042	0.039	0.040	0.053
Jilin	0.008	0.009	0.010	0.012	0.013	0.018	0.021	0.027	0.030	0.034	0.040	0.027
Heilongjiang	0.010	0.012	0.011	0.012	0.012	0.014	0.014	0.016	0.017	0.020	0.021	0.023
Shanghai	0.140	0.155	0.163	0.155	0.172	0.162	0.159	0.156	0.168	0.181	0.184	0.185
Jiangsu	0.151	0.198	0.255	0.285	0.322	0.414	0.505	0.554	0.608	0.702	0.791	0.712
Zhejiang	0.056	0.063	0.059	0.067	0.076	0.090	0.104	0.126	0.143	0.177	0.205	0.216
Anhui	0.013	0.013	0.012	0.014	0.016	0.024	0.032	0.038	0.051	0.071	0.086	0.091
Fujian	0.057	0.061	0.066	0.064	0.079	0.093	0.103	0.110	0.112	0.124	0.147	0.155
Jiangxi	0.011	0.012	0.012	0.016	0.018	0.021	0.027	0.033	0.038	0.051	0.062	0.065
Shandong	0.052	0.070	0.079	0.099	0.104	0.122	0.152	0.172	0.196	0.247	0.269	0.228
Henan	0.011	0.012	0.013	0.017	0.019	0.028	0.041	0.094	0.116	0.150	0.160	0.153
Hubei	0.014	0.016	0.019	0.026	0.029	0.033	0.042	0.050	0.061	0.077	0.086	0.086
Hunan	0.011	0.011	0.012	0.016	0.019	0.028	0.034	0.052	0.059	0.073	0.083	0.078
Guangdong	0.313	0.338	0.388	0.439	0.586	0.648	0.722	0.823	0.913	1.050	1.253	1.403
Guangxi	0.012	0.013	0.013	0.013	0.013	0.014	0.017	0.020	0.023	0.028	0.031	0.027
Hainan	0.030	0.037	0.032	0.030	0.027	0.032	0.027	0.028	0.030	0.030	0.033	0.041
Chongqing	0.014	0.014	0.015	0.018	0.020	0.035	0.040	0.050	0.073	0.112	0.121	0.142
Sichuan	0.024	0.031	0.032	0.042	0.037	0.060	0.071	0.093	0.105	0.105	0.120	0.129
Guizhou	0.012	0.014	0.014	0.013	0.014	0.015	0.017	0.018	0.019	0.021	0.024	0.026
Yunnan	0.016	0.016	0.015	0.014	0.015	0.017	0.016	0.018	0.019	0.020	0.022	0.026
Shaanxi	0.015	0.017	0.017	0.017	0.019	0.022	0.023	0.025	0.030	0.037	0.046	0.045
Gansu	0.027	0.033	0.031	0.030	0.028	0.032	0.027	0.027	0.028	0.030	0.031	0.036
Ningxia	0.063	0.066	0.065	0.057	0.060	0.069	0.090	0.106	0.099	0.090	0.074	0.072

TABLE 5 Results of LR tests.

Null hypothesis (H_0)	LR-test statistics	Critical value ($\alpha = 0.01$)	Decision
Cobb–Douglas function is applicable	418.923	10.501	Reject H_0

Among the factors that influence EE (inefficiency), the four models all showed that the coefficient of IURC is significantly positive (coefficient values are 0.139, 0.142, 0.143, and 0.135, respectively), while the coefficient of RD is significantly negative (coefficient values are −0.650, −0.397, −0.408, and −0.401, respectively). This shows that IURC can significantly promote the inefficiency of environmental technology, while RD can significantly hinder the inefficiency of environmental technology. That is, IURC has a significant inhibitory effect on the EE of HTM, while RD has a significant promoting effect on the EE of HTM.

All four models show that the coefficients of MAR, ES, and HC are significantly negative. This shows that HC, ES, and MAR play a significant role in promoting the EE of HTM. Model 4 shows that the effects of GS and FDI on EE are not significant. Model 4 also shows that the coefficient of EAST is not significant, while the coefficient of CEN is significantly positive. This shows that location factors also have a significant impact on EE.

To further examine the relationship between IURC and EE, Table 7 shows the results of adding the interaction terms of IURC and the R&D investment. Models 5, 6, 7, and 8 were added control variables by stepwise regression. The variation coefficients of the four models are all greater than 0.95 and are significant at a 1% significance level, which shows that the stochastic frontier model is more accurate than the traditional production function. At the same time, the test results also show that the translog production function has good applicability to the sample data.

Among the factors that influence EE (inefficiency), the four models show that the coefficient of IURC was significantly positive (0.157, 0.166, 0.167, and 0.160, respectively), while the coefficient of RD was significantly negative (−0.719, −0.489, −0.473, and

TABLE 6 Estimates of the direct effect of IURC.

Variables	Model 1		Model 2		Model 3		Model 4	
	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic
Production function								
Constant	1.264***	3.313	0.721***	3.439	0.746***	3.090	0.613**	2.565
t	−0.124**	−2.162	−0.054	−1.577	−0.068*	−1.878	−0.044	−1.115
lnK	−0.451	−1.575	−0.695***	−3.417	−0.624***	−3.193	−0.709***	−2.981
lnL	−1.102***	−4.960	−0.777***	−5.117	−0.823***	−5.624	−0.730***	−3.972
$0.5t^2$	0.001	0.255	0.005***	2.910	0.004***	2.692	0.005***	3.001
$0.5(\ln K)^2$	−0.012	−0.115	0.147**	2.287	0.129**	1.984	0.164**	2.130
$0.5(\ln L)^2$	0.132***	2.629	0.193***	6.423	0.189***	6.320	0.200***	5.458
t × lnK	0.020	0.573	−0.032*	−1.759	−0.026	−1.368	−0.038*	−1.799
t × lnL	0.013	0.621	0.046***	3.906	0.045***	3.782	0.050***	3.608
lnK × lnL	0.084	0.585	−0.134	−1.549	−0.118	−1.363	−0.160	−1.500
Explanation for inefficiency								
Constant	4.543***	19.922	3.210***	19.294	3.073***	16.642	3.075***	17.699
IURC	0.139***	4.328	0.142***	7.639	0.143***	7.025	0.135***	6.218
RD	−0.650***	−10.589	−0.397***	−14.988	−0.408***	−15.798	−0.401***	−15.472
MAR	−0.023***	−13.340	−0.014***	−11.170	−0.012***	−7.575	−0.013***	−9.206
ES			−0.272***	−7.526	−0.271***	−6.716	−0.239***	−5.582
HC			−0.591***	−16.434	−0.583***	−5.766	−0.566***	−9.224
GS					0.004**	2.152	0.004	1.543
FDI					0.001	0.450	−0.001	−0.188
EAST							0.078	1.129
CEN							0.119**	2.451
Model diagnostics								
σ^2	0.113***		0.065***		0.066***		0.063***	
γ	1.000***		0.964***		0.986***		0.960***	
Log likelihood	−68.261		41.912		44.527		48.127	
LR test	285.759		506.105		511.334		518.534	

The symbols *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

TABLE 7 Estimates of the dual effects of IURC.

Variables	Model 5		Model 6		Model 7		Model 8	
	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic
Production function								
Constant	0.260	0.987	0.616***	18.182	0.429*	1.796	0.469**	2.000
t	−0.067	−1.448	−0.009	−0.798	−0.063*	−1.939	−0.051	−1.311
lnK	−0.178	−0.766	−0.874***	−3.123	−0.500**	−2.399	−0.583***	−2.695
lnL	−1.147***	−6.499	−0.615***	−2.877	−0.841***	−5.521	−0.789***	−5.149
$0.5t^2$	0.004***	2.668	0.008***	6.103	0.005***	2.897	0.005***	3.091
$0.5(\ln K)^2$	−0.005	−0.073	0.223***	10.201	0.112	1.616	0.141**	2.050
$0.5(\ln L)^2$	0.117***	4.620	0.219***	8.892	0.180***	5.568	0.193***	6.389
t × lnK	−0.013	−0.708	−0.059***	−14.117	−0.029	−1.482	−0.036*	−1.794
t × lnL	0.027***	3.159	0.057***	15.547	0.045***	3.533	0.050***	4.035
lnK × lnL	0.088	1.128	−0.224**	−2.569	−0.100	−1.060	−0.137	−1.543
Explanation for inefficiency								
Constant	4.359***	28.987	3.379***	24.014	3.089***	17.953	3.161***	17.068
IURC	0.157***	4.568	0.166***	10.322	0.167***	8.293	0.160***	7.611
RD	−0.719***	−31.412	−0.489***	−14.034	−0.473***	−15.247	−0.481***	−13.320
IURC × RD	−0.068***	−6.647	−0.039***	−2.778	−0.032***	−4.039	−0.030***	−3.711
MAR	−0.022***	−15.529	−0.014***	−12.628	−0.012***	−8.548	−0.013***	−8.535
ES			−0.243***	−20.662	−0.283***	−7.490	−0.257***	−6.550
HC			−0.500***	−9.187	−0.431***	−6.455	−0.419***	−6.074
GS					0.004**	2.035	0.004*	1.955
FDI					−0.002	−0.878	−0.005	−1.282
EAST							0.107	1.583
CEN							0.078*	1.694
Model diagnostics								
σ^2	0.101***		0.085***		0.064***		0.062***	
γ	1.000***		0.964***		0.985***		0.977***	
Log likelihood	−39.913		36.351		52.769		55.118	
LR test	342.455		494.981		527.817		532.517	

The symbols *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

−0.481, respectively). This shows that IURC hinders the EE of HTM, while RD significantly promotes the EE of HTM. In these four models, the interaction terms of IURC and R&D investment are significantly negative (−0.068, −0.039, −0.032, and −0.030, respectively). This shows that there is a complementary effect between IURC and R&D investment, which significantly promotes HTM's EE.

The four models all show that the coefficients of MAR, ES, and HC are significantly negative. This confirms that HC, ES, and MAR all promote the EE of HTM. Both Models 7 and 8 show that the influence of GS was significant and positive, while that of FDI was not significant. Model 8 also shows that location factors have a significant impact on EE. When comparing the estimated results of the factors affecting EE in Tables 3, 4, it is found that the sign and significance of the coefficient values of the explanatory variables are consistent. This also shows that the estimation of the links between IURC and the EE of HTM is robust.

4.3. EE of China's HTM

Since both government support and regional differences have significant impacts on the EE of HTM, and IURC and R&D investment have significant complementary effects, the analysis result of Model 8 on the EE of HTM is more accurate. The EE results of China's HTM based on Model 8 are shown in Table 8.

As can be seen in Table 8, the EE of China's HTM is on the low side from 2006 to 2017. The average EE of the whole country is only 0.346, while that of the eastern area is 0.595, and that of the central and western areas are 0.199 and 0.171, respectively. In the eastern area, the HTM's EE in Guangdong is the highest, which is much higher than that in other provinces. However, the EE of HTM in Hebei and Hainan is much lower than that of other provinces in the eastern area, and lower than the average value of the western and central areas. In west and central China, most provinces except Sichuan and Chongqing have low EE values. This also shows that

TABLE 8 Environmental efficiency of China's HTM.

Area	Mean	Rank	Area	Mean	Rank
Eastern region	0.595		Anhui	0.231	15
Guangdong	0.965	1	Jiangxi	0.180	16
Shanghai	0.898	2	Jilin	0.143	19
Jiangsu	0.888	3	Shanxi	0.129	20
Beijing	0.804	4	Heilongjiang	0.102	25
Tianjin	0.709	5	Western region	0.171	
Shandong	0.678	6	Sichuan	0.387	9
Fujian	0.593	7	Chongqing	0.338	10
Zhejiang	0.544	8	Shaanxi	0.177	17
Liaoning	0.239	14	Guangxi	0.126	21
Hebei	0.151	18	Ningxia	0.125	22
Hainan	0.076	28	Gansu	0.123	23
The central region	0.199		Guizhou	0.105	24
Henan	0.292	11	Yunnan	0.080	26
Hubei	0.273	12	Inner Mongolia	0.078	27
Hunan	0.246	13	Overall	0.346	

TABLE 9 Results of the robustness test of the direct effect of IURC.

Variables	Model 9		Model 10		Model 11		Model 12	
	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic
Production function								
Constant	0.626**	2.504	0.510**	2.131	0.513**	2.212	0.408	1.574
lnK	−0.590***	−3.230	−0.712***	−5.009	−0.816***	−4.937	−0.780***	−4.510
lnL	−0.973***	−6.912	−0.789***	−6.963	−0.695***	−5.854	−0.705***	−5.757
$0.5(\ln K)^2$	0.014	0.355	0.043	1.463	0.075**	2.218	0.070*	1.953
$0.5(\ln L)^2$	0.077***	2.894	0.081***	3.602	0.096***	4.684	0.092***	3.813
lnK × lnL	0.152**	2.393	0.106**	2.187	0.061	1.225	0.068	1.223
Explanation for inefficiency								
Constant	4.091***	26.348	2.973***	14.662	2.773***	14.863	2.816***	14.631
IURC	0.111***	4.576	0.145***	7.616	0.128***	6.335	0.120***	5.844
RD	−0.542***	−22.752	−0.383***	−13.538	−0.362***	−15.180	−0.365***	−13.742
MAR	−0.021***	−17.216	−0.014***	−10.731	−0.011***	−7.435	−0.012***	−8.078
ES			−0.315***	−8.277	−0.278***	−7.106	−0.241***	−6.648
HC			−0.377***	−8.244	−0.461***	−8.646	−0.444***	−7.131
GS					0.004*	1.805	0.003*	1.742
FDI					−0.001	−0.511	−0.003	−0.691
EAST							0.088	1.345
CEN							0.123***	2.731
Model diagnostics								
σ^2	0.108***		0.059***		0.064***		0.062***	
γ	0.882***		0.502***		0.615***		0.608***	
log likelihood	−81.936		3.554		12.692		17.142	
LR test	336.205		507.186		525.462		534.361	

The symbols *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

TABLE 10 Results of the robustness test of the dual effects of IURC.

Variables	Model 13		Model 14		Model 15		Model 16	
	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic
Production function								
Constant	−0.035	−0.134	0.342	1.498	0.074	0.288	0.263	1.106
lnK	−0.239	−1.340	−0.703***	−4.415	−0.520***	−3.088	−0.690***	−4.629
lnL	−1.097***	−8.429	−0.713***	−6.119	−0.831***	−7.010	−0.715***	−6.668
$0.5(\ln K)^2$	−0.034	−0.931	0.054*	1.719	0.021	0.589	0.059*	1.958
$0.5(\ln L)^2$	0.070***	2.984	0.087***	4.299	0.076***	3.008	0.093***	4.768
lnK × lnL	0.185***	3.296	0.080*	1.693	0.121**	2.101	0.069	1.545
Explanation for inefficiency								
Constant	4.101***	27.418	2.950***	19.239	2.764***	11.537	2.911***	15.083
IURC	0.151***	6.094	0.150***	7.288	0.140***	7.370	0.148***	6.644
RD	−0.679***	−19.825	−0.417***	−15.868	−0.434***	−11.199	−0.441***	−13.051
IURC × RD	−0.067***	−5.694	−0.025***	−3.784	−0.036***	−3.281	−0.028***	−4.030
MAR	−0.020***	−16.850	−0.013***	−10.719	−0.011***	−5.893	−0.012***	−8.526
ES			−0.306***	−7.889	−0.276***	−6.042	−0.266***	−6.861
HC			−0.388***	−7.109	−0.347***	−3.830	−0.318***	−4.629
GS					0.004	1.441	0.003*	1.756
FDI					−0.003	−0.972	−0.007*	−1.810
EAST							0.116*	1.885
CEN							0.086**	2.025
Model diagnostics								
σ^2	0.102***	11.912	0.065***	12.905	0.066***	11.093	0.061***	13.585
γ	0.816***	10.367	0.679***	27.911	0.780***	23.006	0.652***	13.236
Log likelihood	−65.363		17.602		18.218		23.588	
LR test	369.353		535.282		536.514		547.253	

The symbols *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

improving EE is particularly urgent for sustainable development in Chinese HTM.

4.4. Robustness test

Do different forms of production functions lead to inconsistent estimates? To this end, we change the form of the production function, that is, excluding the time variable t from Equation 9, and then reanalyze the impact of IURC on the EE of HTM. Table 9 shows the results of the robustness test for the direct effect of IURC. All four models show that IURC is significantly positively correlated with the environmental technology inefficiency of HTM, indicating that the direct effect of IURC on the EE of HTM is significantly negative.

Table 10 shows the results of the robustness test for the dual effects of IURC. All four models show that although IURC has a negative direct impact on the EE of HTM, IURC has a positive indirect effect on the EE of HTM through its complementary effect with RD. In addition, the same conclusion is obtained by using the Cobb–Douglas production function to estimate. Thus, the estimated result will not change due to the change in the form of the function. Therefore, the estimated results of this article are robust.

It should be noted that the LR test of the time variable t shows that Equation 9 containing the time variable *t* is more applicable to the sample data. We take the estimated results of excluding the time variable t as a supplement to clarify whether the change in the form of the function will lead to the deviation of the estimated results. It shows that the estimated results are consistent regardless of whether the time variable *t* is considered.

4.5. Discussion

Compared with traditional pollution-intensive industries, there are relatively few literatures on the EE of HTM. The results of this article show that IURC significantly inhibits the EE of Chinese HTM, while R&D investment has a significant positive effect on the EE of China's HTM. This is analogous to the research conclusion of Peng et al. (2022).

The direct effect of IURC on HTM's EE is significantly negative. The possible reason is that, overall, the environmental technology obtained through IURC is not at the forefront of technology. At the same time, these technologies are easy to be replaced by foreign technologies (Peng et al., 2018). From the point of view of cost and benefit, backward enterprises will not actively purchase environmental technology from domestic universities and scientific research institutions, while domestic technology leading enterprises are reluctant to transfer their own environmental technology to other enterprises for maintaining their own technological advantages. All these things make it difficult for IURC to have a direct and positive effect on the EE of HTM.

Research and development investment has significantly improved the EE of China's HTM. R&D investment increases the environmental technology accumulation of HTM enterprises in the production process and urges these enterprises to launch more environmentally friendly new products and technologies (Chen et al., 2020), which has a significant positive impact on the EE of HTM.

In addition, both Models 5, 6, 7, and 8 show that there is a significant complementary effect between IURC and R&D investment, and this complementary effect significantly promotes the EE of HTM. As the environmental technology gap between Chinese high-tech enterprises is relatively small, R&D investment has enhanced the absorptive capacity of HTM enterprises to indigenous technology (Spithoven et al., 2010; Aldieri et al., 2018). These not only make the purchased indigenous technology easy to be digested and absorbed by the receiver, but also enable the technology receiver to develop more environmentally friendly technologies based on absorbing indigenous technology. As a result, the receiver improves EE in the process of absorbing and improving the acquired indigenous technology.

The results also indicate that in developing countries, external technology does not necessarily contribute to efficiency improvement, but the complementary effect of external technology and R&D has a positive impact on efficiency. Similar studies, Danquah (2018) confirmed that although import has an obstructive effect on the efficiency of sub-Saharan African countries, the complementary effect of import and R&D promotes its efficiency (Danquah, 2018). Barasa et al. (2019) found that although foreign technology has a negative impact on the technical efficiency of African manufacturing enterprises, the complementary effect of foreign technology and R&D investment is very important to improve efficiency (Barasa et al., 2019).

However, different from Peng et al. (2022), this article focuses on the direct and indirect effects of IURC on the EE of HTM. This article found that although IURC cannot directly improve EE, it has a positive impact on the EE of HTM through its complementary effect with R&D investment. This means that ignoring the indirect effect will exaggerate the adverse impact of IURC on HTM's EE. In addition, Peng et al. (2022) used the SBM-Tobit model to analyze the influencing factors of EE of HTM, which did not consider the impact of random factors, while the PP-SFA model proposed in this study further improved the reliability of the analytical results.

5. Conclusion and policy implications

In this study, a translog stochastic frontier model considering undesirable outputs was proposed by combining the PP model with the SFA. Based on the interprovincial data of Chinese HTM from 2006 to 2017, this study analyzed the links between IURC and HTM's EE. The results show that IURC has both a significant negative direct effect and a significant positive indirect effect on the EE of HTM. On the surface, IURC suppresses the improvement of EE. However, there is a significant complementary effect between IURC and R&D investment, which has a significant positive impact on the EE of HTM. The results also confirm that there are significant regional differences in HTM's EE in China. In general, there is much room for improvement in the EE of China's HTM.

Although IURC has a direct inhibitory effect on the EE of HTM, there is a significant complementary effect between IURC and R&D investment. Therefore, in the process of actively promoting the green development of HTM, we should not only pay attention to increasing R&D investment in environmental technology, but also pay attention to promoting IURC. In the process of facilitating HTM enterprises to introduce indigenous technology from universities and scientific research institutions, decision-makers should pay more attention to improving the institutional environment of IURC. All of these can have a positive impact on the EE of China's HTM. With the transfer of HTM from eastern China to other regions, the green development of eastern HTM will depend more on R&D investment. In the process of undertaking the transfer of HTM, the central and western provinces should combine the local industrial foundation and the technological capacity of enterprises and introduce suitable indigenous technology to improve the technological process, to promote the transformation of HTM to green development. At the same time, the central and western regions should also learn from the experience of IURC in the eastern region to improve the market-oriented management level of their technology transfer institutions.

There are also some shortcomings in this study. China's HTM includes computer manufacturing, medical equipment manufacturing, and other subsectors, which have different environmental pollution status and environmental technology level. It is necessary to deeply analyze the EE of HTM and its influencing factors in specific subsectors. In addition, the differences in industrial base and environmental policies between the three areas of China will also affect decision-making on IURC and R&D investment. However, we reckoned without these factors in this article, which will be the next focus of research.

Data availability statement

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

Author contributions

FP: conceptualization, methodology, software, validation, formal analysis, data curation, writing—review and editing, supervision, and project administration. XZ: conceptualization, writing—original draft preparation, and formal analysis.

Both authors had read and agreed to the published version of the manuscript.

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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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EDITED BY
Andrzej Klimczuk,
Warsaw School of Economics, Poland

REVIEWED BY
Huwei Wen,
Nanchang University, China
Xin Zhao,
Anhui University of Finance and Economics, China
Kaiyang Zhong,
Zhejiang University, China
Shulei Cheng,
Southwestern University of Finance and Economics, China

*CORRESPONDENCE
Yuanxiao Hong
✉ hyx021@zjnu.edu.cn
Shouchao He
✉ hsc@wzut.edu.cn

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The influence of digital economy development on urban carbon emission intensity in the Yangtze River Economic Belt: Mediating mechanism and spatial effect

Lindong Ma[1,2], Yuanxiao Hong[1]*, Shouchao He[3]*, Haibei Luo[4], Guangming Liu[5], Jinhui Zheng[6], Yuntian Xia[7] and Deheng Xiao[8]

[1]Xingzhi College, Zhejiang Normal University, Jinhua, China, [2]School of Management, Zhejiang University of Technology, Hangzhou, China, [3]School of Economics and Management, Wenzhou University of Technology, Wenzhou, China, [4]College of Modern Science and Technology, China Jiliang University, Hangzhou, China, [5]School of Economics and Management, Huangshan University, Huangshan, China, [6] School of Economics, Zhejiang University of Technology, Hangzhou, China, [7]School of Economics and Management, Hefei Normal University, Hefei, China, [8]School of Government, University of International Business and Economics, Beijing, China

The iterative upgrading of digital technology and the implementation of "carbon-peaking and carbon neutrality" national strategy provide an opportunity for the synergistic integration of digital economy and green economy in China, thus, whether the development of digital economy can curb urban carbon emission intensity (CEI) remains to be answered. Based on the panel data of 110 cities in the Yangtze River Economic Belt (YREB) region from 2011 to 2020, this paper investigated the impact of digital economy on CEI by using the dual fixed-effect model, the mediating mechanism model and the spatial Durbin model. The main results are as follows: (1) The development of digital economy in the YREB region can lower down CEI, promote the rationalization and upgrading of industrial structure, and improve cities' green innovation capacity; (2) CEI was reduced through the intermediary effect of industrial structure optimization and upgrading and green technology innovation; (3) Digital economy shows a significant positive spatial correlation, and exerts a spatial spillover effect of reducing CEI in surrounding cities with obvious spatial heterogeneity; (4) Digital economy has a stronger inhibitory impact on CEI in the downstream cities and cities within the urban agglomerations; (5) In addition to digital infrastructure, the remaining components of digital economy, directly and indirectly, diminish CEI. At last, according to the research findings, suggestions for digital economy development in the YREB region are put forward.

KEYWORDS

digital economy, carbon emission intensity, mediating mechanism, spatial effect, Yangtze River Economic Belt, China

1. Introduction

Global warming is a great challenge facing humanity. The continued increase in greenhouse gas emissions will adversely affect agricultural production, socioeconomic activities, and human livelihoods, and ultimately hinder progress toward global sustainable development. In China, carbon emissions increased from 8.83 billion tons (2011) to 9.90

billion tons (2020),[1] accounting for a large proportion of the world's total carbon emissions, and the carbon emission reduction is grim. In September 2020, President Xi Jinping pledged at the United Nations (UN) General Assembly to peak carbon emissions by 2030 and achieve carbon neutrality before 2060. China's carbon peaking and carbon neutrality goals not only show China's determination to reduce greenhouse gases, but also the essential requirement for China's high-quality development (Panpan et al., 2020). China's carbon emission reduction significantly impacts the global economy and environment (Wang C. et al., 2019). The Yangtze River Economic Belt (YREB) region accounts for more than 40% of China's total economic output. It is an vital growth momentum of the national economy and the most promising region to achieve the "double carbon" target. Along with economic development, a large amount of CO_2 emitted by fossil energy consumption has caused severe ecological problems. The conflict between economic development, resource use, and environmental protection needs to be solved urgently (Wang R. et al., 2019; Siqin et al., 2022). This paper studies the CEI of Yangtze River Economic Belt, which is important for enhancing low-carbon economic development and reducing regional carbon emissions. With the advancement of Chinese-style modernization, China's economy is facing the transformation of industrial structure led by the digital economy. The White Paper on China's Digital Economy Development mentioned that the volume of China's digital economy has increased from 9.5 trillion yuan in 2011 to 39.2 trillion yuan in 2020. As digital technology upgrades quickly, China's digital economy and the real economy have reached deep integration. It promotes digital industrialization and industrial digitization, realizes the rational allocation of production factors, and optimizes energy structure. In the background of China's "double carbon" target and economic transformation development, the synergy between economic development and ecological protection ask for higher standards in carbon emission management to solve the dilemma between the ecological environment and economic development. Then, a pivotal question to be answered is whether the development of digital economy can reduce a city's CEI. If it is valid, what is the mechanism of their interaction? Moreover, is there a difference in the spatial distribution and characteristics of the CEI effect caused by the digital economy over cities? Is there a spatial effect? Working out the above issues will help clarify the link between the digital economy and CEI. The conclusions of this study also can provide an empirical basis and decision reference for cities' low-carbon development.

With continuous innovation of network information technology, the digital economy is affecting all aspects of the economy, society, and environment with high penetration, scale effect, and network effect. Since the "Double Carbon" target and the Digital China Strategy were put forward, the government and academia have been focusing on taking full advantage of the digital economy to promote low-carbon development. The existing literature can be divided into three themes. Firstly, based on the relationship between the digital economy and total carbon emissions. Three views exist in this perspective: (1) Positive view that the development of digital economy has contributed to carbon emissions reduction. There are a number of articles demonstrating its positive effects from different perspectives by using different methods. For example, digital finance is part of the digital economy and can effectively reduce carbon emissions (Zhang and Liu, 2022). Digitalization development has beneficially promoted the technological transformation and upgrading, and strengthened green technological innovation (Ma Q. et al., 2022), thus changing the structure of energy consumption, which in turn promotes energy conservation and carbon emission reduction (Yi et al., 2022). It has also been found in industrial division and scale studies that the development of digital economy in recent years has beneficially expanded the economic scale and proportion of tertiary industries (Wang J. et al., 2022), thus reducing the share of polluting industries, which leads to carbon emission reduction. In addition to decreasing local carbon emission, some scholars also found that the development of digital economy exerts huge spatial spillover effect, thus contributing to carbon emission reduction in the surrounding areas (Yi et al., 2022). (1) Negative view that digital economy development is detrimental to carbon emission reduction. Dong et al. (2022) argued that digital economy can indirectly increase carbon emissions *per capita* by promoting economic growth, industrial structure upgrading and financial development. Zhang L. et al. (2022) pointed out that digital economy is detrimental to improving energy efficiency, which indirectly increases total carbon emissions. Yu and Zhu (2023) stated that digital economy strengthens carbon emissions by increasing energy intensity and promoting economic expansion. (2) Other views with complex results. Some scholars have found an inverted U-shape relationship between digital economy and total carbon emissions with a threshold effect (Chen X. et al., 2022; Li and Wang, 2022; Zhao S. et al., 2022). Secondly, based on the relationship between digital economy and carbon emission efficiency. Zhang et al. (2022b) theoretically elaborated the influence mechanism of digital economy on carbon emission efficiency, and on the basis of measuring carbon emission efficiency with EBM, demonstrated empirically that digital economy can improve carbon emission efficiency through intermediary variables such as energy intensity, but the spatial spillover effect on neighboring cities is not obvious. Based on the NDDF model calculating carbon emission efficiency in 285 cities in China, Zhang and Liu (2022) demonstrated that digital finance can beneficially contribute to the improvement of urban carbon emission efficiency and there are beneficial spatial spillover effects. Thirdly, based on the relationship between digital economy and carbon emission intensity. Gu et al. (2023) explored the relationship between digital economy and carbon emission intensity based on 13 cities in the Beijing-Tianjin-Hebei urban agglomeration and concluded that the digital economy can effectively reduce CEI, and analyzed its spatial spillover effect based on the space adjacency matrix. China is vigorously promoting the construction of urban agglomerations, therefore, Yan et al. (2022) and Xiaohan et al. (2022) explored the contribution of digital economy development to lowering carbon emission intensity in six urban agglomerations in China and found that the construction of urban agglomerations beneficially contributed to the reduction of carbon emission intensity by comparison. Sun et al. (2023), based on the panel data of 30 provinces in China with mediating variables (technological innovation and energy structure),

1 https://www.bp.com.cn/content/dam/bp/country-sites/zh_cn/china/home/reports/statistical-review-of-world-energy/2021/BP_Stats_2021.pdf (2022-10-01).

concluded that digital finance had a strong and sustained effect on the reduction of carbon emission intensity. The above research provides a theoretical basis and empirical reference for exploring the impact of digital economy on carbon emissions, some scholars have identified the digital economy in reducing urban or provincial carbon emissions intensity, and urban agglomeration perspective has also received academic attention (Xiaohan et al., 2022). Due to the large development gap between the east and west of China, the existing literature applied different measurement methods and selects different indicator variables. So whether there exists a unified indicator system and method based on the national level regions in China, which can also achieve micro and macro comparison, to explore the impact of digital economy on CEI and its internal mechanisms more comprehensively and objectively? We can see from the existing literature, based on the cities within urban agglomerations, there is a spatial spillover effect of the digital economy on CEI, does it exist among cities in non-urban agglomerations? Whether there are differences in spillover effects between regions? The digital economy is a comprehensive indicator, are there differences in the impact of its various component parts on CEI? Are there spatial spillover from each component as well? The above fields are still a blank to be explored. We try to answer the above questions by empirical analysis, using the panel data of 110 cities from 2011 to 2020 in Yangtze River Economic Belt in China.

As mentioned above, this study conducts analysis into the influencing mechanism and spatial effects of the digital economy on CEI based on the panel data in 110 cities in the YREB region from 2011 to 2020. The research is conducted as follows: (1) This study objectively calculates the digital economy development level in YREB region by constructing a scientific digital economy development indicator system. (2) This study uses the two-way fixed effects model to evaluate the impact of digital economy development on CEI. (3) This paper studies the mediating mechanisms of industrial structure rationalization and upgrading and green technology innovation in the situation of digital economy influencing CEI. (4) This study analyzes the spatial distribution characteristics of digital economy and CEI in the YREB region, and then applies the spatial Durbin model to assess the spatial spillover effect of digital economy on CEI. (5) The regressions were categorized according to geography and whether they were within urban agglomerations. (6) The regression of the CEI is classified according to each component of the digital economy. (7) Robustness tests.

The potential contributions are as follows: First, in term of research area, the impact of digital economy on CEI is evaluated from multiple dimensions based on uniform indicators and calculation methods: urban agglomeration versus non-urban agglomeration, a comparison among East China, Central China and West China, obtaining beneficial direct effect and spatial spillover effect. Second, in term of research content, this paper explores whether the digital economy has an mediating effect on CEI. According to the significant improvement of green innovation and the acceleration of industrial structure upgrading brought by digital economy, green innovation and industrial structure are selected to verify the intermediary effect. Third, this study uses the concept of spatial location to thoroughly explore the spatial correlation of the digital economy on CEI in the YREB region, as well as spillover effects. Fourth, with spatial heterogeneity, the spatial differences in the impact of the digital economy on CEI are discussed. Further, the influencing factors of the digital economy on CEI is explored for a more detailed and comprehensive understanding of its role.

2. Theoretical basis and research hypothesis

2.1. Direct effect of digital economy development on CEI

Established research and real-life practice show that the digital economy can create carbon emission reduction effects from multiple aspects and dimensions. A brief description follows. First, combining digital technology with the traditional production process, in the common development of the digital economy and the real economy, promotes the flow speed, scientific integration, and utilization of all links, realizes the transformation from inefficient industries to efficient ones, effectively optimizes the allocation of resources, and promotes productivity development. The Index Climate Action Roadmap proposes that digital technology solutions can reduce 15% of global CO_2 in manufacturing, energy, transportation, buildings, agriculture and other areas. It is a critical technological factor in achieving carbon reduction. Specifically, the digital economy can provide a networked environment. Online shopping and a paperless office lifestyle eliminate geospatial constraints and reduce the use of transportation and office consumables (Li et al., 2021). As a result, they significantly reduce transportation and production energy consumption, thereby reducing city carbon intensity. Second, in terms of environmental governance. Digital technologies can accelerate the spread of information and improve the effectiveness of environmental education, raising public awareness of environmental protection. It enhances citizens' monitoring role of government regulation and corporate carbon emission reduction through open access to government data and other means (Yang et al., 2020). Hampton et al. (2013) suggest the use of digital technology (e.g., big data, cloud computing, etc.) can help governments develop scientific carbon policies, help regulators implement policies and predict future development trends scientifically and effectively, and reduce environmental pollution as much as possible. Third, in terms of stimulating enterprises. The use of digital technology is forcing companies to pay attention to environmental benefits and external effects. It will prompt enterprises to use digital technology to transform and upgrade traditional industries, and promote the intellectual development of industries, thus improving enterprises' resource allocation rate and productivity. Resource allocation is one of the main factors affecting carbon emissions. Therefore, developing the digital economy can enhance enterprises' green transformation and reduce carbon emissions. So, we have the hypothesis H1.

> *H1*: The digital economy development can reduce CEI in the YREB region.

2.2. Mediating mechanism of digital economy on CEI

The digital economy promotes industrial structure optimization through efficiency improvement, economy of scale, precise allocation, cost savings and innovation empowerment. This paper evaluates the industrial structure optimization from two aspects: industrial structure rationalization and industrial structure upgrade, then discusses how the digital economy development influences those two aspects, eventually affects CEI as a result. First, enterprises can achieve efficient access to information and efficiency by using digital technology, thus reducing the negative impact of information asymmetry or incompleteness, thus reducing ineffective production processes, and improving the efficiency of limited resource utilization (Ren et al., 2021). Digital trading platforms and industrial internet platforms can improve the coordination of resources between industries, and promote the rational allocation of resources. They can reduce enterprises' energy consumption and then reduce CEI (Chen et al., 2019). Secondly, along with the deepening of industrial digitization and digital industrialization, the rapid development of tertiary industries such as digital services, the rise of the Internet of things and the rapid growth of e-commerce, the industrial structure has been optimized. In addition, the application of digital technology has promoted the transformation of industries into technology-intensive industries, which in turn has improved the level of industrial structure. In terms of the impact of industrial structure optimization on carbon emissions, Zhu and Shan (2020) stated that most of the industries undergoing digital transformation are clean industries with high efficiency and low energy consumption, which leads to low CEI. It is confirmed that the rationalization and upgrading of the industrial structure have a positive effect on reducing regional carbon emissions in the YREB region. So we bring the hypotheses H2a and H2b.

> *H2a*: Digital economy development reduces CEI by the upgrading of industrial structure in the YREB region.
>
> *H2b*: Digital economy development reduces CEI by enhancing the rationalization of industrial structure in the YREB region.

The digital economy is a critical factor in promoting technological innovation. Green innovation refers explicitly to technological innovation that results in environmental sustainability goals, which play an important role in the low-carbon transformation of industries (Xu et al., 2021; Dou and Gao, 2022). Specifically, first, the digital economy breaks through the original geographic spatial restrictions through cyberspace, enabling the entire flow of production factors. It can attract upstream and downstream industries to form virtual clusters, promote knowledge and technology spillover, and enhance cities' overall green innovation level (Halbert, 2011; Tang et al., 2021). Second, driven by digital technology, new financial services can improve the financial environment and structure and reshape the financial industry (Zhang et al., 2022b). With the help of digital technologies such as big data, banks can conduct comprehensive research and reasonable deployment to help enterprises improve their credit rationing structure and alleviate their debt financing risks and constraints. Therefore, with the gradual expansion of new businesses such as green credit, financial support can be provided for enterprises' green innovation, helping them to sustain their green innovation and long-term development (Zhang A. et al., 2022). Third, enterprises use digital technology to collect information on consumers' green consumption preferences and provide intelligence to support the production of green and innovative products. Digital technology can also force enterprises to improve the efficiency of green innovation and avoid wasting resources (Kafouros, 2006; Paunov and Rollo, 2016). In summary, the digital economy significantly impacts green innovation through the penetration of digital technology applications. In the study of green innovation to reduce carbon emissions, Gu et al. (2023) proposed that improving green innovation can alleviate technical problems such as insufficient new energy storage and power consumption, and then reduce carbon emissions by optimizing the energy structure. In addition, the promotion of green innovation will help to eliminate high energy-consuming and polluting enterprises, thus reducing carbon emissions. So, we get the hypothesis H3.

> *H3*: The digital economy development reduces CEI through green technology innovation in the YREB region.

2.3. Spatial spillover effect of digital economy on CEI

According to the relevant theories of economic geography, spatial proximity or economic distance can accelerate or slow down the spread of knowledge innovation. Technology spillover can accelerate the flow of production factors, which have positive or negative effects on the surrounding areas. Digital economy development provides new ways and opportunities to reshape the spatial pattern of economic production. The "spillover" of digital economy is determined by the inherent qualities of digital technology. Due to the high mobility and replicability of digital technology, and less influenced by geographical constraints, the digital economy can realize the industrial and economic activities to move across regions with strong spatial spillover effects (Li and Wang, 2022; Zhang et al., 2022b). First, with the innovation of digital technology, digital economy is developing rapidly. Enterprises, universities and academic institutions across the regions have more opportunities to exchange and cooperate with each other in technology research and development. Talents and data can flow freely across the regions, achieving intellectual spillover and information spillover. Second, the development of digital economy has accelerated the process of digital transformation of the real economy. All industries and fields are undergoing digital transformation, which has greatly improved the production efficiency and commodity circulation efficiency, which in turn improves the utilization rate of urban resources and generates resource spillover effects. As a result, carbon emissions can be reduced. Third, digital technology is used to achieve collaborative detection and governance. It helps to exert the effect of collaborative governance to maximize and rationalize production factors, thus achieving the purpose of reducing CEI as well as promoting the low-carbon coordinated development of the YREB region (Li and Wang, 2022). In an empirical study based on the spatial spillover of CO2, Yue et al. (2021) and Liu and Liu (2019) stated that carbon emissions can influence the local ecological environment, and cause the chain reaction in the surrounding cities as well. Therefore, it is spatially significantly correlated. In summary, we propose hypothesis H4.

H4: There are spatial spillover effects on the impact of the digital economy on CEI.

3. Variable definition and model construction

3.1. Variable definition

3.1.1. Dependent variables

Carbon emission intensity (CEI). Because of the significant differences in economic development among cities in the YREB, this paper applies the CEI to evaluate the level of carbon emissions in cities (Cary, 2020). CEI is the amount of CO2 produced per unit of real GDP. Referring to previous research (Chen et al., 2020; Banruo and Zijie, 2021), this study uses the consumption of petroleum gas, natural gas, and electricity consumption of the whole society to estimate energy consumption. Among them, China's urban power generation is still dominated by coal, so coal-fired power generation is used to measure CO_2 emissions (Wang Y. et al., 2022). The formula is as follows:

$$CO_2 = C_n + C_p + C_e = kE_n + vE_p + \varphi(\eta \times E_e) \quad (1)$$

$$CEI = CO_2 / GDP \quad (2)$$

In equation (1), *CO2* is the total energy-related carbon emission of the city; C_n, C_p, and C_e, respectively, represent the CO_2 emissions generated by natural gas, liquefied petroleum gas, and electricity consumption of the whole society; E_n is the consumption of natural gas, E_p is the consumption of liquefied petroleum gas, E_e is the electricity consumption of the whole society; k is the emission coefficient of natural gas, v is the emission coefficient of liquefied petroleum gas, η is the ratio of coal power to the total power generation, and φ is the coefficient of the coal power emission. Among them, the CO_2 emission coefficient refers to the previous research (Panpan et al., 2020) and the "Provincial Greenhouse Gas Inventory Compilation Guide," and this study sets the CO_2 emission factors of natural gas, liquefied petroleum gas, and coal power fuel chain as 2.162 2 kg/m^3, 3.101 3 kg/kg and 1.302 3 kg/kW·h, respectively. In equation (2), *CEI* is the urban carbon emission intensity, and *GDP* is the gross domestic product.

3.1.2. Independent variables

Digital economy development index. This study refers to Wang and Guo (2022) and Li et al.'s (2021) digital economy development index measurement method. As shown in Table 1, we use six indicators to construct the digital economy index system. Then we use the entropy weight method to calculate cities' digital economy comprehensive index.

3.1.3. Intervening variables

(1) Industrial structure optimization, containing two submitting parties of industrial structure rationalization (*Isr*) and industrial structure upgrade (*Isu*). Based on Yigen and Zhen (2021) research, this study measures the level of industrial structure upgrading by the weighted average of the proportion of the GDP of the secondary and tertiary industries, that are 0.4 and 0.6, respectively. And the industrial structure rationalization index is measured with the Theil index. The formula is as follows.

$$Isr = \sum_{i=1}^{n} \left(\frac{G_i}{G}\right) \ln\left(\frac{G_i}{L_i} / \frac{G}{L}\right) \quad (3)$$

From equation (3), n is the number of industrial parties; i is the industrial sector; G is the city GDP; L is the number of employees;

TABLE 1 Digital economy development comprehensive index system.

Target layer	Criterion layer	Index layer	Description (unit)
Digital economy development	Digital infrastructure	The density of long-distance optical cables	Cable length per square kilometer (km)
		Mobile Internet	The mobile phone switch capacity per 100 people
		Broadband internet	Internet broadband ports per 100 people
	Digital industry development	Industrial base	Percentage of computer services and software employees
		Telecommunications output	Total telecom service *per capita*
		online shopping and E-commerce development	Total postal service *per capita*
	Digital innovation capabilities	Supported by digital innovation elements	Science and technology expenditure (10^4 RMB)
		Digital innovation output level	Number of digital economy-related patents per 10^4 people
		Digital high-tech penetration	The degree of penetration of digital high-tech applications in listed companies
	Digital finance	Breadth of coverage	Digital Financial Inclusion Breadth Index
		Use depth	Digital financial inclusion usage depth index
		Degree of digitalization	Digital Financial Inclusion Digitalization Index

Gi/*G* is the output structure; *Gi*/*Li* is the productivity of the industrial sector *i*; *G*/*L* is the yield of the industry.

(2) Green technology innovation (*Gti*). This study measures it as the sum of the number of green technology invention patents (Zeng et al., 2022). Referring to the Technology Fields and IPC Classification Number Comparison Table released by OECD (Organization for Economic Cooperation and Development), the coverage of green technology is settled by establishing the corresponding relationship between green technology and IPC classification, mainly involving water pollution control, soil pollution control and air pollution control and other technologies (Zhang et al., 2022a). The patent data is regarded as the output index of enterprise innovation, which can measure the level of regional independent innovation and reflect the innovation situation of enterprises. Thereby, this study adopts the number of green patents as an indicator of green innovation in referring to Tang et al. (2021).

3.1.4. Control variables

Referring to Zhang et al. (2022a), Zhao X. et al. (2022), Xu et al. (2021), and Wang and Guo (2022b). The control variables are selected as follows: (1) Environmental regulation intensity (*Eri*). It is issued by governments as a command-control tool to manage the ecological environment (Zhang et al., 2022a) and is calculated by discharging three wastes (SO_2, wastewater, and soot). (2) Science and technology support (*Sts*). Local financial expenditures on science and technology as a percentage of GDP for the year indicate science and technology support. (3) The population density index (*Pdi*). Demographic factors have an important relationship with carbon emissions, especially regional populations (Xu et al., 2021). The increase in carbon dioxide emissions is mainly caused by population growth and increased human activities. However, population growth may also improve energy efficiency and alleviate environmental pressure due to "Agglomeration Effect" and "Shared Benefits" (Xie et al., 2019). (4) Economic development level (*Edl*). China's economic growth relies on energy, whose excessive consumption will inevitably produce large amounts of carbon dioxide (Wang and Guo, 2022). The level of economic development is measured by the real GDP *per capita* of the region. (5) Urbanization development level (*Udl*). It is expressed by the urbanization rate, that is the proportion of the urban household registration population in the total household registration population. The specific description of each variable are shown in Table 2.

3.2. Model construction

3.2.1. Fixed effects model

This study uses a fixed effects model to analyze the impact of urban digitalization on urban carbon emission intensity. The model is as follows Li et al. (2019) and Zhang et al. (2022b).

$$\ln CEI_{it} = \alpha_0 + \alpha_1 \ln Dei_{it} + \alpha_2 \ln\left(X_{it}\right) + \mu_i + \delta_t + \varepsilon_{it} \quad (4)$$

In this model, *i* is the city; *t* is the year; *CEI* is the carbon emission intensity; *Dei* is the digital economy index; X_{it} is the Control variables; μ_i is an individual fixed effect, δ_t is the time fixed effect, and ε_{it} is random error.

3.2.2. Mediating model

As mentioned in the above assumptions, industrial structure optimization (industrial structure rationalization, industrial structure upgrading) and green technology innovation are two mediating factors for the digital economy to reduce carbon emissions. Based on this, the mediation model is constructed as follows.

$$\ln Y_{it} = \beta_0 + \beta_1 \ln Dei_{it} + \beta_2 \ln\left(X_{it}\right) + \mu_i + \delta_t + \varepsilon_{it} \quad (5)$$

$$\ln CEI_{it} = \gamma_0 + \gamma_1 \ln Dei_{it} + \beta 1 \gamma_2 \ln Y_{it} + \gamma_3\left(X_{it}\right) + \mu_i + \delta_t + \varepsilon_{it} \quad (6)$$

In model (5), Y is an intervening variable, which refers to industrial structure upgrading, industrial structure rationalization, and green technology innovation index. In model (6), $\beta 1\ \gamma_2$ is the mediating effect, showing that digital economy development affects CEI through green technology innovation or industrial

TABLE 2 Variables' explanatory and descriptive statistics.

Category	Variable	Interpretation	Mean	Std. dev.	Max	Min
Dependent variable	*CEI*	Urban carbon emission intensity	0.3121	0.0973	1.5084	0.0189
Independent variable	*Dei*	Digital economy development index	0.3231	0.7613	0.8792	0.03780
Intervening variable	*Isu*	Industrial structure upgrading	1.3072	0.8829	5.2691	0.6167
	Isr	Industrial structure rationalization	0.4022	0.3891	0.7564	0.0019
	Gti	Green technology innovation index	1,021	3,749	16,864	11
Control variable	*Eri*	Environmental regulation intensity	0.1595	0.2271	0.8354	0.0001
	Sts	Science and technology support	0.2494	0.2691	6.0412	0.0438
	Pdi	The population density index	2.1376	2.9832	7.0778	0.5583
	Edl	Economic development level	10.7185	0.5906	15.6751	8.7725
	Udl	Urbanization development level	0.5181	0.3287	0.8934	0.3145

structure optimization. The other variables are the same as model (4).

3.2.3. Spatial Durbin model

The spatial spillover effects of the digital economy are evident (Gu et al., 2023; Yu and Zhu, 2023), and urban carbon emissions will generate negative externalities on the surrounding urban environment, and it has an obvious spatial correlation (Wang and Guo, 2022). Therefore, this study constructs the spatial Durbin model to verify the spatial effect of the digital economy on CEI (Lv et al., 2022). The model is as shown below.

$$\begin{aligned}\ln CEI_{it} = \varphi_0 + \rho_0 w \ln CEI_{it} + \varphi_1 \ln Dei_{it} + \\ \rho_1 w \ln Dei_{it} + \varphi_2 X_{it} + \rho_2 w X_{it} + \\ \mu_i + \delta_t + \varepsilon_{it}\end{aligned} \tag{7}$$

In model (7), ρ_0 is the autocorrelation coefficient; *Xit* is the control variable; *W* is the spatial weight matrix; ρ_1 is the coefficient of independent variables; ρ_2 is the coefficient of control variables' spatial interaction term.

There are four types of spatial weight matrices commonly used in academic research: first-order adjacency spatial weight matrix (W_1), geographic distance spatial weight matrix (W_2), economic distance spatial weight matrix (W_3), and geographic economic nested spatial weight matrix (W_4). The geographic distance spatial weight matrix and the economic distance spatial weight matrix examined the effects of geographic and economic factors on the spatial distribution characteristics of the variables, respectively. The geographic-economy nested spatial weight matrix includes geographical factors and economic development factors, all spatial weight matrices are as follows:

$$\mathrm{W}_1 = \begin{cases} 1\ i \text{ and } j \text{ are adjacent} \\ 0\ i \text{ and } j \text{ are not adjacent} \end{cases} \tag{8}$$

$$\mathrm{W}_2 = \begin{cases} 1/d_{ij}\ \mathit{if}\ i \neq j \\ 0\ \mathit{if}\ i = j \end{cases} \tag{9}$$

$$\mathrm{W}_3 = \begin{cases} 1/\left|\overline{GDP_i} - \overline{GDP_j}\right|\ \mathit{if}\ i \neq j \\ 0\ \mathit{if}\ i = j \end{cases} \tag{10}$$

$$\mathrm{W}_4 = \begin{cases} \varphi 1/d_{ij} + (1-\varphi)1/\left|\overline{GDP_i} - \overline{GDP_j}\right|\ \mathit{if}\ i \neq j \\ 0\ \mathit{if}\ i = j \end{cases} \tag{11}$$

Where element d_{ij} of W_2 and W_4 represents the nearest highway mileage of city *i* and *j*. GDP_i and GDP_j of W_3 and W_4, respectively, represent the annual *per capita* GDP of cities *i* and *j*. φ represents the weight of the geographic-economy nested spatial weight matrix. Referring to Wang and Guo (2022), it is taken as 0.5. Besides, this paper has standardized the spatial weight matrix in the empirical analysis.

3.3. Data sources

This study adopts the panel data of 110 cities in the YREB region from 2011 to 2020. All city data are derived from the "China Urban Statistical Yearbook," "China Energy Statistical Yearbook," "China statistical yearbook on the environment," annual statistical reports, and statistical bulletins for each city or province. The digital financial inclusion index is derived from the "Digital Financial Inclusion Index System and Index Compilation" (Guo et al., 2020). The missing data were filled using linear interpolation and the mean method. To try to mitigate the effect of heteroskedasticity, this study took logarithms for all variables when conducting regression analysis.

4. Direct effects and mediating mechanism

4.1. Direct effects

To verify the impact of the digital economy on CEI in the YREB region, a double fixed-benchmark regression with time effect and the individual effect was conducted on the model (4). The regression results are shown in Table 3, and the difference between the two regression results lies in whether control variables are included or not. It can be found that the coefficients of *lnDei* in columns (1) and (2) are significantly negative at the significance levels of 1%, which indicates that the digital economy development in the YREB region has a significant impact on decreasing CEI. To be more detail, when *lnDei* increases by 1%, lnCEI decreases by 0.199% accordingly, which confirms hypothesis H1. The reason may be that the development of the digital economy in the Yangtze River Economic Belt has obvious advantages compared with other regions, such as the development of the digital industry in Zhejiang and the digital transformation of the manufacturing industries in Jiangsu, Shanghai, Wuhan and Chongqing, which realize the deep integration and coordinated development of digital technology and high-carbon emission fields such as industry, electricity, transportation. In addition, by building smart cities, we can

TABLE 3 Benchmark regression results.

Variable	*lnCEI* (1)	*lnCEI* (2)
lnDei	−0.413*** (−10.372)	−0.199*** (−8.165)
lnEri		0.015 (1.426)
lnSts		−0.021* (−1.897)
lnPdi		−0.113** (−2.194)
lnEdl		−0.648*** (−5.993)
lnUdl		−0.036*** (−3.29)
Constant	−10.013 (−90.001)	−12.623***(−31.957)
City FE	YES	YES
Year FE	YES	YES
R^2	0.701	0.765
Observations	1,100	1,100

***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively; The values in parentheses are *t* values.

improve the efficiency of urban operations, environmental management, and digital government services to promote low-carbon transformation cities and reduce CEI.

The control variables are as follows. Economic development and urbanization development both affect CEI at a significance level of 1%. The possible explanation is that economic development and urbanization advancement make citizens more aware of environmental protection and strengthen government regulatory actions, leading to an increase in sewage costs, which reverses the effects on carbon emissions. Urban economic growth causes technological innovation, institutional change, and economic restructuring, which help reduce the intensity of urban carbon emissions. The population density and science and technology support negatively affect CEI at the significance levels of 5% and 10%, respectively. On the one hand, the increased population density will increase the total amount of carbon emissions due to the resources increase as the population increase, but the economic growth benefits and the more efficient and rational use of resources, especially economies of scale, will lead to a decrease in CEI. Increasing government investment in science and technology can encourage companies and research institutions to accelerate research in green and digital technologies and to promote the application of advanced green technologies in production. In addition, by using digital technologies such as machine learning and big data, companies can achieve emission reductions more accurately. The positive effects of *Eri* on CEI did not pass the *t*-test. The reason behind it is that the *Eri* increases when the government steps up efforts to regulate activities that pollute the environment, thereby reducing carbon emissions. At the same time, it will also cause many enterprises to move out due to excessive pollution costs or non-compliance with environmental protection requirements, which may eventually lead to economic stagnation or even retrogression. Therefore, the effects of *Eri* on CEI do not pass the significance test.

4.2. Mediating mechanism

This part uses the stepwise inspection method to analyze the regression results of models (5) and (6), and judge the mediating effect of *Dei* on CEI in the YREB region. From Table 4, we can find that the coefficient of *lnDei* on *lnIsu* is significantly positive at the 1% significance level, presenting that the digital economy development in the YREB region has substantially improved the upgrading of industrial structure, which confirms hypothesis H2a. Moreover, in columns (2) and (3), we can see that the coefficients of *lnDei* on *lnIsr* and *lnGti* are significantly positive at the significance level of 1%, indicating that the development of digital economy has vigorously promoted the industrial structure rationalization and green technology innovation in the YREB region, which firms hypotheses H2b and H3.

As shown in Table 5, the effects of *Dei* on CEI are all significant after adding three mediating variables separately. The specific analysis is as follows. In column (1), the coefficient of *lnIsu* on *lnCEI* is significantly positive at the significance level of 10%. The above definition of intermediary variables indicates that the digital economic development in the YREB region reduces CEI through industrial structure upgrading, which confirms hypothesis H2a. In columns (2) and (3), the coefficients of *lnIsr* and *lnGti* are significant at the 1% and 5% significance levels, respectively. It indicates that improving industrial structure rationalization and increasing green technology innovation can significantly reduce CEI. According to the above analysis, it can conclude that similar results, confirm H2b and H3.

The above research confirms that *Dei* can significantly reduce CEI in the YREB region after adding *Isu* and that *Isu* significantly reduces CEI. To strengthen the verification of hypotheses H2a, H2b, and H3, we adopt Bootstrap method to further test the mediating effect. The Bootstrap sampling method is about whether

TABLE 4 Digital economy and mediating variables.

Variable	*lnIsu* (1)	*lnIsr* (2)	*lnGti* (3)
lnDei	0.373*** (9.356)	0.452*** (5.166)	1.461*** (7.152)
lnEri	0.167 (1.579)	0.216** (2.406)	0.416** (2.310)
lnSts	0.239** (2.041)	0.127* (1.791)	0.319* (1.892)
lnPdi	−0.362 (−1.089)	−0.213 (−0.194)	−0.354 (−0.994)
lnEdl	0.239*** (4.514)	0.248* (1.903)	0.168** (2.073)
lnUdl	0.137** (2.392)	0.096*** (4.591)	0.106 (1.094)
Constant	−4.083 (−1.091)	−5.012 (−1.279)	12.325*** (5.267)
City FE	YES	YES	YES
Year FE	YES	YES	YES
R^2	0.701	0.695	0.785
Observations	1,100	1,100	1,100

***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively; The values in parentheses are *t* values.

TABLE 5 Mediating variables and CEI.

Variable	(1) *lnCEI*	(2) *lnCEI*	(3) *lnCEI*
lnDei	−0.129*** (−4.132)	−0.146*** (−7.593)	−0.179*** (−3.653)
lnIsu	−0.081* (−1.892)		
lnIsr		−0.051*** (−6.243)	
lnGti			−0.061** (−2.516)
lnEri	0.013* (1.826)	0.015* (1.726)	0.009 (1.021)
lnSts	−0.011* (−1.697)	−0.019** (−2.391)	−0.009* (−1.867)
lnPdi	−0.203** (−1.994)	−0.197*** (−2.893)	−0.190*** (−2.904)
lnEdl	−0.341** (−2.393)	−0.352* (−1.937)	−0.371** (−2.206)
lnUdl	−0.041** (−2.493)	−0.081* (−1.893)	−0.079** (−2.216)
Constant	−11.231*** (−30.017)	−11.513*** (−20.612)	−11.317*** (−27.263)
City FE	YES	YES	YES
Year FE	YES	YES	YES
R^2	0.801	0.804	0.798
Observations	1,100	1,100	1,100

***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; The values in parentheses are *t* values.

the product term of regression coefficient a and regression coefficient b contains the number 0 within the 95% confidence interval. If the number 0 is not included, it means it has a mediating effect. The results of Bootstrap test with 1,000 samples are presented in Table 6. The multiplication items of the regression coefficients of the three mediating variables do not contain the number 0 within the 95% confidence interval, and they are all significant at the significance level of 1%, which confirms the existence of mediating effects.

5. Spatial analysis of the digital economy and the CEI

5.1. Spatial distribution of the digital economy and the CEI

(1) Spatial distribution of the digital economy. ArcGIS *10.8* is applied to visualize the spatial distribution of the digital economy in the YREB region, as presented in Figure 1. On the whole, the urban digital economy has been developing over the past 11 years. During this period, the digital economy index proliferated from 2011 to 2021, and the growth rate of many cities exceeded 100%, indicating that the digital economy was in a rapid development stage. Especially from 2015 to 2021, the digital economy development of downstream in the YREB region has changed from the original core "multi-point" sporadic distribution to the "group" aggregation form. This may be integrated with the Yangtze River Delta city cluster, which is beneficial to promote coordinated regional development and information sharing, and then enhances the formation of economies of scale and integration benefits.

(2) The spatial distribution of CEI. It can be found from Figure 2. that the CEI of most cities has decreased significantly on the whole over the past 11 years, and it is more obvious in the eastern cities but sees less improvement in cities in the Midwest. Among these cities, Shanghai's CEI has been getting lower every year. It indicates that Shanghai has paid attention to lower down carbon emissions while developing its economy, and has enhanced the development of low-carbon economy. However, Pu′er City has been at the high point of CEI and the decrease is not obvious, which may not only be related to its carbon reduction realization but also related to its special development stage of economic development and the general lack of improvement in surrounding cities, as well as the development level of the natural environment and digital economy.

5.2. Spatial correlation analysis

The global Moran index is adopted to evaluate the spatial correlation of digital economy (Zeng et al., 2022; Zhao and Sun, 2022). Before performing a spatial correlation analysis, it needs to create and apply the spatial weight matrices. To analyze the spatial effect more scientifically and comprehensively, the study refers to the existing literature (Li et al., 2022; Zhao and Wang, 2022) and constructs four types of spatial weight matrices, and the results are shown in Table 7.

When Moran's I>0, spatial correlation among regions is positive; Moran's I<0 means that spatial correlation among regions is negative; Moran's I = 0 indicates no correlation.

The results show that the global Moran value of the digital economy is between 0.248 and 0.411 and passes the 10% significance test, which indicates that the digital economy development shows a positive spatial correlation under W_1. As can be seen from Table 6, by the same token, it can be found that Moran's I >0 in terms of W_2, W_3, and W_4, and can pass the 10% significance test in most years. In summary, the digital economy has apparent positive spillover effects.

5.3. Spatial effect analysis

To make it suitable for this study, firstly, the Wald test and LR test were operated, and the results showed that both of them passed the 1% significance test, thus rejecting the original hypothesis of using the SLM model or SEM model, proving that the spatial error term and spatial lag term existed at the same time, therefore, this study used the Spatial Durbin model (SDM) to start the analysis, and the calculated Hausman test results passed the 1% significance test, then the fixed effect model was chosen. Due to the existence of spatial correlation, it is difficult to carry out accurate estimation using the OLS method, so the Quasi-maximum likelihood estimate (QMLE) is used for estimation (Feng et al., 2022; Weixiang et al., 2022; Xie et al., 2022). The results are presented in Table 8. The coefficient of *lnDei* in column W_1 is significant at the 1% significance level. It shows that the development of digital economy can greatly curbs the CEI in the YREB region, which is consistent with the previous outcome. The spatial coefficient of *lnDei* is significant at the 5% significant level, which tells us that the development of digital economy in a given city has a spillover effect on the CEI of the surrounding cities. The coefficients of *lnDei* in columns W_2, W_3, and W_4 are all significant at

TABLE 6 Bootstrap test.

Directory	(1) *lnIsu*		(2) *lnIsr*		(3) *lnGti*	
	bs1	bs2	bs1	bs2	bs1	bs2
95% Confidence interval	−0.8479	−0.7276	−0.7869	−0.8003	−0.8521	−0.5712
	−0.4954	−0.4011	−0.2446	−0.2841	−0.3096	−0.2018
P>|z|	0.002	0.000	0.000	0.000	0.000	0.000
Mediation effect	Exist	Exist	Exist	Exist	Exist	Exist

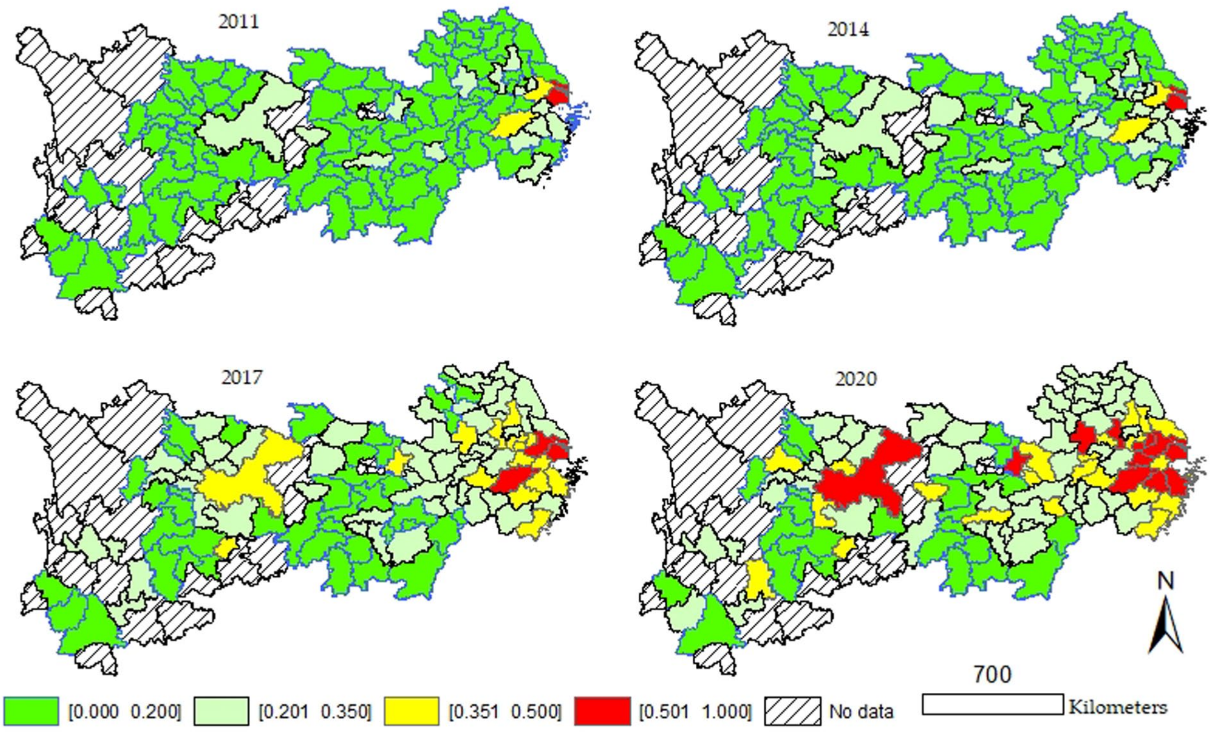

FIGURE 1
Spatial distribution of the digital economy.

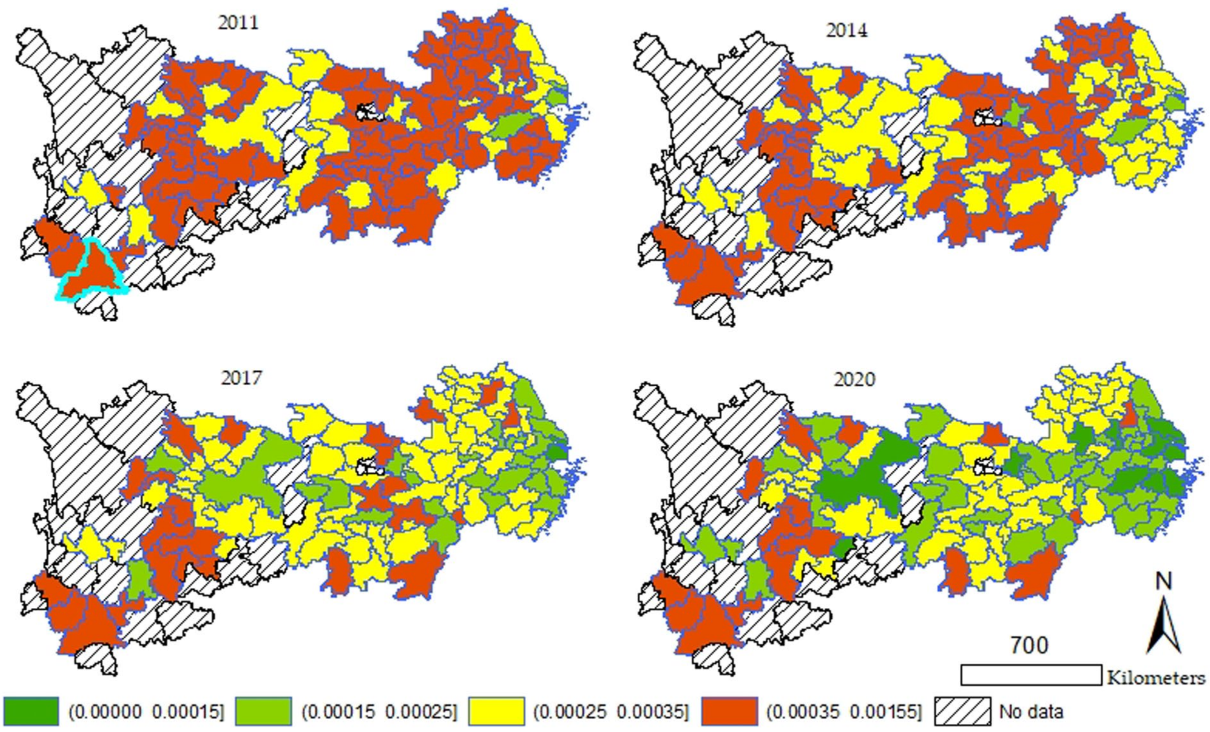

FIGURE 2
Spatial distribution of the CEI.

the significance level of 1% and the interactive effect on the CEI of the surrounding cities are all significant at the 10% level. This suggests that the indirect impact of the digital economy on CEI is significant and cannot be ignored. That is, the development of digital economy has an inhibitory effect on CEI not only in local cities, but also in neighboring cities, and they are of same importance. The above findings confirm that the digital economy offers a positive spatial spillover effect.

The coefficients of control variables in column W_4 are significant, displaying that the environmental regulation, science and technology support, population density, and economic and urbanization development of the sample cities greatly influence the urban CEI. In the sixth line, the coefficient of *lnEdl* is significantly positive for reducing CEI in all spatial weight matrices. It indicates that economic development has beneficially promoted the reduction of CEI and has a spatial spillover effect on surrounding cities, showing that the carbon emissions per unit economy are significantly reduced, and the extensive economic development mode of the Yangtze River Economic Belt has been changing to intensive development and has entered the development stage on the right side of the *Kunze* curve. This may have something to do with the intensive green development guided by the government and the practice of the "Two Mountains Theory" (Ma et al., 2022a). The development of urbanization (the seventh line *lnUdl*) has beneficially promoted the reduction of CEI in the process of converting the rural population to the urban population, along with the further expansion of the urban scale and the further rationalization of the layout. The scale of industry, especially the tertiary industry, has realized the scale effect of population agglomeration, reduced energy consumption, improved the green intensive effect, and ultimately promoted the reduction of CEI. With the advancement of urbanization, people's awareness of carbon reduction has been strengthened, which in turn has promoted the reduction of CEI, especially in the comparative effect and role model power of surrounding cities, which may explain why the spatial effects are so significant.

TABLE 7 Moran's *I* statistic of the urban digital economy.

Year	W_1	W_2	W_3	W_4
2011	0.411***	0.291*	0.147*	0.121*
2012	0.391**	0.206*	0.139*	0.103*
2013	0.397**	0.232*	0.121**	0.092*
2014	0.382*	0.198*	0.192*	0.095*
2015	0.361**	0.201*	0.131*	0.093*
2016	0.299*	0.182*	0.098	0.090
2017	0.296***	0.173*	0.082*	0.079*
2018	0.282***	0.157	0.113	0.064
2019	0.259**	0.152*	0.084*	0.061*
2020	0.248**	0.149*	0.081**	0.062*

***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively.

5.4. Spatial heterogeneity analysis

To further consider whether spatial heterogeneity exists in regions regarding the impact of the digital economy development on CEI, this study is carried out from the perspectives of sub-region and urban agglomeration. The division of regions (the upper, middle, and lower reaches of the Yangtze River Economic Belt) and urban agglomerations (Ma et al., 2022b) (the Yangtze River Delta urban agglomeration, the

TABLE 8 Regression of results.

Explanatory variables	W_1		W_2		W_3		W_4	
	x	$W \times x$	x	$W \times x$	x	$W \times x$	x	$W \times x$
lnDei	−0.292*** (−2.951)	−0.079** (−2.191)	−0.221*** (−2.908)	−0.059** (−2.869)	−0.235*** (−2.906)	−0.019* (−1.780)	−0.202*** (−4.955)	−0.064** (−2.252)
lnEri	0.059 (1.011)	0.016*** (2.964)	−0.118 (−0.986)	0.070* (1.772)	0.114 (0.952)	0.039 (0.325)	−0.110* (−1.796)	0.042* (1.976)
lnSts	−0.032* (−1.883)	−0.011* (−1.839)	−0.046** (−3.379)	−0.032* (−1.744)	−0.046*** (−3.411)	−0.044 (−1.851)	−0.036* (−1.814)	−0.036 (−1.048)
lnPdi	−0.139* (−1.789)	−0.049 (−0.547)	−0.014* (−1.752)	−0.132 (−1.266)	0.017 (1.006)	−0.049** (−2.433)	−0.020* (−1.723)	−0.039* (−1.803)
lnEdl	−0.548*** (3.784)	−0.052** (−2.075)	−0.404** (−2.094)	−0.107* (−1.793)	−0.641** (−2.011)	−0.125*** (−3.368)	−0.682** (−2.489)	−0.343* (−1.799)
lnUdl	−0.075*** (3.183)	−0.091** (−2.457)	−0.061** (−2.630)	−0.228* (−1.861)	−0.063* (−1.842)	−0.029* (−1.857)	−0.081** (−2.102)	−0.134*** (−3.910)
rho	0.401*** (17.677)		0.497*** (16.570)		0.451*** (11.832)		0.424*** (14.028)	
City FE	YES		YES		YES		YES	
Year FE	YES		YES		YES		YES	
Observations	1,100		1,100		1,100		1,100	
R-squared	0.792		0.774		0.617		0.806	
log-likelihood	2,457.327		2,396.623		2,294.237		2,127.236	

***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively; The values in parentheses are *t* values.

middle reaches of the Yangtze River and the Chengdu-Chongqing urban agglomeration) are covered in this study. Because the impact of spatial heterogeneity is mainly taken into consideration, subsequent studies based on the W_1 are used to carry out the estimation. Based on the three regions in the upper, middle, and lower reaches of the Yangtze River Economic Belt and whether they belong to urban agglomerations, regional heterogeneity regarding the digital economy influencing CEI is tested, and the regression results are shown in Table 9.

In the downstream region, the digital economy has a significant inhibitory effect on CEI in the region, and will also significantly promote the decline of CEI in neighboring cities. The reason may be that the downstream region has more obvious advantages in the development of digital infrastructure and digital industry, and because the downstream region has gathered a large number of digital innovation talents and digital industry, it can better play the role of digital empowerment with various advantages, so the reduction of CEI is more obvious. In the midstream region, the development of the digital economy can reduce the CEI of cities in the region, and the effect on neighboring areas is also obvious. This may be because the cities in the central region are still in the stage of rapid digital development, the industrial layout and regional functionalization brought by the construction of digital infrastructure are reasonable and beneficial to the improvement of energy utilization, and the core cities in the midstream region have obvious advantages. In the upstream region, the digital economy development variables have not passed the significance test, which may be because the development of the digital economy in the upstream region is still in its infancy, and the level of digital development is generally disclosed (see Figure 1), which cannot form the diffusion effect with scale and agglomeration, and the effect of digital empowerment is minimal, which leads to the insignificant effect of the digital economy on the reduction of urban CEI.

From the perspective of urban agglomeration heterogeneity, the development of the digital economy can effectively reduce CEI within urban agglomerations and can affect neighboring areas through spillover effects and reduce the CEI of surrounding cities. In non-urban agglomeration areas, the development of the digital economy has no significant impact on the mitigation effect of urban CEI. This is mainly due to the relatively high level of digital economy development in cities in urban agglomerations (see Figure 1), the initial formation of scale and agglomeration effect, and the existence of preferential measures such as policy coordination and resource sharing within urban agglomerations, coupled with its own relatively high level of digital industrialization, so its role in reducing CEI is obvious. Non-urban agglomeration cities have limited geographical location advantages and resources, and in most areas the digital economy is in its infancy, resulting in a lack of obvious mitigation effects on urban CEI. Intuitively, the spatial evolution of CEI is from Figure 2. Can also be well-verified.

Therefore, considering the heterogeneity of spatial regions, the digital economy dividends in downstream areas and cities belonging to urban agglomerations are more fully released, and their impact on CEI is more significant, while the effect of the digital economy in upstream and non-urban agglomeration cities is not obvious.

5.5. Decomposition of the role of digital economy on CEI

To further investigate the specific factors that affect urban CEI in the development of digital economy, Digital industry development, Digital infrastructure, Digital innovation capabilities and Digital finance in the digital economy indicator system are used as independent variables to conduct empirical tests, whose results are shown in Table 10. From the results in column (1) of Table 10, it is clear that digital infrastructure construction does not have a significant effect on the CEI of the city. This indicates that the increase in digital infrastructure coverage produces a double-from effect. On the one hand, it promotes the formation of informal environmental regulations as well as digital empowerment to achieve energy saving, emission reduction, and economic development (Wen et al., 2022; Hanjin et al., 2023). On the other hand, the production and construction of digital economy facilities will generate large amounts of resources and energy consumption, and even pollute the environment, which in turn generates large amounts of carbon emissions. These two effects offset each other so that the effect of digital infrastructure on CEI in the region is not significant. However, digital infrastructure reduces the CEI of neighboring cities, which indicates that the environmental improvement effect generated by the coverage of digital economy facilities has some spillover effect (e.g., the spillover effect of information technology), affecting neighboring regions. From column (2) of Table 10, the development of the digital industry has a significant negative effect on the CEI of both the region

TABLE 9 Regression results of the spatial heterogeneity test.

Explanatory variables	Upstream	Midstream	Downstream	Urban agglomeration	Non-urban agglomerations
lnDei	−0.107 (−1.101)	−0.191** (−2.344)	−0.306*** (−4.312)	−0.298*** (−3.872)	−0.097 (−1.067)
$W \times lnDei$	−0.021 (−1.107)	−0.061* (−1.907)	−0.088** (−2.074)	−0.127*** (−3.303)	−0.142 (−1.105)
Control	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	330	360	410	670	430
R-squared	0.574	0.704	0.808	0.795	0.591
log-likelihood	1,120.812	1,294.102	1,239.735	1,155.916	1,190.152

***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively; The values in parentheses are *t* values.

TABLE 10 Decomposition of the role of the digital economy on CEI.

Variables	(1)		(2)		(3)		(4)	
	x	$W_1 \times x$	*x*	$W_1 \times x$	*x*	$W_1 \times x$	*x*	$W_1 \times x$
lnDigital infrastructure	−0.243 (−0.235)	−2.103** (−1.999)						
lnDigital industry development			−6.237*** (−10.176)	−11.673** (−2.479)				
lnDigital innovation capabilities					−0.191*** (−6.411)	−2.260** (−1.981)		
lnDigital finance							−3.682*** (−8.912)	−5.746*** (−13.255)
Control	YES		YES		YES		YES	
City FE	YES		YES		YES		YES	
Year FE	YES		YES		YES		YES	
Observations	1,100		1,100		1,100		1,100	
R-squared	0.195		0.433		0.394		0.332	
log-likelihood	−2,123.102		−2,005.217		2,412.033		−2,219.331	

*** and ** represent the significance levels of 1%, and 5%, respectively; The values in parentheses are *t* values.

and the neighboring regions, which indicates that the development of the digital economy industry has a double-slave effect, not only promoting economic development, but also having an emission reduction effect on urban carbon emissions. This may be that the development of digital industry promotes the transformation and upgrading of industrial structure leading to more reasonable layout. Meanwhile, it also promotes the development of traditional industrial production factor resources, turning them from low marginal returns into high marginal returns (Cheng et al., 2021). It not only promotes the optimization of factors and energy allocation, but also promotes the upgrading of energy structure and reduces urban carbon emissions (Zhao S. et al., 2022). From the results of column (3) in Table 10, digital innovation capacities have a significant pro-decrease effect on the CEI of cities. This indicates that the improvement of digital innovation capabilities is one of the paths through which the digital economy affects the CEI of cities, and hurts neighboring regions. Probably, because digital innovation has a significant spillover effect, and innovation factors spill over to promote the development of digital innovation in neighboring regions, which can better achieve resource optimization, and thus reduce the level of CEI in cities while promoting economic development. The results of column (4) are in Table 10 shows that the coefficients of digital inclusive finance are all significantly negative, which indicates that digital inclusive finance has a significant negative effect on urban CEI. This is because digital inclusive finance can improve the efficiency of urban life and financial services, and optimize resource allocation, for example, digital payment systems, digital currency and payment apps can reduce the carbon emission of residents' offline behavior by realizing online life payment, online registration, ticket purchase, and online traffic ticket payment, etc. On the other hand, digital inclusive finance can also reduce carbon emissions in corporate financing behaviors by improving the financial accessibility of enterprises (He and Yang, 2021), which can facilitate and promote efficient economic and social development at the same time.

5.6. Robustness test

We further analyze the influence of digital economy development on CEI in the YREB region. The Robustness test mainly involves substituting the dependent variables, excluding low-carbon pilot cities and municipalities directly under the central government, and using explanatory variables with a one-period lag as instrumental variables.

5.6.1. Substitution of the dependent variable

The level of economic development are important factors affecting carbon emission intensity. According to the available literature (Zhang and Liu, 2022), carbon emission efficiency is calculated by combining the input of production factors such as energy, and the output of economic development, including the undesirable output of carbon emission. Therefore, carbon emission efficiency is used to replace CEI for verification. The selection and calculation method of carbon emission efficiency indicators mainly refer to the previous related literature (Gao et al., 2021; Chen J. et al., 2022; Lyu et al., 2023), and the input indicators are selected from the factors of the production labor force, capital, and energy consumption, the desirable output is the GDP, and the undesirable output is the carbon emission at the end of the year. The super-SBM model (Lyu et al., 2023) is used to calculate the carbon emission efficiency. Carbon emission intensity was replaced by carbon emission efficiency, and the results were obtained as shown in Table 11.

5.6.2. Excluding the low-carbon pilot cities in China

China has been exploring the construction of low-carbon cities since 2008, and launched the first batch of low-carbon pilot areas in 2010, which has had a significant impact on local low-carbon development (Zhang, 2020). Therefore, low-carbon pilot cities are excluded from the YREB region for regression. The results are presented in column (2) of Table 11, which are consistent with the results in Table 7, proving that the SDM regression results are robust.

5.6.3. Excluding municipalities directly under the central government

Under China's special regime, municipalities, which are directly under the central government, have distinct economic, political and aggregate economic advantages that some conventional cities do not have. Therefore, we exclude these cities for regression. Column (3) of Table 11 shows the regression results, which are significantly negative as well.

5.6.4. Endogenous test

The previous findings have shown that the digital economy development can reduce the CEI in cities. However, there may be endogeneity that makes the results potentially biased. Based on the topic of this paper and the reference to the relevant literature, endogeneity may come mainly from two sources. One is omitted variables (Zhao and Wang, 2022). Although this study has adopted control variables and fixed effects model, there are still some other elements that may affect the digital economy and CEI, such as local policies and emergencies, that are not included in the model. The other source is two-way causality. The other source is the two-way cause and effect of the digital economy and CEI. The digital economy development can reduce the urban CEI. However, in recent years, with the development of low-carbon cities and the implementation of various government environmental strategies, more high-tech enterprises attracted while the industrial structure transformation and upgrading was accelerated, which may strengthen the urban digital economy development.

In empirical studies, lagged endogenous variables are often used as instrumental variables to mitigate endogeneity (Zhao and Wang, 2022). Therefore, the lagged digital economy is an instrumental variable to investigate the relationship between the digital economy and CEI. The lagged variable is strongly correlated with the present value of the digital economy, which can affect the regional CEI through the present value. And conversely, the lagged digital economy will not be affected by the current CEI. Therefore, it is feasible to use the lagged digital economy as an instrumental variable of the digital economy. The regression results are shown in column (4) of Table 11. The coefficients of *lnDei* are close to that with SDM in Table 7. Therefore, it indicates that the regression results in Table 7 are robust.

6. Conclusions and policy implications

The digital economy development is an inevitable choice for cities to achieve low-carbon development. This paper studies the influencing mechanism and spatial spillover effects of digital economy development on CEI by applying two-way fixed effects model, mediating effect model and spatial Durbin model, based on the panel data of 110 cities in the YREB region from 2011 to 2020.

To cope with the drastic global climate change and achieve the "double carbon" target, strengthening digital transformation, improving the level of innovation, and continuously optimizing and upgrading the industrial structure are the key to China's economic development. The digital economy development is a suitable choice for cities to carry out low-carbon development. Based on the data of 110 cities in the YREB from 2011 to 2020, this paper explores the influencing mechanism, spatial effect, regional heterogeneity, and single decomposition force of digital economy on CEI by using the double fixed effect model, mediated effect model and spatial Durbin model. The following findings were drawn: (1) The digital economy development can significantly reduces CEI in the YREB region. Environmental regulation, science and technology support, population density, economic and urbanization development can all affect CEI. (2) The results of mediating effect test show that the digital economy development can promote the rationalization and upgrading of industrial structure, and enhance cities' green technology innovation as well, which eventually result in decreasing the CEI in the YREB region through the intermediary effect. (3) The digital economy shows an obvious positive spatial correlation with a spatial spillover effect on CEI. (4) There is an obvious spatial heterogeneity in digital economy's effect on CEI. The inhibitory impact of digital economy development on carbon emissions in the eastern regions is strong. Meanwhile, cities located in the urban agglomerations are more affected by the digital economy. (5) Except for digital infrastructure, all components of the digital economy are effective in directly reducing CEI in local cities, and present obvious spatial spillover effects of reducing CEI in neighboring cities.

TABLE 11 The regression results of the robustness test.

Explanatory variables	(1)	(2)_	(3)_	(4)
	Carbon emission efficiency	Low-Carbon Pilot Projects	Excluding municipalities	Lag one-period instrumental variable
lnDei	−0.411*** (−3.689)	−0.221** (−2.413)	−0.301*** (−4.734)	−0.201*** (−3.089)
$W_1 \times lnDei$	−0101*** (−2.813)	−0.031* (−1.761)	−0.065*** (−5.384)	−0.052** (−2.239)
Control	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	1,100	930	1,080	990
R-squared	0.510	0.599	0.757	0.504
log-likelihood	2,033.125	2,431.237	1,622.314	2,115.132

***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively; The values in parentheses are *t* values.

Based on the findings in this study, the following policy recommendations are made.

(1) The government of the YREB region needs to further support the development of digital economy comprehensively in order to take full advantage of digital economy in reducing CEI. First, the government should formulate and improve the policies and regulations related to the digital economy development, form a good institutional guarantee and market atmosphere for the digital economy development, especially in the construction of digital infrastructure. Secondly, the government should improve the establishment of cloud service platforms bearing digital technologies, and promote the clustering and synergistic effect of virtual industrial space. The government should play the unified coordination mechanism of urban clusters, improve the efficiency of resource utilization, and thus better play a synergistic role of the whole industrial chain. Third, it should strengthen the practical use of digital technology in enterprise production process, residents' life and urban governance, enhance the construction of digital infrastructure, improve the efficiency of data circulation, and provide technical support for urban carbon emission reduction.

(2) The government of the YREB region should strengthen the regional digital synergy to promote industrial structure optimization and green technology innovation. Firstly, each government in the region should guide local enterprises to optimize and transform and upgrade their industries and encourage them to carry out green technology innovation according to the overall layout of the national region and combined with the actual situation of the region. Secondly, the government should formulate special policies, such as purchasing services, special loans and other support policies, to promote local enterprises to realize digital transformation. The government should provide support for small-scale service and manufacturing enterprises who have difficulties in realizing digitalization quickly, so as to improve the digitalization level of industries in the region as a whole, thereby achieving energy saving, lowering CEI, and achieving better development. Third, the government should strengthen the protection and support of green intellectual property rights, and at the same time, eliminate or upgrade the backward production capacity. The government should promote the buyout of some general and effective green technology patents to provide motivation for the green technology innovation in enterprises, and the effectiveness of green patents. It should achieve targeted production reduction or even shutdown some enterprises that cannot achieve transformation and upgrading or green transformation.

(3) The Spatio-temporal evolutionary characteristics of the digital economy development show obvious gaps among cities in the YREB region. Based on the differences in the digital resources and digital development of various cities, first, the government should formulate digital development strategies according to local conditions, make good use of the radiation-driven effect of Shanghai and Zhejiang's digitalization and carbon emission reduction, and create digital industries with regional characteristics. Second, the government should develop competitive tax incentives and fiscal science and technology spending policies to support relatively backward cities in digital economy development. In addition, the government should use measures such as improving service networking, nurturing digital professionals, and accelerating digital infrastructure construction to reduce the digital economy development gap between cities.

The shortcomings of this study deserve further exploration. First, the limitations of the data, because county-level data is incomplete, limit the further use of county data for dual validation of indicator variables and the selection of research samples, and future county-based research is also worth looking into. Second, although the current study findings pass the robustness test, the magnitude of the external shock effect and the timing of the effect deserves further in-depth excavation. Finally, although we have systematically studied the differences between regions in the east, central, and west using the YREB as an example, and also studied the different magnitudes of forces between urban and non-urban agglomerations, etc., it is also worthwhile to research, such as the coastal urban belt between the north and the south or the Hu Huanyong line based on the geographical perspective.

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

LM and YH: conceptualization, formal analysis, and writing–original draft. GL and SH: funding acquisition, resources, and supervision. HL and JZ: investigation, data curation. LM and SH: methodology. YX, DX and HL: project administration, software, and visualization. YH: validation and writing–review and editing. All authors contributed to the article and approved the submitted version.

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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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EDITED BY
Magdalena Klimczuk-Kochańska,
University of Warsaw,
Poland

REVIEWED BY
Huwei Wen,
Nanchang University,
China
Pablo Ponce,
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Ecuador
Robina Iram,
Jiangsu University,
China
Cristiana Tudor,
Bucharest Academy of Economic Studies,
Romania

*CORRESPONDENCE
Xiuwu Zhang
✉ zxwxz717@hqu.edu.cn

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Impact of digital technology on carbon emissions: Evidence from Chinese cities

Yang Shen[1], Zhihong Yang[2] and Xiuwu Zhang[1,3]*

[1]Institute of Quantitative Economics, Huaqiao University, Xiamen, Fujian, China, [2]School of Economics and Management, Northwest University, Xi'an, Shaanxi, China, [3]School of Statistics, Huaqiao University, Xiamen, Fujian, China

Introduction: Promoting the development of digital technology is an important step in meeting the challenge of global climate change and achieving carbon peaking and carbon neutrality goals.

Methods: Based on panel data of Chinese cities from 2006 to 2020, this paper used econometrics to investigate the impact and mechanism of digital technology on carbon emissions.

Results: The results showed that digital technology can significantly reduce carbon emission intensity and improve carbon emission efficiency. These results remained robust after changing the estimation method, adding policy omission variables, replacing core variables, and solving the endogeneity problem. Digital technology can indirectly reduce carbon emissions by promoting green technological innovation and reducing energy intensity, and it plays a significant role in the carbon emission reduction practices of carbon emission trading policies and comprehensive national big data pilot zones. The replicability, non-exclusivity, and high mobility of digital technology help to accelerate the spread of knowledge and information between different cities, which leads to a spillover effect on carbon emission reductions. Our unconditional quantile regression model results showed that digital technology's carbon emission reduction effect continuously decreases with increases in carbon dioxide emissions.

Discussion: The results of this paper provide evidence for the potential use of digital technology in achieving the goal of carbon neutrality, which is of great significance for achieving high-quality innovation and promoting the green transformation of the economy and society.

KEYWORDS

digital technology, industrial robot, carbon reduction, green technological innovation, artificial intelligence, carbon neutrality, spatial spillover effect

1. Introduction

Reducing greenhouse gas emissions, curbing global temperature increases, and striving to achieve the goal of carbon neutrality are initiatives and shared pursuits of humanity in the face of the climate change crisis (Xiao and Peng, 2023). According to the sixth assessment report of the IPCC, "Climate Change 2021: Basis of Natural Science," increases in carbon emissions have led to the accelerated warming of the atmosphere, ocean, and land; the frequent occurrence of extreme weather events such as heat waves, heavy precipitation, droughts and typhoons; and the degradation of nature at an unimaginable speed, posing a significant threat to human survival and the ecological environment. From 2011 to 2020, which is considered the hottest decade in Earth's recent history, the global surface temperature rose by 1.09 degrees Celsius compared with the global temperature during the Industrial Revolution. The fifth assessment report of the United Nations Intergovernmental Panel on Climate Change (IPCC) outlined the scientific rationality of global warming caused by greenhouse gas emissions, among which CO_2 comprises the most significant proportion. Reducing CO_2 emissions will effectively mitigate the problem of global warming. Therefore, "carbon control" is a crucial measure taken by all countries to mitigate global climate change. Human beings and their cities need to face the challenges and opportunities brought by climate change, and they need to progress toward low-carbon transformation at all levels (Holtz et al., 2018). Climate has typical primary attributes of global public goods. In order to deal with the significant global environmental problem of climate change and effectively overcome the "tragedy of commons," it is urgent to establish an international coordination mechanism for climate change to develop low-carbon economies. The international coordination mechanism for climate change (represented by the United Nations Framework Convention on Climate Change, the Kyoto Protocol, and the Paris Agreement) is based on the principle of "common but differentiated responsibilities" for developed and developing countries, which determines the emission responsibility and emission reduction actions of each country. The realization of the low-carbon transformation of economic development has increasingly become the consensus of the international community to deal with global climate change. As of September 2019, 60 countries have pledged to achieve net zero carbon emissions by 2050 according to the United Nations Framework Convention on Climate Change (UNFCCC).

Carbon emissions mainly come from fossil fuel consumption. Under the constraints of technology and energy structures, carbon emissions are an inevitable byproduct of economic and social development. China is highly dependent on high-carbon fossil energy consumption, and the resource and energy utilization efficiency still requires improvements (Miao et al., 2019). Statistics from the National Bureau of Statistics show that sustained and rapid economic and social development in 2021 generated a massive demand for fossil energy. The total energy consumption for the year was 5.24 billion tons of standard coal, representing a year-on-year increase of 5.2%; coal energy consumption accounted for 56%, while clean energy consumption such as natural gas, water, electricity, and nuclear power only accounted for 25.5%. With the rapid urbanization and industrialization processes, the demand for energy has remained large, and China has faced severe pressure regarding carbon emission reductions (Shi et al., 2018). Since 2006, China has become the world's largest emitter of CO_2. In 2019, China's carbon emissions accounted for 28.8% of the world's total emissions, surpassing the combined share of the United States, the European Union, and Japan (Gao et al., 2019). At the 75th UN General Assembly held in 2020, the Chinese government proposed that China will increase its independent national contributions, adopt more effective policies and measures to peak its CO_2 emissions by 2030, and strive to achieve carbon neutrality by 2060. China's "14th Five-Year Plan" also includes a proposal to "implement a system with carbon intensity control supplemented by total carbon emission control," aiming to reduce energy consumption and CO_2 emissions per unit of GDP by 13.5 and 18%, respectively. Effectively reducing urban carbon emissions has become an urgent practical problem for sustainable economic development.

For a long time, technological progress has been regarded as an essential driving force in solving the profound internal contradiction between economic growth and carbon emission reductions (Li et al., 2017; Xie et al., 2021). The Fourth Industrial Revolution, represented by digital technology (DT), is accelerating changes in the fundamental mode of global economic development and leading to changes in production and organization modes. As a strategic technology for scientific and technological revolution and industrial transformation, DT has and will play a vital role in combating climate change and brings significant opportunities for low-carbon development (Haseeb et al., 2019; Zhang and Li, 2022). Especially in the recent, critical period of rapid economic growth and high-quality development, DT has been endowed with higher green expectations (Axon, 2020; Li et al., 2021; Yang J. 2021). DT can not only reduce information asymmetry through system integration to optimize resource management and decision-making processes, improve government supervision efficiency and reduce supervision costs but also optimize the industrial structure and accelerate the GTI of enterprises through dematerialization instead of the demand for emission-intensive products, thus providing a driving force for carbon emission reductions (Tang et al., 2021). However, DT itself is based on electricity, and the development and operation of energy-intensive infrastructures such as cloud, blockchain, and data centers will lead to more carbon emissions (Yi et al., 2022). With the development of DT, the operating power, speed, and network bandwidth of computers and servers are constantly improving. This will promote the overall digital transformation of society and accelerate the growth of carbon emissions in the digital industry. The development of DT requires large-scale data generation, transmission, and processing, which increases energy consumption in the operation of the digital industry while the total amount of carbon emission exponentially increases; as such, the carbon emissions of the digital industry equal those of the aviation industry (Jones, 2018; Park et al., 2018; Zhou et al., 2019). The more that energy consumption in a data center is optimized, the more energy is consumed. The "Jevons paradox" is therefore becoming feasible.

An urgent question: can DT be used as a "Chinese solution" to reduce urban carbon emissions? If this logic holds, how does DT help reduce carbon emissions? Is there heterogeneity? Clarifying the abovementioned issues will help us better understand the relationship between DT and the low-carbon economy under current conditions. The possible contributions of this paper are as follows. First, the study was based on the facts that the industrial sector is the primary source of carbon emissions and that the manufacturing sector is becoming more automated and intelligent across the production process; this paper innovatively used robot technology to represent DT, verified its influence on carbon emission intensity at the city level, and analyzed whether modern information technology provides technical dividends in terms of the ecological environment. Secondly, based on mechanisms of green technological innovation (GTI) and energy consumption intensity, this paper explored the influence of digital empowerment on carbon emission performance, which enriches and expands the literature on the ecological benefit evaluation of DT. Thirdly, the non-linear influence of DT on carbon emissions was tested using an unconditional quantile model, and a heterogeneity test was conducted according to urban resource endowment and carbon emission control, which helps explain the heterogeneity of the influence of DT on carbon emissions in different regions. Finally, this study considered the spatial spillover effect of DT in reducing carbon emissions. The research conclusions are helpful for the joint actions of administrative departments in different regions to achieve peak CO_2 emissions and carbon neutrality as soon as possible.

2. Literature review

As a new economic form, digital economy undoubtedly has economic, societal, and environmental impacts, and this study considered the influence of DT on carbon emission reductions. In order to evaluate recent research progress, we divided the relevant literature into the following two categories for review.

2.1. The economic effects of digital technology

The influence of the digital economy on economic development is multi-dimensional. At the micro level, digital transformation can significantly improve the information-processing capability of enterprises, promote the flow of information elements within enterprises (Shen and Yuan, 2020), improve the innovation capability of enterprises (Manesh et al., 2020), promote EGS performance (Cheng and Zhang, 2023; Wang et al., 2023; Zhong et al., 2023), optimize organizational structures, and enhance production and operation processes (Hess et al., 2016). Boland et al. (2007) studied the influence of DT on innovation and found that enterprise-distributed technology has strong "technical penetration," which can meet the needs of the complex business–ecology relationship. Using empirical research on Chinese A-share data, He and Liu (2019) found that the digital transformation of enterprises promoted improvements in enterprise performance. At the industry level, some scholars have found that digital technologies can not only improve the efficiency of traditional industries but also trigger the interactive integration and development of multiple industries and lead to new industrial changes. Chen and Yang (2021) found that the digital economy, as a new force of economic transformation, could improve a labor-intensive and heavy industry-based industrial structure to an industrial structure with a high technology level and environmental friendliness. At the macro level, the iterative application of the new generation of information technology helps to optimize ecological systems and policy environments, stimulate the vitality of social innovation, and improve the efficiency of resource allocation. Zhao et al. (2020) found that the digital economy can enhance entrepreneurial activity and promote high-quality economic development using empirical research on the panel data of 222 cities above the prefecture level in China. In addition, several studies have analyzed the impact of DT on trade in services (Zhou L. et al., 2023), total factor energy efficiency (Fu et al., 2023; Huang et al., 2023), knowledge innovation (Orlando et al., 2020; Wang and Li, 2023), economic growth (Qu et al., 2017), air pollution (Yang Z. et al., 2023), and green total factor productivity (Guo et al., 2022; Zhao et al., 2022).

2.2. Impact of digital technology on carbon emissions

The core connotation of the "science and technology for goodness" concept is that science and technology can promote economic development and industrial transformation while enabling society to achieve sustainable development. DT not only produces huge economic benefits but also significantly impacts the current "environmental debt" and carbon emissions because the digital economy has two primary characteristics. First, the application of DT in various economic activities leads to improvements in efficiency. Second, DT leads to more energy consumption, especially the demand for electricity. The former lowers carbon emissions, while the latter increases carbon emissions. Therefore, scholars' conclusions regarding DT's effects on carbon emissions are not consistent. The carbon emission reductions enabled by DT are mainly discussed from two angles: optimizing industrial structures and improving energy efficiency. In optimizing industrial structures, DT has continuously penetrated the service industry, becoming a new engine of service trade and promoting the formation of new green industries. The integrated development of emerging and traditional industries based on data elements and the application and promotion of DT in production practice will promote the transformation of industrial structures into technology-intensive and environment-friendly forms (Zhang and Wang, 2023). Choi (2010) used panel data from 151 countries to investigate the impact of the Internet on service trade and found that the digital economy improved the "non-long-distance trade" of traditional services with the help of DT and information technology and promoted the rapid development of service trade. Furthermore, as an important production factor, data are clean and efficient, which can reduce the dependence on and destruction of natural resources, as well as promote the digital transformation of traditional enterprises. Dong F. et al. (2022) empirically tested the panel data of 60 countries and found that the digital economy had significantly reduced carbon emission intensities by upgrading industrial structures. Technological progress is the main source of economic development, and it often leads to improvements in resource allocation efficiency and production efficiency (Zhou P. et al., 2023). Some studies have also discussed the relationship between digital technologies, energy consumption intensity, and total factor energy efficiency. The rapid development of the digital economy based on digital technologies effectively reduces carbon emissions, which aids the promotion energy saving and emission reductions across the whole production life cycle and provides a new research perspective for our sustainable development and carbon emission reductions (Sahoo et al., 2021; Zhao et al., 2021). DT will reduce power consumption, especially the energy consumption of industrial sectors (Wang J. et al., 2022). Digital transformation is essential to improve energy consumption and reduce carbon emissions. Other studies have pointed out that digital technologies can reduce carbon emissions by promoting manufacturing agglomeration (Li X. et al., 2022), ease the financing constraints of enterprises (Yang G. et al., 2023), improve public awareness (Wang Q. et al., 2022b), and strengthen environmental regulation (Liu et al., 2023).

Zhang et al. (2021) argued that the digital economy has broken the restrictions of geography, time, and space while promoting efficiency improvements in all aspects from production to sales. Based on the panel data of 278 cities in China, Yu et al. (2022) found that when green energy efficiency is low, the digital economy promotes carbon emissions and that when green energy efficiency is high, the digital economy reduces carbon emissions. Green energy efficiency has a threshold variable effect in the relationship between the digital economy and carbon emissions. However, not all researchers believe that DT has a positive effect on the environment. Dhar (2020) pointed out that DT also consumes a large amount of energy, resulting in significant electricity costs. Zhang Q. et al. (2022) pointed out that due to the rebound effect, the scale expansion of DT will increase energy demands and have adverse effects. Hittinger and Jaramillo (2019) found that while smart devices bring convenience to life, the large amounts of data transmission and remote processing supported by data centers consume significant amounts of energy. Sun et al. (2021) found that data centers in the United States consume about 2% of the country's electricity. Jiang et al. (2021) used simulations to show that, without any policy interventions, the bitcoin industry in China is expected to generate 130.5 million tons of carbon emissions in 2024, which will become a major obstacle to China's carbon neutrality goal.

Researchers have explored the digital economy's economic effects and application value from the perspectives of the macro-economy, structural transformation, and environmental governance, engaging in the valuable exploration of the relationship between information and communication technology and carbon emissions. However, the existing literature ignores an important question: Can DT improve carbon emission performance? If so, what path can be used to implement this impact? In this paper, we attempted to integrate DT and carbon emissions into a unified framework, and we studied the realization of the strategic goal of carbon emission reductions under digital empowerment at the city level.

3. Theoretical analysis and research hypothesis

Economic growth is the most important factor of carbon emissions, and reducing carbon emissions is the key to achieving green growth (Chen and Golley, 2014). On the basis of endogenous growth theory, we introduce data, energy input and environmental pollution as input elements to conduct mechanism analysis. According to the framework of endogenous growth, digital technology has direct carbon reduction effect and indirect carbon reduction effect through green technological innovation and energy intensity reduction.

3.1. Direct impact of digital technology on reducing carbon emissions

DT is defined as a combination of information, computing, communications, and connectivity technologies (Bharadwaj et al., 2013). It converts various kinds of information into binary numbers that computers can identify and use to perform operations, processing, storage, transmission, dissemination, and restoration.

According to endogenous growth theory, DT can be seen as a new type of high-quality capital product of enterprises that has resulted in remarkable technological progress by reducing the marginal cost of production. As in typical Schumpeterian patterns of technological progress, DT can break through the time and space constraints of traditional knowledge and technology exchange to a significant extent and spawn new technologies, industries, and formats that are closely related to energy production and consumption—such as energy storage technology, smart grids, new energy industries, intelligent transportation, and distributed energy use systems—that affect urban energy-use efficiency. The high-efficiency integration of AI, distributed energy production and utilization technology, and energy storage technology enables the measurement, control, and prediction of energy from production and transmission on the supply side to consumption and service on the demand side, thus realizing the intensification and refinement of the energy supply. Furthermore, DT can shorten clean energy's research and development cycle through the accurate three-dimensional modeling of natural and geographical conditions to continuously reduce the cost of renewable energy power generation. Clean power generation, such as wind and photovoltaics, will gradually replace fossil fuels (Schulte et al., 2016).

As capital goods, DT can replace other input factors such as energy input, directly reducing the input of high energy consumption factors and reducing carbon intensity; DT can also change the configuration of the production function $F(\bullet)$, i.e., improve the efficiency of resource allocation. DT's function is to improve the information and intelligent operation level of society and the allocation efficiency of production factors in the market (Wang et al., 2021; Wu, 2021). As has been found in some literatures, DT can digitally transform the energy production process and improve total factor energy efficiency (Xu W. et al., 2022), promoting the transition to the green economy.

An important aspect of carbon emission reductions is the real-time supervision, disclosure, and control of carbon emissions (Zeng et al., 2021). According to transaction cost theory, in cases of information asymmetry, both parties may face high transaction costs that will affect the daily business decisions of enterprises. Improvements in the digital infrastructure will lower the cost of information acquisition and dissemination. The rapid dissemination of a large amount of enterprise production and operation data brings new opportunities for the development and efficiency improvements of various industries, effectively improving resource utilization efficiency and reducing carbon emissions (Luo and Yuan, 2023). DT comprises real-time data collection technologies such as the Internet of Things, intelligent sensors, and edge computing. It can sense, analyze, act, and provide feedback on carbon information and is a crucial vehicle for improving the disclosure of carbon information (Zheng et al., 2021). As transaction costs are reduced, according to multi-dimensional sensors, DT enables different enterprise departments and production operations to form connections, communicate across different networks, and dynamically collect various elements, energy, and other information related to enterprise sewage discharge activities in real time. The effective monitoring and accurate predicting of carbon emissions can be used to reduce the costs of monitoring carbon information and improve monitoring efficiency to optimize the carbon emission reduction decisions of governments and enterprises. DT has also facilitated the public's access to information on environmental pollution and assisted government departments in improving environmental governance and reducing corporate carbon emissions through informal environmental regulation channels. In addition, AI has facilitated the sharing of data elements; it can be used to construct intelligent management systems for energy interconnection and global energy distribution networks utilizing element circulation and knowledge and technology spillovers. Traditional chimney-style independent system and island-style management frameworks have evolved into a unified framework management, with comprehensive applications used to realize the overall planning, coordination, and optimization of the whole chain in order to promote the low-carbon development of society and improve energy-use efficiency. Most importantly, carbon trading and finance operations must be connected to DT.

A final important step in reducing total carbon emissions is accelerating the transformation of the emerging technology, advanced manufacturing, and modern service industries (Yang, 2021). Relying on "Metcalfe's Law" of digital networks, DT is reshaping the traditional production model and has produced strong economies of scale, scope, and long tails. It has achieved good results in cross-industry emission reductions (Koomey et al., 2013; Beier et al., 2018; Weigel and Fischedick, 2019). DT is deeply integrated with key carbon emissions areas such as power, industry, transportation, construction, and agriculture. With the gradual popularization of digital carbon reduction applications in these areas, DT can effectively promote energy consumption reductions throughout the life cycle in key carbon emission industries and release the carbon reduction potential of technology. DT can effectively empower enterprises with intelligent green manufacturing and energy management, lead the innovation of green processes and services, and further promote the development of the industry toward intelligent and green practices while increasing the industry's added value and reducing energy consumption and carbon emissions (Lyu and Liu, 2021). For example, in the industrial field, DT optimizes production processes, improves production efficiency, and saves production costs by enhancing the intelligent interconnections of factories, information integration, data-driven decision making, and human–computer collaboration. The automation of the production process and the intelligence of the decision-making process will drive significant changes in the manufacturing process, improve the efficiency of the use of resources such as energy and capital, realize simultaneous improvements in production and carbon efficiency, and significantly reduce the overall social energy consumption.

Based on the above analysis, the following two research hypotheses are proposed.

> H1: DT has emission reduction effects and can significantly reduce urban carbon intensity.
>
> H2: DT can reduce carbon emissions by reducing the energy intensity.

3.2. Indirect channel of green technological innovation

According to the definition of green growth, economic green growth results from technological progress and technological efficiency improvements (Chen and Golley, 2014). As a special kind of environmentally biased technological progress, GTI is essential to reducing energy consumption and controlling carbon emissions (Liu et al., 2020). DT changes A(t) in the production function and promotes GTI. DT also has a strong technology spillover effect, which drives technological innovation in other industries through the change of A(t) to improve the sustainability of green growth.

The three essential ways to promote the peaking of carbon emissions and the goal of carbon neutrality are to continuously reduce the proportion of fossil energy consumption, improve energy efficiency, and develop clean energy, all of which require the support of advanced technological progress, especially the development of GTI. The low carbonization of industries and consumer terminals continuously uses green technologies to transform or replace carbon-based energy technologies that result in high levels of energy consumption and pollution. GTI promotes the deepening adjustment and two-way optimization of energy and industrial structures, encourages green product R&D and market competition, significantly reduces carbon emissions per unit GDP, and ensures economic efficiency improvements and green low-carbon transformation in terms of energy conservation and power conversion. GTI is also widely used in enterprise production and citizens' lives. It can boost cleaner enterprise production, enhance energy efficiency, promote green energy consumption, reduce resource consumption from the production and consumption sides, spawn new energy consumption patterns, and reduce carbon emissions from enterprise production and resident consumption to realize the source prevention and control of carbon emissions. The use of GTI in the energy field can accelerate the development of photovoltaic, wind power, and renewable energy sources and effectively promote the transformation of energy consumption structures to green, low-carbon, and clean energy structures that can directly reduce carbon emissions. Finally, GTI can effectively control the cost of decarbonization and provide corresponding technical support for the research, development, and large-scale application of CO_2 utilization, capture, and storage technology, leading to the "technology dividend" effect and promoting improvements in carbon emission performance.

GTI requires massive R&D investment. R&D innovation activities are characterized by high adjustment costs, uncertain results, and sunk input, making enterprises less willing to take initiatives to carry out GTI. DT can effectively reduce the cost of information search and social transaction costs, as well as promote the agglomeration of innovation resources, which is conducive to realizing technology innovation with high efficiency and low energy consumption (Xing et al., 2019). Generally speaking, digital networks not only promote the healthy and efficient development of digital industrialization with the help of universal and enabling technologies and network connection effects but also bring new production factors such as information, technology, and data to industrial development. This process improves comprehensive technical efficiency and R&D innovation efficiency. Digital networks can strengthen the diffusion effect of digital low-carbon technologies, help accelerate the efficiency of information flow, reduce the cost of knowledge transfer, alleviate information asymmetry in the technology market, promote the green technology spillover of knowledge to other industries and sectors, and facilitate the digital and low-carbon transformation of traditional enterprises. With the help of DT, enterprises can quickly shift toward intelligent and flexible directions, gradually change their energy consumption modes in actual operation, reduce redundancy and intermediate consumption in the production process, stimulate the vitality of scientific research and innovation, and improve carbon emission performance (May et al., 2016). Additionally, DT will force enterprises to develop and apply clean technologies and to promote the formation of DT-based green raw material procurement strategies, low-carbon product production and transformation, intelligent logistics warehousing and sales circulation, and carbon emission reductions.

Technological progress will also drive "learning by doing." DT has a technology spillover effect on production and innovation activities, therefore optimizing internal production processes and management organization forms through learning by doing and reducing some variable costs (Zhu et al., 2022). When DT reduces the cost of production, it can compensate for the green production behavior of industrial enterprises. Generally speaking, through technical progress and learning by doing driven by its technology spillover effect, DT has promoted green economic growth.

Based on the above analysis, this paper proposes the third research hypothesis.

> H3: DT can reduce carbon emissions through the channel mechanism that promotes GTI.

4. Research design

4.1. Variables design

4.1.1. Dependent variable

The dependent variable was carbon emissions (CE). Because of the lack of CO_2 monitoring data at the city level in China, this paper used the apparent emission accounting method to measure carbon emissions. The carbon emission sources of cities were set as direct and indirect energy consumption. Direct energy includes liquefied petroleum gas, coal, and natural gas, and indirect energy includes electricity and heat (Zha et al., 2022). Carbon emissions from direct energy sources were mainly calculated based on the carbon emission conversion coefficients of various energy sources published in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Indirect energy carbon emissions were mainly calculated using the corresponding carbon conversion factor to calculate the carbon emissions generated by electricity and heat consumption. It was assumed that there is only one carbon emission factor for the same local power grid (Glaeser and Kahn, 2010), so the calculation of electric energy carbon emissions was mainly based on the baseline emission factor and urban electric energy consumption of the six major power grids in China. It was also assumed that heat energy is generated by different supply modes, mostly the use of raw coal. In this paper, referring to Wu and Guo (2016), the thermal efficiency value was selected as 70%, the average low calorific value of raw coal was selected as 20,908 kJ/kg, and the total amount of heating was converted into the required amount of raw coal. Finally, direct energy consumption and indirect energy consumption carbon emissions were added together to obtain the total carbon emissions of each city.

4.1.2. Core explanatory variable

The core explanatory variable of this study was digital technology (DT). Industry results in high energy consumption and emission levels, and it is the main source of greenhouse gases (Dong M. et al., 2012). According to the International Energy Agency, the Chinese industrial sector's share of carbon emissions from all sources rose from 71% in 1990 to 83% in 2018, and according to the Cady research report, China's industrial sector accounts for about 70% of all industrial emissions in the country. Given the industry's high energy and high emission characteristics, this paper mainly considered the impact of the introduction of DT to the industrial sector on carbon emissions. With the successive proposal and deepening of "Industry 4.0" and "Made in China 2025," the global industrial system is developing toward automation, integration, intelligence, and green practices. In the field of intelligent manufacturing, industrial robots (as a kind of automation equipment that integrates a variety of advanced technologies) reflect the characteristics of modern industrial technology, such as high efficiency and the combination of software and hardware, and have become essential parts of modern manufacturing systems such as flexible manufacturing systems, automated factories, and intelligent factories. Robots are known as a priority of manufacturing. Therefore, this study used the density of industrial robot installations in each city to represent DT.

Acemoglu and Restrepo (2020) constructed an index of robot density at the regional level in the United States based on the idea of the "Bartik instrumental variable" when studying the impact of robot applications on the labor market in the United States. This method has been widely used in subsequent studies on the social effects of robots (Paul et al., 2020). Based on the common practice of the literature (Wang and Dong, 2020; Dauth et al., 2021; Chen et al., 2022; Xu J. et al., 2022; Ge and Zhao, 2023; Yang and Shen, 2023), this paper constructed a robot density index at the level of prefecture-level cities in China. First, International Federation of Robotics (IFR) industry classification data were matched with 14 two-digit industries in the industry classification of China's national economy. Then, based on each industry's robot and employment data, this paper calculated the industrial robot density index at the industry level. Finally, this paper selected the initial year of the statistical sample as the benchmark year to calculate the weight of robot density in each industry in each city in China. The specific calculation formula is

$$DT_{it} = \sum_{s=1}^{14} \frac{employ_{s,i,t=2006}}{employ_{i,t=2006}} \times \frac{Robot_{st}}{employ_{s,t=2006}} \tag{1}$$

In Eq. (1), DT represents digital technology, $Robot_{st}$ represents the number of industrial robots installed in industry's in year t, $employ_{s,i,t=2006}$ represents the number of people employed in industry s in City i in 2006, $employ_{i,t=2006}$ represents the total number of people employed in City i in 2006, and $employ_{s,t=2006}$ represents the total number of jobs in industry s in 2006.

4.1.3. Mechanism variable

The mechanism variable of this study was green technology innovation (GTI). The quantity and quality of green technology patents can significantly reflect the level of green technology in a region (Zhang and Bai, 2022). In 2010, the World Intellectual Property Organization (WIPO) developed the IPC Green Inventory based on the UNFCCC guidelines linked to the existing IPC classification system and divided green technologies into seven specific areas. This paper used the number of green invention patents to measure GTI. We established the patent type, IPC classification number, announcement date, and application address from the website of China Patent Publication and Announcement of the State Intellectual Property Office through advanced inquiry, and we considered this information along with the patent database of listed companies in China to identify the number of green invention patents authorized by each city in each year.

4.1.4. Control variables

In order to alleviate the endogeneity problem caused by the omission of important variables to the model as much as possible and to obtain more accurate estimation results, this paper selected six control variables according to the existing literature on the influencing factors of carbon emissions (Lenonard, 1984; Valérie, 1999; Dong B. et al., 2012; Bernauer and Koubi, 2013; Danlami et al., 2017; Sapkota and Bastola, 2017; Sheraz et al., 2022). Population density was measured as the ratio of urban area to the resident population at the end of the year, the level of economic development was measured as GDP *per capita*, financial support was measured as loan balance *per capita*, industrial structure was measured as the ratio of the secondary industry's added value to GDP, foreign direct investment was measured as the amount of foreign direct investment utilized by each city, and the intensity of fiscal expenditure was measured as the ratio of government public general budget expenditure to GDP measures.

4.2. Econometric model

To test the impact of DT on carbon emissions, we constructed the following econometric model.

$$\begin{aligned} CE_{it} = \theta_0 + \alpha_1 DT_{it} + \alpha_2 PD_{it} + \alpha_3 LED_{it} + \alpha_4 FS_{it} \\ + \alpha_5 IS_{it} + \alpha_6 FDI_{it} + \alpha_7 FEI_{it} + \nu_t + \lambda_i + \varepsilon_{it} \end{aligned} \quad (2)$$

In Eq. (2), i and t represent city and time, respectively; ε_{it} represents the random disturbance term subject to the white noise process; θ_0 represents the constant term; α represents the regression coefficient; λ_i represents the individual fixed effect; and ν_t represents the time fixed effect.

In order to alleviate the endogeneity of the channel test and the defects of the mediating effect test as much as possible, this paper focused on explaining the influence mechanism of GTI on carbon emissions as part of theoretical analysis and research hypothesis by referring to the idea of the mediating test proposed by Jiang (2022); as such, only the influence of DT on GTI was tested here, and a significantly positive DT regression parameter on GTI indicates that DT can reduce carbon emissions through the channel mechanism of promoting GTI. Classical panel data models only consider individual fixed effects and point-in-time fixed effects to reveal time differences that do not vary across individuals and individual differences that do not vary over time in a sample. Considering the impact of various uncertain factors on entire economies, there is heterogeneity in the response of different individuals to these shocks. In order to overcome the endogeneity and inherent defects of the mediation test method as much as possible, this paper expanded the traditional two-way fixed effect model into an interactive fixed model to establish a mediating effect test equation because an interactive fixed effect model could better fit the data (Bai, 2009). The equations expressing the influence of DT on GTI are

$$GTI_{it} = \theta_0 + \beta_1 DI_{it} + \beta_2 Control_{it} + \nu_t + \lambda_i + \delta_i' F_t + \varepsilon_{it} \quad (3)$$

$$EI_{it} = \theta_0 + \beta_1 DI_{it} + \beta_2 Control_{it} + \nu_t + \lambda_i + \delta_i' F_t + \varepsilon_{it} \quad (4)$$

In Eqs. (3) and (4), the meaning of each code symbol is consistent with that for Eq. (2). Control represents the information set for the control variable, β is the regression coefficient, $\delta_i' F_t$ represents interactive fixed effects (which can be regarded as the product of multidimensional individual effects and multidimensional time effects), F_t is the common factor, and δ_i is the factor load.

4.3. Data sources and descriptive statistics of variables

Following the principle of data availability, this paper used the panel data of 269 Chinese cities from 2006 to 2020 as statistical samples. The original data of the relevant variables involved in the econometric model were mainly sourced from the China Statistical Yearbook, China City Statistical Yearbook, China Energy Statistical Yearbook, China Electric Power Yearbook, National Intellectual Property Office, National Bureau of Statistics, International Federation of Robotics and EPS Database. For very few missing values, we used an interpolation method. The descriptive statistical analysis of each variable is shown in Table 1.

TABLE 1 Descriptive statistics of variables.

Variables	Code	Standard error	Mean	Min	Max
Digital technology	DT	1.2774	0.3821	0.0001	21.6515
Carbon emission	CE	1.1448	6.0509	2.0189	9.5846
Green technology innovation	GTI	1.6087	9.9619	4.2047	15.5293
Population density	PD	0.8815	5.8079	1.5476	7.9155
Level of economic development	LED	0.7055	10.4686	4.5951	13.0557
Financial support	FS	1.1129	10.2185	7.5835	13.8749
Industrial structure	IS	0.2521	3.8248	2.3684	4.4502
Foreign direct investment	FDI	1.8439	9.9179	1.0986	14.9413
Financial expenditure intensity	FEI	0.9361	14.5539	11.72107	18.24054
Energy intensity	EI	−9.6284	0.5735	−11.2660	−7.5322

5. Empirical analysis

5.1. Baseline regression analysis

Commonly used fitting models for panel data include the Pooled OLS (POLS), fixed effects (FE), and random effects (RE) models; deciding which method was most suitable for sample data in this study required further testing. As seen in Table 2, the results of the F-test rejected the original hypothesis at the level of 1%, indicating that the FE model was better than the POLS model. Furthermore, the results of the Hausman test rejected the original hypothesis at the level of 1%, indicating that the FE model was superior to the RE model. Therefore, this paper mainly analyzed how DT affects carbon emissions according to the regression results of the FE model. As Ozokcu and Ozdemir (2017) stated that Pesaran cross-sectional dependence (Pesaran CD) test is be used here in order to test whether residuals are correlated across countries or not. A Wooldridge test is used to detect serial correlation in panel data. As can be seen from Table 2, the serial correlation and cross-sectional dependence of panel data needed to be alert. Hoechle (2007) stated that it is better to use Driscoll-Kraay (DK) standard errors, if the model is heteroskedastic, autocorrelated, and cross-sectionally dependent. Therefore, considering that there may be heteroscedasticity, cross-section correlation, and sequence correlation in panel data estimation, this paper uses DK standard error for correction by referring to the ideas of existing literature (Driscoll and Kraay, 1998; Dabbous and Tarhini, 2021; Zakari et al., 2022).

In Table 2, column (1) shows the results of not adding any control variables, column (2) shows the results of adding all control variables and not adding individual fixed and time fixed effects, column (3) shows the results of adding individual fixed and time fixed effects but not adding control variables, column (4) shows the results of including all control variables and fixed effects, but the common standard error is used, and column (5) reports the result of DK standard error. The results without individual and time effects showed that the impact of DT on carbon emissions was significantly positive; that is, the digital transformation of enterprises and the use of modern DT may increase carbon emissions. However, the POLS model was the result of uncontrolled factors that change with time, and the reliability of its regression results was low. The results of the two-way fixed effect model in columns (3) and (4) show that the DT regression parameters on carbon emissions were −0.0081 and −0.0102, respectively, and both of them were significant at the level of 1%; these results indicated that DT can reduce carbon emissions, which preliminarily confirmed the research hypothesis 1. In addition, to test whether DT can improve carbon emission efficiency while reducing carbon emissions, this paper replaced carbon emission intensity in formula (2) with carbon emissions per unit of gross domestic product. The results in column (5) of Table 2 show that the DT regression coefficient of carbon emission efficiency was −0.0301, which was significant at the level of 1%; these results indicated that DT can not only reduce carbon emission intensity but also reduce CO_2 emissions per unit of GDP and improve carbon emission efficiency, so DT is essential in dealing with climate change and promoting carbon emission reductions. The main role of DT in emission and carbon reductions is to provide real-time carbon information, and the deep application of DT in the carbon footprint and carbon sink fields can aid the promotion of the digital monitoring, accurate emission measurement and prediction, planning, and implementation efficiency of the energy industry, thus significantly improving energy-use efficiency and directly or indirectly reducing the carbon emissions. Additionally, the DT embedded in the production and development of energy can promote the transformation of energy and the transformation of the energy industry, thus constantly promoting the development of renewable energy, accelerating the substitution of traditional fossil energy consumption, enabling the optimization and upgrading of energy production and consumption structures, and significantly reducing the total amount of urban carbon emissions. Finally, DT can improve traditional industries by reducing their carbon emissions and improving their carbon emission efficiency through technology and management innovation.

TABLE 2 Baseline regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
DT	0.3256*** (11.25)	0.0227*** (2.83)	−0.0081* (−1.67)	−0.0102*** (−2.07)	−0.0102*** (−10.18)	−0.0301*** (−8.43)
LED		−0.0291 (−0.68)		0 0.0845*** (3.72)	0.0845*** (2.97)	−0.1450* (−2.06)
PD		0.2061*** (13.02)		0.7716*** (5.65)	0.7716*** (7.54)	0.5267*** (7.03)
FS		0.4968*** (19.39)		0.0597** (2.32)	0.0597* (1.88)	−0.0131 (−0.32)
IS		0.3940*** (6.24)		0.1559*** (3.11)	0.1559 (1.65)	−0.2947*** (−5.21)
FDI		0.1373*** (14.54)		0.0054 (0.92)	0.0055 (0.72)	−0.0095 (−0.87)
FEI		0.1097*** (4.99)		0.1550*** (4.13)	0.1550*** (3.26)	−0.1196** (−2.60)
Individual effect	No	No	Yes	Yes	Yes	Yes
Time effect	No	No	Yes	Yes	Yes	Yes
R-squared	0.1320	0.5868	0.3665	0.3906	0.3906	0.4512
Hausman test				Prob>chi2 = 0.000		
F-test				Prob > F = 0.000		
Pesaran CD test				49.772***		
Wooldridge test				189.95***		

***, **, and * indicate significance at 1, 5, and 10%, respectively; t-statistics are reported in parentheses.

5.2. Robustness test

The benchmark regression results shown in Table 2 demonstrate that the impact of DT on carbon emissions was found to be significantly negative, which initially confirmed the research hypothesis that DT can reduce carbon emissions. In order to verify the robustness of this conclusion, we used four methods. We first used the robust regression of the S-estimation method to deal with outliers. There may be a small number of outliers in a conventional dataset, and the fair value obtained by FE estimation is not an unbiased estimator. Robust regression modifies the objective function in ordinary least squares regression to fit most data structures while also identifying potential outliers, strong influence points, or structures that deviate from the model assumptions. We secondly increased the number of policy omission variables because the impact of DT on carbon emission is affected by policies related to carbon emission management and digital infrastructures. During the sample period, Chinese government implemented a carbon emission trading policy and a national comprehensive big data experimental zone policy in 2011 and 2016, respectively. The former quantifies and capitalizes carbon emissions, endows them with the attributes of carbon-emitting commodities, and guides enterprises to control and reduce greenhouse gas emissions using market mechanisms. The latter is used to carry out systematic experiments in areas with relatively complete digital infrastructures, focusing on tasks such as data resource management and sharing, data center integration, data resource applications, and big data industry agglomeration. By constantly summing up practical experiences that can be used for reference, replicated, and popularized, the radiation-driven and demonstration-leading effect of the experimental area could finally be formed; considering the importance of policy variables in China's economic operation, this paper incorporated two policies into its model. We thirdly replaced the number of explanatory variables. It takes some time for industrial robots to be installed and constructed over introduction, installation, and production to large-scale application, and the optimization of industrial technology and production processes also needs practical exploration. The influence of DT on carbon emissions may have a specific time lag. This paper used the time lag of DT to replace the original variable. Finally, feasible generalized least squares (FGLS) substitutes the residual vector of each cross-section individual into the covariance matrix of cross-section heteroscedasticity, and the generalized least squares (GLS) method is used to decompose the population variance matrix, and the regression residuals are transformed into residuals satisfying the classical assumptions, and then the ordinary least squares (OLS) method is used for regression. FGLS can correct heteroscedasticity, cross-sectional dependence, and serial correlation caused by panel data and improve the consistency and effectiveness of parameter estimation.

According to the robustness test results shown in Table 3, the DT fitting coefficients of carbon emissions of the four tested methods were −0.0101, −0.0099, −0.0109, and −0.2228, respectively. All of them passed the significance test, indicating that the conclusion that DT reduces carbon emissions was still valid in all models. This, in turn, proved that the benchmark regression results were robust and H1 was valid.

5.3. Endogenous test

Although more control variables were added to the model to alleviate the endogenous problem of missing variables, the endogenous problem caused by measurement errors and reverse causality was still an unavoidable obstacle for causal inference in this paper. For example, in the process of improving the new digital infrastructure, information technologies such as big data, 5G communication, and AI are constantly developing, the public's attention to environmental pollution and greenhouse gases is constantly increasing, and the cost of obtaining environmental information is gradually decreasing, which will make local governments pay more attention to the ecological environments of cities, strictly regulate high-energy-consuming enterprises, and urge enterprises to pay attention to improvements in cleaner production technology for a long time with the help of administrative powers. At the same time, the level of mature intelligence and DT is constantly increasing and the sustainable development and application of clean technologies and industries will eventually produce carbon emission reduction effects. Accordingly, extensive economic development modes are dominant in areas with high carbon emission levels even though technical levels and total productivity are still relatively low. Furthermore, the GDP assessment mechanism forces administrative departments to pay more attention to economic growth and pay less attention to ecological environments. The path of DT in promoting technological innovation and industrial structure upgrading is challenging, and the digital infrastructure in these areas may need to be revised.

This paper used two-stage least squares (2SLS) regression to eliminate endogenous problems. Regarding the setting of tool variables, this paper continued to refer to Bartik's concepts and used the interaction of the first-order lag and difference terms of DT as the first tool variables. In order to prevent the problem of weak tool variables, this paper used the lagging second order of DT as the second tool variable. According to the endogenous test results shown in Table 4, the DT regression parameters of the two kinds of instrumental variables were −0.1115 and 1.4820, respectively, and both of them passed the significance test, which indicated that the influence of instrumental variables on DT was significant and met the principle of correlation. The instrumental variable validity test results

TABLE 3 Results of robust test.

Variable	Method 1	Method 2	Method 3	Method 4
DT	−0.0101* (−1.69)	−0.0099*** (−8.93)	−0.0109*** (−6.06)	−0.2228** (−2.31)
Control variable	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes

*** and * indicate significance at 1 and 10%, respectively; *t*-statistics are reported in parentheses.

TABLE 4 Results of endogenous tests.

Variable	First stage	Second stage	SYS-GMM
DT		−0.0115** (−2.05)	−0.0109*** (−3.00)
IV 1	−0.1115* (−1.71)		
IV 2	1.4820*** (112.37)		
Control variable	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes
Time effect	Yes	Yes	Yes
F-test		6353.943	
AR(1)			0.000
AR(2)			0.696
Sargan test			0.397

***, **, and * indicate significance at 1, 5, and 10%, respectively.

showed that the LM statistic rejected the unidentifiable original hypothesis at the 1% level; the F-statistic was 6353.94, much larger than 19.93 of the 10% critical value, indicating that there was no weak tool variable problem. According to the second stage results, the DT regression coefficient of carbon emissions was −0.0015, and it passed the 5% significance test. In addition, in order to further reflect the rigor of the causal inference relationship in this paper, we also convert the static panel data model into a dynamic panel model, and then use the generalzed method of moments (GMM) to eliminate the endogeneity. By introducing the lag term with two or more lag periods as the instrumental variable and satisfying all the moment conditions as far as possible, the GMM estimation method obtains a better estimator. In essence, GMM is also an instrumental variable method. Traditional econometrics estimation methods, such as the ordinary least square method, instrumental variable method, and maximum likelihood method, have their own limitations. That is, its parameter estimator can only be reliable when it satisfies some assumptions, such as when the random error term of the model follows normal distribution or a known distribution. However, GMM does not need to know the accurate distribution information of the random error term, allowing the random error term to exist in heteroscedasticity and sequence correlation, so the obtained parameter estimator is more effective than other parameter estimation methods. The estimation methods of the dynamic panel data model include differential GMM and system GMM. Since the former will generate errors under the influence of weak instrumental variables in the estimation process, while the latter has the advantages of solving the unrecognized individual differences, the influence of variables not taken into account, and the correlation between variables and random items in the estimation, we use system GMM for empirical analysis. According to the results of SYS-GMM in Table 4, the regression coefficient of digital technology is 0.0109 and significant at the 1% level. Meanwhile, the results of AR (1) and AR (2) show that there is no sequence correlation, and the results of the Sargan test show that there is no overidentified problem. These results show that the SYS-GMM model constructed in this paper is effective, and the conclusion that digital technology can reduce carbon emissions is still valid.

To sum up, the results showed that DT's carbon emission reduction effect was still valid after eliminating endogenous problems.

5.4. Mechanism analysis

In order to reveal DT's carbon emission reduction mechanism according to the intermediary effect test equation constructed for research hypotheses 2 and 3, this paper used the interactive fixed effect model for regression calculation.

According to the mechanism analysis test results shown in Table 5, the DT regression coefficients of energy intensity and GTI were −0.0243 and 0.0699, respectively, and both were significant at the 1% level, indicating that DT can promote carbon emission reductions through the channel mechanisms of promoting GTI and reducing energy intensity. H2 and H3 were therefore verified. Under the background of increasingly scarce raw materials (represented here by energy) and worsening environmental pollution, GTI can improve production efficiency, promote sustainable growth, and be a critical link in reducing carbon intensity and carbon emissions, which mainly come from burning fossil energy in high-carbon-emission industries. Therefore, GTI will improve the total factor energy efficiency while promoting the transformation and upgrading of high-energy-consuming enterprises and indirectly affect urban carbon emissions. DT has a strong technology spillover effect that can strengthen the diffusion range, degree, and speed of advanced energy-saving and emission reduction technologies in the field of cleaner production, promote the rapid popularization and application of advanced technologies, further bring about iterative innovation of energy-saving and emission reduction technologies, promote smart industrial clusters, and expand the ecological scene of cleaner industry application, thus reducing carbon emissions. Digital networks, which rely on the Internet, can significantly reduce the social transaction and information search costs, effectively reduce barriers to the flow of production factors between regions, and therefore accelerate the flow of factors, which is conducive to enterprises' access to innovative resources in the value network, thus promoting the overall GTI capability of a city. The development of DT enables enterprises to analyze users' environmental protection needs in real time, which helps enterprises to arrange innovation and production activities according to users' differentiated and dispersed needs (Peng and Tao, 2022). Therefore, DT can reduce carbon emissions through the channel mechanism of promoting GTI.

5.5. Heterogeneity tests

Our benchmark regression results showed that the development of the DT is generally conducive to reducing regional carbon emission intensity. So, does this carbon emission reduction effect have a general rule in different regions? In order to test the heterogeneous regional effect of DT on carbon emissions, this paper classified urban samples according to the classification standard of carbon emission regulation intensity and the development degree of DT facilities. For robustness, this paper added carbon emission trading and comprehensive big data experimental zone policies to control the impact of carbon emission control and digital infrastructure perfection on carbon emissions. Pilot cities and non-pilot cities were divided into two categories by using the pilot status of the two policies in cities. According to the regression results of the carbon emissions trading pilot and comprehensive big data experimental zone policies shown in Table 5, the DT pilot city regression parameters of the two types of policies

TABLE 5 Mechanism and heterogeneity test results.

Variable	Mechanism test		Carbon emission trading policy		Comprehensive big data experimental zone policy	
	EI	GTI	Pilot cities	Non-pilot cities	Pilot cities	Non-pilot cities
DT	−0.0243*** (−4.31)	0.0699*** (4.06)	−0.0217*** (−7.96)	0.0189* (2.10)	−0.0265*** (−7.49)	0.0193*** (2.78)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
N	4,035	4,035	1,365	2,670	1,005	3,030

*** and * indicate significance at 1 and 10%, respectively; *t*-statistics are reported in parentheses.

TABLE 6 Regression results of unconditional quantile model.

Variable	10%	25%	50%	75%	90%
DT	−0.0811*** (−3.46)	−0.0524*** (−3.54)	−0.0394*** (−3.41)	−0.0211* (−1.79)	0.0618*** (3.50)
Control variable	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes

*** and * indicate significance at 1 and 10%, respectively; *t*-statistics are reported in parentheses.

were −0.0217 and −0.0265, respectively, and both of them passed the significance test of 1%. However, the DT regression parameters in non-pilot cities were 0.0189 and 0.0193, respectively, and both of them passed the significance test. The results showed that DT can significantly reduce the total carbon emissions in pilot cities but significantly increase the carbon emissions in non-pilot cities. A possible reason is that the economic development model of non-pilot cities mainly depends on energy-intensive industries that are more dependent on natural resources, so the pace of industrial structure upgrading lags. The characteristics of industrial structure also have an important influence on the pressure of the urban ecological environment (Zhang B. et al., 2022). For example, in a non-pilot city with a carbon emissions trading policy, the economic development process has not been affected by the carbon market price and the intervention of administrative forces. The primary characteristics of such a city are a high industrial proportion, low total factor energy efficiency, and low level of green technology, and it still faces high pressure regarding carbon emission reduction. Furthermore, non-pilot cities are mainly areas with low economic development levels in the central and western regions; these areas have gradually become "pollution shelters" for transferring energy-intensive industries to developed regions in recent years. The path dependence caused by the "resource curse" makes it difficult for DT and environmental policies to quickly and significantly change the original industrial structure (Li and Zhan, 2022). The dependence on production technology also prevents these areas from adopting cleaner production technology in a short time, and the use of DT is often accompanied by specific energy consumption and carbon emission trends that lead to the significant positive impact of DT on carbon emissions in non-pilot cities (Shi and Li, 2020).

5.6. Non-linearity test

Considering that quantile regression can be used to eliminate extreme interference and describe a conditional distribution in an overall way (Han et al., 2021), five representative quantiles (10, 25, 50, 75, and 90%) were selected to correspond to regions with different carbon emission levels in order to investigate the nonlinear influence of DT on regional carbon emission levels. Table 6 shows that the DT regression parameters from the 10 to 75% quantiles were all significantly negative and that the fitting parameters showed a downward trend, indicating that the emission reduction effect of DT continued to decline with the increase in carbon concentration. In particular, at the 90% sub-site, we found that the DT regression parameter was 0.0618, and it passed the significance test at the level of 1%, indicating that DT does not reduce carbon emissions at this subsite but increase the carbon emissions of similar cities.

Regions with higher concentrations of CO_2 use more energy, and economic development is more dependent on high-carbon natural resources. These regions often have a single industrial structure, and resource-intensive industries dominate. Therefore, it is challenging for DT to generate technology dividends in these regions, and it even generates carbon emissions due to excessive electricity consumption. In 2010, the eastern coastal areas of China launched a policy to transfer energy-intensive industries to developed areas. The economic development model of the eastern coastal areas has achieved a qualitative leap through the industrial gradient transfer, and the high-end manufacturing and modern service industries have rapidly developed; this has lowered the carbon emission concentrations in regions with higher economic development levels. Following these developments, DT can play a better primary role in economic production and a more significant role in carbon emission reductions.

5.7. Empirical analysis of the spatial effect

With its technical advantages of network distribution and decentralization, DT breaks geographical space and time constraints and deepens the correlation degree of economic activities between regions. If the spatial correlation between economic variables is ignored, estimation results will be biased. According to the first law of geography, the correlation between regions is related to distance; the farther the distance, the less the correlation. Since geographic distance factors, regional economic development levels, and other non-geographic factors may affect DT's spillover effect, this paper adopted the weight matrix of economic and geographic distance to depict spatial correlations. As seen in Table 7, the global Moran index (Moran's I) results based on the weighted matrix of economic distance and geographical distance showed that the coefficient of carbon emission and DT was significantly positive, indicating a positive spatial correlation. In order to verify whether the impact of DT on carbon emissions has a spatial spillover effect, this study incorporated a standard two-dimensional panel econometrics model into the spatial location information for verification. However, the regression coefficient value of the spatial econometric model cannot directly reflect the spatial spillover of DT, so this paper adopted the spatial regression with partial differential method to decompose the spatial spillover effect of DT on carbon emissions. The results of correlation diagnostic tests showed that the optimal model of sample data in this study was a two-way fixed effect spatial autoregressive (SAR) model.

Due to the strong dependence of the spatial econometric model on the weight matrix, this paper also calculated the economic distance weight matrix results for the sake of robustness. Table 8 shows the total effect decomposition results of the SAR. The effect decomposition results show that under the two cases of economic distance, the economic and geographic nested matrix, the direct spillover effect, and the total effect of DT on carbon emissions passed the significance level test; furthermore, the influence coefficients were negative, indicating that the estimated results were robust. The results in Table 8 show that carbon reductions in a given region can be achieved with local DT and surrounding cities' DT. In other words, DT has a positive spatial spillover effect on carbon reduction. A possible reason for the spatial spillover effect of DT in reducing carbon emissions is that the rapid development of DT has realized the cross-regional integration and synergistic effect of resources. An essential feature of modern DT is that it weakens the physical space–time distances and enhances the relevance and permeability of regional economic activities using efficient information transmission (Huang et al., 2023). Digital technologies have accelerated the free flow of labor, capital, and knowledge factors of production. Through digital networks, the business, logistics, and capital flow of enterprises operate at high speeds, promoting the innovation of relevant technical knowledge and the adjustment of industrial layouts and bringing digital dividends to realize carbon emission reductions in different regions. At the same time, surrounding cities can take the application of DT as the starting point, the development of a low-carbon economy as the entry point, green and low-carbon industrial clusters as the approach, and local digital infrastructure and resource endowment as the basis to form a green digital economy development mode with the close division of labor, high-efficiency and energy-saving practices, and carbon emission reductions. Therefore, the high-speed transmission of digital information can be used to realize the mutual sharing of carbon emission monitoring data between regions and help the joint prevention and control of carbon emissions between regions.

6. Conclusions and policy implications

6.1. Conclusions

The Index Climate Action Roadmap released by the Global Climate Action Summit in 2020 states that DT solutions in the fields of energy, manufacturing, agriculture, land, construction, services, transportation, and traffic management can help the world reduce carbon emissions by 15%. DT has profoundly changed the habits and motivations of producers, consumers, and investors, and it has provided technical support for enterprises in digital production sectors to reduce emissions and consumption and for non-digital sectors to reduce emissions. This research focused on the digital and intelligent transformation of the manufacturing industry. It innovatively used industrial robots as a proxy variable of DT to investigate its impact on carbon emissions. This paper also evaluated the role of digital infrastructure and carbon emission control systems in the DT process to reduce carbon emissions. Unlike previous nonlinear studies, this paper used unconditional quantiles to test the

TABLE 7 Moran's I of DT and CE.

Year	DT	CE	Year	DT	CE
2006	0.283*** (8.827)	0.415*** (12.50)	2014	0.163*** (5.34)	0.460*** (13.84)
2008	0.327*** (10.30)	0.409*** (12.27)	2016	0.231*** (7.30)	0.472*** (14.17)
2010	0.307*** (9.58)	0.435*** (13.09)	2018	0.241*** (7.65)	0.455*** (13.67)
2012	0.183*** (6.12)	0.439*** (13.20)	2020	0.241*** (7.65)	0.429*** (12.91)

*** denotes significance at the 1% level. z-statistics are reported in parentheses.

TABLE 8 Spatial effect decomposition of SDM.

Variable	Economic distance			Economic and geographical distance		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
DT	−0.0011** (−2.04)	−0.0012* (−1.74)	−0.0112** (−2.04)	−0.0098** (−2.01)	−0.0011* (−1.70)	−0.0109** (−2.01)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes

** and * are significant at the 5 and 10% levels, respectively. *z*-statistics are reported in parentheses.

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nonlinear relationship between DT and carbon emissions to make the regression results more consistent with objective reality. Finally, this study used SAR to verify the spatial spillover effects of digital technologies to reduce carbon emissions. Considering the rapid development of DT in China, the urgent task of carbon emission reductions, and the data of 269 cities in China from 2006 to 2020, this paper used the installation density of robots to represent DT according to robot technology use information in the industrial production sector. The influence mechanism of DT development on regional carbon emissions and its heterogeneous effects were empirically tested in multiple dimensions. The major conclusions of this study are as follows.

1. The real-time monitoring provided by digital technologies can significantly reduce urban CO_2 intensity while improving carbon emission efficiency. In other words, DT can significantly reduce carbon emissions. This conclusion was still found to be valid after changing the estimation method, adding policy omission variables, substituting variables, and solving the endogeneity problem, which had strong robustness.
2. The results of the channel test showed that DT reduces the defects of risk uncertainty, limited technical conditions, and asymmetric market information in the process of R&D innovation; stimulates the willingness and ability of enterprises to engage with GTI; and can effectively reduce CO_2 emission intensity. That is, DT can promote carbon emission reductions through the channel mechanism of promoting enterprises' GTI. In addition, digital technologies can enable the digital transformation of energy management and improve overall energy efficiency. In other words, DT can achieve energy conservation and emission reductions.
3. The impact of DT on carbon emissions is characterized by heterogeneity. The carbon emission reduction effect of DT was found to be more significant in regions with solid carbon emission control and better DT facilities. In regions without carbon trading policies and weak DT facilities, DT increases carbon emissions and does not pay technological dividends. Our unconditional quantile regression results showed that DT has had a significantly positive impact on carbon emissions at 90% of the studied loci, which means that DT cannot reduce carbon emission in areas with high CO_2 concentrations. The spatial econometrics model results showed that DT has a spatial spillover effect on carbon emission reductions. That is, the carbon emission of a certain region will be affected by not only the local DT but also the DT of the surrounding cities.

Our study using panel data of Chinese cities showed that DT has a carbon reduction effect, which is consistent with the conclusions of some studies that use provincial-level data from China, such as Meng et al. (2022) and Wang Q. et al. (2022a). Of course, our results are also consistent with some conclusions using transnational panel data analysis, such as Choi (2010), Dong F. et al. (2022), Li Y. et al. (2022). According to endogenous growth theory, DT is a creative destructive force (Aghion and Howitt, 1992). Therefore, according to the theory, we identified mechanisms of promoting GTI and reducing energy intensity, which extends the discussion on carbon reduction mechanism of DT in the existing literature.

Of course, our results are different from those of Dhar (2020), Noussan and Tagliapietra (2020), Dong K. et al. (2022), and others who think that the impact of DT on the environment will be intensified with the expansion of DT scale. The difference in the existing research conclusions is due to differential proxy variables selected for measuring DT and the different measuring of carbon emissions. Unlike Stanford H A I (2019), who built the index system of DT in terms of R&D, technical performance and industrial development, we use industrial robots as a proxy variable of DT, because industrial robots directly reflect the development degree of DT. In China, R&D spending on DT is difficult to clarify. Using industrial robots as proxy variables also reduces the problem caused by the linearity of the index. We use the carbon emission coefficient method to calculate the carbon emission level at the city level, which is more scientific than the input–output method. Because China compiles an input–output table every 5 years, the input–output method is difficult to reflect the real impact of DT on CO_2, especially in recent years, DT has shown explosive growth. In addition, the conclusion of the study may also be influenced by regional heterogeneity. For example, estimates based on developed countries may differ from estimates based on emerging countries, where DT is still in rapid development (Dong K. et al., 2022); In regions with environmental incentives, DT is more likely to promote GTI, and the estimated value should be different (Aghion et al., 2021). DT in China is in the stage of rapid development, and the creative destruction of DT has improved the traditional energy-dependent industrial structure and technological innovation path. At the same time, China is also actively responding to the global climate change mitigation action and reducing carbon emissions in many cities. This is also in accordance with the results of nonlinear analysis in our paper, that is, DT, as a general-purpose technology, is in a rapid development stage. It can promote the innovation of manufacturing production processes and stimulate the second innovation. Under the regulation of green development policies such as the government's carbon trading policy, it will exert the carbon reduction effect.

6.2. Policy implications

Based on the above research conclusions, this paper proposes the following policy recommendations.

1. The development of DT and boost the transformation of low-carbon cities should be accelerated. Administration should vigorously promote the construction of digital technologies such as 5G, cloud computing, the Internet of Things, and related digital infrastructure, as well as guide social and democratic capital to invest in the high-quality development of the digital industry. Relevant administrative departments can guide the in-depth integration and innovative application of digital technologies such as blockchains, industrial robots, and AI with the energy and environment fields and traditional departments through the promulgation of laws and regulations or incentive measures, and they can promote the continuous emergence of new technologies, industries and formats related to low-carbon fields. These practices will accelerate the transformation and upgrading of DT-enabled energy industry departments, optimize the allocation of energy resources, and promote the large-scale utilization of clean energy and

improvements in energy efficiency. Enterprises should pay attention to the technical dividend of digital development, speed up digital investments, actively use DT to optimize resource allocation and management change, improve energy utilization efficiency and reduce carbon emissions. Finally, relevant authorities should promote the transformation of traditional industries toward digitalization and intelligence. With the help of DT, the development potential of urban green transformation should be improved and the role of advanced technology in reducing carbon emissions and improving carbon performance should be given full play.

2. Authorities should correctly handle the relationship between DT and carbon emission by implementing DT according to local conditions to promote carbon emission reduction strategies. In areas with inadequate digital infrastructures and a strong dependence on natural resources, the development of DT may increase carbon emissions. However, the role of DT in energy saving and emission reduction cannot be denied. Developing DT requires an excellent digital infrastructure and more application scenarios. Administrative departments should speed up the digital transformation of industrial bases and resource-based cities according to their resource endowment and economic development advantages, relying on regional resource endowment and industrial development realities. Cities with poor economic development should establish digital industries according to their development characteristics, as well as make full use of DT to transform traditional industries in an overall and whole-chain way while enhancing the suitability of DT to urban industrial structure adjustment with different industrial attributes and resource endowments. Based on new digital technologies, urban development should accelerate the cultivation of new business forms and models and speed up the technological progress and GTI of enterprises. We should strengthen low-carbon technological innovation and digital transformation in resource-based industries, break the curse of structural energy and resources, and constantly unleash the vitality of low-carbon transformation in cities empowered by digital construction. In regions with vital digital infrastructure and carbon emission control, it is necessary to continuously optimize the industrial structure, continuously promote the high-quality integration of DT and the real economy, constantly realize the convergence and multiplier effects of digitalization and industrialization, improve energy efficiency, and stimulate the carbon emission reduction effect of DT.
3. As digital and real integration enters the deep-water zone, because of the mismatch between the skills of current digital talents and the needs of industrial enterprises, digital talents with high levels of integration and strong professionalism should be actively cultivated. It is necessary to cultivate not only senior professional talents who focus on DT development and digital enterprise operation but also first-line technical talents who operate and maintain digital production lines. We should build a digital talent training system that combines academic education, vocational education, and vocational practice, and we should forge a "main force" of multi-level and overall digital transformation. Furthermore, in view of the lack of confidence and capital shortage of enterprises in digital transformation, it is necessary to build a policy system of digital–real integration that conforms to the actual situation and facilitates development and to propose practical measures to support the R&D and introduction of DT to help enterprises overcome difficulties and overcome risks in the process of digital transformation.
4. New infrastructure should be the strategic resource and base for economic and social development. With the acceleration of digital transformation, DT and critical industries are constantly infiltrating and merging. Although the energy consumption and carbon emissions of communication networks and data centers continue to increase, these organizations can promote economic growth and carbon emission reductions of society to a significant extent and promote the low-carbon and harmonious development of the digital economy of society as a whole. We should accelerate digital transformation; constantly carry out technological innovation and industrial structure optimization; promote the development of communication infrastructure toward low-carbonization, digitalization, and intelligence; and promote the coordinated development of DT and "double-carbon" strategy in the communication industry. We should make use of its network advantages, increase cooperation and integration among industries, promote reductions in energy consumption, slow down the growth rate of carbon emissions, and realize the win–win cooperation of leading development and the goal of "double carbon."

6.3. Limitations

1. Measuring the level of digital development in cities can be challenging. In future studies, based on the pilot list of smart manufacturing demonstration factories and digital economy industrial parks, it will be helpful to use regression discontinuity design (RDD), difference-in-differences (DID), and synthetic difference-in-differences (SDID) for the policy evaluation of carbon reduction effects of digital technologies. Similarly, how to accurately measure urban carbon emissions remains a challenging task. Although the study included as many sources of urban carbon emissions as possible, it still faced the problem of inaccurate measurement of carbon emissions. In future studies, it is necessary to consider more carbon sources in assessing carbon emissions. It will be beneficial to use remote sensing data of luminous lamps and GDP data to correct carbon emissions in cities with remote sensing data repeatedly.
2. An essential feature of DT is that it is not constrained by spatial distance. The spatial econometric models used in this study were not cutting edge. In future studies, a semi-parametric spatial model and geographically and temporally weighted regression can be used to estimate the spatial effect.
3. As a typical large-sample research paradigm, this paper reveals the impact of DT on carbon emissions, which can provide a more reliable theoretical basis for policymaking. However, this paper cannot provide detailed guidance for enterprises to introduce and install industrial robots to reduce carbon emissions and environmental pollutants, and relevant case studies must be urgently supplemented.

4. This paper mainly used two variables to explain the channel mechanism of DT to reduce carbon emissions: energy intensity and GTI. Because DT is extensive and inclusive, future research can further elaborate the relationship of DT and carbon emissions from cities through the channels of virtual industrial agglomeration, factor price distortion, and supply chain effect.

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

XZ conceived and designed the experiments, project administration, and funding acquisition. ZY performed the formal analysis and wrote sections of the manuscript. YS conceptualization, resources, data curation, methodology, software, validation, formal analysis, and writing—original draft and editing. All authors contributed to the article and approved the submitted version.

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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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EDITED BY
Magdalena Klimczuk-Kochańska,
University of Warsaw, Poland

REVIEWED BY
Xing Li,
Shanghai University of Finance and Economics, China
Muammer Koç,
Hamad Bin Khalifa University, Qatar

*CORRESPONDENCE
Jian Luo
✉ luojianxishuai@163.com

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How will industrial collaborative agglomeration affect the efficiency of regional green development?

Baoliu Liu[1], Jian Luo[2]*, Kengcheng Zheng[2], Feng Wu[3] and Xiongfei Zhao[1]

[1]School of Economics and Management, Beijing University of Technology, Beijing, China, [2]School of Finance and Taxation, Zhongnan University of Economics and Law, Wuhan, China, [3]Institute of Technology Management, National Tsing Hua University, Hsinchu, Taiwan, China

The integrated development of various industries in China is essential for promoting long-term sustainable development and achieving carbon neutrality. In this study, we analyze panel data from 30 Chinese provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) covering the period between 2005 and 2020 to investigate the impact of collaborative agglomeration between productive service and manufacturing industries on green development efficiency. We utilize a mediation effect model to examine the role of technological innovation in driving the relationship between industrial collaborative agglomeration and regional green development efficiency. Our findings reveal that the collaborative agglomeration of the productive service and manufacturing industries has a significant positive effect on improving regional green development efficiency. We also identify a non-linear relationship, indicating a double threshold effect. Technological innovation plays an important role in facilitating industrial collaborative agglomeration and promoting the efficiency of regional green development. Moreover, our results demonstrate significant regional heterogeneity in the impact of industrial collaborative agglomeration on regional green development efficiency. Based on these findings, we propose several policy recommendations to achieve high-quality regional economic development, including improving the quality of industrial synergy and agglomeration between regions, strengthening the intermediary promotion role of technological innovation, and enhancing regional green productivity.

KEYWORDS

industrial collaborative agglomeration, technological innovation, green development efficiency, mediation effect, threshold effect

1. Introduction

Green development is a crucial aspect of attaining high-quality economic growth, emphasizing the need to focus on energy consumption, conservation and emission reduction while promoting regional economic growth. To enhance the level of regional green development, we must consider both economic and ecological performance. Industrial agglomeration serves as a critical driving force for economic development and has a significant impact on improving the ecological environment (Peng et al., 2023). However, due to the continuous adjustment and upgrading of industrial structures, traditional single specialized agglomerations are no longer effective in reflecting the differences between production and intermediate products. We must consider not only the decline of the production advantages of traditional manufacturing but also increase the proportion of productive service industries, improve technological innovation, and enhance enterprise adaptability to external environments (Wood, 2006). Given the strong correlation between productive service and manufacturing industries, achieving coordinated development between them is crucial for promoting the green development of the economy.

The Chinese government's ambitious development goals of peaking carbon emissions by 2030 and achieving carbon neutrality by 2060 present significant challenges to the transformation and development of traditional energy-intensive industries (Tian and Sun, 2022). To achieve these goals, it is crucial to decrease investment in high-emission and high-pollution projects while increasing promotion of new energy projects. This strategy ensures that relevant enterprises can improve their capability and level of sustainable development (Wang et al., 2023). Traditional measures of economic development efficiency focus primarily on capital and labor factor input, whereas green development efficiency emphasizes resource input and environmental cost, better reflecting the potential for regional economic growth and green development strength (Ge et al., 2023). Improving the efficiency of regional green development and achieving high-quality economic growth require greater exchange and integration among different industries to provide a steady stream of impetus for regional economic development. In fact, industrial collaborative agglomeration—a special form of agglomeration economy that involves productive service industry and manufacturing industry working together—can effectively promote regional economic development and realize dual development in energy-saving and emission reduction (Chen et al., 2022).

The study aims to investigate how the synergistic agglomeration of productive services and manufacturing affects the level of regional green development and whether it can promote the transformation of regional economies from traditional to innovative growth models. Additionally, the research seeks to identify the role of technological innovation in this impact. Solving these problems is critical for promoting China's industrial restructuring and implementing the coordinated development strategy. Therefore, this study aims to shed light on these issues and provide practical insights for policy-makers.

2. Literature review

Industrial collaborative agglomeration was first proposed by Ellison and Glaeser (1997) to refer to the spatial agglomeration phenomenon of heterogeneous industries, and scholars have conducted in-depth research on this aspect. And with the development of specialization, the degree of interdependence between productive services and manufacturing industries has become increasingly close, gradually forming a mutually complementary and mutually reinforcing coordination relationship (Kelle, 2013; Liu et al., 2023).

Research on the efficiency of industrial collaborative agglomeration and green development focuses primarily on research methods, impact evaluation, and analysis of impact mechanisms. The measurement of industrial collaborative agglomeration includes various indices such as the E-G index, D-O index, Colocalization index, γ index, and θ index. Ellison et al. developed an industrial collaborative agglomeration index based on the "target model" to better reflect differences in industrial resources (Ellison and Glaeser, 1997). Duranton and Overman (2005) improved the division idea of geographical concentration by constructing the D-O index and then analyzed the agglomeration trend of the manufacturing industry. Billings and Johnson (2016) focused on industrial agglomeration within a single urban area, analyzed its influencing factors by constructing a colocalization index, and found that retail and consumer service industries were less affected by externalities.

Related scholars have used China's prefecture-level city panel data to analyze the degree of industrial collaborative agglomeration by constructing the γ index and θ index, confirming that industrial collaborative agglomeration can effectively improve urban production efficiency and industrial collaborative agglomeration (Chen et al., 2020; Zheng et al., 2022). In terms of evaluating the impact effect, researchers primarily focus on analyzing the impact of industrial collaborative agglomeration on production efficiency. Some scholars use the dynamic panel regression model to examine the impact of productive service industry and manufacturing agglomeration on manufacturing production efficiency, finding that it plays a significant role in promoting manufacturing total factor productivity (Dong et al., 2021). Other scholars have analyzed the impact of industrial agglomeration at the city level on air pollution and found an inverted "N" relationship between the two (Hao et al., 2022). Furthermore, it is observed that industrial agglomeration can reduce urban air pollution levels by influencing environmental regulation, technological progress, and industrial structure upgrading. Some scholars have also studied the impact of industrial collaborative agglomeration on urban total factor productivity and green innovation efficiency, finding a significant positive facilitative effect between the two (Hong et al., 2020; Yuan et al., 2020). In terms of the impact mechanism, some scholars have used the threshold panel regression model to identify that industrial agglomeration mainly affects regional environmental pollution by improving the industrial structure and technological innovation level. Others believe that the impact of industrial agglomeration on the efficiency of urban green development has both positive and negative externalities. Through these analyses and studies, it is confirmed that industrial agglomeration can significantly improve the level of green productivity and provide insights for further research at a theoretical level (Lanoie et al., 2008; Cieślik and Ghodsi, 2015; Xie et al., 2017).

Indeed, there are studies on the innovation effect generated in the process of regional industrial collaborative agglomeration. Researchers have analyzed knowledge exchange between different industries in China and found that there are significant correlation characteristics between cluster technology innovation and regional industrial structure, which plays an important role in promoting the improvement of regional technological innovation (Xu et al., 2022a,b). Scholars have also examined the impact and mechanism of industrial collaborative agglomeration on urban innovation from the perspective of cities and found that it can promote urban innovation by optimizing the allocation of innovation resources and increasing market scale (Wu et al., 2019). Some researchers have also investigated the spatial effect of industrial collaborative agglomeration on regional technological innovation from a spatial perspective and identified differences in the level of industrial collaborative agglomeration under different geographical locations.

While previous research primarily focused on single industrial accumulation, the relationship between productive service and manufacturing agglomeration and green development requires further investigation. Since the concept of green development was proposed, scholars have explained this concept, its strategic significance, and its development mechanism (Zeng and Zhao, 2009; Cuiyun and Chazhong, 2020). Therefore, from the perspective of technological innovation, this study integrates industrial collaborative agglomeration, technological innovation, and green development efficiency into a unified analysis framework, analyzing the impact mechanism of industrial collaborative agglomeration on regional green development efficiency to provide specific guidance for regional low-carbon economic development.

Compared to previous studies, this paper provides the following marginal contributions: Firstly, it integrates industrial synergy, technological innovation, and regional green development efficiency into a unified analysis framework. By analyzing the mediating role of technological innovation, this paper can better clarify the interaction among the three factors. Secondly, this paper considers the nonlinear impact of industrial collaborative agglomeration on regional green development efficiency and examines whether there is a threshold effect. This approach can provide a more comprehensive understanding of the relationship between industrial collaborative agglomeration and green development. Thirdly, this paper analyzes the heterogeneous impact of industrial collaborative agglomeration on regional green development efficiency. This aspect allows for the identification of differences in impact across different regions, providing insights that can be useful for policymakers.

3. Theoretical mechanism and research hypothesis

3.1. The positive externality of industrial collaborative agglomeration on the efficiency of green development

Industrial synergistic agglomeration reflects the spatial proximity of enterprises in different industries due to different complementarities and production needs. Its impact on regional green development efficiency is mainly reflected in positive externalities and negative externalities (Chertow et al., 2008).

Positive externality impact refers to the process of coordinated agglomeration of productive service industry and manufacturing industry, which promotes regional green development. On the one hand, it produces a technology spillover effect through the exchange and cooperation among different enterprises. This phenomenon is conducive to the dissemination and spillover of knowledge and technology among industrial agglomeration areas, helping enterprises master advanced production technology and methods, thereby reducing pollution control costs, improving regional pollution control capabilities, and optimizing regional emission reduction technologies (Appold, 1995).

On the other hand, coordinated agglomeration can create economies of scale. It achieves centralized consumption of resources in different regions, realizes centralized pollution control, and forms a certain development scale by attracting enterprises with similar economic activities to join. This process promotes the sharing of capital, labor, and other factor resources, optimizes the efficiency of resource element allocation, and provides a strong guarantee for local development and services (Zhang et al., 2022).

> Hypothesis 1: Industrial collaborative agglomeration can exert positive externality effects, thereby promoting the improvement of regional green development efficiency.

3.2. The negative externality impact of industrial collaborative agglomeration on the efficiency of green development

The negative externalities caused by industrial collaborative agglomeration mainly refer to the process of coordinated agglomeration of productive service industries in the process of regional green development efficiency. Firstly, there is the market competition effect. The agglomeration of different industries in the same region may lead to the accumulation of a large number of production factors and not take advantage of the rational allocation and development of resources in other regions. On the other hand, it also leads to competitive effects, forcing enterprises to continuously improve their competitiveness and technological innovation level, to achieve a virtuous cycle of regional development (Martinus et al., 2020). Secondly, it creates a crowding effect. The agglomeration between industries causes excessive consumption of resources in agglomeration areas, increasing the emission of pollutants from enterprises. This phenomenon is not conducive to the proper management of the ecological environment and poses new challenges to the green development of the regional economy (Nie et al., 2021).

> Hypothesis 2: Industrial collaborative agglomeration can exert negative externality effects, thereby improving the efficiency of regional green development.

3.3. The indirect mechanism of action played by technological innovation

Relevant studies show that industrial collaborative agglomeration integrates innovation factors and saves innovation costs by generating knowledge and technology spillover effects (Amiti, 2005). This integration provides a basis for improving the regional technological innovation level. The intercorrelation of inputs between different industries also helps to improve the level of human capital, which in turn generates technological innovation effects. The improvement of the technological innovation level promotes the synergistic agglomeration and development of different industries through growth and knowledge spillover effects, forming a mutually reinforcing development situation (Yang et al., 2022). Therefore, the coordinated agglomeration development of the productive service industry and manufacturing industry not only directly promotes the efficiency of regional green development but also indirectly achieves regional green development by improving the level of technological innovation (Angel, 2002). The role of technological innovation in promoting regional green development is mainly through the reform of production technology of high-emission and high-pollution enterprises, the improvement of clean production technology, the technical reduction of negative impacts on environmental protection in the process of enterprise development, the promotion of regional technological progress, and the elimination of traditional backward industries (Caniëls and Romijn, 2003). The process of industrial collaborative agglomeration promoting regional green development, by leveraging the effect of technological innovation, optimizing the efficiency of resource allocation, and ensuring the establishment of a circular economy system, will have an important impact on the high-quality development of the regional economy.

> Hypothesis 3: In the process of promoting the efficiency of regional green development, industrial collaborative agglomeration may play an intermediary role in promoting technological innovation.

3.4. The nonlinear impact of industrial collaborative agglomeration on regional green development efficiency

Indeed, the improvement of the level of collaborative agglomeration between the productive service industry and the manufacturing industry requires a long-term development stage. In the early stages of development, the green development effect of technological progress may not be very significant due to the large amount of capital required to invest in innovative activities. However, with the continuous change of technology, the positive impact of green technology innovation will continue to strengthen. This phenomenon will attract the input of high-end factors, realize the rational allocation of factor resources, and help promote the long-term sustainable development of regional green development efficiency. Therefore, in the process of realizing relevant development, different industries may have a non-linear relationship with regional green development. This relationship will be affected by the constraints of relevant factors (Shijie et al., 2021). It is essential to recognize these complex relationships and understand how they interact with each other to promote regional green development efficiently. Only through coordinated efforts and long-term planning can the full potential of industrial collaborative agglomeration be realized and the goal of sustainable development achieved.

> Hypothesis 4: Industrial collaborative agglomeration may have a non-linear relationship with regional green development efficiency, that is, there is a threshold effect.

4. Model setting and data description

4.1. Model settings

4.1.1. Fixed-effect model

To verify the impact of industrial collaborative agglomeration on regional green development efficiency, the following regression model can be constructed:

$$Green_{it} = \alpha_0 + \alpha_1 ICA_{it} + \alpha_2 Z_{it} + \mu_i + \gamma_t + \delta_{it} \tag{1}$$

Among them, $Green_{it}$ represents the green development efficiency of province i's t-th year, ICA_{it} represents the collaborative agglomeration index of productive service industry and manufacturing industry in province i's t-th year, Z_{it} is the set of control variables, and μ_i represents the regional fixed effect, γ_t represents the time fixed effect, δ_{it} is the random error term.

4.1.2. Mediation effect model

To investigate the influence mechanism of industrial collaborative agglomeration on the efficiency of green development, this paper adopts the mediation effect model and treats technological innovation as an intermediate variable. Based on the methods of previous research (Muller et al., 2005), we first examine the influence of the core explanatory variables on the dependent variable when no intermediary variables are added. We then investigate whether the core explanatory variables have a significant influence on technological innovation as an intermediary variable. Finally, we put the core explanatory variables and the technological innovation variable into the model at the same time to compare their coefficients and determine the degree of their respective contributions to explaining the variance in the dependent variable. The specific model is constructed as follows:

$$tec_{it} = \beta_0 + \beta_1 ICA_{it} + \beta_2 Z_{it} + \mu_i + \gamma_t + \delta_{it} \tag{2}$$

$$Green_{it} = \lambda_0 + \lambda_1 ICA_{it} + \lambda_2 tec_{it} + \lambda_3 Z_{it} + \mu_i + \gamma_t + \delta_{it} \tag{3}$$

Among them, the tec_{it} represents the level of technological innovation in the t year of province i, and the meaning of the remaining variables is consistent with the above.

4.1.3. Panel threshold model

To investigate the non-linear effect of industrial collaborative agglomeration on regional green development efficiency, this paper adopts the threshold regression model. The threshold regression model can capture the non-linear relationship between the independent variable and the dependent variable by dividing the sample into separate subgroups based on a specific threshold value. Drawing on Hansen's research method (Hansen, 1999), the threshold regression model can be constructed as follows:

$$Y_{it} = \beta_i x_i + \varepsilon_i q_i \leq \gamma \tag{4}$$

$$Y_{it} = \beta_i x_i + \varepsilon_i q_i > \gamma \tag{5}$$

Where β are regression parameters; q is the threshold variable; r is the size of the threshold, if there are two or more thresholds, the model structure must be expanded, this paper uses the double threshold model to analyze, taking the industrial collaborative agglomeration index as the threshold variable, the specific model form is as follows:

$$\begin{aligned} \ln Green_{it} = \mu_i + \beta_1 I\left(\ln ICA_{it} \leq \gamma_1\right) + \beta_2 I\left(\gamma_1 < \ln ICA_{it} \leq \gamma_2\right) \\ +\beta_2 I\left(\ln ICA_{it} > \gamma_2\right) + \beta n \sum_{k=1}^{4} Z_{i,k,t} + \varepsilon_{it} \end{aligned} \tag{6}$$

Where i, t region and time, μ_i represent the eigenvalues of the observation, $I(.)$ As an indicative function, $\varepsilon_{it} \sim \mathrm{iidN}(0,\delta^2)$ is a random perturbation term, and other variables have the same meaning as above.

4.2. Variable selection and data source

4.2.1. Variable selection

1. Variable to be explained: Green Development Efficiency (Green). To measure the efficiency of regional green development, this paper adopts the method of Zhang et al. (2014) and selects capital (k), labor (l), and energy input (e). The expected output is the level of economic development (y), and the undesired output is the level of environmental pollution (b). Capital investment is measured by the fixed asset investment of the whole society (100 million yuan) in the year, labor input is measured by the total number of employees of the whole society (10,000 people) at the end of the year, and energy input is measured by the total energy consumption of the whole society (10,000 tons of standard coal). The level of economic development is measured by the per capita GDP (10,000 yuan), and the level of environmental pollution is measured by the amount of industrial wastewater, exhaust gas, and solid waste. Based on the research methods of Lin and Guan (2023) and Lin and Qiao (2023), the non-radial direction distance function of all factors and the SBM-DEA model are used to measure the efficiency of regional green development. The non-radial direction distance function can handle both desirable and undesirable outputs simultaneously, and it can effectively measure the efficiency of regional green development. The SBM-DEA model is a widely used method for evaluating the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs. It can also be used to identify the best-performing DMUs and provide insights into potential areas for improvement. By using these methods to measure the efficiency of regional green development, we can obtain a comprehensive and objective assessment of the level of economic growth and environmental protection in a region. This analysis can provide a baseline for evaluating the effectiveness of policies aimed at promoting sustainable development and inform future policy decisions aimed at improving the efficiency of regional green development.
2. Core explanatory variable: To calculate the Industrial Collaborative Agglomeration Index (ICA), this paper refers to the research methods of predecessors (Ding et al., 2022) and mainly selects the relevant data of productive service industries and manufacturing industries in 30 provinces, municipalities (autonomous regions) in China from 2005 to 2020 as the basis of calculation. The specific calculation formula is as follows:

$$ICA_{ij} = \left[1 - \frac{\left|LQ_{mi} - LQ_{mj}\right|}{LQ_{mi} + LQ_{mj}}\right] + \left[LQ_{mi} + LQ_{mj}\right] \tag{7}$$

Among them, LQ_{mi} and $LQ_{m,}$respectively, indicate the regional entropy index of the i and j industries in the i and j regions, and ICA_{ij} indicates the degree of industrial collaborative agglomeration of i industry in the j region.
3. Mediating variable: technological innovation (*TEC*). To measure the level of technological innovation in each region, this paper uses the number of patents granted as a proxy for innovation output. The number of patents granted is a widely used indicator of technological innovation and can provide a quantitative measure of the level of innovation activity in a region.
4. Control variables: level of openness (*FDI*), measured by the ratio of foreign direct investment to GDP in each region; Human resources (*HR*), measured by the ratio of the number of students enrolled in regular colleges and universities in each region to the total number of students in the region; Government expenditure (*GOV*), measured by the ratio of regional government expenditure to regional GDP; Level of resource endowment (*CAP*), measured by the ratio of fixed asset investment to labor force employed in each region. The descriptive statistics for each variable are shown in Table 1.

4.2.2. Data sources

This paper utilizes panel data from 30 provinces and cities in China (excluding Tibet, Hong Kong, Macao, and Taiwan) between 2005 and 2020, obtained from official sources such as the China Statistical Yearbook, China Energy Statistical Yearbook, China Environment Statistical Yearbook, and regional statistical yearbooks. To ensure data accuracy and rationality, the following data processing methods are employed: first, the interpolation method is used to complete missing data, resulting in a complete panel dataset; second, logarithms are applied to account for dimensional differences between different sample data and large variance fluctuations. Third, constant price treatment is applied to the data related to the price index in the sample, using 2005 as the base period.

TABLE 1 Descriptive statistical results for each variable.

Variable	Type	Sample	Mean	Standard deviation	Maximum	Minimum
Green	The variable being explained	480	0.936	0.377	1.752	0.930
ICA	Explanatory variable	480	1.224	0.112	1.495	0.960
TEC	Mediation variable	480	3.705	6.261	48.102	0.010
FDI	Control variables	480	0.026	0.193	0.092	0.001
HR		480	0.151	0.099	0.624	0.030
GOV		480	0.035	0.042	0.725	0.005
CAP		480	0.526	0.836	1.236	0.002

TABLE 2 Results of industrial collaborative agglomeration on regional green development efficiency.

Variable	lnGreen	
	(1)	(2)
lnICA	0.165*** (2.65)	0.024** (2.19)
lnFDI		0.325* (1.72)
lnHR		0.168** (2.16)
lnGOV		0.193* (1.85)
lnCAP		−0.015* (−1.70)
Constant	1.235** (2.53)	2.085*** (4.30)
Fixed time	Yes	Yes
Individual fixation	Yes	Yes
N	300	480
R^2	0.0670	0.828

*, **, *** representative significant levels of 10, 5, and 1%, respectively, and the values in parentheses are t-values.

5. Analysis of empirical results

5.1. Benchmark regression analysis

Prior to conducting the benchmark regression, it is necessary to address the issue of multicollinearity. After conducting a test analysis, it was discovered that the variance expansion coefficient of the variables is markedly lower than the value typically required by experience, indicating an absence of multicollinearity issues. Furthermore, this paper selects the fixed-effect model for analyzing the impact of industrial synergy agglomeration on regional green development efficiency, with the specific regression results presented in Table 2.

Table 2 presents the regression results, indicating that in column (1) without control variables, industrial synergy agglomeration has a significantly positive effect on regional green development efficiency at a 1% significance level. Even after adding control variables in column (2), the regression coefficient of green development efficiency remains significant. This suggests that industrial synergy agglomeration can effectively facilitate the integration of different factors and significantly enhance the efficiency of regional green development during times of rapid growth.

TABLE 3 Regression results for mediation effects model testing.

Variable	(1) lnGreen	(2) lntec	(3) lnGreen
lnTEC			0.048*** (3.36)
lnICA	0.024** (2.19)	0.054** (2.33)	0.015*** (3.43)
lnFDI	0.325* (1.72)	0.408* (1.85)	0.378* (1.79)
lnHR	0.168** (2.16)	0.285*** (3.53)	0.098** (2.19)
lnGOV	0.193* (1.85)	0.813** (2.22)	0.738** (2.13)
lnCAP	−0.015* (−1.70)	−0.064** (−2.18)	−0.036** (−2.35)
Constant	2.085*** (4.30)	1.237** (2.29)	4.792*** (3.67)
N	480	480	480
R^2	0.828	0.715	0.802

*, **, *** representative significant levels of 10, 5, and 1%, respectively, and the values in parentheses are t-values.

5.2. Mediation effect estimation results

This paper employs the mediation effect model to empirically examine the impact of industrial synergy agglomeration on regional green development efficiency, as well as the role of technological innovation as an intermediary. The regression results of this analysis are presented in Table 3.

Table 3 displays the regression results of the impact of collaborative agglomeration between the productive service industry and manufacturing industry on regional green development efficiency, with technological innovation serving as the mediating variable. Model (1) focuses on the effect of industrial synergy agglomeration on green development efficiency. It is observed that an increase in industrial synergy agglomeration significantly promotes regional green development at a 5% significance level. This can be attributed to the fact that an improved industrial agglomeration level fosters closer cooperation and exchange among enterprises, leading to enhanced resource utilization efficiency and factor productivity, while also promoting technological spillover effects between industries and facilitating the adoption of green production technologies by firms.

In addition, an improved industrial agglomeration level also facilitates the internalization of pollutant emissions, reduces regional resource consumption levels, and promotes regional green development. Model (2) examines the impact of technological

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innovation on regional green development efficiency, which is significantly positive at a 5% level, indicating that technological innovation can serve as an effective intermediary variable. Model (3) incorporates both industrial synergy agglomeration and technological innovation into the regression model, revealing that the role of industrial synergy agglomeration in promoting green development efficiency is significantly strengthened. This provides further evidence supporting the hypothesis that technological innovation plays a mediating role in the process of industrial synergy agglomeration on regional green development efficiency.

The impact of the degree of opening up on regional green development efficiency was found to be positive, but not statistically significant. This may be attributed to the insufficient absorption and transformation capacity of foreign enterprises, leading to a less notable promotion of green development efficiency. On the other hand, the impact of human capital on green development efficiency was significantly positive. Effective accumulation of human capital and rational allocation of capital structure can optimize and adjust inter-industrial structures, transforming low-end and high-pollution industries into high-tech industries with lower energy consumption and pollution levels, hence promoting green development. Moreover, the impact of government fiscal expenditure on regional green development efficiency was also found to be significantly positive, indicating that increased fiscal expenditure can facilitate the realization and application of production technology achievements, while improving the level of regional green technology innovation. However, the level of resource endowment exerted a significant inhibiting effect on green development efficiency, further emphasizing the importance of enhancing regional resource utilization efficiency in promoting better development levels of regional green development.

5.3. Robustness test

To ensure the accuracy of the empirical results, this study employs robustness tests using the following methods: (1) inclusion of lagging variables to account for any potential lag in the impact of industrial synergy agglomeration on green development efficiency; (2) substitution of intermediary variables by using the number of patent applications in each region instead of the level of technological innovation; and (3) exclusion of samples from municipalities directly under the Central Government, given their unique economic development characteristics that may be more constrained by institutional and political factors. The regression results are presented in Table 4, which demonstrate that even with the inclusion of lagging variables, substitution of explanatory variables, or exclusion of municipality samples, the impact of industrial synergy agglomeration on regional green development efficiency remains significantly positive, largely consistent with the benchmark regression results. This further confirms the robustness of the model. Additionally, technological innovation was found to play an important mediating role in promoting green development efficiency through industrial synergy agglomeration. The regression results of the robustness tests are also presented in Table 4.

TABLE 4 Robustness test results of mediation effect.

Variable	lnGreen	lntec	lnGreen
lnTEC			0.078*** (4.25)
lnICA	0.025** (2.31)	0.048** (2.13)	0.052*** (3.27)
lnFDI	0.270** (2.16)	0.063* (2.09)	0.708** (2.02)
lnHR	0.032** (2.35)	0.149*** (3.28)	0.482** (2.18)
lnGOV	0.185* (1.71)	0.107** (2.35)	0.647** (1.99)
lnCAP	−0.191*** (−3.68)	0.092** (2.38)	−0.054** (−2.07)
Constant	1.748** (2.04)	0.347** (2.48)	5.148*** (3.14)
N	480	480	480
R^2	0.848	0.803	0.799

*, **, *** representative significant levels of 10, 5, and 1%, respectively, and the values in parentheses are t values.

5.4. Further heterogeneity analysis

Given the differences in regional economic development levels and resource endowments, there may be variations in the impact of coordinated agglomeration of production-oriented service industries and manufacturing industries on the efficiency of green development across different regions. To further investigate this potential differentiation, the study area is divided into three regions: Eastern, Central, and Western, with the specific estimates presented in Table 5.

Table 5 presents the regression results for different regions, indicating that industrial synergy agglomeration and technological innovation significantly promote the improvement of regional green development efficiency in the eastern region. Moreover, after incorporating the mediation variable, the promotion effect is significantly enhanced across the eastern, central, and western regions, with the eastern region exhibiting a higher level of promotion than the central and western regions. This could be attributed to the relatively good economic development level and industrial structure foundation of the eastern region, which can attract significant resource agglomeration, human capital, and foreign investment, providing a solid foundation for the coordinated agglomeration and development of productive service industries and manufacturing industries, which in turn generates economies of scale and technological innovation effects, enhances resource allocation efficiency, and improves economic green development levels. On the other hand, due to the weak economic development strength and low level of industrial structure in the central and western regions, issues such as low innovation efficiency and excessive pollutant emissions from enterprises during the process of industrial synergy agglomeration are more likely to occur, leading to greater environmental destruction than economic promotion, which is not conducive to high-quality development of the regional economy.

5.5. Threshold model regression results

In the process of industrial synergy agglomeration affecting the efficiency level of regional green development, there may

TABLE 5 Regression results of heterogeneity analysis.

Variable	Eastern region			Central region			Western region		
	lnGreen	lntec	lnGreen	lnGreen	lntec	lnGreen	lnGreen	lntec	lnGreen
lnTEC			0.024*** (3.16)			0.048** (2.36)			0.072** (2.31)
lnICA	0.053*** (2.89)	0.048*** (2.93)	0.018*** (3.01)	0.008** (2.48)	0.069** (2.18)	0.015** (1.99)	0.017** (2.08)	0.082* (1.72)	0.047** (2.01)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
λ	0.118** (2.48)	0.247*** (3.89)	0.097** (2.09)	0.148** (2.42)	0.249*** (4.18)	0.028** (2.15)	0.168* (1.86)	0.242* (1.90)	0.084** (2.17)
Timeeffect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.824	0.890	0.847	0.718	0.755	0.648	0.747	0.827	0.783
Mediation effect			Yes			Yes		Yes	

*, **, *** representative significant levels of 10, 5, and 1%, respectively, and the values in parentheses are t values.

be a threshold effect, whereby only when the level of regional industrial synergy agglomeration reaches a certain scale does it promote the efficiency of regional green development. This paper employs an industrial synergy agglomeration threshold variable and uses a threshold regression model to investigate the threshold effect of industrial synergy agglomeration on the efficiency of regional green development. As shown in Table 6, the threshold value and threshold number of the threshold variables were first determined by the regression model. The results indicate that the single threshold effect of industrial synergy agglomeration was significant at a 1% level, while the double threshold effect was significant at a 5% level, and the triple threshold failed the significance test, indicating that the threshold number is two and the threshold values are 0.824 and 0.927, respectively, revealing a threshold effect on the impact of industrial synergy agglomeration on green development efficiency. Therefore, this paper analyzes the double-threshold model of industrial synergy agglomeration selection, with the specific regression results presented as follows.

Table 7 presents the regression results of the threshold effect model, revealing that for different levels of industrial synergy agglomeration development in various regions, when the level of regional industrial synergy agglomeration is below the first threshold of 0.824, industrial synergy agglomeration has a promoting effect on the improvement of regional green development efficiency, but the effect is not significant. When the level of regional industrial synergy agglomeration is between the first threshold of 0.824 and the second threshold of 0.927, it has a significant promoting effect on the improvement of regional green development efficiency. When the level of regional industrial synergy agglomeration is above the second threshold of 0.927, its positive effect on regional green development efficiency increases. Specifically, the impact of industrial synergy agglomeration on the efficiency of regional green development can be divided into three stages. In the early stage of industrial synergy agglomeration development, due to production factors, transaction costs, and location differences, various industries may not establish a good relationship between knowledge, technology, and economy, leading to an expansion of knowledge spillover and crowding effects generated during the process of single industrial agglomeration, which may not be utilized to improve regional green technology innovation levels. However, with the continuous improvement of the level of regional industrial synergy agglomeration, it can better play the role of positive externalities, realize centralized consumption of resources and treatment of pollutants, build a circular economy system, and promote the efficiency of regional green development. Nevertheless, excessive concentration of resources resulting from a high level of regional industrial synergy agglomeration may not be conducive to the rational allocation of resources, thereby weakening the promotion of green development efficiency.

6. Conclusions and policy recommendations

6.1. Research conclusion

In summary, this paper provides a theoretical analysis of the mechanism underlying industrial synergy agglomeration and technological innovation on the efficiency of regional green development. Using data from 30 provinces and cities in China between 2005 and 2020, we employed the non-radial distance function of all factors and the SBM-DEA model to measure regional green development efficiency. The study also used a mediation effect model to investigate the mediating role of technological innovation in promoting the impact of industrial synergy agglomeration on green development efficiency, and

TABLE 6 Significance test and threshold estimation results of threshold variables.

	Model	*F*-value	*P*-value	BS times	Threshold estimate	Critical value		
						10%	5%	1%
Industrial collaborative agglomeration	Single threshold	12.134	0.005	500	1.824	4.018	10.436	14.267
	Double threshold	10.425	0.038	500	1.927	5.742	9.472	18.274
	Triple threshold	4.128	0.124	500	2.240	8.142	15.244	25.428

TABLE 7 Estimation results of threshold model.

Variable	Variable interval	Coefficient	*t*-value	*P*-value
Industrial collaborative agglomeration	ICA $\leq$ 0.824	0.0171	1.122	0.634
	0.824 < ICA $\leq$ 0.927	0.047	3.189	0.001
	ECR $\geq$ 1.240	0.058	4.266	0.000

incorporated a threshold model to examine the non-linear relationship between the two. Results indicate that industrial synergy agglomeration has a significant positive effect on the development of regional green development efficiency, with a non-linear promotion relationship that exhibits a double threshold effect at threshold values of 0.824 and 0.927, respectively. The intermediary effect shows that technological innovation plays an important intermediary role in the process of industrial synergy agglomeration to promote regional green development efficiency. Additionally, the analysis of regional heterogeneity reveals that the intermediary promotion effect is most significant in the eastern region, with a considerable impact in the central and western regions as well.

6.2. Policy recommendations

Based on the research conclusions above, we propose the following policy recommendations:

Firstly, it is recommended to enhance the quality of collaborative agglomeration between productive service industries and manufacturing industries by promoting their deep integration. To achieve this, the government should consider the local economic development level and the industrial structure of the manufacturing industry when formulating policies, increase investment in productive service industries, adopt functional industrial policies to promote knowledge spillover and technology coupling between these industries, strengthen top-level design between them, and guide productive service industries to form regional agglomerations through the construction of industrial parks. These measures will help to strengthen the connection and cooperation between the two industries. Additionally, inter-regional exchanges should be strengthened, and inter-regional coordinated development achieved through differentiated policies and measures. Further, industrial transfer measures in the eastern region should be improved, the industrial structure level of the central region enhanced, and the high-quality development of industrial structure in the western region promoted, to improve the overall efficiency of resource allocation and realize the ascending development of industrial collaborative agglomeration.

Secondly, we recommend strengthening the intermediary promotion role of technological innovation in enhancing the positive impact of industrial collaborative agglomeration on regional green development. This can be achieved by promoting cross-industry technology exchange and cooperation during the coordinated development of productive service industries and manufacturing industries, leveraging the knowledge and technology spillover effects generated through industrial collaborative agglomeration, and improving the role of inter-industrial collaborative agglomeration in promoting technological innovation. Furthermore, we should improve the flow of factor resources among regions, promote the development and application of information technology, increase investment in knowledge-intensive production-oriented service industries such as scientific and technological research and development, and ensure that the effect of technological innovation is maximized while playing a vital role in promoting regional green development.

Thirdly, we recommend improving the efficiency of transforming scientific and technological innovation achievements to raise the level of regional green productivity. To achieve this, it is necessary to increase scientific and technological expenditure, improve the cultivation of technological innovation ability for enterprises, enhance the level of technological research and development in enterprises, reduce negative externalities caused by pollution emissions from enterprises, and improve the level of human capital to enhance the independent innovation ability of enterprises. Additionally, optimizing the allocation of resources and establishing a resource sharing mechanism among different regions can promote the integrated development of industries and facilitate the green development of industrial clusters, ultimately leading to the high-quality development of regional economies.

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

JL, KZ, FW, and XZ performed the material preparation, data collection, and analysis. BL wrote the first draft of the manuscript. All authors contributed to the study conception and design, commented on previous versions of the manuscript, read, and approved the final manuscript.

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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EDITED BY
Magdalena Klimczuk-Kochańska,
University of Warsaw, Poland

REVIEWED BY
Jintao Lu,
Taiyuan University of Science and Technology, China
Kristina Rudžionienė,
Vilnius University, Lithuania
Lingli Qing,
Guangzhou College of Commerce, China

*CORRESPONDENCE
Jinsong Zhang
✉ hsdzhjs@163.com

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Does environmental information disclosure drive corporate sustainable growth? A new insight into U-shaped relationship

Jinsong Zhang* and Mengmeng Wang

Accounting School, Harbin University of Commerce, Harbin, China

Due to the increasing rate of economic development and the increasingly serious problem of environmental degradation, environmental information disclosure has become an important basis for promoting carbon peaking and carbon neutrality, and an important way for enterprises to carry out green governance to achieve sustainable development. This study uses empirical research methods to analyze the relationship between environmental information disclosure and corporate sustainable growth in the context of green governance using panel data of Chinese A-share listed companies in Shanghai and Shenzhen from 2012 to 2021. The empirical tests conclude that there is a U-shaped relationship between environmental information disclosure and corporate sustainable growth, which decreases and then increases, and the U-shaped relationship is transmitted through innovation inputs. The U-shaped relationship between environmental information disclosure and corporate sustainable growth is weakened by firm size and enhanced by equity incentives. In addition, further group analysis reveals that the above U-shaped relationship is more significant in non-state enterprises than in state-owned enterprises.

KEYWORDS

green governance, environmental information disclosure, corporate sustainability, innovation inputs, U-shaped relationship

1. Introduction

The United Nations Framework Convention on Climate Change (UNFCCC) and the Paris Agreement has come to an agreement on the principles and goals of the international community to jointly address climate change, requiring all parties to work toward limiting temperature rises to 1.5°C based on the principle of common but differentiated responsibilities. However, the global response to climate change still faces many challenges. The 27th Conference of the Parties to the United Nations Framework Convention on Climate Change (COP27) is held in Sharm El Sheikh, Egypt, on November 6, 2022. China anticipates that COP27 will advocate that all parties translate their national autonomous contribution targets into solid actions, fully and accurately implement the principles and goals of the UNFCCC and the Paris Agreement, make significant progress on the adaptation and financing issues that most concern developing countries, and promote the creation of a fair, reasonable, cooperative, and win-win global green governance system to address climate change. The Chinese government has aggressively transformed its method of governing, put the green idea into practice, and elevated green governance to a prominent position in light of the current historical context. Enterprises, the primary cause of environmental concerns, must pay attention to environmental issues and carry out their obligations for environmental governance in addition to using social resources and generating income for society. Environmental information disclosure is viewed by many nations as an essential tool for enhancing the execution of company green initiatives and creating corporate green governance systems, and it has slowly evolved into a development trend for global responsible governance. Environmental information disclosure now fully expresses many market participants' rights to know about environmental pollution and to take part in environmental governance, making it not only a crucial part of enterprises' own green governance activities but also a crucial way for the outside world to understand enterprises.

Academics have begun to focus primarily on the study of environmental information disclosure in this backdrop. On the one side, researchers have dug into the variables that affect how environmental information is disclosed. According to the Xin et al. (2020), a random effects regression analysis of manufacturing enterprises revealed ownership structure, debt level, industry type, and firm size as significant determinants of environmental information disclosure. The average age of executives and executive excess remuneration, respectively, might favorably enhance environmental information disclosure, as per research by Ma et al. (2019) and Li et al. (2019). In addition to these, stringent external environmental legislation, media attention, and political factors all increase environmental information disclosure (Garcia-Sanchez et al., 2013; Wang, 2020; Zheng et al., 2020). On the other side, environmental information disclosure has had some economic consequences for companies as a voluntary instrument for environmental regulation, however research on this topic is conflicting. Odriozola and Baraibar-Diez (2017) found by analysis that environmental disclosure has a significant impact on corporate reputation. The argument in support of environmental information disclosure is that it can persuade non-compliant corporations to reduce emissions by reorganizing their capital elements and upgrading their energy structure, which will have a favorable influence on their businesses' economies (Li et al., 2019; Wang L. et al., 2020; Wang S. et al., 2020; Yongliang et al., 2020; Daqian et al., 2021). Under the opposite viewpoint, environmental disclosure has an offsetting impact on corporate performance since it increases the expense of environmental management and drives investors to respond negatively (Yang et al., 2020) which is detrimental for corporate development (Jia and ZhongXiang, 2022). Pedron et al. (2020) even argue that environmental information disclosure is irrelevant to accounting returns due to the short duration. A review of the existing literature reveals that existing studies on the economic consequences of environmental disclosure remain highly controversial, and exploring the potential mechanisms of their different effects is still of significant academic value. In view of this, this paper proposes a nonlinear relationship between environmental disclosure and sustainable corporate growth and examines the transmission mechanism of innovation inputs.

In accordance with the theory of sustainable development, development is not just a financial preoccupation, and economic growth that exclusively focuses on production value cannot grasp the essence of development. Based on the idea, economic development must be carried out while ensuring environmental protection, ongoing resource utilization, and perpetual coordination between the economy, environment, and resources. In January 2016, the United Nations officially launched the 2030 Agenda for Sustainable Development, which involves three dimensions of sustainable development-the environmental dimension, the social dimension, and the economic dimension. In the context of advocating sustainable development, it is of considerable theoretical and practical value to study how to use environmental information disclosure as an important vehicle for the environmental governance dimension, which in turn has an impact on corporate sustainable growth. Dameng et al. (2021) concluded that environmental information disclosure is a signal to uphold environmental responsibility after examining how environmental information disclosure affects sustainability from the standpoint of green innovation, which makes it easier for businesses to raise capital and, as a result, promotes corporate green innovation. However, this perspective is not comprehensive in studying corporate sustainable growth, and environmental information disclosure not only conveys positive information to the market, but also generates negative impacts that are detrimental to corporate sustainable growth, such as increased disclosure costs and exposure of environmental management deficiencies, which are not discussed in existing studies. This paper argues that the relationship between environmental information disclosure and corporate sustainable growth is more complex and non-linear in nature. In order to fill the gap of the existing studies, this study aims to verify that there is a complex U-shaped relationship between environmental information disclosure and sustainable corporate growth in a sample of a-share listed companies in Shanghai and Shenzhen from 2012 to 2021, which first decreases and then increases. We also examine the mediating role of innovation investment in this relationship and the moderating role of firm size and equity incentives, and further compare the differences in the U-shaped relationship between state-owned and non-state-owned firms.

This research provides three contributions to previous literature. First of all, it fills a gap in the investigation of the influence on corporate sustainable growth that merits additional investigation in the existing research on the economic consequences of environmental information disclosure, which is primarily focused on short-term economics and the conclusions are highly contentious. In order to explain the conflicting phenomena of economic effects in earlier studies and to render the research findings more in line with objective reality, this study suggests a more intricate U-shaped link between environmental information disclosure and corporate sustainable growth. In contrast to previous recent studies that use questionnaires or single indicators to do this, this research uses content analysis to quantify environmental information disclosure and updates the scoring technique to give new variable measures (Ricky et al., 2022). Secondly, the mechanism of the non-linear relationship between environmental information disclosure and corporate sustainable growth is further explored, which extends the understanding of existing studies on the path of the role of environmental information disclosure. It is clarified that the U-shaped relationship arises because of the reciprocal effects of environmental information disclosure on the strengths and weaknesses of firms. It is also found that innovation inputs are the main transmission factor of this relationship, i.e., the U-shaped effect of environmental information disclosure on innovation inputs and then the positive linear effect of innovation investment on corporate sustainable growth is the key to the total U-shaped effect. In addition, based on the above study, firm size and equity incentives are included in the analysis framework to reveal the differential factors affecting the U-shaped effect of environmental information disclosure on corporate sustainable growth. This allows companies to comfortably implement environmental disclosure strategies in different contexts. Finally, China is a significant actor in international environmental governance whereas previous studies are biased toward industrialized nations. The world's largest developing country is China. This study employs Chinese firms as its research sample in order to enhance the theoretical framework of environmental information disclosure in the Chinese setting. When it comes to environmental governance, other developing countries can use the study's conclusions as a guide.

2. Mechanistic analysis and hypotheses

2.1. The relationship between environmental information disclosure and corporate sustainable growth

The "Environmental Information Disclosure Measures," which outlined legal requirements for environmental information disclosure at the enterprise and governmental levels, were made public by China's Environmental Protection Bureau (EPA) in 2007. This marked an informational stage in China's pollution control and green governance of corporate transformation. Corporate environmental information disclosure, in contrast to general information disclosure, refers to the practice of releasing and accepting public oversight of the environmental impacts and environment-related performance data caused by an enterprise's production and operation process. The society is informed in a genuine manner about the enterprise's environmental policies, aims, environmental inputs, environmental liabilities, environmental benefits, etc. Environmental information disclosure is a powerful tool for companies to demonstrate their commitment to green governance. It also serves as a crucial foundation for the practice of sustainable development, the promotion of carbon peaking, and the advancement of carbon neutral activity.

According to signaling theory, Hepei and Zhangbao (2022) show that negative news exposed by environmental information will damage the producer's reputational image leading to increased production costs, but with the strengthening of environmental management, it will prompt firms to take the initiative to optimize resource allocation and enhance green total factor productivity, which is beneficial to corporate sustainable growth. So, depending on the level of environmental management, environmental information disclosure may have positive or negative effects on industrial green growth, ultimately leading to a U-shaped or inverted U-shaped nonlinear effect. This paper argues that there exists a U-shaped link between environmental information disclosure and the sustainable growth of firms. The increase in the cost of environmental information disclosure leads to the ban on the corporate sustainable growth, when the higher the level of environmental information disclosure, the worse the corporate sustainable growth. From another angle, however, the resource advantage makes environmental information disclosure and corporate sustainable growth positively correlated, the higher the level of environmental information disclosure, the stronger the corporate sustainable growth.

The gains of environmental protection, according to conventional neo-classical economists, must necessarily be offset by higher private costs for industries and decreased competitiveness. Increasing societal benefits will inevitably come at the expense of manufacturers since environmental protection activities try to internalize harmful environmental externalities, and the resulting implied offsetting relationship will negatively affect development (Ricky et al., 2022). The externalities, particularly the negative externalities, that define environmental information is connected to the detrimental effects of environmental information disclosure on corporate sustainable growth. When corporations disclose environmental data, the public is simultaneously exposed to the results of environmental management and environmental harm. Numerous sectors with significant energy consumption and pollutant emissions have had detrimental effects on China's environment (Tao et al., 2020). Environmental management flaws and environmental damage fines will almost certainly negatively impact a company's reputation, which is bad for business growth. Additionally, the incentive of environmental information disclosure forces companies to change their original optimal production resource allocation, which increases the investment in environmental management and adds additional operating costs and economic burdens to companies (Bing et al., 2020), while sacrificing other projects with more investment potential and increasing opportunity costs (Lijun et al., 2021), which is prone to resource misallocation due to economic risks and inhibits corporate sustainable growth.

Different from the study previously given, a number of theories explain the encouraging effect of environmental information disclosure on the corporate sustainable growth. First of all, according to the theories of signal transmission, the disclosure of environmental information by businesses to the public and many investors is a sort of green governance signal. It has the ability to concurrently intervene in a variety of investments and financing decisions made by investors, financial institutions, and other stakeholders (Yu et al., 2018). Leveraging resources derived through public trust may help achieve first-mover advantage, increase barriers to market entrance (Ricky et al., 2022), improve market performance, and promote environmental company development (Ricky et al., 2022). The external governance pressures that businesses experience causes them to actively disclose environmental information in a way that more closely aligns with public expectations. This improves market competitiveness and increases corporate green goodwill. Finally, environmental information disclosure is a policy requirement put forward by the government to polluting enterprises, and the transmission of environmental information can improve the government's recognition of the enterprise. The higher the government's recognition of the enterprise, the stronger the government protection faced by the enterprise's development, the easier it is to obtain government support for relevant planning approval procedures as well as development measures, and the business risks of the enterprise are mitigated, which likewise promotes the corporate sustainable growth.

Environmental information disclosure does have some inhibitory effects on corporate sustainable growth, but the benefits it receives in terms of resources are growing. As environmental information disclosure increases, the impact of the latter will gradually outweigh the former, having different effects on businesses' ability to develop sustainably. Consumers and investors are unable to judge businesses fairly when they provide less environmental information (Ricky et al., 2022), which may lower the ease of financing and social trust of businesses, drive up expenses, and lessen the effectiveness of resource allocation. However, the agency issue in the management process is decreased, information asymmetry's negative effects are significantly lessened, and the advantage of resource acquisition gradually grows as the degree of environmental information disclosure increases. The space for the inhibitory impact to operate is now progressively shrinking, the inhibitory effect is being mitigated, and the promotion effect is becoming progressively more pronounced (Xiaoling et al., 2023). When environmental information disclosure reaches a high level, strong environmental governance signals can be sent, corporate reputation and image are stable, and it is easier to capitalize on investor confidence to get more outside investment and financing benefits. Disclosure of environmental information is becoming more important in encouraging the corporate sustainable growth. In conclusion, the U-shaped impact of environmental information disclosure on the corporate sustainable growth is caused by the inhibitory effect, which predominates when the level of environmental information disclosure is small, and the promoting effect, which takes the lead when the level of environmental information disclosure is large. This conclusion is based on the superposition of the two effects. As a result, the following hypothesis is put forth:

> *H1*: Environmental information disclosure and corporate sustainable growth have a U-shaped relationship.

2.2. The mediating effect of innovation inputs on the relationship between environmental information disclosure and corporate sustainable growth

For enterprises, technical innovation is the key to development, and the environmental information disclosure has the dual effects of crowding out innovation inputs and fostering them (Ricky et al., 2022). The few resources are a reflection of the crowding out effect that environmental information disclosure has on innovation inputs. Businesses will strengthen their environmental management investments, scale up their environmental protection investments, and control and reduce pollutant emissions in order to quickly meet local governments' regulatory requirements in the short term and avoid facing legal repercussions (Qinglin and Huaqi, 2022). The competitive cash flow impact will result in a crowding out effect on innovation inputs (Ricky et al., 2022). Environmental information disclosure, however, may also help to mitigate harmful elements in the innovation process and encourage innovative inputs as a powerful corporate governance device (Jiang et al., 2021). The firm, as an organization entrenched in the resource dependency relationship, has the problem of resource constraint, which indicates that the enterprise survival depends on its capacity to acquire external resources, according to the study of resource dependence theory. The cumulative effect of environmental information disclosure can strengthen the capacity of the company to acquire resources, enhance the enterprise's desire to innovate, and boost stakeholders' general impression of the enterprise (Ricky et al., 2022). It is challenging for the public to properly comprehend environmental information due to low levels of environmental information dissemination, and at this point, the crowding-out effect on innovation inputs is greater than the promotion effect, making environmental information disclosure unfavorable to enterprise innovation investment. When environmental information disclosure is at a medium to high level, the promotion effect gradually appears, promoting the level of innovation inputs to increase. Therefore, the inputs in innovation by businesses displays a trend of dropping and then growing when environmental information disclosure changes from a low to high degree. Thus, the following hypothesis is put forth:

> *H2*: The relationship between environmental information disclosure and innovation inputs is U-shaped.

The Theory of Economic Development, J. Schumpeter's Ger-man-language treatise from 1912, was the first to discuss innovation. He contends that internal factors, chief among them innovation, are what cause the capitalist system to disrupt the preexisting equilibrium and achieve the new one. Innovation inputs and outputs may aid businesses in gaining long-term competitive advantages and are crucial to their growth. According to the analysis of innovation theory, firms, as micro-component units of macro-economy, inputs in technological innovation can improve the original production efficiency and production technology, forming an innate competitive advantage and intangible resources with path dependency (Yujuan and Lu, 2022), and contribute to the corporate sustainable growth. In addition, the increase in innovation inputs will also send positive signals to the market, raise investors' expectations for the development of the firm, and reduce financing constraints (Ricky et al., 2022). Thus, it is clear that innovation investment has a positive impact on the corporate sustainable growth.

The crowding out effect will lower the innovation inputs and impede the corporate sustainable growth, according to the study above, when the environmental information disclosure is at a low level. The reputation advantage plays a role when the amount of environmental information disclosure is at a medium-high level, and the favorable resources encourage businesses to invest in innovation, which also encourages corporate sustainable growth. In other words，the U-shaped correlation between environmental disclosure and corporate sustainable growth is a consequence of the U-shaped effect of environmental disclosure on innovation inputs, which in turn has an impact on corporate sustainable growth. On the basis of this, the following hypothesis is put forth:

> *H3*: The U-shaped association between environmental information disclosure and corporate sustainable growth is mediated by innovation inputs.

2.3. The moderating effect of firm size on the relationship between environmental information disclosure and corporate sustainable growth

Depending on their own resources and capacities, businesses have vastly varying responses to the dual implications of environmental information disclosure on corporate sustainable growth. Firm size is the core index to de-scribe the amount of enterprise resources and ability, which determines the degree of response of corporate sustainable growth to the effect of environmental information disclosure. The higher the scale of listed firms compared to small businesses, the greater the influence of their business practices on society (Ricky et al., 2022), and they are more likely to attract public notice and become the subject of government regulation (D'Amato and Falivena, 2020). Therefore, enterprises must actively address stakeholder demands and expectations for environmental responsibility in order to secure exclusive investment from stakeholders to support sustainable growth of companies (Cheng et al., 2021). In order to gain and keep the legitimacy of operation, more and better environmental information might be published in order to win over stakeholders (Acabado et al., 2020). As a result, the cost of environmental information disclosure increases with firm size, but larger enterprises are also better equipped to minimize marginal cost due to the scale impact of resource utilization, which lessens the deterrent effect of cost growth on sustainable development. For the promotion effect, once a large-scale enterprise with a good reputation is formed, social evaluation will be relatively stable (Yusof et al., 2020), making the positive halo effect of the reputation of a large enterprise less effective than that of a small enterprise. The promotion impact of environmental information disclosure on the long-term development of businesses is diluted the higher the degree of environmental information disclosure, the smaller the marginal benefit of good reputation in bigger organizations.

To sum up, when environmental information disclosure is below the threshold, the higher cost forces businesses to use resources to create scale advantages to lower marginal costs and mitigate the detrimental effects of environmental information disclosure on the long-term sustainability of their operations. When environmental information disclosure is above the threshold, as the degree of environmental information disclosure increases, the development-related resources obtained by the halo effect generated by good reputation of small-scale enterprises have more marginal compensation effect on the disclosure cost. At this time, the promotion of corporate sustainable growth is furthered by the function that environmental information disclosure plays. Based on this, the following hypothesis is proposed:

> *H4*: The U-shaped relationship between environmental information disclosure and corporate sustainable growth is negatively moderated by firm size.

2.4. The moderating effect of equity incentives on the relationship between environmental information disclosure and corporate sustainable growth

Research on equity incentives is a current topic in several disciplines, including management and economics, and has an increasingly prominent role and place in the capital markets. As a corporate incentive, equity incentives will result in the management benefit encroachment impact and benefit synergy effect. The compensation received cannot cover the cost of disclosure when the level of environmental information disclosure falls below the threshold, which hinders the corporate sustainable growth. When management equity incentive grows and control rights are acquired, the monitoring role of businesses in relation to management weakens. The demand for reputation and exercise profit will cause the management benefit encroachment effect and exacerbate the inhibition effect of environmental information disclosure on the management benefit encroachment effect if the management does not meet the exercise conditions to promote the corporate sustainable growth through their duty responsibility and diligence.

The increase in equity incentive will prevent the conflict of interest resulting from the unreasonable distribution of residual control and residual income caused by incomplete contracts when environmental information disclosure is higher than the threshold (Umeair et al., 2021). The compensation of stakeholders' resources generated by good reputation covers the cost of disclosure and promotes the corporate sustainable growth. Equity incentives provide a connection between management's interests and the enterprise's long-term worth in this situation (Xu, 2019). It will boost management's motivation and decrease their self-interest (Jones et al., 2019). Additionally, it encourages businesses to meet their environmental obligations through green governance and to make financial and economic decisions that support corporate sustainable growth (Zhao and Lin, 2020). Therefore, the "benefit synergy" effect improves the contribution of environmental information disclosure to encouraging t corporate sustainable growth when the environmental information disclosure is higher than the threshold value.

In conclusion, the rise in equity incentive exacerbates the negative impact of environmental information disclosure in corporate sustainable growth when it is below the threshold. The greater the equity incentive when the environmental information disclosure is over the threshold, the greater the beneficial impact of environmental information disclosure on corporate sustainable growth. On the basis of this, the following hypothesis is suggested.

> *H5*: The U-shaped association between environmental information disclosure and corporate sustainable growth is positively moderated by equity incentives.

In summary, the conceptual model of this paper is shown in Figure 1.

3. Data and empirical model

3.1. Data collection and the sample

This paper takes the 2012–2021 Shanghai and Shenzhen A-share listed companies as the initial sample, and excludes the delisting warning sample companies (ST and *ST). To avoid the effect of extreme values, the sample firms were subjected to a one-percent tailing. The websites of the Shanghai and Shenzhen stock exchanges, annual reports of listed companies, independent corporate social responsibility reports, sustainability reports, and environmental reports are used to gather environmental information disclosure data for listed companies. The CSMAR database provided the financial data. Finally, from this article, 19,207 samples of data were gathered.

3.2. Definition of main variables

3.2.1. Dependent variable: corporate sustainable growth

Corporate sustainable growth. Robert C. Higgins, an American finance expert, proposed the sustainable growth model in 1977, which

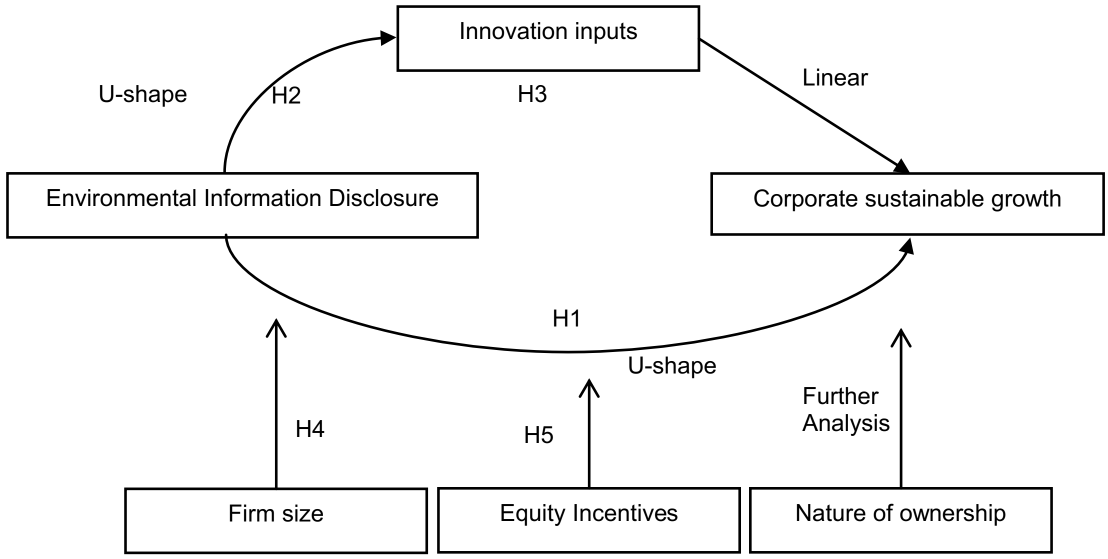

FIGURE 1
Conceptual model of the main research content.

introduced the sustainable growth issue from qualitative analysis to quantitative analysis. However, many experts and scholars have taken a negative attitude toward this model, arguing that the assumptions of the model are too harsh and not in line with the actual operating conditions of enterprises. Therefore, many scholars have tried to change the assumptions or relax the basic conditions to make it more consistent with the actual situation of enterprises. Among them, the most typical one is the static and dynamic model of sustainable growth proposed by James-C-Van Horne in 1988 (Burger and Hamman, 1999).The Van Horn and Higgins sustainable growth models are the most often used methods for evaluating a corporate sustainable growth. Although simple and straightforward, the Higgins sustainable growth model is poorly matched with the business environment of enterprises and ignores their dynamic growth. The Van Horn sustainable growth static model is used to construct the sustainable growth index of enterprises, which measures the sustainable growth capability of listed companies. The specific calculation is as follows:

Sustainable growth rate = net sales margin * asset turnover * ending equity multiplier * earnings retention rate/(1 − net sales margin * asset turnover * ending equity multiplier * earnings retention rate).

3.2.2. Explanatory variable: environmental information disclosure

Environmental information disclosure. While earlier researchers measured environmental information disclosure by the total number of sentences or even words related to environmental information in the annual report, studies related to environmental information disclosure have recently measured environmental information disclosure by the content and extent of environmental disclosure of enterprises (Mendes et al., 2018; Fonseka et al., 2019; Tadros and Magnan, 2019). Based on the nine environmental information contents of "the State encourages voluntary disclosure of enterprises" in China's Environmental Information Disclosure Measures (Trial), the dis-closure criteria of listed companies' environmental information disclosure guidelines [Supervision (2008) No. 18] and listed companies' environmental information disclosure guidelines (2010 Draft for Public Opinions) published by Shanghai Stock Exchange, as well as the annual reports of listed companies, The sample businesses' environmental information disclosure material is broken down into the following five categories for score evaluation: (1) environmental management disclosure; (2) environmental liability disclosure; (3) environmental regulation and certification disclosure; (4) environmental performance and governance disclosure; and (5) information on the carrier of environmental information disclosure.

The details of the assignment are displayed in Table 1, and once the five indicators of each firm are evaluated and added together, the score of environmental information disclosure of each sample company is determined. We first calculate the maximum possible score of environmental information disclosure for each sample company, which is 42. The actual score of environmental information disclosure for the company is then divided by the maximum possible score of environmental information disclosure in order to reflect the level of environmental information disclosure of various companies. The degree of environmental information disclosure increases with a higher score. The following is the calculating formula:

$$\text{EID} = \text{EIDi Score} \,/\, \text{Highest EID Score}.$$

$$\text{EIDi is the environmental information disclosure of the } i - \text{th enterprise.}$$

3.2.3. Mediating variable: innovation inputs

Innovation inputs. The logarithm of Innovation investment amount, the ratio of R&D investment to total assets, and the ratio of R&D investment to primary business income are the three metrics currently used to quantify innovation investment (Jingchang et al., 2021). Because of several reasons, including

TABLE 1 Environmental information disclosure indicators.

Environmental management disclosure (Each disclosure is given a value of 1, or 0 if it is not)	Environmental protection concept	Environmental liability disclosure (No description equals 0, a qualitative description equals 1, and a quantitative description equals 2)	Wastewater discharge
	Environmental goals		COD emissions
	Environmental management system		SO2 emissions
	Environmental education and training		CO2 emissions
	Environmental protection special action		Soot and dust emissions
	Environmental incident response mechanism		Industrial solid waste generation
	Environmental honors or awards		
	The "three simultaneous" system		
Environmental regulation and certification disclosure (Each disclosure is given a value of 1, or 0 if it is not)	Key pollution monitoring units	Environmental performance and governance disclosure (No description equals 0, a qualitative description equals 1, and a quantitative description equals 2)	Exhaust gas emission reduction treatment
	Pollutant emissions meet the standard		Wastewater abatement treatment
	Sudden environmental accidents		Dust, smoke and dust management
	Environmental violations		Solid waste utilization and disposal
	Environmental petition cases		Noise, light pollution, radiation and other governance
	ISO14001 certification		Cleaner production implementation
	ISO9001 certification		
Information on environmental information disclosure carriers of listed companies	Annual reports	Information on the environment disclosed in a listed company's annual report is given a value of 1, else 0	
	Social responsibility report	If a listed company's social responsibility report discloses environmental data, it is given a value of 1, otherwise it is given a value of 0	
	Environmental report	If the listed company discloses the environmental report separately to the public, the value is 1, otherwise it is 0	

unreasonable expectations brought on by China's unsatisfactory capital market, the absolute quantity of R&D investment is not comparable. This study takes the ratio of innovation investment to revenue as a measure of the level of innovation investment, with a bigger ratio indicating a higher level of innovation investment (Xu et al., 2020).

3.2.4. Moderating variables: firm size and equity incentives

Firm size. Depending on the research goal and the data's accessibility, there are numerous relevant firm size measurements. The three most frequently used indicators in prior studies are sales, number of employees, and total assets. Other indicators to measure enterprise scale include cost of sales, number of subsidiaries, market value of stocks and bonds, and enterprise added value (George et al., 2021; Ricky et al., 2022). In general, total assets are the resources that a corporation may now manage, and they are represented by the sum of liabilities and owners' equity. The logarithm of total assets is used in this study as a measurement.

Equity Incentives. The model of equity incentives in practice is complicated. Common models of equity incentive settlement include equity options, restricted shares, performance stocks, employee stock ownership plans, etc. (Jones et al., 2019; Martin et al., 2019). But no matter what kind of incentive mode will eventually be reflected in the incentive object shareholding ratio changes. Using the method of Denton et al. (2018) for reference, this paper measures the intensity of management equity incentive by using the proportion of the total shares held by directors, supervisors and senior managers in the total share capital.

3.2.5. Control variables

The following control variables were chosen with reference to prior research literature in order to minimize the influence of potential variables on the study's findings and to control other elements that affect the corporate sustainable growth (Osazuwa et al., 2017; Radu and Francoeur, 2017; Mendes et al., 2018; Fonseka et al., 2019). Two jobs in one, which is given a value of 1 when the general manager and chairman are in the same position and a value of 0 when they are not. Shareholding of institutional investors, measured by the ratio of the number of shares held by institutional investors to the total number of shares. Shareholding concentration as shown by the proportion of shares held by the largest shareholder. By calculating the logarithm of the number of board members and supervisory board members, respectively, the size of the board of directors and the supervisory board is determined. Employee intensity is determined by dividing the total number of employees by the annual operating income. The ratio of current assets to current liabilities is known as the current ratio. The ratio of total liabilities to total assets is known as the gearing ratio. Return on assets is calculated by dividing the company's annual earnings by the total asset value. In addition, annual and industry dummy variables are set in this paper to control for annual and industry fixed effects, and the definitions of each variable are detailed in Table 2.

TABLE 2 Variable definitions.

Variables	Symbols	Names	Definitions
Dependent variable	SGR	Corporate sustainable growth	Van Horne model
Explanatory variable	EID	Environmental information disclosure	Environmental information disclosure score
Mediating variable	R&D	Innovation inputs	Ratio of R&D investment to operating revenue
Moderating variables	FS	Firm size	Total assets are taken as the natural logarithm
	SHA	Equity incentives	The ratio of the number of shares held by directors and supervisors to the total number of shares
Control variables	DUAL	Two jobs in one	If the general manager and the chairman of the board are combined, the value is 1, otherwise it is 0
	INS	Shareholding of institutional investors	Ratio of shares held by institutional investors to the total number of shares
	CON	Shareholding concentration	Percentage of shareholding of the largest shareholder
	BOA	Board size	The number of board members is taken as a logarithm
	SUP	Supervisory board size	The number of supervisory board members is taken as a logarithm
	EMP	Employee intensity	Ratio of the number of employees to the operating revenue for the year
	LIQ	Current ratio	Ratio of current assets to current liabilities
	LEV	Gearing ratio	Ratio of total liabilities to total assets
	ROA	Return on assets	Ratio of net income, interest expense, and income tax to average total assets
	YRAR	Year	Dummy variables
	Industry	Industry	Dummy variables

3.3. Regression model

The following model is set up in this paper based on the aforementioned analysis in order to validate the non-linear relationship between environmental information disclosure and corporate sustainable growth, the mediating effect of innovation inputs, and the moderating effect of firm size and equity incentives.

When studying U-shaped relationships, researchers usually use the above model and focus on whether β_2 is significant (Lind and Mehlum, 2010). According to the step-by-step procedure, the first step is to ensure that β_2 is significant and the direction is consistent with theoretical expectations; the second step is that the slope of the relationship between Y and X must be steep enough at the minimum and maximum values of the independent variable; and the third step is that the 95% confidence interval of the turning point $-\beta_1/2\beta_2$ should be within the range of the values of the independent variable. Based on this, this study constructs a regression model to test the u-shaped relationship first, and then verifies the extreme value confidence interval by robustness test.

TABLE 3 Descriptive statistics.

Variables	*N*	Mean	S.D.	Min	P50	Max
SGR	19,207	0.065	0.060	−0.024	0.052	0.324
EID	19,207	0.181	0.160	0.024	0.119	0.690
R&D	19,207	0.046	0.045	0	0.036	0.262
FS	19,207	22.138	1.284	19.953	21.936	26.19
SHA	19,207	0.162	0.209	0	0.028	0.689
DUAL	19,207	0.304	0.460	0	0	1
INS	19,207	0.421	0.254	0.002	0.438	0.907
CON	19,207	0.344	0.145	0.088	0.324	0.736
BOA	19,207	2.235	0.172	1.792	2.303	2.708
SUP	19,207	1.48	0.184	1.386	1.386	2.079
EMP	19,207	1.379	0.968	0.104	1.165	5.246
LIQ	19,207	2.702	2.687	0.362	1.804	17.088
LEV	19,207	0.394	0.196	0.052	0.382	0.904
ROA	19,207	0.062	0.055	−0.273	0.056	0.232

4. Results

4.1. Descriptive statistics and correlation analysis of variables

The findings of the descriptive analysis for the 19,207 samples are displayed in Table 3. The corporate sustainable growth of Chinese listed firms is inconsistent, as seen by the sample corporate average sustainable growth rating of 0.065, which ranges from −0.024 to 0.324. The average score for environmental information disclosure is 0.181, which is a low overall level. As a result, improving environmental information disclosure has important practical ramifications for the study in this article. Table 4 displays the findings from the study of the association between the variables in this essay. The correlation coefficient between corporate environmental information disclosure and corporate sustainable growth is 0.037, and it passes the 1% significance level test, according to statistical results of the correlation between the variables. The specific link warrants additional investigation since the correlation coefficient between innovation inputs and corporate sustainable growth was −0.039 and passed the 1% significance level test. The majority of the other control variables have a substantial positive correlation with the explained variable, as do company size and equity incentive. In this

TABLE 4 Correlation matrix.

Variables	SGR	EID	R&D	FS	SHA	DUAL	INS	CON	BOA	SUP	EMP	LIQ	LEV	ROA
SGR	1													
EID	0.037***	1												
R&D	−0.039***	−0.194***	1											
FS	0.107***	0.417***	−0.273***	1										
SHA	0.028***	−0.219***	0.226***	−0.405***	1									
DUAL	0.015**	−0.122***	0.153***	−0.206***	0.254***	1								
INS	0.095***	0.239***	−0.216***	0.447***	−0.692***	−0.191***	1							
CON	0.040***	0.116***	−0.176***	0.180***	−0.093***	−0.025***	0.479***	1						
BOA	0.003	0.168***	−0.124***	0.265***	−0.206***	−0.175***	0.231***	0.013*	1					
SUP	−0.024***	0.212***	−0.165***	0.339***	−0.294***	−0.182***	0.272***	0.106***	0.318***	1				
EMP	−0.155***	−0.194***	0.277***	−0.377***	0.153***	0.096***	−0.146***	−0.065***	−0.061***	−0.088***	1			
LIQ	−0.040***	−0.171***	0.322***	−0.387***	0.284***	0.131***	−0.170***	−0.021***	−0.125***	−0.164***	0.170***	1		
LEV	0.068***	0.183***	−0.324***	0.562***	−0.325***	−0.155***	0.234***	0.068***	0.156***	0.247***	−0.270***	−0.666***	1	
ROA	0.673***	0.058***	−0.044***	−0.031***	0.119***	0.048***	0.078***	0.096***	0	−0.047***	−0.084***	0.166***	−0.257***	1

***Significance at the 1% level; **Significance at the 5% level; *Significance at the 10% level.

research, the variance inflation factor (VIF) values are further assessed to prevent the issue of multi-collinearity among variables. The measured findings show that there is no significant multicollinearity among the variables because all of the VIF values are less than 10, which is consistent with the measured results.

4.2. Analysis of regression

In order to determine if environmental information disclosure and corporate sustainable growth are related, this study first employs the linear regression approach. The results are displayed in Table 5. The findings of the linear relationship test show that corporate sustainable growth is hampered by the environmental information disclosure. The quadratic component of environmental information disclosure is then used in this research in order to build Model 2 and test the U-shaped connection in accordance with the more intricate nonlinear relationship of mechanism analysis. Results reveal that there is a U-shaped association between environmental information disclosure and corporate sustainable growth, with the coefficient of the quadratic component being 0.0215 and passing the significance test. To put it another way, corporate sustainable growth has a tendency of falling and then increasing with an increase in environmental information disclosure, which supports hypothesis 1.

The combination of the two positions of general manager and chairman can help to lessen the principal agent problem and advance the long-term sustainability of the company, according to the regression results of the control variables, which show that the coefficient of the variable of two positions in one is significantly positive at the 10% level. The coefficient of institutional investors' shareholding is notably positive at the 1% level, showing that the more institutional investors participate in a business, the more they support its long-term growth. At the 1% level, share concentration, board size, supervisory board size, and employee intensity all show strongly negative trends, demonstrating that too many redundant members and excessive share size are detrimental to corporate sustainable growth. The fact that enterprises with high gearing often have fewer financing limitations and have more capital may help to explain why the coefficient of gearing variable is notably positive at the 1% level. The improvement in business profitability can offer the essential financial security for sustainability, as shown by the coefficient of the return on assets variable being considerably positive at the 1% level.

Additionally, models 3 and 4 validate the intrinsic influence mechanism of the U-shaped relationship. The findings indicate a nonlinear link between environmental information disclosure and innovation inputs. The second term's coefficient in Model 3 is markedly positive, demonstrating that environmental information disclosure over the threshold can encourage innovation inputs, which means that the U-shaped influence effect holds. In model 4, the coefficient of the quadratic term with significance declines, the coefficient of the innovation inputs variable is significantly positive, and the coefficient of the interaction term between environmental information disclosure and innovation inputs is not significant. This shows that the link between innovation inputs and corporate sustainable growth is unaffected by the contingent effect of environmental information disclosure. In conclusion, innovation input functions as a mediator in the U-shaped link between environmental information disclosure and corporate sustainable growth. In other words, by affecting the innovation inputs, environmental

TABLE 5 Regression results of main effects and mediating effects.

Variables	(1)	(2)	(3)	(4)
	SGR	SGR	R&D	SGR
EID	−0.0117***	−0.0239***	−0.0250***	−0.0209***
	(0.0021)	(0.0064)	(0.0054)	(0.0071)
EID2		0.0215**	0.0234***	0.0190*
		(0.0106)	(0.0090)	(0.0107)
R&D				0.0831***
				(0.0109)
R&D*EID				−0.0183
				(0.0563)
DUAL	0.0012*	0.0012*	0.0054***	0.0008
	(0.0007)	(0.0007)	(0.0006)	(0.0007)
INS	0.0062***	0.0063***	0.0035***	0.0060***
	(0.0015)	(0.0015)	(0.0012)	(0.0015)
CON	−0.0187***	−0.0186***	−0.0232***	−0.0168***
	(0.0024)	(0.0024)	(0.0020)	(0.0024)
BOA	−0.0067***	−0.0066***	−0.0017	−0.0065***
	(0.0019)	(0.0019)	(0.0016)	(0.0019)
SUP	−0.0115***	−0.0115***	−0.0048***	−0.0111***
	(0.0018)	(0.0018)	(0.0015)	(0.0018)
EMP	−0.0021***	−0.0020***	0.0073***	−0.0026***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
LIQ	0.0001	0.0001	0.0028***	−0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0002)
LEV	0.0832***	0.0832***	−0.0239***	0.0851***
	(0.0023)	(0.0023)	(0.0020)	(0.0023)
ROA	0.8218***	0.8220***	−0.0425***	0.8254***
	(0.0058)	(0.0058)	(0.0050)	(0.0058)
Year	YES	YES	YES	YES
Industry	YES	YES	YES	YES
CONS	0.0247***	0.0255***	0.0238***	0.0235***
	(0.0056)	(0.0056)	(0.0047)	(0.0056)
N	19,207	19,207	19,207	19,207
R^2	0.5353	0.5354	0.3991	0.5377

***Significance at the 1% level; **Significance at the 5% level; *Significance at the 10% level.

information disclosure affects corporate sustainable growth, which verifies hypotheses 2 and 3.

Table 6 displays the test findings for the moderating impact of firm size and equity incentives. Model5 is the regression result of adding the moderating variable firm size. The coefficient of the interaction term between firm size and environmental information disclosure is significantly negative, which shows that firm size moderates the impact of environmental information disclosure on corporate sustainable growth and that the moderating effect is negative, i.e., firm size weakens the effect of environmental information disclosure on corporate sustainable growth, supporting hypothesis 4. Model 6 is the regression result of adding the moderating variable equity incentives. The quadratic interaction term's coefficient is significantly positive, demonstrating that equity incentives have a positive moderating effect on the U-shaped relationship between environmental information disclosure and corporate sustainable growth. This finding supports hypothesis 5, which states that equity incentives strengthen the role of environmental information disclosure on corporate sustainable growth.

TABLE 6 Results of the analysis of moderating effects and heterogeneity tests.

Variables	(5)	(6)	SOEs	NSOEs
	SGR	SGR	SGR	SGR
EID	−0.4695***	−0.0139*	−0.0171*	−0.0349***
	(0.1056)	(0.0076)	(0.0102)	(0.0082)
EID2	0.7638***	0.0012	−0.0018	0.0470***
	(0.1741)	(0.0124)	(0.0157)	(0.0144)
FS	−0.0019***			
	(0.0006)			
FS*EID	0.0198***			
	(0.0047)			
FS*EID2	−0.0327***			
	(0.0076)			
SHA		0.0129***		
		(0.0034)		
SHA*EID		−0.0959***		
		(0.0320)		
SHA*EID2		0.2228***		
		(0.0601)		
Controls	YES	YES	YES	YES
Year	YES	YES	YES	YES
Industry	YES	YES	YES	YES
CONS	0.0673***	0.0227***	−0.0018	0.0304***
	(0.0144)	(0.0056)	(0.0092)	(0.0075)
N	19,207	19,207	5,782	13,425
R^2	0.5359	0.5361	0.5852	0.5310

***Significance at the 1% level; **Significance at the 5% level; *Significance at the 10% level.

4.3. Robustness testing

4.3.1. Endogeneity

This article employs a one-period lagged sustainability indicator to examine the outcomes provided in Table 7 in order to reduce the endogeneity issue and also to determine if the usefulness of environmental information disclosure is sustainable. The regression results are in line with the initial study and lend credence to hypothesis 1.

4.3.2. Substitution of dependent variables

This work chooses replacement variables for robustness testing to reduce the possibility of regression outcomes from a single

TABLE 7 The results of robustness tests.

	(2)	(1)	(2)	(3)	(4)	(5)	(6)
	L.SGR	SGR	SGR	R&D	SGR	SGR	SGR
EID	−0.0198**	−0.0139***	−0.0275***	−0.0200***	−0.0285***	−0.4337***	−0.0175***
	(0.0028)	(0.0018)	(0.0053)	(0.0055)	(0.0058)	(0.0869)	(0.0063)
EID2	0.0241*		0.0238***	0.0163*	0.0243***	0.6710***	0.0055
	(0.0136)		(0.0087)	(0.0091)	(0.0089)	(0.1430)	(0.0102)
R&D					0.0607***		
					(0.0092)		
R&D*EID					0.0432		
					(0.0468)		
FS						−0.0028***	
						(0.0005)	
FS*EID						0.0182***	
						(0.0039)	
FS*EID2						−0.0287***	
						(0.0063)	
SHA							0.0167***
							(0.0028)
SHA*EID							−0.0834***
							(0.0262)
SHA*EID2							0.1787***
							(0.0491)
Controls	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES
CONS	0.0308***	−0.0017	−0.0009	0.0209***	−0.0021	0.0584***	−0.0043
	(0.0074)	(0.0046)	(0.0046)	(0.0048)	(0.0046)	(0.0119)	(0.0047)
N	13,834	18,299	18,299	18,299	18,299	18299.0000	18299.0000
R^2	0.3291	0.6572	0.6574	0.4019	0.6590	0.6580	0.6583

***Significance at the 1% level; **Significance at the 5% level; *Significance at the 10% level.

TABLE 8 U TEST results.

Extreme point: 0.5555					
Variable	Obs	Mean	S.D.	Min	Max
EID	19,207	0.1805	0.1602	0.0238	0.6905

measure. Sustainable growth rate is calculated using the following formula:

$$\left(\text{Net income / average balance of total owner's equity}\right)^{*}\left[\begin{array}{l}1-\text{dividend per share before tax /}\\ \left(\text{net income current value / average balance of paid}-\text{in capital}\right)\end{array}\right].$$

The opening balance and closing balance are averaged to get the aforementioned average balance. Table 7 displays the test's results, which are robust and leave the key conclusions unaltered.

4.3.3. Changing the sample interval

In this paper, considering the spread of the new crown epidemic and economic depression since 2020, the 2012–2019 A-share listed companies in Shanghai and Shenzhen are selected to test the main, mediating and moderating effects, which are not different from the above results. The manufacturing companies in the sample with high environmental impact are also selected for regression analysis, and the results remain robust. The results are not presented due to space limitation.

4.3.4. Further verification of the U-shaped relationship

The transformation method is used to evaluate the U-shaped relation. Table 8 displays the U TEST results. As can be observed, the sample's minimum value is 0.0238 and its maximum value is 0.6905, with the extreme point for the major impact predicted to be 0.5555. The first U TEST hypothesis is disproved since the tested extreme point falls inside the data range. As a result, we believe that the relationship is U-shaped. It affirms the robustness of the U-shaped link between the environmental information disclosure and the corporate sustainable growth.

4.4. Further analysis

Enterprises are under greater and more scrutiny as a result of growing government regulation, media examination, and public inspection. Due to a lack of resources and the rising costs associated with environmental infractions by businesses, non-state-owned enterprises (NSOEs) must demonstrate a greater sense of environmental governance reform and environmental pioneer statement. In order to meet the requirement of winning over investors and consumers through environmental information disclosure, they are more driven to make modifications to their current environmental facilities, production processes, and emission practices. However, state-owned enterprises (SOEs) generally have poor decision-making efficiency, multiple redundant assets and other lethargic phenomena. This difference makes it difficult for SOEs to carry out green governance. The efficiency of implementing social responsibility through environmental information disclosure is lower than that of NSOEs, so that they are not as sensitive to the economic consequences of environmental information disclosure as NSOEs.

Therefore, with different nature and sensitivity of corporate ownership, the effect of environmental information disclosure on corporate sustainable growth is also different. SOEs receive government subsidies when their environmental information disclosure falls below the threshold, which also lessens the negative consequences of their environmental information disclosure on corporate sustainable growth compared to NSOEs. Because NSOEs are more profit-oriented and are forced to expend more effort due to a lack of corporate resources to have the possibility of achieving corporate sustainable growth, the effect of environmental information disclosure on corporate sustainable growth is also stronger than that of SOEs when it is above the threshold. To examine the heterogeneity of the major impacts in this study, which is based on the Chinese setting, the sample was split into SOEs and NSOEs. The results are shown in Table 6. SOEs do not have significant coefficients in the second term of environmental information disclosure. Due to their unique status, Chinese SOEs often respond to increasing government guidance and looser financial restrictions. The ability of SOEs to disclose environmental information is distorted by the government's involvement in resource allocation and is less economically sensitive, making the effect insignificant. However, in Table 6, it can be seen that the coefficient of the quadratic term is significant for NSOEs. The impact of environmental information disclosure on long-term corporate sustainability can be more accurately described among NSOEs. Therefore, the U-shaped effect of environmental information disclosure on the corporate sustainable growth of non-SOEs is more significant compared to SOEs.

5. Conclusion and discussions

In environmental management, the paradox of "each party is concerned and each party is working independently" still exists. A new "One Planet" concept of green governance must be developed under the cosmology of One Planet, which can objectively reflect the status of environmental governance of listed companies as key actors of green governance. This study tests and draws the following findings using A-share listed businesses from 2012 to 2021 in Shanghai and Shenzhen as examples. First, environmental data disclosure affects innovation inputs and corporate sustainable growth in a U-shaped manner, respectively. Additionally, innovation inputs are used to conduct the U-shaped interaction between environmental information disclosure and the corporate sustainable growth. Further investigation reveals that firm size, equity incentives, and type of property rights influence the U-shaped association between environmental information disclosure and corporate sustainable growth. When a company is small, its equity incentive intensity is high, and it is not state-owned, the U-shaped link between environmental information disclosure and corporate sustainable growth is more significant. This is in contrast to the few studies that focus on examining the propagation mechanisms in terms of innovation subsidy effects and social media attention effects and use board characteristics to test their moderating role, with previous studies ignoring the role of innovation inputs (Consuelo et al., 2021). This paper complements the mediating path role of innovation inputs and verifies the moderating role of equity incentives and firm size. It helps firms to clarify the intrinsic mechanism and context of the role in order to better respond to their sustainable growth strategies.

5.1. Theoretical and practical implications

The findings of this paper also have important theoretical and practical values. First, it expands and enriches the existing research on the economic consequences of environmental information disclosure, clarifies its role path and mechanism of action, and makes its inquiry system more complete. Secondly, this research offers some insight into corporate environmental management. Governments in China are aggressively promoting green governance and speeding up the publication of environmental data at the moment. This study discovers a U-shaped link between environmental information disclosure and corporate sustainable growth, showing that enterprises need to break the threshold to achieve sustainability, which lengthens their cycle. Businesses must weigh the pros and cons of significant cost–benefit decisions when disclosing environmental information and understand the significance of ongoing environmental information disclosure. Enterprises must also modify firm size and equity incentives in accordance with their internal governance environment if they want to continue their long-term growth. Finally, this research offers some insight into how government policy is created. When an enterprise's environmental information disclosure falls below the threshold value, the company must disclose it in order to avoid penalties, which drives up the cost of complying with environmental laws and regulations and discourages investment in new ideas. Through other industrial policies like environmental subsidies, governments may support innovation and corporate sustainable growth. When an enterprise's environmental information disclosure exceeds a threshold value, a governance boundary between the government and the enterprise should be established. Following the environmental information disclosure, the external monitoring role should be fully utilized to give the enterprise a true image of environmental protection and to create favorable conditions for the enterprise to obtain external financing.

5.2. Limitations and future directions

Although the present study is meaningful, it also has some limitations. Firstly, based on various scoring criteria, the content analysis approach used to assess environmental information disclosure yields diverse findings. Because environmental information disclosure is subjective, the accuracy of the analysis's findings may suffer. Secondly, there are several types and characteristics of environmental information disclosure, and this work does not examine them in further detail per context. It will be feasible to categorize the released information into different categories as the context for environmental information disclosure gets richer and more standardized, and the effects of each particular type may then be further investigated in future research. Finally, the study conducted in this paper on environmental information disclosure in developing nations may not be relevant in other nations with distinct cultural climates and economic systems, hence more testing is required to show that the research approach is repeatable and generalizable.

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

MW: software. MW and JZ: writing-review and editing—original draft. JZ: supervision. All authors contributed to the article and approved the submitted version.

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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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EDITED BY
Piotr Toczyski,
The Maria Grzegorzewska University, Poland

REVIEWED BY
Lucian Belascu,
Lucian Blaga University of Sibiu, Romania
Inna Cabelkova,
Czech University of Life Sciences
Prague, Czechia

*CORRESPONDENCE
Feng Peng
✉ pengfeng@whu.edu.cn

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The impact of technology transfer on the green innovation efficiency of Chinese high-tech industry

Shuzhen Zhou[1] and Feng Peng[2]*

[1]China Three Gorges University Library, China Three Gorges University, Yichang, China, [2]Research Center for China Industry-University-Research Institute Collaboration of Wuhan University, Wuhan University, Wuhan, China

Promoting technology transfer is an important strategic measure for China to promote industrial innovation. However, there is little research exploring the influence of technology transfer on the green innovation efficiency (GIE) of China's high-tech industry (HTI). From the perspective of process, green innovation in HTI is a continuous three-stage system including research and development (R&D), commercialization, and diffusion. Therefore, we measure the GIE of China's HTI by using a three-stage network data envelopment analysis (NDEA) model considering environmental pollution and establish a series of regression models to investigate the role of the two main ways of technology transfer, domestic technology acquisition (DTA) and foreign technology introduction (FTI), in improving the GIE of HTI. The results show that the average GIE of China's HTI is 0.7727 from 2011 to 2020. Except for Jiangsu, Guangdong, Qinghai, and Xinjiang, green innovation in HTI in other provinces in China is inefficient. DTA has significantly promoted GIE in HTI. FTI has a positive impact on the GIE of HTI but is not statistically significant. The robustness test confirmed these results. This study is helpful to understand the differences between the effects of DTA and FTI on the GIE of China's HTI, to provide a basis for adjusting technology transfer policies.

KEYWORDS

green innovation efficiency, technology transfer, environmental pollution, high-tech industry, three-stage network data envelopment analysis

1. Introduction

High-tech industry (HTI) refers to technology-intensive industries with high research and development (R&D) intensity and high product added value. It is characterized by innovation and environmental friendliness. It plays an important role in enhancing the competitiveness of the manufacturing industry and promoting economic structural optimization, making it a crucial area in international competition. Technology transfer is an important pathway to promote green development in industries (Fernandes et al., 2021; Zheng et al., 2022). China has actively pursued practical exploration of technology transfer. In September 2017, the State Council of China issued the National Technology Transfer System Construction Plan, with a view toward using technology transfer to provide support for improving the capability of green innovation. According to data released by the National Bureau of Statistics of China, the domestic technology acquisition (DTA) expenditure of Chinese HTI increased from 2.0241 billion yuan in 2011 to 25.1917 billion yuan in 2020. Foreign technology introduction (FTI) funds decreased, however, from 6.9650 billion yuan in 2011 to 18.0730 billion yuan in 2020 (as shown in Figure 1). Facing the dual constraints of limited innovation resources and deteriorating ecological environment (Peng et al., 2022), it is essential to examine the relationship between technology transfer and green innovation capability from

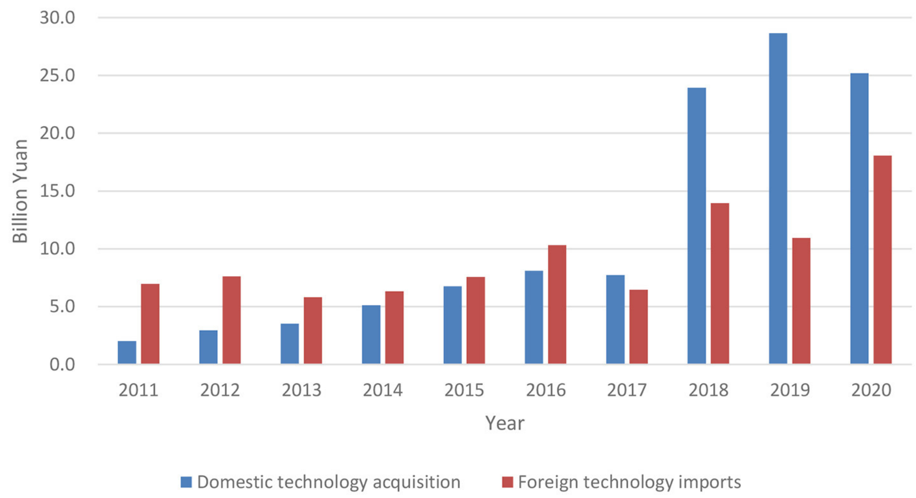

FIGURE 1
Expenditure of two types of technology transfer from 2011 to 2020.

the perspective of process to promote the sustainable development of Chinese HTI. Relevant empirical studies, however, remain lacking.

Some studies have evaluated the green innovation efficiency (GIE) of Chinese HTI. Research to date can be divided into two categories: (1) the "black-box" perspective, which regards the green innovation of HTI as a "black-box" and evaluates the input-output conversion efficiency of this "black-box" (Li L. et al., 2018; Luo et al., 2019); and (2) the process perspective, which regards the green innovation of HTI as a multistage continuous process and evaluates the input-output efficiency of each stage (Deng et al., 2020). Compared with the "black box" perspective, the process perspective can further our understanding of industrial GIE and its components.

Some research has analyzed the impact of technology transfer on GIE in HTI from the "black box" perspective. Liu et al. (2020) found that in the areas with strong competitiveness of HTI, DTA was significantly positively related to the GIE of HTI, whereas the role of FTI was just the opposite. However, few studies have examined the differences between the two ways of technology transfer in improving the efficiency of green innovation from a process perspective (Liu et al., 2020). In addition, when measuring GIE in HTI, existing studies often choose sulfur dioxide (SO2) emissions as a single undesirable output indicator, which may lead to measurement bias of the results of GIE (Yang et al., 2020).

There are two main contributions in this paper. First, from the perspective of process, we decomposed the green innovation process of HTI into three stages: R&D, commercialization, and diffusion. On this basis, a three-stage index system of green innovation in HTI was constructed, and the network data envelopment analysis (NDEA) model considering environmental pollution was used to measure the GIE of inter-provincial HTI in China. Second, after measuring the GIE, a series of regression models are constructed to examine the differences between the two ways of technology transfer, DTA and FTI, in promoting the GIE of HTI.

In Section 2, we review the theoretical literature on the impact of technology transfer on GIE in HTI. In Section 3, we introduce our research methods, including the three-stage NDEA model and the regression model. In Section 4, we provide estimated results of the impact of technology transfer on industrial GIE. In Section 5, we render conclusions and limitations.

2. Theoretical background

The use of technology transfer can help enterprises overcome internal constraints that affect their green development, such as lack of capacity or input (Ghisetti et al., 2015). Technology transfer plays a crucial role in facilitating green innovation (Leiponen and Helfat, 2010; Hu et al., 2017). DTA and FTI are the two main types of technology transfer (Li et al., 2020; Qian et al., 2022).

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DTA is an important channel to obtain external technology. Enterprises can obtain the technical knowledge needed for their product or process innovation from local universities and research institutions to supplement or replace expensive R&D activities (Caloghirou et al., 2004). Because the technology gap of these domestic enterprises is relatively small, recipients can better digest, and absorb domestic technology (Deng and Lu, 2021). Furthermore, the same knowledge background of domestic enterprises can reduce transaction costs and information asymmetry (Li, 2011). Some high-tech enterprises improve the efficiency of innovation through industry-university-research cooperation (Chen et al., 2016). It is often difficult for developing countries to acquire specialized, diversified, and advanced technical knowledge when acquiring domestic technologies, however, and it

TABLE 1 Input-output variables in the process of three-stage green innovation.

Phase	Category	Item	Variable
R&D phase	Input	Original input	R&D expenditure
			R&D full-time equivalent
	Output	Intermediate	Number of patent applications
			Number of patents in force
Commercialization phase	Input	Intermediate	Number of patent applications
			Number of patents in force
		Additional input	New product development expenditure
	Output	Intermediate	Sales income of new products
Diffusion phase	Input	Intermediate	Sales income of new products
		Additional input	Number of new product development projects
	Output	Desirable output	Revenue from main business
		Undesirable output	SO_2 emissions
			Solid waste emissions

may be difficult to help them accelerate their innovation process (Elia et al., 2020).

FTI is another important channel of technology transfer. Latecomer countries can carry out technological innovation based on introduced technology and catch up technologically in a short time (Awate et al., 2015; Yu et al., 2019). The introduction of high technology will enable developing countries to obtain technology spillover effects (Belitz and Molders, 2016). Nevertheless, technology introduction may cause developing countries to fall into the "technology dependence trap," which can lead to the inhibition of their independent innovation capacity (Laursen and Salter, 2006; Choi, 2017). In addition, the introduced technology may contain highly polluting mechanical equipment, which may cause damage to the environment (Peters and Hertwich, 2006; Tukker et al., 2013). Therefore, the influence of FTI on GIE is uncertain.

Green innovation requires enterprises to deal with complex technological and economic problems, therefore, requires knowledge input from different technological sources (Cainelli et al., 2015; Ketata et al., 2015). The effectiveness of green innovation is influenced by the source of technical knowledge, but most importantly, by the combination of technical knowledge in the green innovation process (Ben Arfi et al., 2018). Therefore, the process perspective will provide a new understanding of the differences in the role of different technology transfer modes in the improvement of GIE in HTI.

3. Methodology

3.1. Model

To analyze the influence of technology transfer on the GIE of Chinese HTI, we set the following model:

$$GIE_{it} = \alpha_0 + \alpha_1 DTA_{it} + \alpha_2 FTI_{it} + \gamma_k \varnothing_{it} + \varepsilon_{it} \tag{1}$$

where the subscripts i and t represent the province and year, respectively; GIE represents the GIE of HTEs; DTA represents the domestic technology acquisition; FTI represents the foreign technology introduction; $\varnothing$ is the control variable vector; and ε represents the random error.

3.2. Dependent variable

From the perspective of process, the green innovation process of HTI can be divided into three stages: R&D, commercialization, and diffusion (Lin et al., 2023). The input-output variables of these three stages are shown in Table 1.

The input in the R&D stage is R&D full-time equivalent and R&D expenditure (Wang et al., 2016; Du et al., 2019). Its output is patent applications and patents in force (Zhang et al., 2019). These outputs are also inputs in the commercialization phase. Supplementary input in the commercialization stage is the expenditure for new product development (Du et al., 2019). The output is the sales income of new products. This output is also the input of the diffusion phase. The supplementary input in the diffusion stage is the number of new product development projects (Chen et al., 2021b). The desirable output of the diffusion stage is the main business income (Lin et al., 2023), and its undesirable output is environmental pollution emissions. Due to the availability of data, SO2 emissions and wastewater emissions were selected as undesirable outputs in this paper (Yang et al., 2020; Chen et al., 2021a).

Stochastic frontier analysis (SFA) and DEA are common methods used to measure GIE. The SFA method offers advantages in dealing with measurement error and statistical interference (Zhu et al., 2021), but it is difficult to use when dealing with the input-output efficiency evaluation of multiple stages and multiple outputs (Li T. et al., 2018). The DEA method is often used to measure the relative efficiency of the same kind of decision-making units (DMUs) with multiple

TABLE 2 Descriptive statistical results.

Variable	Mean	Std. Dev.	Min	Max	Observations
GIE	0.7727	0.1601	0.3942	1.0000	300
DTA	0.0854	0.3819	0.0000	5.7734	300
FTI	0.0337	0.0623	0.0000	0.5273	300
ES	0.3955	0.1670	0.0676	0.7961	300
ML	83.0340	13.3334	34.3984	100.0000	300
FDI	9.8640	10.0181	0.0000	53.5211	300
HC	0.7547	0.8235	0.0172	3.6267	300
ER	5.6386	2.7307	1.6413	16.4889	300

inputs and outputs (Tang and Qin, 2021), and it can provide improvement basis for increasing desirable outputs and reducing undesirable outputs of non-effective DMUs (Liu et al., 2020).

From the process perspective, the process of green innovation in HTI includes multiple stages and involves a variety of inputs and outputs. Therefore, the network DEA model is needed to measure GIE (Cook et al., 2010; Du et al., 2019).

Assume that x_{ij}^{l} and y_{rj}^{l} represent the ith input and the rth output of the jth DMU at the lth node (phase), respectively; $z_{f_{(l,l')}j}^{(l,l')}$ represents the intermediate output of the jth DMU between the lth node (phase) and the l'th node (phase); and the subscript $f_{(l,l')}$ indicates the number of intermediate outputs between the lth node (phase) and the l'th node (phase), $f_{(l,l')} = 1, \cdots, F_{(l,l')}$. The NDEA model can be expressed as follows (Tavana et al., 2013):

$$\gamma^{*} = \min_{\theta_k,\lambda,S^-} \sum_{l=1}^{k} W_l \left(\theta_l - \varepsilon_x^l \sum_{i=1}^{m_l} \frac{w_i^{l-} S_i^{l-}}{x_{i_0}^{l}}\right) \tag{2}$$

$$\begin{aligned}
s.t.&\\
&\sum_{j=1}^{n} x_{ij}^{l}\lambda_j^{l} + S_i^{l-} = \theta_h x_{i0}^{l},\\
&\sum_{j=1}^{n} y_{rj}^{l}\lambda_j^{l} \geq y_{r0}^{l},\\
&\sum_{j=1}^{n} z_{f_{(l,l')}j}^{(l,l')}\lambda_j^{l} = \sum_{j=1}^{n} z_{f_{(l,l')}j}^{(l,l')}\lambda_j^{l'},\\
&i = 1,\cdots,m_l,\ l = 1,\cdots,k,\\
&r = 1,\cdots,s_l,\ l = 1,\cdots,k,\\
&f_{(l,l')} = 1,\cdots,F_{(l,l')},\ \forall (l,l'),\\
&\theta_l \leq 1,\ l = 1,\cdots,k,\\
&\lambda_j^{l} \geq 0,\ j = 1,\cdots,n,\ l = 1,\cdots,k,\\
&s_i^{l-} \geq 0,\ i = 1,\cdots,m_l,\ l = 1,\cdots,k,
\end{aligned}$$

where w_i^{l-} represents the weight of the ith input of the lth node (phase), which satisfies $\sum_{i=1}^{m_l} w_i^{l-} = 1$; ε_x^l is used to measure the dispersion of various inputs of the lth node (phase); ε_x^l represents the relaxation of the ith input of the lth node (phase); and W_l represents the weight of the lth node (phase).

3.3. Explanatory variables and control variables

3.3.1. Explanatory variables

Explanatory variables include DTA and FTI. DTA is measured by the ratio of the expenditure on the purchase of domestic technology to the main business income of HTI. FTI is measured by the ratio of expenditure on the introduction of foreign technology to the main business income of HTI.

3.3.2. Control variables

In addition to these two types of technology transfer, the existing literature also has identified other influencing factors of GIE in HTI, including enterprise scale (ES), marketization level (ML), foreign direct investment (FDI), human capital (HC) level, and environmental regulation (ER) (Li L. et al., 2018; Li T. et al., 2018; Peng et al., 2018; Zhang et al., 2022).

(1) ES

Green innovation is costly and risky. Large-scale enterprises have more abundant resources for green innovation, and thus, they are more able to bear the costs and risks of green innovation (Li T. et al., 2018). As the enterprise grows in scale, however, its innovation management efficiency also may decrease (Zhu et al., 2021).

(2) ML

The cooperation between technology suppliers and consumers has an important impact on improving the utilization rate of technology (Li L. et al., 2018). The market is a platform for technology transfer and diffusion. A mature market can enhance the cooperation between technology suppliers and demanders, thus promoting the transfer and diffusion of technology more effectively (Li T. et al., 2018).

(3) FDI

FDI from developed countries usually has technology spillover effect on enterprises in developing countries (Sari et al., 2016;

Vujanovic et al., 2022). This provides a technological basis for enterprises in developing countries to achieve green innovation (Feng et al., 2018; Luo et al., 2021).

(4) HC

The HC level affects firms' ability to absorb external technologies (Kneller and Stevens, 2006; Huang et al., 2019). Firms with higher HC levels are better able to adopt external technologies than others (Blalock and Gertler, 2009; Guo et al., 2022).

(5) ER

ER increases the expenditure of controlling environmental pollution for enterprises and squeezes out the funds for technological innovation (Zhang et al., 2021). ER, however, also can encourage enterprises to carry out technological innovation, which may introduce more benefits (Li and Zeng, 2020).

These factors are widely used in the empirical study of GIE in Chinese HTI. Zhang et al. (2022) confirmed that ES is significantly positively correlated with industrial GIE. Li T. et al. (2018) confirmed that ML has a positive impact on GIE. Peng et al. (2018) found a significant positive correlation between FDI and GIE. Yang et al. (2022) found that the HC level has a significant positive impact on GIE. Li L. et al. (2018) found that ER has a significant negative impact on GIE. Therefore, we chose FDI, HC level, ML, ER, and ES as control variables.

FDI is expressed as a ratio of the number of foreign-funded enterprises in HTI (Xu et al., 2020). ML is expressed by the ratio of non-state-owned enterprises in the main business income of this (Wang et al., 2021). HC level is expressed by the proportion of employees in the local population (Wang and Zhao, 2021). Per capita GDP is used as the proxy variable for ER (Antweiler et al., 2001). ES is expressed by the average value of the main business income of enterprises (Li T. et al., 2018).

The data used to calculate SO2 emissions and solid waste emissions come from the China Environmental Statistics Yearbook 2012–2021. Data used to calculate environmental regulation come from the China Statistical Yearbook 2012–2021. The data used to calculate other variables come from the Statistical Yearbook of China's High-tech Industry 2012–2021.

The descriptive statistical results of the variables are shown in Table 2. Considering the integrity of the data, we selected the panel data of 30 provinces in China from 2011 to 2020 to examine the impact of technology transfer on the GIE of China's HTI.

4. Results and discussion

4.1. Measurement of GIE

Based on the panel data of 30 provinces in China from 2011 to 2020, we use equation (2) to calculate the GIE of China's HTI (see Table 3).

As shown in Table 3, Jiangsu, Guangdong, Qinghai, and Xinjiang are the provinces with high GIE in China's HTI, and the green innovations of these four provinces are all effective. Except for these four provinces, green innovation in HTI in other provinces is ineffective. Among them, Heilongjiang has the lowest green innovation efficiency, with an efficiency value of only 0.5053. The average GIE of China's HTI is 0.7727.

4.2. Regression results

The value of GIE calculated by the NDEA model is between 0 and 1. For restricted dependent variables, the use of OLS regression can lead to inconsistent estimates. Tobit regression is a common method to analyse this type of sample data (Chen, 2014). Therefore, we use the Tobit model to analyse the impact of technology transfer on the GIE of China's HTI.

Equation (1) is used to analyse the influence of technology transfer on GIE in HTI. Model 1, Model 2, and Model 3, respectively, introduced a series of control variables by stepwise regression method. These control variables include ES, ML, FDI, HC, and ER. The final estimated results are shown in Table 4. The results of the likelihood ratio test (LR test) confirm that the Tobit regression method of random effects should be used for all three models.

Models 1, 2, and 3 show that DTA has a significant positive impact on GIE. The coefficients are 0.0231, 0.0209, and 0.0210 respectively. Models 1, 2 and 3 also show that there is a positive correlation between FTI and GIE, with coefficients of 0.0191, 0.0486, and 0.0692 respectively, but it is not statistically significant. The coefficients of ES and ML are significantly positive, indicating that both ES and ML can promote GIE. After considering ER, the impact of FDI and HC on the GIE is no longer significant. The relationship between ER and GIE forms an inverted U. This relationship shows that moderate ER is conducive to green innovation, but that strict ER may be harmful to GIE in HTI.

For comparison, Table 5 shows the estimated results of the fixed-effects model (using Cluster-Robust Standard Errors). It can be found that whether using Tobit random effect model or fixed effect model, the results show that DTA has a significant positive impact on GIE. The FTI is positively related to GIE, but it is not statistically significant.

4.3. Robustness test

We used three methods to test the robustness of the estimates. First, we introduced more control variables into the regression model. Considering the influence of location factors, MID is used to represent the dummy variable of the central region, and WEST is used to represent the dummy variable of the western region. Model 7 shows that although location factors have a significant impact on GIE, the estimation results of independent variables do not change with the addition of more control variables. Second, this paper uses short panel data ($N = 30$, $T = 10$). Due to the small-time dimension T, it is difficult to test the hypothesis of autocorrelation and heteroscedasticity. In this case, we use the panel corrected standard error (PCSE) method to give a consistent estimate. Model 8 shows that the estimates are still robust. Finally, the regression model used to discuss the impact of technology transfer on GIE may have endogenous problems (Zhou et al., 2020).

TABLE 3 GIE in Chinese HTI.

Province	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
Beijing	0.6728	0.6906	0.6548	0.6635	0.6206	0.7345	0.7412	0.7176	0.7530	0.7175	0.6966
Tianjin	0.6792	0.7137	0.7283	0.6720	0.6633	0.7112	0.6865	0.6370	0.6484	0.6130	0.6753
Hebei	0.6060	0.6516	0.6201	0.6023	0.6121	0.7261	0.7096	0.6700	0.7164	0.6104	0.6525
Liaoning	0.6724	0.6890	0.6726	0.6949	0.6335	0.6630	0.6680	0.6525	0.6884	0.6434	0.6677
Shanghai	0.9945	1.0000	1.0000	0.9020	0.7685	0.8593	1.0000	1.0000	1.0000	1.0000	0.9524
Jiangsu	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Zhejiang	0.6565	0.6906	0.6611	0.6825	0.6843	0.7562	0.7661	0.7355	0.7730	0.7280	0.7134
Fujian	1.0000	0.8790	0.9158	0.9036	0.8136	0.8841	0.9578	0.9066	0.9583	0.8595	0.9078
Shandong	0.7047	0.7339	0.7300	0.7277	0.6771	0.7418	0.7373	0.7121	0.7476	0.6647	0.7177
Guangdong	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hainan	0.5032	0.6299	0.5680	0.5733	0.5135	0.7012	0.6880	0.6728	0.7274	0.5637	0.6141
Shanxi	0.7045	0.7559	0.7708	1.0000	0.8495	0.9260	0.8851	0.8471	0.8735	0.7907	0.8403
Jilin	0.6409	0.6853	0.5435	0.7022	0.6652	0.7421	0.7120	0.6522	0.7060	0.5474	0.6597
Heilongjiang	0.4521	0.5104	0.4771	0.5141	0.4524	0.6880	0.5422	0.4858	0.5215	0.4093	0.5053
Anhui	0.5683	0.6703	0.6567	0.7026	0.6963	0.7675	0.7744	0.7669	0.8178	0.7504	0.7171
Jiangxi	0.6514	0.7148	0.6815	0.7759	0.7184	0.7713	0.7787	0.7673	0.8018	0.7442	0.7405
Henan	0.6941	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9694
Hubei	0.6045	0.6800	0.6816	0.6768	0.6790	0.7605	0.7689	0.7423	0.7792	0.7112	0.7084
Hunan	0.6587	0.7714	0.7321	0.7103	0.6974	0.7766	0.7702	0.7324	0.7772	0.7072	0.7334
Inner Mongolia	1.0000	1.0000	1.0000	1.0000	0.7230	0.7567	0.7676	0.7805	0.8140	0.7080	0.8550
Guangxi	0.6401	0.7537	0.7919	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.8911	0.9077
Chongqing	0.7209	0.8759	1.0000	0.9217	0.8966	1.0000	1.0000	1.0000	1.0000	1.0000	0.9415
Sichuan	0.6491	0.6978	0.6838	0.6837	0.7069	0.8197	0.8063	0.7687	0.8117	0.7878	0.7416
Guizhou	0.3942	0.4351	0.4270	0.5380	0.5403	0.6872	0.7018	0.6946	0.7266	0.6355	0.5780
Yunnan	0.4972	0.6183	0.6300	0.6083	0.5200	0.7102	0.7185	0.7138	0.7796	0.7434	0.6539
Shaanxi	0.4963	0.5048	0.4949	0.5397	0.6045	0.7028	0.7095	0.6859	0.7107	0.6865	0.6136
Gansu	0.4665	0.5734	0.5760	0.5811	0.5827	0.7217	0.7198	0.7097	0.7603	0.7061	0.6397
Qinghai	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Ningxia	0.5296	0.7320	0.6845	0.7583	0.9087	0.8871	0.8563	0.7902	0.8286	0.7956	0.7771
Xinjiang	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Instrumental variable (IV) method is a common method to deal with the endogeneity of panel data (Lu et al., 2018). We use lag variables as a tool to deal with endogeneity problems. In Model 9, the Wald test shows that the original hypothesis of exogenous is accepted. At the same time, the results of the independent variables are also robust (see Table 6).

5. Discussion

Some studies use the NDEA model to measure the innovation efficiency of China's HTI (Chen et al., 2018; Wang et al., 2020), but these studies do not consider environmental pollution in the innovation process of HTI. Differently from previous research, this paper uses the three-stage network DEA model to measure the GIE of China's HTI, because this deepens our understanding of the GIE in China's HTI.

DTA has significantly promoted GIE in Chinese HTI. This result is in accord with the findings of Liu et al. (2020), even though the two studies apply different measurement methods for dependent variables and independent variables (Liu et al., 2020). Under the development concept of green innovation, China actively supports enterprises to form strategic alliances with universities and research institutes for collaborative technological research. This enhances the green innovation capability of Chinese HTI; thus, DTA has a significant positive effect on the GIE of HTI.

The impact of FTI on the GIE of China's HTI is not significant. This result is different from the discovery made by Liu et al. (2020),

TABLE 4 Influence of technology transfer on GIE in Chinese THI.

Variables	(1)	(2)	(3)
DTA	0.0231**	0.0209**	0.0210**
	(2.25)	(2.04)	(2.12)
FTI	0.0191	0.0486	0.0692
	(0.24)	(0.59)	(0.86)
ES	0.4076***	0.3608***	0.3069***
	(8.64)	(7.16)	(5.72)
ML	0.0037***	0.0034***	0.0030***
	(6.67)	(6.20)	(5.46)
FDI		−0.0034***	−0.0007
		(−2.63)	(−0.44)
HC		0.0578**	0.0135
		(2.48)	(0.48)
ER			0.0311***
			(3.24)
ER^2			−0.0013***
			(−2.78)
Constant	0.3030***	0.3314***	0.2691***
	(5.95)	(6.46)	(4.91)
Log likelihood	357.5537	361.7736	367.2400
LR test	294.16***	270.77***	280.48***
Observations	300	300	300
Number of province	30	30	30

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE 5 Estimated results of fixed effect model.

Variables	(4)	(5)	(6)
DTA	0.0213***	0.0190***	0.0202***
	(3.95)	(3.54)	(3.79)
FTI	0.0329	0.0633	0.0932
	(0.40)	(0.64)	(0.78)
ES	0.4274***	0.3777***	0.3008***
	(5.53)	(4.46)	(3.60)
ML	0.0033***	0.0031***	0.0027**
	(3.09)	(2.78)	(2.38)
FDI		−0.0029*	0.0033*
		(−1.70)	(1.85)
HC		0.0684*	−0.0195
		(1.75)	(−0.44)
ER			0.0447***
			(2.98)
ER^2			−0.0017**
			(−2.22)
Constant	0.3245***	0.3413***	0.2251**
	(3.76)	(3.81)	(2.36)
Observations	300	300	300
Number of province	30	30	30

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

who found that FTI hinders GIE in areas where HTI is highly developed. Although FTI will produce a technology spillover effect to some extent (Belitz and Molders, 2016). However, due to the lack of the technology absorptive capacity of most enterprises, it is difficult for China's HTI to obtain the corresponding economic and environmental benefits, so its impact on the GIE of HTI is not significant.

Existing research on the GIE of China's HTI generally regards green innovation as a "black box" (Li L. et al., 2018; Luo et al., 2019). According to the process perspective, green innovation in HTI is a three-stage system including R&D, commercialization, and diffusion. Therefore, we establish a three-stage NDEA model considering environmental pollution to measure GIE. This method provides an improved method for measuring the GIE of China's HTI.

The effectiveness of green innovation is affected by the source of technological knowledge, but most importantly by the combination of technological knowledge in the process of green innovation (Ben Arfi et al., 2018). However, there is little literature on the impact of various ways of technology transfer on GIE in China's HTI from a process perspective (Liu et al., 2020). We bring the two main ways of technology transfer, DTA and FTI, into a unified framework and discuss the impact of technology transfer on GIE from a process perspective. This research has deepened our understanding of the role of technology transfer in improving GIE in HTI.

6. Conclusion

Based on panel data from 30 provinces in China from 2011 to 2020, we used the three-stage NDEA model to evaluate the GIE of China's HTI and used the Tobit model to analyze the impact of DTA and FTI on the GIE of HTI. The results show that the average GIE of China's HTI is 0.7727. Except for four provinces, green innovation in most provinces is ineffective. DTA significantly promotes the improvement of GIE of China's HTI, while the impact of FTI on the GIE of HTI is not significant.

6.1. Implications for practice and policy

At present, the competition in high-tech field is increasingly fierce, and DTA has become an important approach to elevate GIE in Chinese HTI. In the process of actively promoting the construction of the national technology transfer system, China should pay more attention to improving its national technology trading network platform to provide information resources for high-tech enterprises to obtain appropriate domestic technologies. Moreover, it should actively support high-tech

TABLE 6 Results of robustness tests.

Variables	(7)	(8)	(9)
	Tobit	PCSE	IV-Tobit
DTA	0.0215**	0.0484**	0.0466***
	(2.17)	(2.23)	(3.00)
FTI	0.0865	0.0658	0.0563
	(1.08)	(0.70)	(0.26)
ES	0.2789***	0.1797***	0.1752***
	(5.17)	(5.51)	(3.50)
ML	0.0032***	0.0064***	0.0065***
	(5.70)	(12.99)	(12.63)
FDI	0.0002	−0.0025***	−0.0027**
	(0.14)	(−3.80)	(−2.46)
HC	0.0358	0.0663***	0.0673***
	(1.34)	(13.27)	(5.65)
ER	0.0326***	0.0255***	0.0168
	(3.46)	(3.25)	(1.57)
ER^2	−0.0013***	−0.0011***	−0.0006
	(−2.67)	(−2.66)	(−1.04)
MID	0.0786	0.0454***	0.0441*
	(1.41)	(5.51)	(1.87)
WEST	0.1630***	0.1472***	0.1481***
	(3.07)	(11.27)	(6.47)
Constant	0.1498**	−0.0251	0.0005
	(2.14)	(−0.49)	(0.01)
LR test	228.38***		
Wald test			0.5990
Observations	300	300	270

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

enterprises to build strategic alliances supporting industrial green innovation with universities and research institutions and should proceed green R&D and commercialization activities in line with market demand.

Although FTI has no significant positive impact on the GIE of HTI, we should not give up opening and technological cooperation. While actively introducing foreign advanced technology, it is necessary to enhance the absorptive capacity to realize the integration and utilization of foreign technological resources. In addition, an international technology transfer platform must be established to provide information services for the introduction of foreign technology. This can not only reduce the opportunity cost of introducing technology to high-tech enterprises, but also improve the applicability of imported technology to these enterprises.

6.2. Limitations and future research

According to the process perspective, we analyzed the influence of DTA and FTI on GIE in HTI under a unified framework and conducted an empirical test on the effect of these two types of technology transfer on efficiency improvements at each stage of green innovation. This study had two shortcomings, though. First, we introduced environmental pollution into the GIE analysis framework to explore the influence of technology transfer on GIE in HTI. However, because of the availability of data, we did not consider other undesirable output factors, such as wastewater and carbon dioxide emissions, when measuring the GIE. Second, Chinese HTI include pharmaceutical manufacturing, aviation equipment manufacturing, communication equipment manufacturing, and other sub-industries. Differences in the technological characteristics of these various sub-industries will affect the decision making about technology transfer. When we studied the relationship between technology transfer and GIE in HTI, we did not consider industry heterogeneity. These areas will be the focus of 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 author.

Author contributions

Methodology, software, validation, formal analysis, data curation, and writing—original draft preparation: SZ. Conceptualization, writing—review and editing, supervision, and project administration: FP. All authors have read and agreed to the published version of the manuscript.

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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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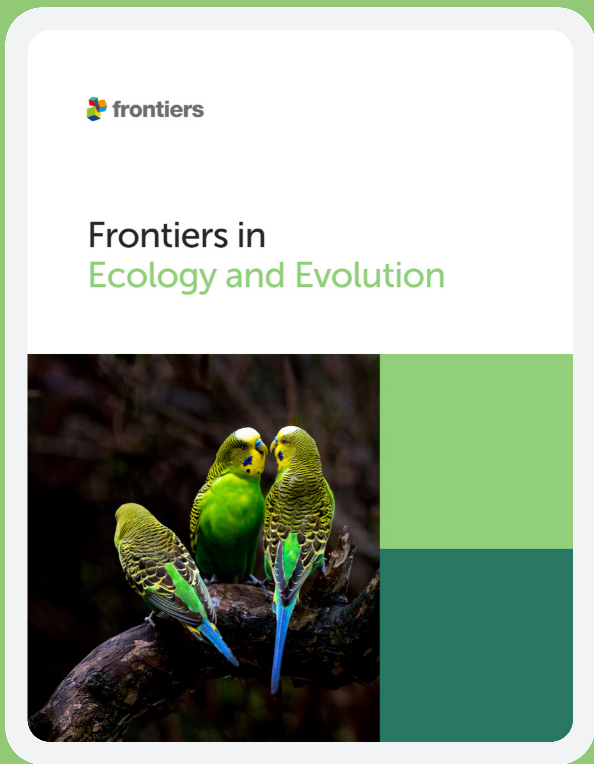

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