Research Topics

Green indicators to inform circular economy under climate change

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Green indicators to inform circular economy under climate change

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Editorial: Green indicators to inform circular economy under climate change

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Editorial on the Research Topic
Green indicators to inform circular economy under climate change

This Research Topic gathers research which makes use of indicators to assess the environmental impact of economies and proposed sustainability transitions. A helicopter view of the combined set of insights reveals a number of relevant trends in this area of research. First, we can distinguish between indicators at different levels (macro versus micro). Second, it is observed that some of the useful indicators in this context are generic in nature, while others specifically focus on environmental aspects or even specific sustainability transitions (e.g., circular economy). Third, the indicator-based research provides useful information for policy makers and multiple stakeholders in general and, given its importance, the financial sector in particular.

The obstacle of climate change is among the major concerns that mankind is experiencing today. Climate change poses remarkable risks to the planet and human health such as extreme weather conditions, decreasing of agricultural productivity, and lack of food.

The quest for solutions to protect the environment in combination with achieving sustainable development is difficult. These solutions should arise out of societal, economic and technological transitions. These proposed transitions are very different in nature, and consequently, it is very difficult to assess the impact of the different transitions on the environment and sustainable development. To tackle this issue, researchers increasingly make use of indicators either describing the state of the environment or the transitions. In this context, the number of available indicators is growing rapidly, and more data is gathered over longer periods in time. Both evaluations allow more detailed and robust (often econometric) analysis.

The aim of these studies is to scan for correlations or causal relations between social, economic, and technological parameters on the one hand and environmental outcomes on the other hand. This field of research is rapidly growing and gaining importance throughout the world. The latter is also demonstrated by the geographical coverage of papers published in the framework of this

Research Topic. The Research Topic encompasses research which covers China, the European Union, Central and Eastern Europe, the Organisation for Economic Co-operation and Development (OECD) countries, the so-called BRICS countries (i.e., Brazil, Russia, India, China and South Africa) and the G7 countries (i.e., Canada, France, Germany, Italy, Japan, the United Kingdom, the United States of America). In addition, authors such as Yu et al. present a comparative analysis for some of these regions.

The number of proposed transitions is rapidly growing, and the transitions are diverse in nature. Consequently, also the number of proposed indicators is expanding, as they aim to capture information on very different aspects of the proposed transitions. Nevertheless, some trends become apparent. First, the current Research Topic presents papers on a wide range of indicators which aim to describe the state and use of technology within an economy. Some of these indicators are rather generic and cover for example "technological spill-over" (Huang and Pei) and "technological innovations" (Ahmad et al.), "economic complexity" (Neagu et al.), "high-tech manufacturing co-agglomeration" (Peng et al.), "import of intermediates" (Huang and Pei), and "producer service industry" (Peng et al.).

A second category of indicators specifically monitors the importance of green infrastructure and carbon-neutral production facilities. Such kind of indicators used in the studies gathered in this Research Topic for example are the "green openness" of an economy (Ahmad et al.), the "green total factor productivity" (Tang and Qin), "green total factor energy efficiency" (Wang et al.), "green development" (Zhang et al.), "carbon neutrality" (Lu et al.) and "eco-investment" (Constantinescu et al.).

While the second category of indicators has a focus on environmental-friendly technology in general, there are also indicators which are specifically designed to monitor trends of specific aspects of sustainability transitions. Examples are the transition towards a more circular economy, or the uptake of renewable energy production and consumption. In this context, this Research Topic gathers studies which make use of indicators such as the "renewable energy technology budgets" (Ahmad et al.) and "green energy consumption" (Peng G. et al.), the set of "circular economy indicators" presented by EUROSTAT (e.g., recycling rates, self-sufficiency of raw materials …) or "circular material use rate" (Platon et al.). These types of indicators allow for more detailed analyses of specific trends in the structure of economies.

This Research Topic is designed to expand the knowledge of the relationship between the environment and various social and economic indicators to enable reliable and long-term plans. As the Research Topic identifies the crucial micro- and macro-determinants of environmental quality and sustainable development, the outcome of the Research Topic provides valuable insights to policy makers in specific.

That link to policy is also apparent from the topics covered in the Research Topic. Many of the presented papers focus on a selection of policies which directly impact an economy's structure and hence the indicators mentioned. This demonstrates the presumed steering potential of policies such as "carbon emission trading schemes", "carbon market pricing", "environmental taxes", or "innovation support". The usefulness of research on these aspects is twofold. First, (often econometric) research assesses the efficiency and impact of existing policies. Second, research identifies possible pathways for the design of future policies which envisage a more sustainable production system.

In addition to policy makers and researchers, the presented studies also provide information to other stakeholders involved in the transition towards more sustainable economies. Economic actors along the value chain of different products can draw important lessons from the presented research. We in particularly would like to stress the importance of the financial sector in this context. Since the papers often focus on technology-related indicators, this straightforwardly leads to analyses which also cover indicators linked to access to funding and financial products in general. Worth mentioning here are the "access to green credit" (Qin and Cao), "financial inclusion" (Ahmad et al.), "eco-investments" (Constantinescu et al.), "financial risk" and "renewable energy technology budgets" (Ahmad et al.), and "supply chain finance" (Liu et al.). Various studies in this Research Topic stress the importance of financial risk as a barrier to sustainable transitions. The latter is especially crucial in case transitions are mainly technology-based (instead of, for example, societal transitions). The mediating role of the financial sector, and possible financial products to tackle that barrier is crucial and deserves attention by both the sector itself and policy makers. Innovative financial products should facilitate the funding for research and development and investments in (the up scaling of) sustainable and green technology and business practises which seek not to harm the natural environment. However, the financial products should also move beyond the pure funding-type of products. Sustainability transitions also for example require insurance products for new products, business models, or innovative services.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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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Analyzing the Effect of Local Government Competition on Green Total Factor Productivity From the Market Segmentation Perspective in China—Evidence From a Three-Stage DEA Model

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Under both Chinese-style fiscal decentralization (vertical competition) and promotion tournament systems (horizontal competition), the economic development system used by the government determines whether local government competition significantly influences green total factor productivity (GTFP). Moreover, market segmentation, an important strategic tool for local government competition, will significantly impact GTFP because of the implied changes in production efficiency and blocked factor flows. This study applies GMM and the mediation effect model to explore the relationship between local government competition and GTFP from the market segmentation perspective using statistical data from 30 provinces from 2006 to 2017 in China. Overall, our results demonstrate that local government competition significantly inhibits GTFP promotion. Local government competition also has a negative impact on GTFP by promoting market segmentation. As a mediating variable, the market segmentation coefficient was statistically significant. Considering regional heterogeneity, in the eastern region, local government competition has no significant inhibitory effect on GTFP. Moreover, market segmentation has no intermediary effect. In the central and western regions, GTFP remains significantly inhibited by local government competition, and the mediation effect of market segmentation is significant. Finally, our empirical results are robust.

Keywords: local government competition, market segmentation, green total factor productivity, mediation effect, China

INTRODUCTION

In the past 40 years of reform and opening-up, China's economy has achieved a "growth miracle," with gross domestic product surging from approximately 367.9 billion to 99 trillion yuan in 1978 and 2019, respectively[1]. Simultaneously, eco-damage and environmental pollution have followed one after another, and emissions of pollutants such as industrial waste haze and greenhouse gases

[1]See in more detail: http://www.stats.gov.cn/.

continue to surge (Ahmed et al., 2020; Lin et al., 2021). The China Ecological Environment Status Bulletin 2019 shows that among the 337 prefecture-level cities, 180 exceeded the ambient air quality standard, accounting for 53.4%[2]. Moreover, the problems of a suboptimal energy structure and low-energy utilization efficiency are more prominent. China's coal consumption has since comprised more than 60% of the total energy consumption. Therefore, although extensive growth modes such as high capital input, high consumption of resources, and high environmental pollution have created an economic "growth miracle," the ecological and social benefits have been seriously undermined, causing China's economy to suffer from the low output and low efficiency (Wu et al., 2020a; Wang J. et al., 2021). Currently, China's economy is in a critical period of transforming development, optimizing economic structure, and changing growth momentum. Promoting efficient change and achieving green economic development has become the major direction of China's future economic development (Ouyang et al., 2019; Zhang et al., 2020). Normally, improving green total factor productivity (GTFP) can become a win-win situation for both economic and environmental performance. Therefore, for China to nurture high-quality economic development in the new era, the deep-rooted motives damaging coordinated development of the economy and environment and further improving GTFP must be determined.

In this context, the worldwide scholarly community has explored various perspectives concerning the causes of ecological degradation (Can et al., 2021a; Ahmed et al., 2021; Yang et al., 2021a). Many scholars attribute the inefficiency of Chinese environmental governance and its ecological plight to the "bottom-to-bottom competition" among local governments in environmental governance. That is, local governments compete to seek lower environmental regulation standards to entice financial and technological resources, resulting in environmental degradation (Zhang et al., 2021). Particularly, after the 1994 tax reform formalized the fiscal decentralization system, competition among local governments increased significantly, as induced by the "GDP-only" performance appraisal system. However, under constrained resources, the environmental problems caused by chaotic competition among local governments are gradually intensifying (Qian and Weingast, 1997). Meanwhile, under the goal-oriented approach of economic growth, local governments inadvertently compete to weaken environmental regulations and shelter-polluting industries regardless of ecological costs, which, in turn, has an essential impact on GTFP.

Market segmentation occurring alongside local government competition in China is often overlooked (Bai et al., 2019). Since China's reform and opening-up, the central government has been reassigning power to local governments, including decentralizing fiscal and taxation, investment and financing, and enterprise management authorities. Although decentralization helps stimulate local development, this process also directly contributes to increasing local protectionism. Local protectionism occurs when local governments protect their key industries through administrative interventions in factor markets, setting trade barriers, or using invisible preferential policies for local economic interests, resulting in market segmentation (Li and Lin, 2017). Market segmentation not only contributes to distorting the economic operation system but also does not facilitate the optimal allocation of factor resources (Hou and Song, 2021). The Chinese government has implemented a series of policy practices to reduce the constraints of market segmentation on economic operations and factor flows. Moreover, China's socialist market economic system has gradually improved in recent years. While the degree and scale of marketization have led to substantial development, the degree of market segmentation has gradually declined (Li et al., 2003). However, because of the constraints of institutional and stage factors, such as the household registration system, non-marketization of interest rates, fiscal decentralization, political promotion tournaments, and enterprise rent-seeking, the development of China's factor market still lags. Existing institutional and regional segmentation results in the non-marketization of labor, capital, energy, and resource allocation, which easily affects the GTFP (Duanmu et al., 2018; Zhang et al., 2021).

Currently, China still has a negative situation of local disorderly competition and market fragmentation. Combining a competent government and an effective market is an essential way to promote GTFP. Therefore, under regional green development, ecological civilization construction, and proper handling of government-market relationships, exploring how to endow the efficiency shift and power shift of economic operations through market and government actions is highly significant for facilitating GTFP improvement to empower high-quality economic development. This study has the following objectives. Based on a more comprehensive portrayal of the relationship between local government competition, market segmentation, and GTFP, we empirically analyze the mechanism of local government competition on GTFP from a market segmentation perspective. Simultaneously, this study must further confirm and explain the following key questions. In the context of competition for economic growth, is local government competition a significant contributor to GTFP? If market segmentation has a transmission effect, is there regional heterogeneity in the effect of market segmentation on GTFP? How does local government competition act on GTFP through market segmentation? Solving these problems would be of great theoretical and practical significance for realizing the transformation of the mode of competition for local governments and breaking the situation of market segmentation to promote the construction of a new mechanism of green development in China from the perspective of the connection between the government and the market.

The marginal contribution of this study is as follows. First, based on the actual market-oriented system reform situation, this study brings local government competition, market

[2]See in more detail: http://www.mee.gov.cn/hjzl/sthjzk/zghjzkgb/202006/P020200602509464172096.pdf.

segmentation, and GTFP into a unified analysis framework. We then discuss the influence mechanism of local government competition on GTFP by market segmentation. This not only enriches the green development theory but also provides a new research perspective for exploring sustainable economic development. Second, a three-stage EDA model was applied for measuring the GTFP. Considering the bias of controlling endogenous estimation, we verify the intrinsic mechanisms of local government competition, market segmentation, and GTFP to determine the dynamic path of urban green development. Third, from the regional heterogeneity perspective, this study analyzes the enhancement or offsetting of the effect of local government competition on GTFP through market segmentation. Our results can provide some guidance for more accurate analyses of the possible problems and drawbacks of the Chinese government and the scientific formulation of relevant policies. Finally, this paper provides a policy basis and theoretical support for developing countries similar to China's economic development.

The following research arrangements are as follows. *Literature review* presents a review of studies related to local government competition, market segmentation, and GTFP. *Three-stage DEA model* presents a three-phase DEA model to measure and analyze GTFP. *Methods* includes the construction of the empirical model and the description of variables. *Results* briefly describes the empirical results. *Discussion* presents the analysis and discussion of the results. Finally, *Conclusion and policy implications* summarizes the study and provides the corresponding policy suggestions.

LITERATURE REVIEW

Local Government Competition and Green Total Factor Productivity

As the economic growth leader and executor of environmental protection policy, the local government's competitive behavior has significant influence on regional economic growth and environmental quality, and this has been examined by scholars. However, few studies have directly examined the effect of local government competition on GTFP. Most existing literature focus on how local government competition affects economic growth or environmental quality. Two views support that economic growth is affected by local governments. The first is that government competition can significantly promote regional economic growth (Oates, 1999). Keen and Marchand, (1997) believe that local government competition can limit the interests of special interest groups, which are beneficial for regional economic development. Hence, under China's special political system, local governments generally use public expenditure and tax policy adjustments to compete for liquidity resources, which inevitably lead to strategic competition (Yılmaz, 2013; Chirinko and Wilson, 2017). Yan et al. (2013) analyzed the path of local government competition on economic growth and found that local governments can encourage investment and accelerate economic growth through land price competition and land revenue expenditure competition. Finally, the diversity of government competition behaviors (financial resource, fiscal expenditure, and infrastructure competition among local governments) and environmentally friendly goods, contributes to local governments having positive effects on economic growth (Hatfield and Kosec, 2013; Deng and Xu, 2013; Yushkov, 2015; Canavire-Bacarreza et al., 2019; Ding et al., 2019).

Second, local government competition inhibits regional economic growth. Some scholars believe that the government increases the intensity of tax incentives and introduces regional competition into the "competition towards the bottom line" to attract residents, enterprises, and capital to the region. The direct consequence is the reduction in the supply capacity of government public goods (Can et al., 2021b). From this perspective, local government competition harms economic growth by distorting tax burdens, reducing the efficiency of resource allocation, and widening regional economic disparities (Cai and Treisman, 2004; Aaberge et al., 2019; Pan et al., 2020; Thanh et al., 2020). Su et al. (2021) highlight that behaviors such as local protectionism, industrial isomorphism, over-investment, and investment wars accompanying the competition process eventually inhibit regional economic growth. Guang-Bin (2005) argues that while administrative decentralization and tax incentives cause local government competition, it does not necessarily help increase investment in infrastructure and local protectionism. However, inter-governmental opportunism and gaming are the important factors affecting economic development. Additionally, Qingwang and Junxue (2009) argued that the 1994 tax-sharing reform significantly changed the pattern of strategic interaction between local governments, effectively curbing competition between extreme regions and significantly weakening competition between local governments, inhibiting regional economic growth. Using a panel dataset of 63 provinces in Vietnam from 2006 to 2017, Thanh and Nguyen (2021) found that decentralization drives significant differences in TFP between high and low self-financing provinces. However, decentralization in high self-financing provinces results in bottom-up competition because of governance reforms. Finally, some scholars have highlighted the uncertainty of local government competition in economic growth. Tang et al. (2011) highlighted that local government competition is a deep-rooted cause of investment impulses in provinces. This, in turn, causes economic fluctuations in China's macroeconomic regulation.

There may be two aspects wherein environmental pollution is affected by local governments: *bottom-to-bottom* competition and *top-to-top* competition. In the case of bottom-to-bottom competition, local governments may compete for high-quality resources, relax environmental control, and indulge enterprises' pollution emission behaviors to encourage promising enterprises to enter the local area. This will lead to environmental degradation and form the "bottom-to-bottom competition" effect of environmental pollution (Oates and Portney, 2003; Banzhaf and Chupp, 2012; van der Kamp et al., 2017; Kuai et al., 2019). Cumberland, (1980) believed that competition among governments would reduce pollution supervision of enterprises and cause environmental deterioration. Meanwhile, under fiscal decentralization, environmental concerns will be ignored (Li et al., 2019). Under top-to-top competition, the local government may improve local environmental supervision standards and transfer pollutants to other areas by adopting more stringent environmental policies to improve the local environmental quality, which forms the "top-to-top competition" effect (Glazer, 1999; List and Gerking, 2000; Albornoz et al., 2009; Haufler and Maier, 2019). Levinson (2003) argued that government competition will help the government prioritize the ecological environment, create environmental conditions for attracting investment, and improve environmental quality. Yan (2012) found that fiscal decentralization can significantly weaken investment in environmental governance through government competition, which, in turn, has positive impact on environmental pollution. Zhang et al. (2021) applied a spatial autoregressive (SAR) model to confirm that local government competition exacerbates haze pollution under factor market distortions.

Market Segmentation and Green Total Factor Productivity

As an equilibrium result of local government competition, market segmentation is mainly manifested in the fact that local governments hinder the cross-regional flow of resources through financial support and policy preference to protect local enterprises and the economy from external fierce impact (Ke, 2015). Since Young (2000) proposed the existence of market segmentation in China, many scholars have discussed the many aspects of market segmentation. Additionally, researchers have found significant differences in the effect of market segmentation on GTFP in different periods (Duffee, 1996; Bancel et al., 2009; Guesmi et al., 2014). In the short term, market segmentation may be conducive to promoting GTFP. Pan et al. (2020) highlighted that local governments have an incentive to divide the market in terms of economic aggregate, fiscal revenue, and employment stability. For example, market segmentation allows local governments to not only protect the market share of local enterprises but also support the development of enterprises with poor local competitiveness and vulnerable industries. Therefore, the local government can obtain sustainable economic growth and more fiscal and tax revenue in the region, which will promote GTFP (Weitzman, 1989; McNabb and Whitfield, 1998).

However, in the long run, interregional market segmentation hinders the flow of factors and spatial mismatch of resources. On the one hand, market segmentation inhibits the free flow of production factors such as resources, energy, and labor among regions. This results in a low level of efficiency in the use of production factors and failure of economies of scale (Poncet, 2003; Hsieh and Klenow, 2009; Hubbard, 2014). For example, Hou and Song (2021) noted the positive spillover effects of market integration on GTFP not only within regions but also in neighboring regions. Simultaneously, in the market segmentation, local protectionism prevails and collusion between government and enterprises is serious, which leads to a lack of fairness and marketization in energy and resource distribution. This significantly inhibits resource allocation and utilization efficiency and, in turn, the improvement of GTFP. Qin et al. (2020) found that market segmentation exacerbates the control of oligopolistic firms in the market, which not only compresses the survival space of SMEs but also severely inhibits the efficiency of factor allocation. On the other hand, market segmentation also hinders diffusion and spillover of technological innovation and regional technical cooperation to a certain extent, which makes applying and promoting new energy-saving and emission-reducing technologies across regions through marketization difficult (Duanmu et al., 2018; Jiang et al., 2020; Zhang et al., 2020). Additionally, trade barriers formed by market segmentation worsen the benign competition between markets, resulting in enterprises losing the power and pressure of technological innovation (Bai et al., 2004; Epifani and Gancia, 2011; Ye and Zhang, 2017). Sun C. et al. (2020) suggested that market segmentation negatively affects the environmental efficiency of the electricity sector by inhibiting technological innovation, and this phenomenon is more significant in regions with poorer institutional quality. Market segmentation also indirectly affects GTFP through the channels of industrial structure, productivity, export trade, investment promotion, and so on (McNabb and Whitfield, 1998; Anouliès, 2016; Chen and Huang, 2016). For example, Bai et al. (2019) highlighted that market segmentation intensifies competition among regions and increases the incentive for local governments to sacrifice the ecological environment for economic growth. This reduces the threshold of environmental regulation and environmental law enforcement, which has negative impact on GTFP. Cheng and Jin (2020) found that agglomeration economies significantly enhance GTFP by improving technical efficiency and technological progress significantly. However, market segmentation can encourage local protectionism, ultimately negatively impacting regional economic growth efficiency. Lai et al. (2021) highlight that market segmentation has an inverted U-shaped effect on the current and future industrial transformation of the region, which is key in improving GTFP.

In summary, a rich theoretical framework and research basis have been proposed by previous scholars to elaborate on the mechanism among local government competition, market segmentation, and GTFP. However, the relationship among the above three needs further discussion. Current research focuses on the impact of local government competition on economic growth and environmental pollution and the relationship between market segmentation and GTFP. Research on local government competition on GTFP in China from the market segmentation perspective is lacking. For instance, Jin et al. (2020) found that excessive cross-jurisdictional competition has a negative impact on GTFP, while moderate competition is important for promoting GTFP. Moreover, Song et al. (2018) reached a similar conclusion. Bin et al. (2016) revealed that strategic decentralization by local governments contributes to GTFP and positively moderates the dampening effect of FDI on GTFP. When measuring market segmentation, scholars mostly consider market segmentation in the product market as a characterization index, which lacks the analysis of market segmentation in other markets. Therefore, this study applies the three-stage DEA model to measure the GTFP from 2006 to 2017. Additionally, market segmentation is incorporated into the framework of local government competition on GTFP. Additionally, the mediation effects model and the generalized method of moments model were used to examine the transmission mechanisms of market segmentation, which further broadened and refined existing research related to GTFP.

THREE-STAGE DEA MODEL

Three-Stage DEA

The relative efficiency of the decision-making unit (DMU) is affected by many factors, such as management inefficiency, statistical noise, and environmental factors. However, the traditional DEA model attributes environmental factors and statistical noise to management inefficiency, which will conceal real efficiency value. Additionally, the analysis of relative efficiency is only affected by management factors. Therefore, to filter and remove the impact of nonoperating factors on efficiency to allow measured efficiency values to more accurately reflect the efficiency level of decision evaluation units, this study uses a three-stage DEA model to measure GTFP (Fried et al., 2002). Through stochastic Frontier analysis, the effects of environmental factors and statistical noise on relative efficiency were effectively eliminated to ensure the robustness of calculation efficiency.

First Stage: Undesirable-Outputs Model

This study selects an undesirable output model (Shyu and Chiang, 2012; Lu et al., 2020). The undesirable output model includes desirable output and undesirable output, which can effectively reduce the influence on raw data changes and subjective factors. The model takes the following form: Set $DMU(X_0, Y_0)$, X_0 is the input, Y_0 is the output. Y_0 includes desirable output (Y^g) and undesirable output (Y^b), that is, $DMU(X_0, Y^g, Y^b)$. Let the production possibility set be $P = \{(x, y^g, y^b) | x \geq X\lambda, y^g \leq Y^g, y^b \geq Y^b\lambda, L \leq e\lambda \leq U, \lambda \geq 0\}$. The specific model is as follows:

$$\rho^* = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_{i0}^-}{X_{i0}}}{1 + \frac{1}{s}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right)} \tag{1}$$

$$Subject\ to \begin{cases} x_0 = X\lambda + s^- \\ y_0^g = Y\lambda - s^g \\ y_0^b = Y\lambda + s^b \\ L \leq e\lambda \leq U \\ s^-, s^g, s^b, \lambda \geq 0 \end{cases} \tag{2}$$

Here, if $\rho^* = 1$, $s^{-^*} = 0$, $s^{g^*} = 0$, $s^{b^*} = 0$, DMU is effective; otherwise, it is not, and, hence, the efficiency value has room for improvement. The efficiency value obtained by undesirable output-bad outputs-C is the comprehensive technical efficiency (TE). The efficiency value obtained from undesirable output-bad outputs-V is pure technical efficiency (PTE). The ratio of Te to PTE was scale efficiency (SE). Through efficiency decomposition, the main factors affecting the comprehensive efficiency value can be measured.

Second Stage: SFA Regression

Because the relative efficiency obtained in the first stage is easily affected by management inefficiency, environmental factors, and statistical noise, this study uses stochastic Frontier analysis (SFA) to incorporate the above factors into a stochastic Frontier analysis model based on input redundancy. Simultaneously, this study takes the input redundancy value of each decision-making unit obtained in the first stage as the explanatory variable. Environmental factors were selected as the explanatory variables. Through regression and adjustment of the SFA, the decision-making units are introduced in the same external environment. The SFA regression model is constructed as follows:

$$S_{mj} = f^m\left(Z_j, \beta^m\right) + \nu_{mj} + u_{mj}, m = 1, 2\cdots, M, j = 1, 2\cdots, N \tag{3}$$

where $S_{mj} = x_{mj} + X_m\lambda$ represents the redundancy value of the M_{th} input variable of the j_{th} DMU in the first stage. Subsequently, Z_j represents the unbalanced regional development factor of the jth DMU, β^m is the parameter estimation value for the unbalanced variable of regional development, and u_{mj} denotes the random interference term.

Then, we use the regression results of the SFA model $(\hat{\beta}^m, \hat{\sigma}_{vm}^2, \hat{\sigma}_{um}^2)$ to adjust the input items of each decision-making unit. All decision-making units are adjusted to the same external environment and the same random disturbance state to obtain PTE excluding other influencing factors. The adjustment method was selected to increase the investment of decision-making units with better external nonoperating factors. The adjustment of the input of each decision-making unit is as follows:

$$\begin{aligned} x_{mj}^A = x_{mj} + \left[max\left\{f^m\left(Z_j, \hat{\beta}^m\right)\right\} - f^m\left(Z_j, \hat{\beta}^m\right)\right] + \left[max\left\{\hat{\nu}_{mj}\right\}\right. \\ \left. - \hat{\nu}_{mj}\right]; m \\ = 1, 2\cdots, M; j = 1, 2\cdots, N \end{aligned} \tag{4}$$

where x_{mj}^A represents the adjusted value of the M_{th} mth input variable of the j_{th} DMU. $[max\{f^m(Z_j, \hat{\beta}^m)\} - f^m(Z_j, \hat{\beta}^m)]$ means adjusting all the decision-making units to the same external environment. $[max\{\hat{\nu}_{mj}\} - \hat{\nu}_{mj}]$ adjusts the random interference of all decision-making units in the same situation. To obtain the estimated value of the random error ($\hat{\nu}_{mj}$), following Jondrow et al. (1982), the following equation is established:

$$\hat{E}\left[\nu_{mj} | \nu_{mj} + u_{mj}\right] = S_{mj} - f^m\left(Z_j, \hat{\beta}^m\right) - \hat{E}\left[u_{mj} | \nu_{mj} + u_{mj}\right] \tag{5}$$

$$E\left[u_{mj} | \nu_{mj} + u_{mj}\right] = \mu_* + \sigma_* \frac{f\left(-\mu_*/\sigma_*\right)}{1 - F\left(-\mu_*/\sigma_*\right)} \tag{6}$$

where $\sigma^2 = \sigma_u^2 + \sigma_\nu^2$, $\mu_* = -\sigma^2\varepsilon/\sigma^2$, $\sigma_*^2 = -\sigma_u^2\sigma_\nu^2/\sigma^2$, $\varepsilon = S_{mj} - f^m(Z_j, \hat{\beta}^m)$. By introducing the corresponding estimation value, this article can get ν_{mj}.

Third Stage: Constructing a Green Total Factor Productivity Index

The adjusted input value and original output value obtained in the second stage are introduced into the undesirable output model to calculate the relative efficiency. Using the regression results of the second stage, we adjust the input of each decision-making unit to keep the output unchanged. The relative efficiency value excluding environmental factors and statistical noise is obtained using the undesirable outputs model. Finally, the efficiency value is analyzed, and that based on the GTFP index is constructed.

Index Selection and Data Processing

This study estimates the GTFP of China under environmental constraints. The input variables, desired outputs, undesired outputs, and environmental variables are treated as follows:

Input variables. Capital stock, labor, and energy are required in the production process. Capital stock is measured by the regional total investment in fixed assets and the fixed assets investment price index. The specific calculation equation is as follows:

$$K_{it} = I_{it} + (1 - \delta_{it})K_{it}$$

where K, I, δ are the capital stock, investment, and depreciation rates, respectively. For depreciation rate processing, Zhang et al. (2004) establish the capital depreciation rate of each province as 9.6%. Moreover, the data to the capital stock are deflated at a constant price in 2006. The employment number of urban units in various provinces is used as the index of labor input. Considering differences in factor endowment, energy consumption scale, and structure in different regions, the energy consumption of coal, natural gas, electricity, oil, and heat is converted into the final energy consumption with a unit of ten thousand tons of standard coal as the measurement index of energy input (Sun et al., 2019; Zhao et al., 2020).

Output variables. The desired outputs are expressed as the GDP of the provinces. Considering the price changes, this study takes 2006 as the base period to deal with the constant price of GDP. Six types of pollution indicators were selected to measure undesired outputs, including industrial sulfur dioxide emissions, total industrial wastewater emissions, industrial nitrogen oxide emissions, industrial smoke (powder) dust emissions, industrial chemical oxygen demand (COD) emissions, and industrial ammonia nitrogen emissions.

Environment variable. Simar and Wilson (2007) highlighted that environmental variables should satisfy the so-called separation hypothesis, that is, select those factors that have an impact on GTFP but are not within the subjective control range of the sample. Therefore, financial development, urbanization, industrial structure, and openness are regarded as environmental variables of the GTFP. Financial development is reflected in per capita GDP (Zhao et al., 2020). The index for measuring the degree of urbanization is the resident population divided by the total population at the end of the year (Sun et al., 2014). This study uses the added value of the tertiary industry divided by the added value of the secondary industry to measure industrial structure (Yang et al., 2021b). Openness is based on the total FDI amount of foreign direct investment (Wu et al., 2020b).

TABLE 1 | Regression results of the first stage.

DMU	1-TE	1-PTE	1-SE
Beijing	1.000	1.000	1.000
Tianjin	0.947	0.957	0.990
Hebei	0.485	0.526	0.921
Shanxi	0.344	0.367	0.938
Inner Mongolia	0.720	0.732	0.985
Liaoning	0.464	0.489	0.950
Jilin	0.505	0.534	0.946
Heilongjiang	0.541	0.555	0.973
Shanghai	1.000	1.000	1.000
Jiangsu	0.872	1.000	0.872
Zhejiang	0.641	0.676	0.948
Anhui	0.502	0.522	0.963
Fujian	0.672	0.696	0.966
Jiangxi	0.512	0.535	0.956
Shandong	0.720	0.909	0.793
Henan	0.503	0.538	0.934
Hubei	0.561	0.584	0.961
Hunan	0.561	0.590	0.951
Guangdong	1.000	1.000	1.000
Guangxi	0.509	0.535	0.950
Hainan	0.697	1.000	0.697
Chongqing	0.506	0.533	0.949
Sichuan	0.512	0.539	0.949
Guizhou	0.362	0.429	0.843
Yunnan	0.404	0.433	0.932
Shaanxi	0.473	0.493	0.960
Gansu	0.378	0.446	0.846
Qinghai	0.311	1.000	0.311
Ningxia	0.267	0.673	0.397
Xinjiang	0.333	0.377	0.884
Mean	0.577	0.656	0.892

Calculation Results of Green Total Factor Productivity in China

First-Stage Estimation Results

In the first and third stages, DEA solver Pro 5.0 is used to measure the efficiency value. **Table 1** shows that when ignoring the interference of environmental factors and random errors, the average value of GTFP, PTE, SE is 0.404, 0.433, and 0.932, respectively. This indicates that the efficiency value can still be significantly improved. Overall, the level of GTFP is not high, and it is mainly restricted by the low level of PTE. From the value of each province, the GTFP of Beijing, Shanghai, and Guangdong are relatively high, with a value of 1.000, reaching the DEA efficiency situation and being at the forefront of production efficiency. However, the GTFP of Hebei, Shanxi, Shaanxi, Gansu, Ningxia, and Xinjiang, and the other 10 regions are all less than 0.500, and DEA is in a situation of inefficiency, demonstrating that the provinces have some room to improve in PTE or SE. TE is easily disturbed by environmental factors and random errors, which cannot reflect the real situation of the efficiency value. Therefore, further separating the environmental factors and random errors to obtain the TE under the same conditions is necessary.

TABLE 2 | Regression results of the second-stage (SFA).

Variables	Labour input slack	Capital stock input slack	Energy consumption input slack
Financial development	3.9,974,084	628.00353	1,058.7633***
	(0.348)	(1.592)	(3.268)
Urbanization	275.70503***	12,061.05***	−2,815.4045***
	(4.959)	(41.257)	(−29.867)
Industrial structure	−12.179,611	−1,359.0588	−1,165.9285***
	(−0.841)	(−1.402)	(−4.470)
Openness	−76.642,066***	−9,408.2617***	−1,183.8227**
	(−5.119)	(−17.428)	(−2.304)
σ^2	23,400.543***	168,382,550***	27,400,435***
	(8.926)	(168,379,690.000)	(27,377,432.000)
γ	0.90,311,339***	0.85,452,375***	0.90,873,159***
	(56.810)	(76.185)	(137.123)
Constant term	−138.85609***	−3,014.0564***	1731.6898***
	(−3.662)	(−5.061)	(2.766)
Log function value	−0.1967	−0.3618	6,54,320,000
LR test	306.68914***	323.48504***	447.6203***

Note: T statistics are put in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.

TABLE 3 | Regression results of the third stage.

DMU	3-TE	3-PTE	3-SE
Beijing	1.000	1.000	1.000
Tianjin	0.866	0.978	0.885
Hebei	0.591	0.631	0.936
Shanxi	0.387	0.498	0.777
Inner Mongolia	0.621	0.707	0.877
Liaoning	0.553	0.596	0.926
Jilin	0.534	0.674	0.792
Heilongjiang	0.574	0.720	0.797
Shanghai	1.000	1.000	1.000
Jiangsu	1.000	1.000	1.000
Zhejiang	0.715	0.753	0.950
Anhui	0.542	0.633	0.857
Fujian	0.709	0.791	0.896
Jiangxi	0.505	0.652	0.775
Shandong	0.835	0.926	0.902
Henan	0.576	0.620	0.928
Hubei	0.615	0.679	0.906
Hunan	0.626	0.706	0.886
Guangdong	1.000	1.000	1.000
Guangxi	0.504	0.642	0.786
Hainan	0.412	1.000	0.412
Chongqing	0.532	0.676	0.787
Sichuan	0.591	0.639	0.924
Guizhou	0.343	0.578	0.593
Yunnan	0.416	0.574	0.725
Shaanxi	0.513	0.630	0.813
Gansu	0.336	0.613	0.549
Qinghai	0.196	1.000	0.196
Ningxia	0.180	0.788	0.229
Xinjiang	0.333	0.520	0.641
Mean	0.587	0.741	0.792

The Second-Stage Estimation Results

Hence, urban unit employment, capital stock, and energy consumption relaxation are considered dependent variables. Stock SFA regression model is then established with four external environmental variables: financial development, urbanization, industrial structure, and openness as independent variables. **Table 2** indicates that the LR one-sided test has passed the significance test. This demonstrates that the SFA method has strong applicability. σ^2 and γ values passed the significance test of 1%, which showed that compared with ν_{mj}, the interference of environmental factors was more significant. Moreover, this proves that a strong relationship between the slack of input factors and selected environmental variables exists. Simultaneously, most of the environmental variables passed the significance test for input slack. Among them, financial development has a significant negative correlation with capital investment slack, a significant positive correlation with energy input slack, and no correlation with labor input slack. This shows that a higher level of financial development increases energy consumption. Urbanization has a positive relationship between labor force and capital investment slack, and there is a significant negative relationship with energy investment slack. Industrial structure, which reflects industrial competition, has no significant impact on the slack of personnel and asset investment. However, it has significant negative impact on energy slack. This may be because China's industrial focus is gradually shifting from the secondary industry to the tertiary industry. Moreover, knowledge-intensive industries are gradually replacing labor-intensive industries, thus significantly reducing energy consumption. Openness in the labor force, capital, and energy slack are significantly negative, showing that the improvement in regional openness is a positive factor for GTFP.

The Third-Stage Estimation Results

After eliminating environmental factors and statistical noise, the efficiency of the third stage changed significantly compared with that of the first stage. This indicates that it is not objective and realistic to attribute all the factors affecting efficiency to management factors without eliminating environmental factors and statistical noise. **Table 3** shows that after the second stage of adjustment, the average value of GTFP is 0.587, which is higher than the preadjustment efficiency value, but still at a low level.

This shows that enterprises can achieve the original output level even if the input is reduced by 41.3% by improving resource utilization efficiency and management. The average value of the adjusted PTE is 0.741, which is a small distance from the front of the efficiency and forms a great contrast with the value before adjustment. The higher level of PTE confirms that China's high-tech industry has a higher level of TE of China's high-tech industry. This indicates that the state and enterprises attach great importance to technological innovation and have achieved certain results in recent years.

The average value of SE of the third stage is 0.792, which is lower than the level before adjustment, and room for improvement at 20.8% remains. This is because enterprises overly focus on the application of technology but neglect moderate-scale production. Compared with the first stage, the TE and PTE increased by 0.010 and 0.085, respectively, whereas the SE decreased by 0.100. The adjusted efficiency results show that the low GTFP is mainly caused by the low level of SE. From the data of each province, Beijing, Shanghai, Jiangsu, and Guangdong are at the forefront of the adjusted production efficiency. Compared with before the adjustment, the number of regions with GTFP values less than 0.500 decreased to 7. This demonstrates that environmental variables have a significant impact on the GTFP in different regions.

METHODS

Model Construction

For analyzing GTFP, most scholars ignore the systematic bias that can result from time-lagged effects. Therefore, this study introduces a one-period lag of the explanatory variables into the benchmark model to constitute a more accurate dynamic panel model, which enables the dynamic interpretation of the model. However, generally endogenous problems in the dynamic models exist. To solve the endogeneity problem, Arellano and Bond (1991) proposed a generalized method of moments (GMM) using instrumental variables to derive the appropriate moment conditions, known as the "Differential Generalized Method of Moments (DIFF—GMM)." The basic principle of the method is to first perform a first-order difference transformation on the original model to eliminate the individual heterogeneous terms in the model. Then, for the transformed difference equation, the lagged variables of the endogenous variables are treated as instrumental variables of the endogenous variables. Although the DIFF-GMM approach reduces the impact of endogeneity on model estimation, DIFF-GMM suffers from a serious "weak instrumental variable" issue in the limited sample condition, resulting in worse accuracy of coefficient estimation results. A solution to this problem was proposed by Arellano and Bover (1995), who proposed the "system generalized method of moments (SYS-GMM) approach" based on a new composite moment condition. The SYS-GMM approach not only provides simultaneous estimation of the original model and the differentially transformed model but can also correct for unobserved individual heterogeneity issues, omitted variable bias, measurement error, and potential endogeneity that often affect model estimation when using mixed OLS and fixed effects methods. Additionally, the SYS-GMM approach reduces the potential bias because of the use of first-order DIFF-GMM estimation approaches. Based on this, the two types of methods of SYS-GMM and DIFF-GMM are chosen to analyze the research problem, where the DIFF-GMM plays more of a robustness check role and the SYS-GMM reflects more of the estimation results of the research issue[3]. The equation is set as follows:

$$GTFP_{it} = \beta_0 + \beta_1 GTFP_{it-1} + \beta_2 ECU_{it} + \sum_{k=3}^{8} \beta_k X_{it} + \varepsilon_{it} \quad (7)$$

where i represents the province, t represents the year, and $GTFP$ represents the green total factor productivity. ECU is a local government competition. X denotes a series of control variables, including government expenditure (GOV), human capital (HUM), marketization (MAR), intellectual property protection (PRO), per capita road area (ROA), and informatization (MES). ε_{it} is the disturbance term[4].

The mediation effect model uses the third variable to explore the internal mechanism of the independent variable influencing the dependent variable. If local government competition (ECU) can affect GTFP by market segmentation ($MSEG$), market segmentation can be used as a mediation variable. Following Baron and Kenny (1986), considering the time lag of GTFP, this study constructs regression models as shown in **Eq. 8** and **Eq. 9** to the indirect effect of local government competition on GTFP. To determine the robustness of the mediation effect and reduce the model's possible endogeneity, the system generalized method of moments (SYS-GMM) and differential generalized method of moments (DIFF-GMM) are applied to estimate the model.

$$MSEG_{it} = \delta_0 + \delta_1 MSEG_{it-1} + \delta_2 MSEG_{it} + \sum_{k=3}^{8} \delta_k X_{it} + \varepsilon_{it} \quad (8)$$

[3]Meanwhile, appropriate instrumental variables can make the estimation results more accurate, thus the Sargan test or Hansen test for the validity of instrumental variables is necessary. The validity of the moment condition can be performed by Sargan test or Hansen test with the original hypothesis that all instrumental variables are exogenous. Therefore, if the instrumental variables are valid, the original hypothesis should not be rejected. However, Iqbal and Daly (2014) argued that the Sargan test method is valid only if the disturbance term is homoskedastic. In addition, Bowsher (2002) suggested that the Sargan test is difficult to reject the original hypothesis when the sample size is small and the instrumental variable is usually considered valid, while the original hypothesis of serially uncorrelated errors is over-rejected in one-step GMM estimation. In view of the above-mentioned disadvantages of the Sargen test and the fact that the Hansen test is often used in practice, the Hansen test is chosen in this article to test the validity of the instrumental variables.

[4]Discussion on the disturbance term (ε_{it}). GMM cannot be used as a consistent estimator unless the disturbance terms are not autocorrelated. To ensure that the moment conditions are not over-constrained, the number of instrumental variables cannot be more than the number of endogenous variables. If lagged endogenous and weakly exogenous variables are used as valid instrumental variables, the absence of autocorrelation in the current disturbance terms (ε_{it}) in the underlying model is necessary. The above situation implies that the disturbance terms (ε_{it}) of the difference model have significant first-order correlation and insignificant second-order autocorrelation. For this reason, we used Arellano-Bond tests for first-order serial and second-order serial correlations in the first-order difference residuals.

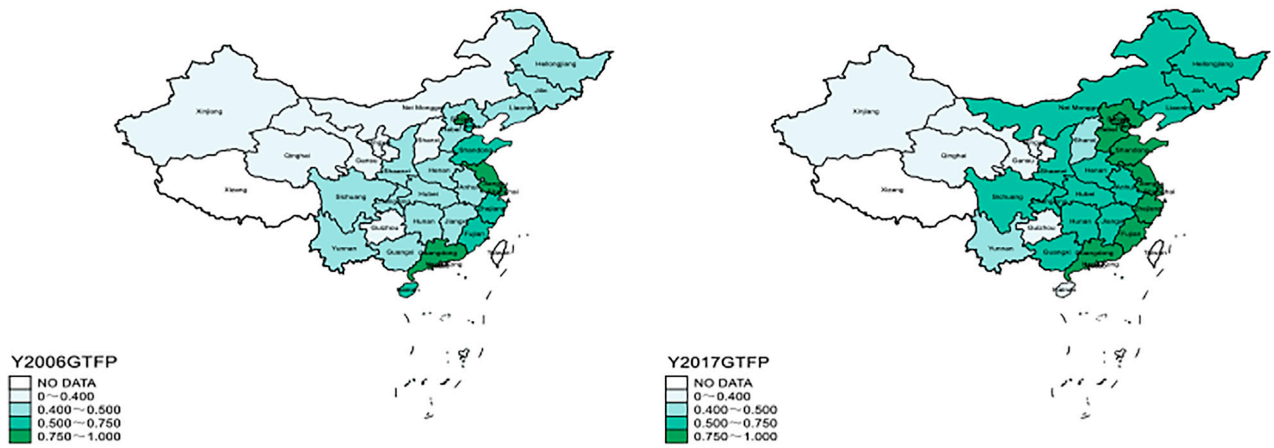

FIGURE 1 | China's GTFP in 2006 and 2017.

$$GTFP_{it} = \varphi_0 + \varphi_1 GTFP_{it-1} + \varphi_2 ECU_{it} + \varphi_3 MSEG_{it} + \sum\nolimits_{k=4}^{9} \varphi_k X_{it} + \varepsilon_{it} \tag{9}$$

Here, $MSEG$ is the mediation variable. If δ_2 and φ_3 are significant, local government competition is implied to have an impact on GTFP by market segmentation, and the mediation effect is $\delta_2 \times \varphi_3$. According to Iacobucci (2012), the discriminant equation for the mediation effect is as follows:

$$Z_{mid} = \frac{Z_\delta \times Z_\varphi}{\sqrt{Z_\delta^2 \times Z_\varphi^2}} \tag{10}$$

The biggest advantage of this method is that the probability of making the first kind of error in statistics is very low, which is usually lower than the significance level, thus ensuring results validity. Z_{mid} in **Eq. 10** determines the significance of the mediation effect when the variable is continuous. In **Eq. 10**, δ represents the influence coefficient of the independent variable (ECU) to the mediation variable ($MSEG$) and the mediation variable ($MSEG$) to the dependent variable ($GTFP$). Z_δ and Z_φ are the Z values of the coefficients a and the coefficient δ, respectively.

Variables Specification

1) Explained variables. GTFP is measured by the third-stage efficiency measured by the three-stage DEA model. Additionally, this article uses Stata 15.0 software to draw the distribution map of China's GTFP. Owing to limited space, this study only lists the distribution of GTFP in 2006 and 2017. **Figure 1** shows that considering geographical distribution, areas with higher GTFP are mainly concentrated in the eastern coastal areas, such as Beijing, Tianjin, Guangdong, Shandong, Fujian, Shanghai, and Jiangsu. However, with time, the number of green areas in China has gradually increased. The promotion of GTFP mainly spreads from the eastern coastal areas to the central region, which shows that the green development policy implemented by China has achieved remarkable results. Although the Chinese government has since faced serious environmental pollution, the central government has always prioritized the construction of ecological civilization and implemented a strict environmental protection system. Simultaneously, the construction of ecological civilization is constantly emphasized by the central government in the assessment indicators of local government officials. These encourage local government officials to prioritize the green elements of economic growth and promote the GTFP.
2) Core explanatory variables (ECU). The government can not only compensate for market deficiency and enhance the standardization of the market mechanism through appropriate administrative intervention but also compel the market to play a decisive role in resource allocation to lead the current trend of economic development. However, the extensive development mode of local government's blind pursuit of GDP growth increases undesired input and output, decreases investment in environmental governance, and increases the difficulty of ecological protection. Therefore, local government competition is characterized by the economic catch-up level of (ECU). Referring to Miao et al. (2017), this study selects the adjacent province dimension and the national provincial dimension to jointly determine the economic catch-up level of each province. The calculation method is as follows:

$$ECU = \frac{NGDP_{it}}{LGDP_{it}} \times \frac{WGDP_{it}}{LGDP_{it}} \tag{13}$$

Among them, $NGDP$ is the highest per capita GDP of neighboring provinces, $WGDP$ is the highest per capita GDP of all provinces in China, and $LGDP$ is the per capita GDP of this province.

3) Mediation variables. Based on the above theoretical analysis, this study selects the market segmentation index as the mediation variable. However, the trade law, production method, and specialization index method used in the existing literature to measure market segmentation have inherent defects, and forming a panel database is difficult (Naughton, 1999; Young,

2000; Poncet, 2003; Bai et al., 2004). Therefore, referring to Shao et al. (2019), this study adopts the relative price index analysis method to measure 65 pairs of market segmentation indices of neighboring provinces and then merges the 65 pairs of indexes of adjacent provinces to obtain the market segmentation index of each province and its adjacent provinces. For instance, Beijing's market segmentation index is the average value of the market segmentation index between Beijing and Tianjin, and between Beijing and Hebei. The market segmentation indices of other provinces and cities adopt the same calculation method. Thus, a total of 360 (= 30 × 12) market segmentation observations are obtained, which show the changes in the market segmentation degree of 30 provinces and all adjacent provinces.

4) Control Variables.

This study selects the following control variables while eliminating the environmental variables that affect GTFP.

Government expenditure (GOV). Increased government spending will stimulate production and demand, which will undoubtedly play a greater role in promoting GTFP. Referring to Hao et al. (2020), government expenditure is measured as the ratio of fiscal expenditure to GDP.

Human capital (HUM). Human capital is an important source of economic growth. Improving the human capital level has a more significant effect on the improvement of GTFP. According to Wu et al. (2020a), human capital is measured by the number of years of education per capita in each province.

Marketization (MAR). Improving the marketization level will lead to the expansion of economic scale and improvement of market potential. However, it will also lead to an increase in polluting enterprises and an in total pollution. Following Li (2015), the proportion of employees in non-state-owned enterprises in various provinces and cities was used to measure the MAR marketization level of marketization (MAR).

Intellectual property protection (PRO). Intellectual property protection promotes the continuous development of innovation by ensuring that the achievements of innovation subjects are not infringed and ultimately affect the GTFP. Referring to Kim et al. (2012), this study uses the quotient of technology market transaction volume and GDP to measure intellectual property protection (PRO).

Transport infrastructure (ROA). The degree of transportation convenience can enhance the factor flow between different regions and affect the GTFP of the region. This study uses the per capita road area of each city to measure the level of traffic infrastructure (ROA) (Sun X. et al., 2020).

Informationalized level (MES). The improvement of information level can promote the speed of information dissemination, and then have an impact on GTFP (Yang et al., 2021b). This article uses per capita posts and telecommunications to measure the level of informatization (MES).

Data Sources

The original data used in the above variables are derived from the China Environmental Statistical Yearbook, China Financial Statistical Yearbook, China Energy Statistical Yearbook, Provincial Statistical Yearbook, China Macro Statistical database, and China Labor Force Statistical Yearbook. **Table 4** shows the multicollinearity test and the descriptive statistics of the data. The variance inflation factor (VIF) of each variable is less than 10, so the multicollinearity problem of the explanatory variables is within the controllable range[5].

TABLE 4 | Variables description.

Variables	N	Mean	Sd	min	max	VIF
GTFP	360	0.587	0.241	0.139	1	—
ECU	360	4.719	3.556	0.553	21.56	1.87
GOV	360	0.222	0.0962	0.0837	0.627	1.50
HUM	360	8.800	0.980	6.594	12.50	3.13
MAR	360	0.708	0.106	0.440	0.899	1.83
PRO	360	0.0105	0.0230	0.000172	0.160	2.32
ROA	360	3.936	2.267	0.000167	10.94	1.94
MES	360	0.177	0.163	6.22e-06	1.438	1.70
MSEG	360	0.0266	0.0248	0.00518	0.271	1.08

RESULTS

Benchmark Regression Results

To verify the robustness of the results, the regression results of the system random effect model, fixed effect model, SYS-GMM, and DIFF–GMM models are presented (see **Table 5**). The coefficients of $L.GTFP$ are significantly positive, demonstrating that GTFP is affected by the early stage. In columns (3)–(6), the p values of AR (2) and Hansen statistics are greater than 0.1. This demonstrates that it is reasonable to include the first lag term of $GTFP$ into the model for regression, and the selection of instrumental variables is effective. In Columns 1) and (2), the impact of *ECU* on GTFP is negative but not significant. Columns 3) and (5), respectively, represent the regression results of SYS-GMM and DIFF-GMM without control variables. Columns 4) and 6) show the regression results of the dynamic GMM after adding control variables. It was found that local government competition significantly inhibited GTFP at the 1% level[6].

Transmission Mechanism Analysis

In the following, based on the double mechanism test of the SYS-GMM and DIFF-GMM models, the transmission mechanism is analyzed from the path of market segmentation (see **Table 6**). The results of the AR 2) test in Columns (1)–6) show that there is no second-order autocorrelation in random error terms, and the Hansen test results show that the selection of instrument variables is effective. Columns 1) and 4) imply that local government competition inhibits the GTFP. The estimation coefficients of local government competition in Columns 2) and 5) are significantly positive, indicating that regional competition intensifies market segmentation. In Column (3), the estimated coefficients of *ECU* and the coefficients of *MSEG* coefficient are significantly negative. After calculation, Z_{mid} values are 2.07 and 3.14, respectively. The mediation effect indicates the existence of a

[5]Following Hair et al. (1995), when the tolerance of the independent variable is greater than 0.1, a range of variance inflation factors less than 10 is acceptable.

TABLE 5 | Benchmark regression results.

Variables	RE	FE	SYS-GMM		DIF-GMM	
	(1)	(2)	(3)	(4)	(5)	(6)
L.GTFP			0.962***	0.803***	0.537***	0.439***
			(397.42)	(53.28)	(233.41)	(21.35)
ECU	−0.004	−0.001	−0.007***	−0.008***	−0.053***	−0.032***
	(−0.83)	(−0.11)	(−15.75)	(−3.62)	(−65.19)	(−3.59)
GOV	−1.205***	−0.154		−0.496***		0.230
	(−6.22)	(−0.57)		(−6.67)		(1.57)
HUM	0.112***	0.067**		0.008		−0.030***
	(4.00)	(2.07)		(1.27)		(−7.81)
MAR	0.466***	0.437**		0.685***		1.285***
	(2.78)	(2.43)		(12.30)		(7.93)
PRO	0.186	−0.841		0.468		2.972**
	(0.17)	(−0.63)		(1.07)		(2.37)
ROA	0.061***	0.056***		−0.005		−0.000
	(6.26)	(4.98)		(−1.58)		(−0.00)
MES	0.016	−0.027		−0.033		−0.132***
	(0.22)	(−0.39)		(−1.22)		(−5.28)
AR (1)			−1.98	−1.93	−1.82	−1.87
			[0.048]	[0.054]	[0.069]	[0.061]
AR (2)			1.26	1.22	1.19	0.91
			[0.207]	[0.224]	[0.233]	[0.361]
Hansen test			28.70	24.61	26.84	26.01
			[0.991]	[0.989]	[0.997]	[0.986]
Constant	−1.900***	−1.691***	0.022***	−0.497***		
	(−8.79)	(−7.30)	(16.81)	(−8.76)		
N	360	360	330	330	300	300

*Note: T statistics are put in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01; Z values are put in [].*

mediation effect of market segmentation, that is, local government competition, inhibits GTFP through market segmentation.

Regional Heterogeneity

Given China's unique geographical conditions and strong heterogeneity of resource endowment, significant differences in the forms of local government competition exist, leading to great differences in performance incentives in the eastern and central-western regions (Wu et al., 2021). Therefore, this study divides the research samples into eastern, central, and western regions to analyze the regional heterogeneity of the results of this study (see **Table 7**).

The AR (2) test results show that there is no second-order autocorrelation in the random error term. The Hansen test shows that the instrumental variable selection is effective. In columns 1)–(3), the effect of local government competition (ECU) on ($GTFP$) and market segmentation ($MSEG$) is not significant in the eastern region, indicating that ECU will not significantly inhibit GTFP. Local government competition does not cause market segmentation. The mediation effect of market segmentation on local government competition and GTFP does not exist. Column 4) shows that ECU in the central-western region inhibits the GTFP. Column 5) shows that ECU promotes market segmentation in the central-western region. The estimated coefficients of ECU and $MSEG$ in column 6) are negative and significant at the 5% level. By calculation, the Z_{mid} value is 1.91, more than 1.65, which indicates that the mediation effect of market segmentation on local government competition and GTFP exists in the central-western regions.

Robustness Test

Referring to Zhang et al. (2019), competition intensity (SF) is used as the local government competition proxy variable, and the specific measurement method is as follows:

$$SF = \frac{1}{TAX}, \quad TAX = \frac{LTAX - PTAX}{LGDP} \tag{14}$$

where TAX is the tax burden level, $LTAX$ is the local tax revenue, $PTAX$ is the personal income tax, and $LGDP$ is the local GDP. This study tests the robustness of the above results by using the OLS, FE and RE, SYS–GMM, and DiFF-GMM models (see **Table 8**). The local government competition in Columns (1)–(5) inhibits the improvement of GTFP, and Columns (1), (3), and (5) indicate that local government competition inhibits the growth of GTFP. **Table 9** shows the results of the robustness test for the mediation effect. The results of the national and regional mediation effect tests show that the mediation effect of market segmentation exists and shows regional heterogeneity. As all test results are consistent with the previous study, the conclusion of this article is robust.

DISCUSSION

Discussion of Benchmark Regression Results

Table 5 indicates that the local government's competition policy, intended to match the economic level of the surrounding areas or the economically developed regions in China, will reduce GTFP

TABLE 6 | Transmission mechanism analysis.

Variables	SYS-GMM			DIFF-GMM		
	(1) GTFP	(2) MSEG	(3) GTFP	(4) GTFP	(5) MSEG	(6) GTFP
L.GTFP	0.803***		0.529***	0.439***		0.380***
	(53.28)		(35.79)	(21.35)		(14.95)
ECU	−0.008***	0.002***	−0.030***	−0.032***	0.005***	−0.036***
	(−3.62)	(3.26)	(−5.64)	(−3.59)	(4.70)	(−6.50)
GOV	−0.496***	0.009	−1.187***	0.230	0.111***	0.511***
	(−6.67)	(1.08)	(−14.45)	(1.57)	(4.09)	(5.81)
HUM	0.008	−0.013***	0.083***	−0.030***	−0.036***	−0.065***
	(1.27)	(−7.66)	(8.42)	(−7.81)	(−23.47)	(−4.33)
MAR	0.685***	−0.017*	0.564***	1.285***	0.067***	1.325***
	(12.30)	(−1.66)	(7.38)	(7.93)	(3.78)	(20.18)
PRO	0.468	0.297***	−0.759*	2.972**	0.367	5.045***
	(1.07)	(7.33)	(−1.93)	(2.37)	(1.22)	(4.22)
ROA	−0.005	0.003***	−0.010**	−0.000	0.007***	−0.006
	(−1.58)	(3.68)	(−2.03)	(−0.00)	(5.13)	(−0.94)
MES	−0.033	0.026***	0.055***	−0.132***	0.023***	−0.106**
	(−1.22)	(6.66)	(2.78)	(−5.28)	(7.85)	(−2.53)
L.MSEG		0.146***			0.235***	
		(13.46)			(11.06)	
MSEG			−0.310***			−1.183***
			(−2.69)			(−4.23)
AR (1)	−1.93	−2.33	−1.85	−1.87	−2.52	−1.86
	[0.054]	[0.020]	[0.064]	[0.061]	[0.012]	[0.063]
AR (2)	1.22	−0.89	1.01	0.91	−1.23	0.92
	[0.224]	[0.373]	[0.315]	[0.361]	[0.218]	[0.360]
Hansen test	24.61	27.37	26.74	26.01	23.23	26.62
	[0.989]	[1.000]	[1.000]	[0.986]	[0.918]	[0.184]
Z_{mid}	2.07	3.14				
Constant	−0.497***	0.113***	−0.961***			
	(−8.76)	(9.41)	(−12.53)			
N	330	330	330	300	300	300

*Note: T statistics are put in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01; Z values are put in [].*

in **Table 5**. Our findings differ from those of Jin et al. (2020), who confirm that local government competition exhibits an inverted U-shaped relationship with GTFP. However, Hong et al. (2020) and Zhang et al. (2021) argued that unregulated competition among local governments contributes to deterioration of environmental quality and reduction of GTFP. Hence, the above results can be interpreted from the following perspectives: to obtain significant economic growth performance, local governments will spare no effort to compete for production factors, enrich the mode of production, and increase the scale of economic growth to maximize economic performance in a limited term (Keen and Marchand, 1997; Oates, 1999; Canavire-Bacarreza et al., 2019). However, most productive projects with small investments and quick results are concentrated in the secondary industry and are both characterized by high pollution and high-energy consumption, which may not be conducive to promoting GTFP (Yushkov, 2015). Second, local governments will also have horizontal competition in terms of fiscal expenditure. For example, local governments prefer to invest in projects such as high-return, quick-impact infrastructure, and expansion of traditional businesses and reduce spending on environmental protection and energy conservation. Additionally, local governments often ignore the slow-acting and heavily invested public services represented by environmental governance, which leads to continued environment deterioration. Finally, owing to the externality of environmental governance, local governments in adjacent regions have been unable to control pollution to prevent free-riding and have fallen into the prisoner's dilemma. Hence, local governments have no incentive to prevent and control pollution, further inhibiting GTFP.

Discussion of Transmission Mechanism Analysis

Columns 1) and 4) indicate that local government competition inhibits GTFP improvement in **Table 6**. Columns 2) and 5) indicate that interregional competition intensifies market segmentation. In Column (3), the local government competition (*ECU*) coefficient and market segmentation coefficient are significantly negative. Z_{mid} value is 2.07 and 3.14, respectively. This indicates that local government competition inhibits GTFP by market segmentation. Our findings adhere to those obtained by Wang J. et al. (2021) and Hou and Song (2021), which also fulfilled our expectations. Hence, market segmentation is conducive to protecting the

TABLE 7 | Regional heterogeneity.

Variables	Eastern region			Central−western regions		
	(1) GTFP	(2) MSEG	(3) GTFP	(4) GTFP	(5) MSEG	(6) GTFP
L.GTFP	1.273***		0.622*	0.711***		0.783***
	(2.69)		(1.93)	(23.65)		(30.04)
ECU	0.257	0.005	0.265	−0.030***	0.006***	−0.017**
	(1.41)	(0.71)	(1.30)	(−3.20)	(3.23)	(−2.05)
GOV	−2.697***	−0.042	−8.965***	−1.144***	0.018	−0.378***
	(−3.10)	(−0.30)	(−3.00)	(−9.25)	(0.66)	(−4.13)
HUM	−0.093	−0.001	0.592***	−0.018	0.010**	−0.030
	(−0.45)	(−0.07)	(2.86)	(−0.52)	(2.15)	(−0.93)
MAR	−1.955	−0.101**	−0.689	−0.253*	−0.043**	0.284
	(−1.22)	(−2.04)	(−0.29)	(−1.78)	(−2.30)	(1.63)
PRO	10.759	−0.072	−5.146**	2.573*	−0.181	−0.949
	(1.17)	(−0.22)	(−2.38)	(1.82)	(−0.76)	(−0.30)
ROA	0.134	0.005	0.065	0.008	0.003***	0.015***
	(1.39)	(1.62)	(0.64)	(0.70)	(2.89)	(2.66)
MES	−0.254	0.048***	0.246	−0.102***	0.033***	0.024
	(−1.04)	(3.51)	(0.93)	(−2.79)	(4.70)	(0.35)
L.MSEG		0.353**			0.478***	
		(2.01)			(10.46)	
MSEG			4.652			−1.990**
			(1.49)			(−2.36)
AR (1)	−1.74	−2.44	−1.12	−1.53	−2.04	−1.62
	[0.081]	[0.015]	[0.262]	[0.126]	[0.041]	[0.106]
AR (2)	0.77	−1.02	−0.98	1.43	0.76	1.42
	[0.439]	[0.309]	[0.326]	[0.154]	[0.450]	[0.155]
Hansen test	2.90	6.19	1.36	17.10	12.80	16.28
	[1.000]	[1.000]	[1.000]	[0.516]	[0.172]	[1.000]
Z_{mid}	0.64	1.91				
Constant	1.436	0.057	−4.769***	0.552*	−0.091*	0.094
	(0.67)	(0.51)	(−3.51)	(1.93)	(−1.74)	(0.43)
N	110	110	110	209	209	209

*Note: T statistics are put in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01; Z values are put in [].*

market share of local enterprises in backward areas and supporting development of local enterprises with poor competitiveness and weak industries (Bian et al., 2019). Therefore, local governments in the region receive sustained economic growth and more tax revenue while they close the local market to ensure employment of local labor, leading to regional non-specialization and factor market segmentation.

Market segmentation inhibits the free flow of production factors such as resources, energy, and the labor force among regions (Young, 2000). The production activities in some regions with relatively abundant energy and resource endowments are limited because of insufficient matching of production factors (Li and Lin, 2017). Meanwhile, in market segmentation, local government intervention leads to a lack of normal and necessary market competition, and there is much collusion between governments and enterprises (Shao et al., 2019). Local governments manage the initial distribution of natural resources, especially that of energy and other production factors. Hence, a close relationship with the government enables enterprises to acquire advantages in price or tilt in quantity in resource allocation, which puts enterprises not closely related to the government in an inferior position because of the lack of fairness in the market environment (Li and Lin, 2017). The above results lead to a lack of fairness and marketization in the distribution of energy and resources, which seriously reduces the allocation efficiency and ultimately inhibits GTFP (Duanmu et al., 2018; Bian et al., 2019; Jiang et al., 2020).

Discussion of Regional Heterogeneity

In the eastern region, local government competition will not significantly inhibit GTFP and promote market segmentation. The mediation effect of market segmentation on local government competition and GTFP does not exist. Our findings are reasonable in that they are also a useful supplement to the studies of Hou and Song (2021), Wang X. et al. (2021), and Zhang et al. (2021). Economic development in the central and western regions is not as good as that in the eastern regions. Moreover, there are a large number of enterprises, and most of which produce light industrial products and high-tech products (Zhang et al., 2021). The performance evaluation standards of the government departments were relatively high. When pursuing economic growth targets, they also prioritize sustainable economic development, presenting a situation of "top-to-top competition" (Wu et al., 2020a). Additionally, the eastern region is rich in capital and labor resources, and the

TABLE 8 | Test results of direct effect robustness.

Variables	OLS	FE	RE	SYS-GMM	DIFF-GMM
	(1)	(2)	(3)	(4)	(5)
L.GTFP				0.798***	0.468***
				(30.90)	(21.96)
SF	−0.012***	−0.0000327	−0.008*	−0.013***	−0.021***
	(−3.48)	(−0.01)	(−1.72)	(−7.52)	(−12.56)
GOV	−2.563***	−0.149	−1.354***	−0.702***	0.223***
	(−15.65)	(−0.49)	(−6.09)	(−7.04)	(2.99)
HUM	0.069***	0.068**	0.104***	−0.022***	−0.031***
	(3.35)	(2.11)	(3.72)	(−4.29)	(−4.66)
MAR	0.274*	0.439**	0.447***	0.805***	1.198***
	(1.84)	(2.42)	(2.67)	(15.65)	(20.94)
PRO	0.812	−0.861	0.058	0.690	2.359**
	(1.06)	(−0.64)	(0.05)	(1.31)	(2.33)
ROA	0.055***	0.056***	0.060***	0.003	−0.002
	(8.01)	(4.93)	(6.10)	(0.62)	(−0.49)
MES	0.332***	−0.027	0.039	−0.044	−0.072***
	(3.51)	(−0.38)	(0.54)	(−1.19)	(−3.53)
AR (1)				−1.98	−1.96
				[0.048]	[0.050]
AR (2)				1.26	1.12
				[0.209]	[0.261]
Hansen test				27.56	25.34
				[0.968]	[0.989]
Constant	−0.963***	−1.703***	−1.683***	−0.155***	
	(−4.40)	(−6.21)	(−6.58)	(−4.93)	
N	360	360	360	330	300

*Note: T statistics are put in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01; Z values are put in [].*

abundance of certain factor resources also weakens the influence of distortion of the factor resource allocation brought about by this type of market segmentation, thus weakening the inhibition of GTFP.

However, Columns (4)–6) indicate that the mediation effect of market segmentation on local government competition and GTFP exists in the central and western regions. On the one hand, owing to the relative lack of financial funds, when local governments implement capital market segmentation, local enterprises lack the necessary funds to innovate and improve their productivity. Hence, enterprises cannot achieve scale expansion and technology upgrade. Finally, the upgrading and optimization of the industrial structure are hindered, and GTFP is also reduced. On the other hand, to complete the performance appraisal and pursue economic growth for the central and western regions, government officials often adopt the "yardstick competition" strategy, causing the economic development model to consider only quantity while neglecting quality. Furthermore, eco-environmental regulation is ignored, and flow factors are absorbed in large quantities to support economic growth in this region. Finally, it will fall into the dilemma of "race to the bottom," which will inevitably lead to local protection and market segmentation (Zhang et al., 2021). However, market segmentation causes deficits in enterprises' power to improve their operations, hinders free flow of factors, and reduces optimal resource allocation in the central and western regions. Moreover, market segmentation harms system innovation and management reform of enterprises, thus reducing their operational efficiency (Bian et al., 2019). Finally, market segmentation reduces the willingness of enterprises to pursue technological innovation, thus inhibiting the R and D of green technologies and GTFP.

CONCLUSIONS AND POLICY IMPLICATIONS

Local government competition (ECU) is crucial in promoting economic growth in China. Exploring the role of market segmentation and GTFP is highly significant to the green and steady development of the regional economy. Using statistical data from 30 provinces in China from 2006 to 2017, this study examines the impact of ECU on GTFP and investigates the mediating effect of market segmentation. Our results are as follows. 1) ECU significantly inhibits increase in GTFP. 2) ECU can not only directly inhibit the promotion of GTFP but also indirectly inhibit GTFP through market segmentation, and market segmentation as a mediation variable is very significant. 3) Considering regional heterogeneity, the effect of ECU on GTFP in the eastern region is positive, but not significant. Moreover, local government competition does not inhibit the growth of GTFP through market segmentation. Hence, ECU promotes market segmentation and inhibits the promotion of GTFP in the central and western regions, and ECU can inhibit the growth of GTFP through market segmentation.

Based on the above research conclusions, the author proposes the following policy implications. Formulating a single assessment index by the superior government is the root of

TABLE 9 | Test results for the robustness of mediation effects.

Variables	National region			Eastern region			Central – western regions		
	GTFP (1)	MSEG (2)	GTFP (3)	GTFP (4)	MSEG (5)	GTFP (6)	GTFP (7)	MSEG (8)	GTFP (9)
L.GTFP	0.798***		0.788***	0.435*		2.530*	0.832***		0.597***
	(30.90)		(72.31)	(1.69)		(1.82)	(27.18)		(6.88)
SF	−0.013***	0.002***	−0.013***	−0.156	−0.001	0.504	−0.027***	0.002***	−0.020**
	(−7.52)	(5.00)	(−7.98)	(−0.78)	(−0.23)	(0.71)	(−9.36)	(3.44)	(−2.55)
GOV	−0.702***	0.019**	−0.742***	−5.016	0.089	10.666	−1.194***	0.037***	−1.524***
	(−7.04)	(2.29)	(−11.61)	(−1.39)	(1.27)	(0.88)	(−7.25)	(2.89)	(−5.28)
HUM	−0.022***	−0.024***	−0.039***	−0.267	−0.015*	−1.817	−0.019	−0.019***	−0.074***
	(−4.29)	(−10.16)	(−3.02)	(−0.39)	(−1.89)	(−0.79)	(−0.85)	(−6.85)	(−2.88)
MAR	0.805***	0.009	0.843***	3.213	−0.068	16.316	0.238*	0.023*	0.837***
	(15.65)	(1.06)	(10.04)	(0.76)	(−0.21)	(0.90)	(1.94)	(1.76)	(4.13)
PAO	0.690	0.585***	0.921	4.745	0.100	75.891	3.188**	−0.156	5.104***
	(1.31)	(9.85)	(1.25)	(0.31)	(0.27)	(0.65)	(2.34)	(−0.30)	(3.74)
ROA	0.003	0.005***	0.000	−0.020**	0.004	−0.372	0.016***	0.002*	0.041***
	(0.62)	(6.83)	(0.14)	(−2.23)	(0.66)	(−1.03)	(3.40)	(1.67)	(5.24)
MES	−0.044	0.026***	−0.006	−0.435	0.042***	0.908	0.028	0.011	0.029
	(−1.19)	(6.75)	(−0.13)	(−0.50)	(5.55)	(1.59)	(0.51)	(0.95)	(0.38)
L.mseg		0.375***			0.454***			0.158***	
		(23.21)			(3.42)			(3.07)	
MSEG			−0.936***			−45.207			−0.717**
			(−4.35)			(−0.88)			(−2.48)
AR (1)	−1.98	−2.82	−1.99	−1.05	−1.66	0.40	−1.61	−2.02	−1.65
	[0.048]	[0.005]	[0.047]	[0.295]	[0.097]	[0.688]	[0.107]	[0.043]	[0.100]
AR (2)	1.26	−0.80	1.32	0.55	−0.66	−0.66	1.38	−0.41	1.41
	[0.209]	[0.424]	[0.186]	[0.584]	[0.508]	[0.507]	[0.169]	[0.681]	[0.159]
Hensen test	27.56	25.24	26.07	5.61	6.49	2.09	16.97	15.36	14.05
	[0.968]	[0.615]	[0.974]	[1.000]	[0.999]	[1.000]	[0.201]	[1.000]	[0.828]
Z_{mid}	3.28	0.22	2.01						
Constant	−0.155***	0.164***	−0.001	2.787	0.170	−1.361	0.546***	0.119***	0.334
	(−4.93)	(8.30)	(−0.02)	(0.45)	(0.51)	(−0.77)	(5.31)	(5.76)	(1.37)
N	330	330	330	110	110	110	209	209	190

*Note: T statistics are put in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01; Z values are put in [].*

local government competition. To achieve political goals, local governments sacrifice long-term interests for short-term and rapid economic development. Moreover, the GDP-oriented performance appraisal system has been widely criticized by society. Therefore, policymakers must improve the performance assessment system, reform the assessment system of local government officials, and facilitate the establishment of a local government competition system guided by high-quality economic development. Additionally, as performance appraisal of local government and the promotion incentive system of officials have strong guiding effect on local government behavior, content related to green development should be added to the performance evaluation index of local government by policymakers. Hence, policymakers should build a government performance appraisal system with economic and environmental coordination.

Second, market segmentation mainly manifests in the direct intervention of local governments through administrative means to restrict market access conditions and enterprise competition. Therefore, policymakers should establish a unified and open market system with orderly competition to further optimize the business environment. Moreover, market access conditions should be further relaxed. A system with a negative list of market access should be implemented uniformly throughout the country. Policymakers should ensure that all regions and all market entities have equal access to the market by law and prohibit all regions from creating a negative list of the nature of market access. This is to ensure fair competition among all market entities. Moreover, policymakers should allow local market regulators to conduct independent supervision and increase enforcement against unfair competition. Simultaneously, preventing and stopping unfair competition, restricting competition in market economic activities, and creating a market environment with fair competition are necessary.

Third, policymakers should formulate preferential tax policies to strengthen support for enterprises' technological innovation. Encouraging enterprises to develop green technology and building a green low-carbon circular development of the economic system will help them achieve green development. Policymakers should increase investment in enterprise technology incubation and R&D to develop the economy and improve GTFP while protecting ecosystem. Additionally, regional development was not balanced. In green transformation, policymakers need to implement differentiated economic policies according to local conditions.

Although this study extensively explores the impact of local government competition on GTFP based on the factor market segmentation perspective, certain limitations deserving further investigation remain. First, this study empirically verifies the role of local government competition on GTFP under the factor market segmentation scenario, which lacks analysis of the influence mechanism of local government competition on GTFP. Therefore, a more in-depth analysis of the influence mechanism will be informative for future research. Second, this study mainly uses provincial-level data for investigating the relationship between local government competition and GTFP based on the factor segmentation perspective. Further research can analyze the impact of local government competition on GTFP based on the market segmentation perspective at the prefecture and county levels, which will provide more precise policy guidance for enhancing GTFP. Finally, this study measures local government competition from the economic competition perspective, which has not been fully established as a comprehensive measure of local government competition. Therefore, more comprehensive construction of local government competition indicators can be conducted in the future using big data technology. For example, local government competition can be remeasured by collecting content about local government competition published on each provincial government's main office website and official media through tools such as Python.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

JT: grasp the theme and research direction, FQ: empirical research and data.

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Carbon Emission Reduction Effects of Green Credit Policies: Empirical Evidence From China

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This paper employs the *Green Credit Guidelines* as green financial policy to investigate whether the implementation of green credit has contributed to the low-carbon economic development. The difference-in-differences method (DID) is then applied to estimate the emission reduction effects. The paper found that green financial policy has effectively reduced pollution and energy consumption in high pollution and high energy consuming industries. As a means of verifying the reliability of the results, propensity score matching difference-in-differences (PSM-DID) applies the match kernels and radius method before the DID. Furthermore, this paper explored the regional and industry heterogeneity in incremental carbon emission reductions. This is the first paper to use Guidelines to measure green finance, in order to achieve indicator innovation and provide corresponding policy advice. To reduce carbon emissions, the government must strengthen the implementation of green credit policy and create a green financial environment tailored to local needs.

Keywords: green credit policy, carbon emission reduction, regional heterogeneity, industry heterogeneity, DID

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INTRODUCTION

In order to develop a green economy, China has formulated a number of green financial policies. Understanding the impact of green financial policies on carbon dioxide emissions is imperative. In particular, policy implementation is critical to reducing carbon emissions. At the third conference of the parties to the United Nations Framework Convention on Climate Change (UNFCCC), held in 1997 in Kyoto, Japan, significant progress was made. After the Kyoto Protocol was adopted, the world entered the post-Kyoto era, when international economic diplomacy gradually shifted its focus to the environment and climate change. Additionally, carbon emissions from industrial development have become such a significant factor that various countries are obliged to factor it into economic development. Nationally Determined Contributions (NDCs) are climate action plans established by all parties to reduce emissions and adapt to climate change impacts. However, carbon dioxide emissions in 2030 are projected to be approximately 5.5% lower than in 2015, which is insufficient to meet the plan described by countries in their NDCs (Roelfsema et al., 2020). Recently, China has experienced rapid economic growth as the largest developing country. The growth of the economy will inevitably result in an increase in energy consumption. In deciding between economic benefits and carbon dioxide emissions caused by energy consumption, how should the Chinese government make a decision? Fortunately, the Chinese government is committed to responding to climate change. In addressing climate change, China is contributing to the global climate governance process based on the demands of its internal sustainable development and its shared responsibility for building a global community of shared future. To participate fully in global climate governance, China's 14th Five-year Plans for social and economic development were committed to implementing such policies so that the value of reduced emissions from oil and coal consumption would be equal to that of increased emissions from natural gas consumption. On February 1, 2021, interim rules for carbon emissions trading management will take effect. It is the first time that the country has clarified the role of enterprises in the reduction of greenhouse gas emissions. In an economic transitional period, maintaining a balance between financial development and carbon emissions is of the utmost urgency.

Development of the financial sector is a prerequisite for economic development, and reducing carbon emissions is an essential component of economic transformation. In 2008, the added value of China's financial sector was 183.134 billion yuan. The financial sector continued to grow in the following years. The added value was 6,112.17 billion yuan in 2016. Accordingly, financial development is inextricably linked to economic development. In terms of the relationship between finance and carbon emission reduction, there are three views. First, financial development would lead to increased carbon emissions by facilitating industrialization. The Climate Change Convention and the Kyoto Protocol stipulate that countries have different allocations of carbon emission rights and distinguish the rights of developed and developing countries at different stages. The international community prefers that the carbon emission rights of developing countries need to be adjusted according to the population (Yao, 2012). In this sense, some scholars have provided evidence of financial development's significantly increasing carbon emissions in developing nations, such as India (Boutabba, 2014), Pakistan (Ali et al., 2015; Shahzad et al., 2017), and Senegal (Asumadu-Sarkodie and Owusu, 2016). Due to China's large population, it has also produced the highest carbon emissions in the world as a developing country. Xiong and Qi (2018) used China's provincial data and found that its financial development would also significantly encourage carbon emissions.

Second, the effects of financial development on carbon emissions are uncertain. Ozturk and Acaravci (2013) found that financial development in Turkey had no significant effects on carbon emissions. Dogan and Seker (2016) also found no significant effects in renewable energy countries. Considering the heterogeneity and differences in the degrees of the financial development of various countries, Acheampong et al. (2020) found that financial development may have reduced carbon emissions as a whole, but the nonlinear and regulatory effects of financial development on carbon emissions were different at different stages of financial development in different countries, so the comprehensive effects could not be determined. Taking different income samples as an example, Ehigiamusoe (2019) found that financial development reduced the carbon emissions of high-income groups but aggravated those of low- and middle-income ones.

Third, there is a nonlinear relationship between financial development and carbon emissions. Charfeddine and Khediri (2016) used a co-integration model and found that the effects of financial development on carbon emissions were a structural mutation phenomenon. Zaidi et al. (2019) showed that the financial development and carbon dioxide emissions in member countries of the Asia-Pacific Economic Cooperation (APEC) had an inverted U-shape, indicating that the expansion of financial development had a nonlinear relationship with carbon emissions, i.e., the former would first stimulate but then suppress the latter. Katircioğlu and Taspinar (2017) believed that the development of the financial industry had a certain inhibitory effect on carbon emissions based on Turkey. To sum up, the discussion on the relationship between financial development and carbon emissions has not been unified. Gök (2020) suggested that research on financial development and carbon emissions depended on the selected financial development indicators, estimation methods, and research objects.

Energy consumption has contributed to a large amount of carbon dioxide emissions during the process of China's economic development. One of the most pressing environmental issues in the world is the greenhouse effect caused by carbon dioxide. In addition, the green transition is an effective way to reduce pollution in economic development. Therefore, to reduce carbon emissions, the financial industry is seeking new ways, such as green credit, green securities, green insurance, and green bonds, to realize green finance. Chen et al. (2018) found that green financial policies serve the purpose of carbon emission reduction through new financial products by controlling the long-term borrowing of high pollution industries. However, modest research has been conducted on the relationship between green finance and carbon emissions. From a national and regional macro level, coal energy consumption, industry value added (Shahzad et al., 2021), environmental taxes (Ghazouani et al., 2021) and environmental regulation (Song et al., 2021) have a significant impact on carbon emissions. Nevertheless, at the corporate level, the effectiveness of macro-control policies needs to be examined. Energy savings and emission reduction have become rigid goals for the green development of the global economy. Growth in the economy increases energy consumption, whereas biomass and renewable energy are conducive to green development (Magazzino et al., 2021a; Mele et al., 2021). In terms of emission reduction, biomass energy has a greater reduction effect than fossil fuels (Magazzino et al., 2021b; Magazzino et al., 2021c). Throughout this paper, the subject of reducing industry-level carbon emissions is explored from a policy perspective. As an effective form of green economic development, is green finance following or running counter to the trend?

This paper used the panel data of 23 industries in 30 provinces from 2007 to 2016, took the *Green Credit Guidelines* published in 2012 as a quasi-natural experiment. The experimental group represents the industry subject to the green credit guidelines, whereas the control group is the industry not affected by the policy. The difference-in-differences (DID) method was used to examine the effects of the *Guidelines* on China's industrial carbon emissions and verify if the green financial policy had reduced the emissions. The explanatory variable is the green financial policy, and the explained variable is the increase of carbon dioxide. The marginal contributions of this study are: 1) the first use of the

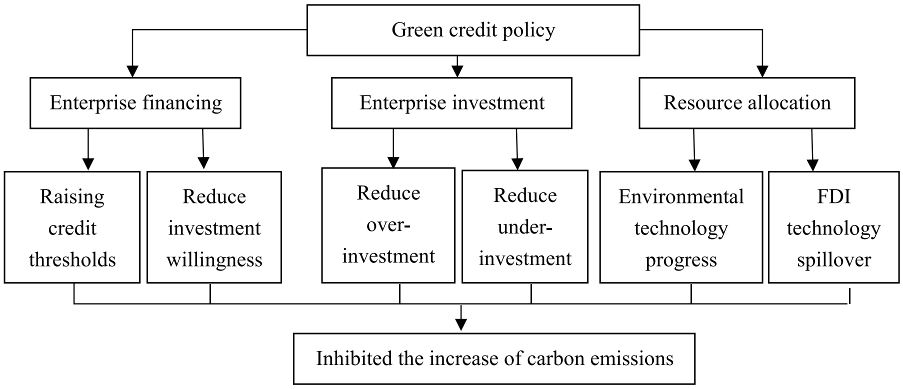

FIGURE 1 | Impact mechanism of green credit policy on carbon emissions.

Guidelines as a green financial policy to measure the variables of green finance and examine the relationship between the policy and carbon emissions; 2) the use of the causal identification of the DID method to examine the effects of green financial policies on carbon emissions and clarify the causal relationship between green finance and carbon emissions; 3) an empirical study of the effects of green financial policies on carbon emission increments of high pollution and high energy consumption industries, as well as a study of regional and industry heterogeneity.

POLICY BACKGROUND AND THEORETICAL ANALYSIS

The green financial policy mentioned in this paper refers to the *Green Credit Guidelines* issued by the China Banking Regulatory Commission (China Banking Regulatory Commission) in 2012. We measured the green credit in accordance with the promulgation of the policy. In these Guidelines, the credit industry has been given a clear definition and a concrete argumentation. Banks and other financial institutions formulate credit guidelines for industries regulated by the government and those with significant environmental and social risks. It is the role of financial institutions to implement green credit policies, link corporate credit lines with environmental performance, such as corporate pollution emissions, and optimize the industrial structure and sustainable development. According to policy requirements, firms are required to provide detailed pollution information to banks. In accordance with the environmental pollution of the firms, the bank controls the credit threshold strictly. Therefore, the credit volume to dirty firms is limited, and firms must reduce pollution emissions in a variety of ways. In the new era of economic development in China, environmental policies are aligned with the goal of reducing carbon emissions. Because the policy's implementation is less affected by local governments, it is possible to reflect the direct impact of green financial policies on industrial carbon emissions.

In accordance with banking microeconomic theory (Stiglitz and Weiss, 1981), there is an information asymmetry between banks and enterprises. The asymmetry of information results in an imbalance in the allocation of financial resources between enterprise property rights and scale. Companies with higher carbon emissions will also receive substantial financial support since financial resources are more readily available to large companies. As a result of the green finance policy, financial institutions are encouraged to establish green financial products that will aid companies in developing clean production methods and reduce greenhouse gas emissions. This paper explores the relationship between green credit policies and carbon emissions resulting from corporate financing, corporate investments, and resource allocation, as shown in **Figure 1**.

First, from the perspective of corporate finance, green financial policies have raised the credit thresholds for industries with high pollution and high energy consumption. Moreover, it reduces the willingness of external creditors to invest in it. On the one hand, credit policy directly affects corporate debt (Demirguc-Kunt and Maksimovic, 1996), which is the foundation of industry debt (Mitton, 2008). Green credit policies limit opportunities for the high pollution and high energy-consuming industries to obtain new loans and restrict their development (Liu et al., 2019). However, only increases in bank loans are affected but those that have already been obtained are not restricted. As a result, the expansion of such industries is limited, thereby affecting the quantity of carbon emissions. On the other hand, government departments transmit corporate environmental information to the market, disclose and expose corporate pollution information, and improve market supervision mechanisms. Such activities affect the investment decisions of external creditors (Michael and Mitchell, 2006), which directly affect the capital operations, business strategies, and production scales of companies, and, in turn, affect carbon emissions. In sum, green financial policies affect corporate carbon emissions by influencing credit thresholds and the willingness of external creditors to invest.

Second, companies will receive inadequate or excessive investment (Richardson, 2006). Green financial policies affect corporate investment decisions, which, in turn, affect corporate carbon emissions. Cash flow is directly linked to corporate investments. In theory, excessive flow signifies excessive investment, whereas insufficient flow signifies insufficient investment. From a quantitative analysis of the effects of green credit policies, Liu et al. (2017) argued that such policies could significantly inhibit investment in energy-intensive industries, as well as limit the debt problems of high pollution and high energy industries (Zhang et al., 2011). Therefore, for high pollution enterprises, green financial policies limit excessive cash flow and curb investment, thereby reducing corporate carbon emissions. However, from the perspective of the opportunity costs of capital utilization, green financial policies encourage investment and development for green enterprises by increasing credit lines and alleviating the lack of cash flow, thereby reducing social carbon emissions. To sum up, at the level of corporate investment, green finance reduces carbon emissions by remedying both underinvestment and overinvestment.

Finally, from the perspective of resource allocation, green financial policy forces industrial transformation and upgrading, which affects environmental technology progress and Foreign Direct Investment (FDI) technology spillover. Acemoglu et al. (2012) proposed advances in environmental technology for energy saving and emission reduction to reduce industrial carbon emissions. The promulgation of the green credit policy reflects if an enterprise has withstood the pressure of transformation. In general, effective implementation can encourage enterprises to improve energy efficiency and reduce carbon emissions. From the perspective of FDI technology spillover based on the “pollution paradise hypothesis,” Javorcik and Wei (2003) believe that multinational companies with high pollution and high emissions are more likely to migrate to countries with weaker environmental standards. In addition, the “Porter hypothesis” that improves the environmental regulation standards of the host country would encourage multi-national research and development of clean technologies and emission reduction, thus further improving sewage pollution (Porter, 1991). The implementation not only restricts the entry of high polluting industries with no threshold but also encourages the entry of low polluting green industries. Green financial policies reduce carbon emissions through progress in environmental technology and through FDI technology spillover.

The above analysis can lead to the conclusion that green credit policies would have different effects on different industries. Looking further from the perspective of different industries, how do green credit policies affect their carbon emissions? According to the *Green Credit Guidelines*, such policies have specific effects on the following three industries. First, industries with high pollution and high energy consumption, i.e., with high carbon emissions, are directly restricted by green credit. After the implementation of green policies, the difficulty of granting credit will increase or become prohibited altogether. Second, green credit policies encourage the development of green industries, such as new energy industries, and banks will grant credit lines to encourage their development. Third, the policy has insignificant effects on the credit lines granted by banks to industries that are neither high pollution and high energy consumption nor green.

TABLE 1 | Policy effect analysis table of double difference method.

	Before (dt = 0)	After (dt = 1)	Difference
Treatment group (du = 1)	$\alpha_0 + \alpha_1$	$\alpha_0 + \alpha_1 + \alpha_2 + \alpha_3$	$\alpha_2 + \alpha_3$
Control group (du = 0)	α_0	$\alpha_0 + \alpha_2$	α_2
Difference	α_1	$\alpha_1 + \alpha_3$	α_3

According to the current industry classification, the green industry, with its weak foundations, has not been classified into a specific industry category. Therefore, what can be compared is the difference between high polluting, high energy-consuming industries and low polluting, low energy-consuming industries. In light of the above analysis, this paper proposes the following hypotheses:

Hypothesis 1. As a green financial policy, green credit policy can inhibit the increase of carbon emissions.

The *Green Credit Guidelines* is non-binding policy, and it takes some time for banks to implement the policies of the *Green Credit Guidelines*. Continuous impact of policy implementation needs to be improved, and the overall impact is lagging. Meanwhile, not all industries with high pollution and high energy consumption will apply for bank credit when the policy are issued. Therefore, the impact of the *Green Credit Guidelines* policy on carbon emissions will require a process. In summary, it is necessary to further consider the time lag when discussing the impact of green finance policies on carbon emissions. Hence, we propose the following hypothesis:

Hypothesis 2. The impact of the Green Credit Guidelines has a time lag effect.

METHODOLOGY AND DATA

Model Setting and Definition of Variables

We have added a flowchart to show the research methodology in the **Supplementary Chart**. The economic policies covered by this study affected particular areas. The DID method can be used to identify econometric models of the shock effects of economic policies and the effects on the gap among regions where the policies have been implemented and not implemented. A model constitutes two differences and can identify the net effect of an economic policy on a certain region. The estimation formula is:

$$y_{it} = \alpha_0 + \alpha_1 du + \alpha_2 dt + \alpha_3 du \times dt + \zeta_{it} \tag{1}$$

where y_{it} is the explained variable, du is a dummy variable for the regions set to 1 for the experimental group but 0 for the control group, and dt is a dummy variable for policy implementation set to 0 or 1 before or after implementation, respectively. $du \times dt$ represents the interaction item between the virtual variables of the region and policy implementation, before which $du \times dt = 0$ and after which $du \times dt = 1$. The effects of the policies can be represented by simplified graphs, as shown in **Table 1**. The coefficient α_3 is the coefficient of $du \times dt$ after the application of the DID method.

According to the theoretical analysis of the second part and the application of the DID method, the model is:

$$\Delta CO2_{ipt} = \alpha_0 + \alpha_1 du_{ipt} + \alpha_2 dt_{ipt} + \alpha_3 du_{ipt} \times dt_{ipt} + X\gamma + \zeta_{ipt}, \tag{2}$$

where i represents the industry, p represents the province, and t represents the year. $\Delta CO2_{ipt}$ is the explained variable representing the increase in carbon dioxide emissions and represents the difference between the quantities in the following and previous years. X is a series of control variable matrices and γ is a coefficient matrix of control variables. du_{ipt} represents the industry affected by the *Green Credit Guidelines* policy and dt_{ipt} is the year after implementation. If the value of α_3 is negative, then the policy is negatively related to the increase in emissions. Thus, implementation can make a significant difference in emission reduction.

For industry, exports (*export*) were controlled by the proportion of export delivery value to sales value. The industry profit rate (*profit*) was measured by the ratio of the total profit to sales output value multiplied by 100%. Industry revenue capacity (*inc_cap*) was expressed as the proportion of main business revenue in paid-in capital. The proportion of national capital was the proportion of national capital to paid-in capital. For province, the natural logarithm of GDP per capita (*lnpgdp*) was controlled. Then, the number of patents per 10,000 people (*ppatent*) was divided by the total number obtained each year by each province and the total number of people was multiplied by 10,000. In addition, the proportion of secondary industry (*indstr*) was expressed as the proportion of secondary industry to GDP. Financial self-sufficiency (*finc_exp*) was fiscal expenditure divided by fiscal revenue.

Sample Selection and Data Sources

The carbon emission data of the explained variables by province and industry were derived mainly from the China Carbon Emissions Database (CEADs) (Shan et al., 2018; Shan et al., 2020). With the joint support of many research institutions, such as the British Research Council, the Newton Foundation, the National Natural Science Foundation of China, and the Chinese Academy of Sciences, scholars from all over the world have compiled China's multi-scale carbon emission inventory.

The CEADs is used for industry matching with the China Industrial Economic Database. Hence, we matched 23 industries, including special equipment manufacturing, transportation equipment manufacturing, chemical manufacturing and so on. In addition, according to the energy consumption per unit of industrial added value, the petroleum refinery industrial, chemical industry, nonferrous metals products manufacturing, smelting and pressing of ferrous metals, and non-ferrous metal smelting are designed as high energy consumption industries. Therefore, the above five industries are experimental group and the remainders represent the control group.

The industry control variables in this paper were derived mainly from the China Industrial Economic Database of the Easy Professional Superior data platform (EPS), which is a comprehensive Social Sciences data service platform including China's macro-economy, financial market, industrial operation, regional economy, foreign trade, and so on. In addition, the provinces' control variables came from the "China Macroeconomic Database" of the EPS data platform. During data processing, the China Carbon Emissions Database was matched with the China Industrial Economic Database. The Green Credit Guideline*s* were implemented in 2012. The data were first compiled in 2007 and last updated in 2016. Therefore, the final sample inspection period was determined to be 2007–2016. However, the selected explained variable in this paper is incremental, so the period of the last research data is 2008–2016. The descriptive statistical tables of the main variables are shown in **Table 2**.

TABLE 2 | Descriptive statistics of main variables.

Variables	Definition	N	Mean	SD
ΔCO₂	Increase in CO_2 emissions(*mt*)	4,873	0.205	2.729
export	Industry export level	4,873	0.114	0.827
profit	Industry profitability	4,873	2.975	4.568
inc_cap	Industry revenue capacity	4,873	6.434	4.532
own	Proportion of state capital	4,873	0.143	0.306
lnpgdp	Real GDP per capita	4,873	10.566	0.517
ppatent	Number of patents per 10,000 people	4,873	7.171	8.952
indstr	The proportion of secondary industry	4,873	47.244	7.750
finc_exp	Financial self-sufficiency	4,873	2.119	0.810

EMPIRICAL RESULTS

Benchmark Regression

After the Hausman test between fixed effects and random effects, the fixed effect model was used to estimate the model in this study. **Table 3** presents the corresponding estimation results. Column (1) shows the control industry-provincial fixed effects. Only the policy effects of the *Green Credit Guidelines* were examined. The results show that the coefficient of $du \times dt$ is significantly negative and the coefficient value is 1.071, indicating that the policy will reduce 1.071 million tons (mt) of carbon emissions in total.[1] Reducing 1.071 mt of carbon dioxide is critical for China's ecological and environmental protection, as well as for the sustainable development. Considering the time effect, Column (2), which is based on Column (1), controls the fixed effects of the year. The coefficient of $du \times dt$ remained highly negative and the change in the coefficient was negligible,

[1]If the coefficient is M, the coefficient indicates that X changes by one unit while Y changes by M units on average. Specifically, the implementation of the policy is expected to affect the carbon emissions of M units. The policy implementation time is 2012, and the research time period is 2008–2016. Specifically, through the implementation of this policy, the carbon increase of the experimental group was reduced by 1.071 million tons after 2012.

TABLE 3 | Benchmark regression.

Explanatory variables	Explained variable: △CO2				
	(1)	(2)	(3)	(4)	(5)
du × dt	−1.071***	−1.067***	−1.072***	−1.063***	−1.071***
	(0.286)	(0.286)	(0.279)	(0.277)	(0.278)
export			0.005**	0.007**	0.004**
			(0.003)	(0.003)	(0.002)
profit			0.008***	0.007***	0.007***
			(0.003)	(0.002)	(0.001)
inc_cap			0.007	0.002	0.002
			(0.016)	(0.015)	(0.015)
own			−0.037	−0.026	−0.020
			(0.174)	(0.176)	(0.179)
lnpgdp			0.154***	0.765**	0.291*
			(0.013)	(0.331)	(0.180)
ppatent			0.012**	0.018**	0.021**
			(0.006)	(0.007)	(0.008)
indstr			0.025**	0.022**	0.014**
			(0.010)	(0.011)	(0.007)
finc_exp			0.065	0.042	0.007
			(0.195)	(0.190)	(0.189)
Constant	0.353***	0.221***	0.434	−7.242	−2.398
	(0.041)	(0.041)	(2.004)	(5.916)	(5.786)
Year FE	N	Y	N	Y	Y
Province-industry FE	Y	Y	Y	Y	Y
Year-Province FE	N	N	N	N	Y
F	7.018	5.904	3.649	6.927	10.811
Adj-R^2	0.010	0.013	0.011	0.014	0.016
N	4,873	4,873	4,873	4,873	4,873

*Notes: Each model controls two variables, treat and t. The standard errors of robustness are in parentheses. ***, ** and * represent significance levels of 1%, 5% and 10%, respectively.*

indicating that policy could have a relatively stable effect on the incremental carbon emissions from the high pollution and high energy industries.

In addition, industry and regional control variables are added in Column (3). Compared with the coefficient in Column (1), the coefficient of $du \times dt$ is still highly negative and mostly unchanged, indicating a relatively stable effect. To examine the individual time effects, the time control variable was added in Column (4). The core explanatory variable was still significantly negative. Based on the three-dimensional panel data composed of province–industry–year, the sample continues to control the year–province fixed effect in Column (5). The results show that the coefficient of $du \times dt$ is still highly negative. Moreover, the coefficient is almost the same as that in Column (1). After a comprehensive consideration of various factors, the effect was relatively stable. Therefore, Hypothesis 1 was supported.

Among the industry control variables, industry export level, and industry profitability had significant positive effects on incremental carbon emissions, signifying that industry revenue capacity and national capital share did not drastically affect incremental carbon emissions. Among the regional control variables, the actual GDP per capita at the provincial level, the number of patents per 10,000 people, and the proportion of the secondary industry had very strong effects on incremental carbon emissions, whereas fiscal self-sufficiency had no significant effect.

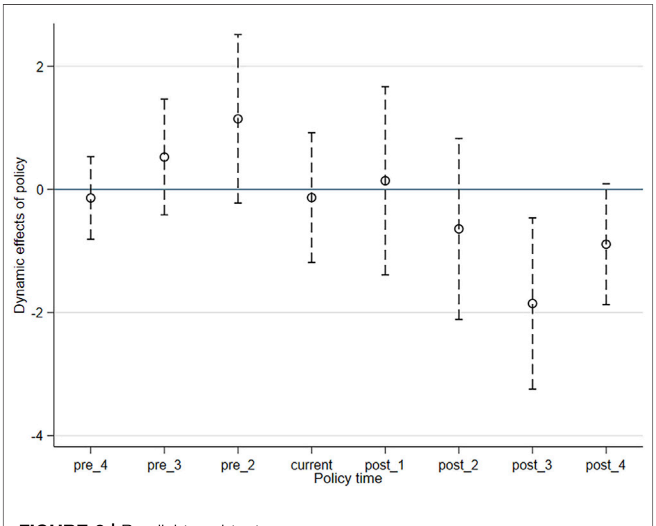

FIGURE 2 | Parallel trend test.

Parallel Trend Test

On the basis of empirical evidence, we also did a parallel trend test. The result is shown in **Figure 2**. Before the implementation of the policy, it is obvious that none of the coefficients are significant, which demonstrates that the differences in carbon emissions between the treatment group and the control group before policy were not significant. The results show that the parallel trend assumption is supported by these results, indicating

TABLE 4 | Analysis of lag effect.

Explanatory variables	Explained variable: △CO2					
	(1)	(2)	(3)	(4)	(5)	(6)
L.du × dt	−1.062***	−1.086***	−1.092***			
	(0.230)	(0.223)	(0.223)			
L2.du × dt				−1.387***	−1.453***	−1.463***
				(0.356)	(0.340)	(0.344)
Control variable	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y
Provinces-industry FE	Y	Y	Y	Y	Y	Y
Year-Province FE	N	N	Y	N	N	Y
F	6.402	5.740	11.425	3.144	6.255	15.553
Adj-R^2	0.012	0.014	0.016	0.017	0.019	0.021
N	4,331	4,331	4,331	3,789	3,789	3,789

Notes: Each model controls two variables, treat and t. *The standard errors of robustness are in parentheses. ***, ** and * represent significance levels of 1%, 5% and 10%, respectively.*

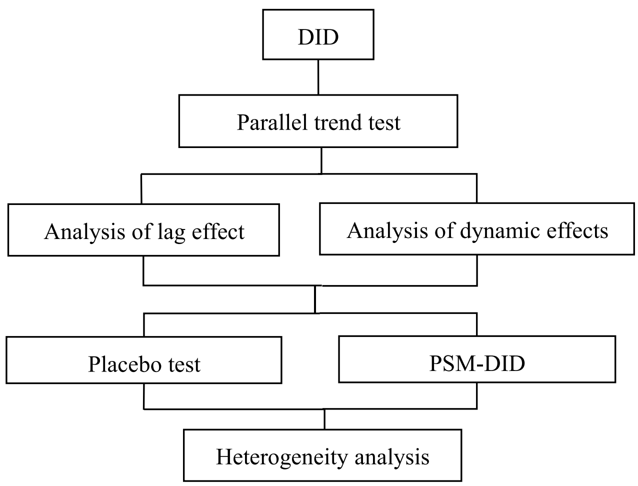

FIGURE 3 | Parallel trend test.

that the application of the DID method to assess the policy is a reasonable and convincing approach.

Analysis of Lag Effect

Considering that the implementation of the policies and the embodiment of the policy's effects need a time cycle This study focused on the time lag's effects on incremental carbon emissions. The results are reported in **Table 4**. The six models include all control variables.

Column (2) is based on Column (1) and increases the fixed effect of time. Column (3) uses Column (2) and adds the year–province fixed effect. The estimation results of the three models show that the regression coefficient of *du* × *dt*'s lagging one period is highly negative. The coefficient's values are 1.062 and 1.092. As more fixed effects are added, the absolute value of the coefficient increases, indicating that the policy's effects are relatively exogenous and the results are relatively stable. Judging from the magnitude of the numerical change, the coefficient has increased, indicating that one year after the policy's implementation had a more obvious effect on the reduction.

Columns (4) to (6) are consistent with the regression methods of Columns (1) to (2) and gradually increase the time and the year–province fixed effects. The only difference is *du* × *dt*'s being set to lag in the second period and still being significantly negative. The absolute value of the coefficient is significantly higher than the baseline regression, indicating that the effect was more obvious 2 years after the implementation.

Analysis of Dynamic Effects

According to the above results, the policy had a reduction effect on the industry's incremental carbon emissions and the effect had a time lag. This study analyzed the dynamic effects of the policy on the incremental carbon emissions. First, to generate *green2009* dummy variables with 2008 as the base period, the policy was assumed to have been implemented in 2009, during which the high pollution and high energy industries take values of 1, whereas the other industries take values of 0. By analogy, seven dummy variables from

TABLE 5 | Dynamic effect analysis.

Explanatory variables	Explained variable: ΔCO2				
	(1)	(2)	(3)	(4)	(5)
green2009	0.499*	0.502*	0.678**	0.665**	0.665**
	(0.244)	(0.247)	(0.261)	(0.256)	(0.256)
green2010	1.225**	1.221**	1.283**	1.285**	1.285**
	(0.569)	(0.574)	(0.597)	(0.607)	(0.607)
green2011	0.079	0.062	0.127	0.139	0.139
	(0.328)	(0.313)	(0.345)	(0.328)	(0.328)
green2012	0.192	0.154	0.055	0.006	0.006
	(0.330)	(0.336)	(0.337)	(0.355)	(0.355)
green2013	−0.142	−0.185	−0.217	−0.280	−0.280
	(0.486)	(0.484)	(0.620)	(0.626)	(0.626)
green2014	−0.224	−0.302	−0.417	−0.502	−0.502
	(0.405)	(0.449)	(0.501)	(0.561)	(0.561)
green2015	−1.576***	−1.576***	−1.719***	−1.714***	−1.714***
	(0.411)	(0.457)	(0.550)	(0.592)	(0.592)
green2016	−1.130***	−1.082***	−0.811	−0.751	−0.751
	(0.392)	(0.372)	(0.489)	(0.462)	(0.462)
Control variable	N	N	Y	Y	Y
Year FE	N	Y	N	Y	Y
Province-industry FE	Y	Y	Y	Y	Y
Year-Province FE	N	N	N	N	Y
F	6.095	7.482	5.428	7.221	7.221
Adj-R^2	0.026	0.026	0.024	0.024	0.024
N	4,873	4,873	4,873	4,873	4,873

*Notes: Each model controls two variables, treat and t. The standard errors of robustness are in parentheses. ***, ** and * represent significance levels of 1%, 5% and 10%, respectively.*

TABLE 6 | Placebo test.

Explanatory variables	Explained variable: ΔCO2					
	(1)	(2)	(3)	(4)	(5)	(6)
dpu × dt	0.330***	0.322***	0.329***			
	(0.100)	(0.098)	(0.101)			
L.dpu × dt				0.378***	0.429***	0.438***
				(0.078)	(0.092)	(0.092)
Control variable	Y	N	N	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y
Province-industry FE	Y	Y	Y	Y	Y	Y
Year-Province FE	N	N	Y	N	N	Y
F	3.467	6.968	9.249	4.314	6.720	35.291
Adj-R^2	0.005	0.008	0.009	0.007	0.009	0.011
N	4,873	4,873	4,873	4,151	4,151	4,151

*Notes: Each model controls two variables, treat and t. The standard errors of robustness are in parentheses. ***, ** and * represent significance levels of 1%, 5% and 10%, respectively.*

green2010 to *green2016* were generated. When the model was estimated, these dummy variables were added to the model together. The estimated coefficient of each dummy variable represents the effects of the policy after its implementation in that year. Then, the dynamic effects of the hypothetical green financial policy were judged. **Table 5** presents the corresponding estimation results.

Columns (1) and (2) do not include the control variables, whereas Column (2) in Column (1) controls the fixed effect of time. The regression results show that the coefficients of *green2009* and *green2010* are significantly positive, i.e., in 2009 and 2010, the incremental carbon emissions of the high pollution and high energy industries increased relative to those of other industries. In 2011 and 2012, the two coefficients were still positive but not significant. Moreover, in 2013 and 2014, the regression coefficient was negative but not significant. From Columns (3) to (5), other control variables were added into the regression. The coefficient of the green dummy variable was not significantly positive until 2015, indicating that the green financial policy had a strong time lag and a reduction effect had only begun to play a role 4 years after the policy's implementation.

Placebo Test

Because the choice of processing groups was determined by energy consumption, the selection has a certain randomness. The placebo

TABLE 7 | PSM-DID test.

Explanatory variables	Explained variable: ΔCO2			
	Kernel matching		Radius matching	
	(1)	(2)	(3)	(4)
du × dt	−0.960***	−0.958***	−0.952***	−0.964***
	(0.226)	(0.228)	(0.233)	(0.225)
Control variable	N	Y	N	Y
Year FE	Y	Y	Y	Y
Province-industry FE	Y	Y	Y	Y
Year-Province FE	Y	Y	Y	Y
Adj-R^2	0.019	0.020	0.300	0.020
N	4,578	4,533	4,453	4,573

*Notes: Each model controls two variables, treat and t. The standard errors of robustness are in parentheses. ***, ** and * represent significance levels of 1%, 5% and 10%, respectively.*

test was performed by changing experimental groups. The metallurgy industry, general equipment manufacturing, special equipment manufacturing, transportation equipment manufacturing, and electrical machinery and equipment manufacturing belong to the heavy industries. Compared with the general industries, their energy consumption is higher. However, they are not industries that have restricted credit in the *Green Credit Guidelines*. We regarded the above five industries as the experimental group (*dpu = 1*) and other industries as the control group (*dpu = 0*). The results are reported in **Table 6**. Under Columns (1) to (3), the control variables, time effects, and individual effects were controlled separately. The estimated coefficients of *dpu × dt* were significantly positive, indicating that the above five industries had increased their carbon emissions more than did the other industries. There was no carbon emission reduction. Considering the time lag, Columns (4) to (7) under the three conditions of controlling province–industry, year–province, and both, we specifically investigated the incremental carbon emissions in the *dpu × dt* lag phase. The results are consistent with Columns (1) to (3). The coefficients of *dpu × dt* were significantly positive, indicating no reduced carbon emissions. In summary, we found from the placebo test that green financial policies stimulated emission reduction only from high pollution and high energy industries. Moreover, this reduction effect had a time lag, thus supporting both Hypothesis 1 and Hypothesis 2.

Propensity Score Matching Difference-in-Differences

According to the above analysis, the policy had a reduction effect on incremental carbon emissions from only high pollution and high energy industries. However, the DID model cannot completely solve the endogenous problem, signifying that the influence of other factors on incremental carbon emissions could not be ruled out. To alleviate possible endogenous problems, we used the PSM-DID method for testing. The results are shown in **Table 7**. Specifically, PSM was used to match samples similar to the experimental group, then the DID method was used for estimation. When a certain experimental observation i is matched, we take a weighted average of all the observations of the control group, and the weight can be determined by the kernel function. The kernel function reflects the degree of similarity of the covariate. If the covariate is similar, the weight for it will be greater.

Columns (1) and (2) are the estimated results of DID after kernel matching. In the absence of control variables, the coefficient of *du × dt* was −0.96. When the control variables were included, the regression coefficient was −0.958. Both coefficients are highly significant with a small difference between them. Columns (3) and (4) show the results of the DID estimation after radius matching. The coefficient of *du × dt* remained significantly negative even when the control variable was added. In addition, there is no significant difference in the coefficient size. From the regression analysis, we found that the coefficient of *du × dt* was relatively minor when compared to the benchmark regression, indicating the possibility of overestimation and that other factors had strengthened the effects of the policy when PSM matching was not used.

TABLE 8 | Regional heterogeneity analysis.

Explanatory variables	Explained variable: ΔCO2			
	East region	Central region	West region	Northeast region
	(1)	(2)	(3)	(4)
du × dt	−1.188**	−1.012*	−0.700*	−2.155**
	(0.465)	(0.549)	(0.421)	(0.924)
Control variable	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Provinces-industry FE	Y	Y	Y	Y
Year-Province FE	Y	Y	Y	Y
F	1.797	1.716	2.033	2.785
Adj-R^2	0.022	0.013	0.031	0.091
N	1,751	1,202	1,417	503

*Notes: Each model controls two variables, treat and t. The standard errors of robustness are in parentheses. ***, ** and * represent significance levels of 1%, 5% and 10%, respectively.*

TABLE 9 | Industry heterogeneity analysis.

Explanatory variables	Explained variable: ΔCO2			
	Industries with state owned capital less than average	Industries with state owned capital greater than average	The average profit of the industry is greater than zero	The average profit of the industry is less than zero
	(1)	(2)	(3)	(4)
$du \times dt$	−1.081** (0.452)	−0.678** (0.321)	−0.036 (1.051)	−0.976*** (0.282)
Control variable	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Provinces-industry FE	Y	Y	Y	Y
Year-Province FE	Y	Y	Y	Y
N	3,487	1,386	181	4,692
F	1.582	1.801	5.691	2.012
Adj-R^2	0.019	0.020	0.300	0.013

*Notes: Each model controls two variables, treat and t. The standard errors of robustness are in parentheses. ***, ** and * represent significance levels of 1%, 5% and 10%, respectively.*

Therefore, the estimation results of the PSM-DID method were more reliable.

Heterogeneity Analysis

To examine the regional differences in the effects of the financial policy, this study analyzed the heterogeneity of green financial policy on the industry's incremental carbon emission reductions from the perspectives of regional and industry heterogeneity. The 30 provinces of mainland China (excluding Tibet) were divided into sub-samples of four regions: eastern, central, western, and northeastern. The eastern region covered the 10 provinces and cities of Beijing, Hebei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan, the central region covered the six provinces of Shanxi, Henan, Anhui, Hunan, Hubei, and Jiangxi. The western region included Inner Mongolia, Xi'an, Gansu, Qinghai, Xinjiang, Yunnan, Sichuan, Chongqing, Guizhou, Guangxi, and 11 other provinces and cities. The northeastern region included Liaoning, Jilin, and Heilongjiang. The last region was separately investigated because of its serious industrial decline.

The regression results in **Table 8** show that the $du \times dt$ coefficient is significantly negative in the four models, indicating that green financial policy had a significant effect on the incremental carbon emission reductions of the high pollution and high energy industries in all four regions. Specifically, the $du \times dt$ coefficient of the eastern region is 1.188, which is greater than those of 1.012 of the central and 0.700 of the western regions. Moreover, the absolute value of the regression coefficient in the northeastern region is 2.155. Thus, the policy's effects were the strongest in the northeastern, followed by the eastern, central, and western regions. The effects in the northeastern region may be related to the decline of its aging industrial foundation, whereas the strengths of the effects in the other regions may be related to their levels of economic development.

To examine the differences in the emission reduction effect of green credit policies, this study examined the effects of the green financial policy on capital heterogeneity and average profit heterogeneity. The results are shown in **Table 9**.

To examine the heterogeneity of capital, the average capital value (0.143) was taken as the sample cut-off point. Columns (1) and (2) respectively represent two sub-samples in which the proportions of state-owned capital are less and greater than the industry average. The results show that in industries where state-owned capital is less than the average, the absolute value of the regression coefficient of $du \times dt$ is relatively larger, indicating that the industries where state capital accounts for a relatively small (or large) amount had been relatively more (or less) affected by green financial policy. The probable reason is the banks' consideration of not only the industry's characteristics but also the state-owned nature of the enterprise when they issue loans.

In order to investigate the differences of the emission reduction effects of green credit policy in different profit margin industries, the industry average profit rate as zero was taken as the sample cut-off point. Columns (3) and (4) respectively represent the regression results of two sub-samples with industry average profit rates of zero and less than zero. According to **Table 9**, the green financial policy had no significant effect on industries whose average profit margins were greater than zero. However, in industries where the average profit margins were less than zero, the policy had a significant and negative effect. The probable reason is the banks' inclinations toward enterprises in industries with high profit margins. Even if they are high pollution and high energy industries, they are still eligible for loans.

CONCLUSION AND POLICY IMPLICATIONS

Financial development, financial globalization, and high-tech industries have a strong connection with environmental ecology (Shahzad et al., 2022). A primary goal of this paper was to determine whether the green credit policy had met the low-carbon economic development. In applying the difference-in-differences method to estimate the emission reduction effects of the policy, this paper adopted the Green Credit Guidelines as a policy shock toward green financial policy. Several conclusions are drawn. Our basic empirical model indicates that green financial policy has significantly reduced incremental carbon emissions in high pollution and high energy consumption industries. According to our simulation of the dynamic effect, there was a time lag and the results were apparent only three to 4 years after the policy was implemented. Additionally, the PSM-DID and placebo test all show the robust result. According to the results of a study of regional heterogeneity, green financial policy had the most impact in the northeastern region, followed by the eastern, central, and western regions. Also, according to the results of the analysis of industry heterogeneity, the effects of green financial policy were stronger in industries with small proportions of state-owned capital and margins less than zero.

The policy enlightenment in this paper is in the following areas. Introducing green credit policies can significantly reduce greenhouse gas emissions. Thus, controlling carbon emissions through macro financial means is positive and effective at the micro level. In addition, the policy effect lags behind. The government should rationally enhance the implementation of green credit policies. Furthermore, the effects of policy implementation vary among regions and industries. Thus, it is important for the government to consider the differences between regions and industries.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://www.ceads.net.cn/ https://data.cnki.net/NewHome/index.

AUTHOR CONTRIBUTIONS

JQ is responsible for data processing and first draft of the study. JC is responsible for the design and literature collection.

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SUPPLEMENTARY MATERIAL

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Financial Inclusion, Technological Innovations, and Environmental Quality: Analyzing the Role of Green Openness

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Undoubtedly, financial inclusion (FIN) contributes to economic development by enabling individuals and businesses, particularly small and medium enterprises, to access financial services. Financial inclusion may also have environmental implications; however, limited studies have looked into the nexus between financial inclusion and environmental quality. Also, the possible impacts of technological innovation and green openness remain unexplored in this nexus. In this context, this article probes the relationship between financial inclusion, technological innovation, green openness, and CO_2 emissions in BRICS countries while controlling for economic growth and energy consumption. Using the panel times series data from 2004 to 2018, this study uses advanced econometric techniques for empirical analysis robust to cross-sectional dependency and slope heterogeneity. The empirical results unveiled that FIN contributes to environmental degradation in BRICS countries. In contrast, technological innovation and green openness pose mitigating effects on emissions, thus promoting environmental sustainability. Environmental degradation is evidenced to enhance due to rising economic growth and energy utilization. Financial inclusion, technological innovation, and green openness Granger cause CO_2 emissions, but not the other way around. Further, technological innovation, green openness, and financial inclusion Granger cause each other. Based on the empirical results, this study recommends that BRICS countries should promote technological innovation, green openness, and at the same time, integrate financial inclusion with environmental policies to achieve climate-related goals.

Keywords: financial inclusion, technological innovation, green openness, environmental quality, BRICS

Abbreviations: CD, Cross-sectional dependence; CO_2, Carbon dioxide; CUP-FM, Continuously updated fully modified; CUP-BC, Continuously updated bias-corrected; EC, Energy consumption; FIN, Financial inclusion; GDP, Economic growth; GOP, Green openness; TI, Technological innovations.

INTRODUCTION

In recent decades, scholars have focused on investigating the drivers of environmental deterioration. In this regard, the literature has reached a consensus that the combustion of fossil energy sources is the prime cause of anthropogenic emissions and consequent climate change. In addition, a plethora of environmental research indicated that economic development is largely responsible for massive energy consumption and environmental deterioration (Saboori et al., 2014; Kanat et al., 2021; Khan et al., 2021; Oláh et al., 2021). Apart from this, studies have unfolded some other determinants, such as financial development, technological innovation, urbanization, globalization, trade openness (Ahmed and Le, 2020; Can et al., 2020; Rafique et al., 2020; Saud et al., 2020), and tourism services (Uslu et al., 2020; Halaskova et al., 2021) among others.

Scholars have given a lot of attention to the effect of financial development on environmental quality because financial development is indispensable for funding cleaner energy projects, and generally, the role of financial development in environmental deterioration is multifaceted. This is because funding cleaner energy technologies projects can benefit the environment but disregarding the environmental impacts of financial investments can stimulate environmental problems (Ahmed et al., 2021). Interestingly, the study of Chibba (2009) introduced the concept of financial inclusion and stated that financial inclusion can play a key role in alleviating poverty. Finical inclusion indicates the inclusiveness of a financial system based on different aspects, such as access to banking services, banking penetration, and usage of a banking system. More precisely, it is defined as the capability to use a variety of financial services and products, such as payments, savings, insurance, remittances, credit, etc. to fulfill the financial needs in an affordable, responsible, and convenient manner (World Bank, 2021).

Theoretical arguments suggest that financial inclusion can enhance or alleviate environmental degradation. For instance, financial inclusion enables small and medium enterprises and individuals to avail financial products and services conveniently at an affordable cost, which makes investments in cleaner technologies more viable (Le et al., 2020; Metzker et al., 2021). Cleaner technologies promote both economic development and environmental sustainability (Jordaan et al., 2017); hence, financial inclusiveness can contribute to CO_2 reduction through this channel. Financial inclusiveness can also be critical for fulfilling the financial requirements of farmers in remote areas where credit constraints limit the usage of green energy, such as solar energy which is considered an affordable clean energy source with less environmental deterioration (IPA, 2017). Also, limiting credit constraints can pave the way towards investment in cleaner energy because credit constraints hinder investment in green energy (Baulch et al., 2018). Conversely, economic activity is predicted to be boosted by growing financial inclusion, which in turn can stimulate energy demand and CO_2 emissions (Qin et al., 2021). Additionally, access to more financial services promotes manufacturing and industrial activities, infrastructure development, and the use of household and other appliances (Ahmad et al., 2021b). Hence, financial inclusiveness is expected to boost environmental deterioration through these channels.

Against this backdrop, investigating financial inclusion, technological innovation, green openness, and CO_2 association is the main aim of this empirical study. it is also an important factor that not only promotes financial products and services but also increases energy efficiency and environmental sustainability. According to Agyekum et al. (2021), improving technological infrastructure boosts credit supply and enhances financial inclusion. Innovation is also critical in increasing productivity and economic progress (Kihombo et al., 2021). Evidently, innovation spurs technological advancement which reduces energy and emissions levels (Mensah et al., 2018) According to Kihombo et al. (2021), curtailing the negative externalities of growth and a high level of technological innovation are required to develop a low-carbon green economy. Hence, it is important to take into account innovation when modeling the effects of financial inclusion on CO_2 emissions.

Besides, Can et al. (2021b) presented the green openness index and suggested that green trade could help to reduce environmental degradation. Thus, we included the green openness index in the model, which consists of environmentally preferable (EP) and traditional environmental (TE) goods. TE goods, (such as pollution control equipment) offer solutions to diverse environmental problems while EP goods (such as solar cars) pose less threat to the environment than their alternatives. Green goods need low energy consumption in their production (Paramati et al., 2021). According to Can et al. (2021a), green trading is a viable solution to establish a green economy that might help in achieving carbon neutrality targets.

Exploring the environmental effects of financial inclusion (FIN), green openness, and technological innovation in the context of BRICS is vital because of the rapid economic progress and massive contribution to world economic growth and environmental deterioration by this country group. Brazil, Russia, India, China, and South Africa (BRICS) have a combined GDP of more than 23% of global GDP, and they contribute a massive 42% to global CO_2 emissions. In addition, the countries, such as China, India, Russia, and Brazil are included among the top seven nations based on their CO_2 emissions and environmental deterioration (Khan et al., 2020). The role of FIN is important in the context of BRICS because these nations strive to accomplish more development, and their financial sectors are required to offer various products and services to fulfill the growing financial requirements of individuals and businesses. In addition, the countries like China, India, and Russia are major players in global trade; hence, studying the potential environmental effects of financial inclusion and green trading in the context of BRICS is reasonable.

Based on this background, this article quantifies the environmental impacts of financial inclusion (FIN), green openness, and technological innovation. As per the best of the authors' knowledge, this is the first study that explores the relationship between financial inclusion, technological innovation, and CO_2 emissions in BRICS nations. Additionally, to empirically assess the influence of green trading on CO_2 emissions, this study includes the green openness index in the model. The authors have not found any empirical research that looked into the impact of green trading on CO_2 emissions in the BRICS economies. Furthermore, the study relied on reliable econometric approaches, such as CUP-FM and CUP-BC methods introduced by Bai et al. (2009), to get robust and reliable long-run findings. The Dumitrescu and Hurlin (2012) panel causality test is also applied to find the causal directions of the linkage between FIN, technological innovation, green openness, and CO_2 emissions.

The remainder of this article is organized as follows. *Literature Review Section* summarizes the literature review and identifies the literature gap. *Materials and Methods Section* provides the theoretical framework, model construction, data, and empirical methods. The empirical findings and discussion are presented in *Results and Discussion Section*. *Conclusion and Policy Implications Section* concludes this work and provides policy recommendations.

LITERATURE REVIEW

Indubitably, a vibrant financial sector can reduce poverty, contributes to economic development, and enhance climate resilience. In recent literature, some studies empirically evaluated the linkage between environmental sustainability and FIN but found contradictory outcomes. For instance, Le et al. (2020) used Driscoll–Kraay SEs for linear panel models to explore the relationship between FIN and environmental deterioration in 31 Asian countries over 2004–2014. Their results show that FIN, when combined with other control variables, such as urbanization, energy use, GDP, and FDI, fuels environmental degradation. Their results suggested that financial inclusion should be aligned with climate policies to nullify the adverse effect of financial inclusion on emissions. Using the GMM method, during the period 2004–2014, Renzhi and Baek (2020) investigated the influence of FIN on carbon emissions in 103 countries. Their findings demonstrated the inverted U-shaped association between FIN and emissions. They highlighted that a higher degree of FIN could curb environmental degradation. In the case of OECD countries, Hussain et al. (2021) studied the impact of FIN and infrastructure on ecological footprint. Their results unveil that FIN deteriorates the environmental quality by increasing ecological footprint while infrastructure is found to disrupt the environmental quality of OECD countries. Likewise, Rehman et al. (2022) examined the impact of FIN and CO_2 in 65 countries from 2004 to 2017 by including national governance to the model. Their results also support that FIN escalates environmental degradation. They further highlighted that national governance negatively and significantly moderates the relationship between FIN and CO_2 emissions.

Recently, Qin et al. (2021) employed panel quantile regression analysis to investigate the linkage between FIN and CO_2 emissions for seven emerging countries over 2004–2016. Their results suggested that FIN positively and significantly affects CO_2 emissions at the 25th and 50th quantiles; however, it does not influence CO_2 at 75th and 95th quantiles. They also suggested enhancing degrees of financial inclusivity to lower the adverse impact of the FIN on environmental quality. Likewise, Chaudhry et al. (2021) also studied the linkage between FIN and ecological footprint (EF) from 2004 to 2018 for 24 OIC member countries. Their study used the dynamic common correlated effects method and found that FIN is significantly and positively correlated with environmental degradation. On the contrary, Du et al. (2022) claimed that FIN improves the environmental quality of selected emerging countries as it is negatively connected with CO_2 emissions.

In the 21st century, countries worldwide are experiencing the Fourth Industrial Revolution wave, and technological innovation is considered one of the important elements to accomplish the SDGs. In this perspective, several studies revealed that technological innovation could be helpful to improve environmental quality, while some studies either found that technological innovation degrades environmental quality or does not affect emissions. For instance, Yii and Geetha (2017) explored the impact of technological innovation on environmental quality in the case of Malaysia. In the short run, their results indicated that innovation in technology is negatively associated with CO_2 emissions. While technological innovation poses an insignificant effect in the long term. Further, their results suggested promoting innovation without any postponement for the sake of economic and environmental sustainability. Henriques and Borowiecki (2017) observe the relation between technological innovation and environmental quality for Europe, North America, and Japan. They conclude that technological innovation mitigates environmental degradation. Further argues that energy transition and technological change have become important contributors to the decreasing levels of emissions in Europe during the last decade.

Lin and Zhu (2019) studied the association between renewable energy technologies and environmental quality in China. The linear regression model confirms that renewable technologies negatively impact CO_2 emissions, implying that renewable energy technologies promote a low-carbon society in China. Ahmad et al. (2020) analyzed the dynamic association between technological innovation and EF in 22 selected emerging countries and reported that technological innovation is the prime offsetting factor in footprint reduction. Wang et al. (2020) found that technological innovation promotes environmental sustainability and further recommended promoting innovation and clean energy use to achieve goals set by COP21 in the N-11 economies. Likewise, Guo et al. (2021) also confirmed the negative correlation between environmental degradation and technological innovation in China. They argued that technological innovation can help to achieve sustainable development goals (SDGs). Likewise, according to Sinha et al. (2020), technological innovation can help to achieve SDGs.

On the other hand, Samargandi (2017) revealed that technological innovation is futile in reducing CO_2 emissions in Saudi Arabia, which depicts that the innovation of technologies is not in the right direction to decrease environmental deterioration.

Further authors suggested that increasing technological progress, particularly in the production process, will reduce CO_2 emissions without harming economic growth. Recently, Adebayo et al. (2021) also found a similar outcome in Chile that technological change failed to decrease consumption-based carbon emissions. Chen and Lee (2020) revealed that technological innovation has no significant relationship with carbon emissions for the global sample. However, their group-wise analysis depicts that technological innovation in high-income countries effectively curbs CO_2 emissions. Besides, scholars have extensively examined the impact of trade on environmental quality. However, only one study is available that investigates the impact of green openness (trading green products) on environmental quality. For instance, Can et al. (2021a) studied the influence of green openness on CO_2 emission for the selected 31 OECD countries from 2007 to 2017. Their empirical results unveiled that green openness negatively affects CO_2 emissions, which portrays that green openness improves environmental quality.

Summing up this discussion, it can be concluded that limited investigations have looked into the effects of financial inclusion on CO_2 emission and illustrated inconsistent results. Besides, the linkage between technological innovation, green openness, financial inclusion, and CO_2 emissions remained unexplored. Further, the literature is silent on how green openness affects environmental quality in BRICS countries. Moreover, previous literature on financial inclusion and environmental quality nexus frequently overlooks cross-sectional dependence (CD) in panel data, resulting in unreliable estimates. As a result, there is a significant gap in the existing studies that must be tackled by using a more advanced estimating technique and examining the role of financial inclusion, technical innovation, green openness, and environmental quality.

MATERIALS AND METHODS

Theoretical Framework and Model Construction

The financial sector plays an important role in facilitating transactions, mobilization and utilization savings, and monitoring financial flows towards productive activities (Puatwoe and Piabuo, 2017). Financial development is inextricably linked to FIN, which fosters the development of financial sectors and institutions and contributes to GDP (Kim et al., 2018). However, the environmental impact of FIN in the literature has documented equivocal evidence. On the one hand, it is assumed that FIN can help to improve environmental quality. For instance, individuals and organizations can benefit from FIN by having easier access to financial services, which can help them implement environmentally friendly technologies. Moreover, improved access to financial services is particularly pertinent for the farmers and low-income households, where they may not have the accessibility of capital and credit facilities to invest in green energy technologies, such as solar and thermal small energy grids, which produce less expensive energy than fossil fuels with less pollution (IEA, 2019). On the other hand, easier access to finance boosts industrial and manufacturing activities, which in turn leads to higher energy use that may create more pollution. Increasing FIN can also speed up access to finance, allowing customers to buy energy-intensive appliances like air conditioners, automobiles, and refrigerators that can boost CO_2 (Wang et al., 2021). In this regard, financial inclusion brings a detrimental impact on environmental quality.

There is growing consensus that technological advancement significantly promotes FIN and environmental sustainability (Senyo and Osabutey, 2020; Ahmad et al., 2021a). Therefore, technological innovation is considered among the viable solutions to combat ecological deprivation and climate change. Endogenous growth theory and ecological modernization theory also support the notion that innovation may help countries achieve sustainable development without affecting the environment (Aghion et al., 1998; Buttel, 2000). However, some scholars believe that technology innovation is a two-edged sword that may increase or alleviate environmental damage. Recent advancements in technologies have made it easier for humans to access natural resources, causing more and more natural oil and mineral depletion. This has resulted in an imbalance of the ecosystem and an increase in environmental pollution.

Theoretically, openness to trade can affect the environmental quality through three main paths (i.e., scale, composition, and technique) (Antweiler et al., 2001). The scale effect refers to the increase in production level causing more environmental pollution. The composition effect specifies that the environmental impact of trade openness is influenced by the industry's structure. Depending on a country's environmental policies and resource abundance, this could be beneficial or detrimental. The technique effect specifies that an increase in income and advancement in technologies promote environmentally friendly production, which lessens environmental pollution (Managi et al., 2009).

Based on the theoretical framework, the model specification for this study is given as:

$$Co_{2_{it}} = \alpha_0 + \beta_1 FIN_{it} + \beta_2 TI_{it} + \beta_3 GOP_{it} + \beta_4 GDP_{it} + \beta_5 EC_{it} + \varepsilon_{it} \tag{1}$$

In **Eq. 1**, CO_2 is the dependent variable indicating carbon dioxide emissions per capita, whereas FIN, TI, GOP, GDP, and EC are the explanatory variables that denote financial inclusion, green openness, economic growth, and energy use, respectively. The symbol "i" characterizes the cross-sections, t indicates the time dimension, α and μ represent the constant and error term, respectively. Variables are converted to a logarithmic form before being used in the empirical analysis, except for financial inclusion because principal component analysis (PCA) is used to construct financial inclusion index.

Data

This article uses the annual data set from 2004 to 2018 for Brazil, Russia, India, China, and South Africa (BRICS). The duration of the research is based on data availability for key variables, such as CO_2 emissions and green openness. The

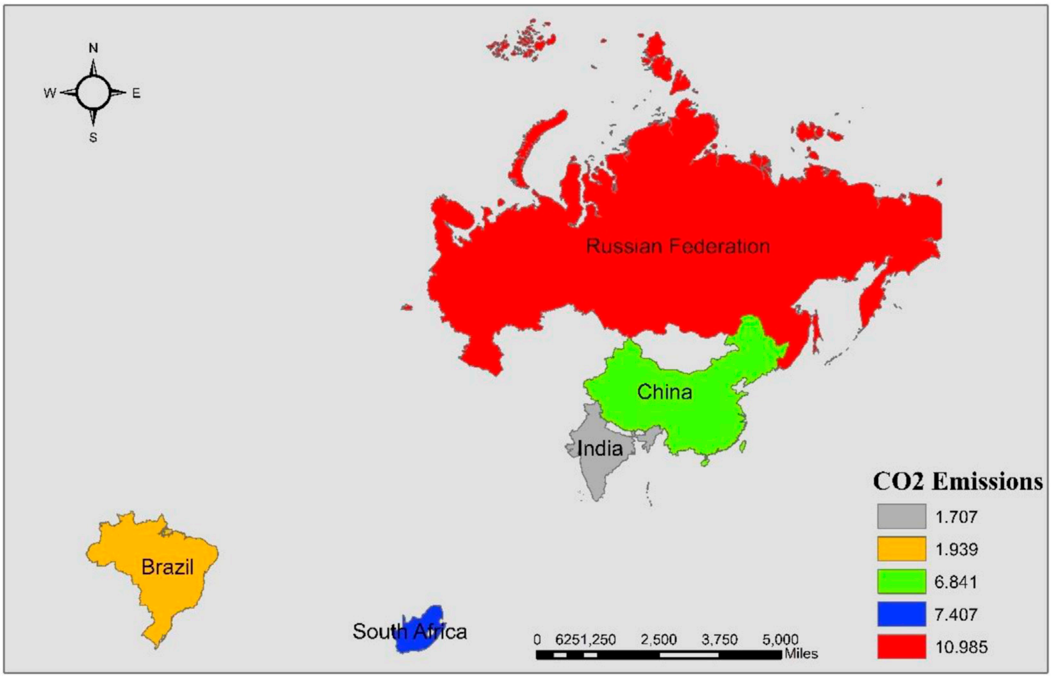

FIGURE 1 | CO_2 emission spatial distributions in BRICS countries for the year 2018. Data Source: IEA (2020).

TABLE 1 | Variable's description.

Variable	Symbol	Measurement	Source
Carbon emission	CO_2	Carbon dioxide emissions (tons per capita)	IEA
Financial Inclusion	FIN	It is an index based on (a) number of ATMs per 100,000 adults, (b) the number of branches of commercial banks, (c) number of commercial banks, (d) outstanding commercial bank loans (% of GDP), and (e) commercial banks' outstanding deposits (% of GDP)	IMF
Technological Innovation	TI	Patent applications (resident + non-resident)	WDI
Green openness	GOP	Green trade openness index	BASSRL
Economic growth	GDP	Per capita constant 2010$	WDI
Energy consumption	EC	kg of oil equivalent per capita	BP

Note. IEA, International Energy Agency; IMF, International Monetary Fund; WDI, World Development Indicators; BASSRL—BETA, akademi social science research lab; BP—BP, statistical renew of world energy.

selection of the starting period of 2004 is linked with financial inclusion data, and the period ended in 2018 is knotted with the data availability of CO_2. This study chooses CO_2 emission (tons per capita) for environmental quality, and its data is retrieved from the International Energy Agency. **Figure 1** depicts the distribution of CO_2 emissions in the BRICS countries indicating that the Russian federation is emitting very high emissions as compared to other panel countries. The five components of the financial inclusion (FI) index are produced through PCA based on five indicators. These elements include the number of ATMs per 100,000 adults, the number of branches of commercial banks, the number of commercial banks, outstanding deposits kept within commercial banks (% of GDP), and the outstanding loans from commercial banks (% of GDP). Technological innovation (TI) is defined as the patent applications of residents and non-resident, and its data is obtained from World Bank. The green openness index (GOP) is based on the country's import and export of green goods as a percentage of GDP. GOP index ranges between 0 and 100 and its higher values indicate greater green openness. GOP data is only available until 2016; therefore, linear interpolation is used to extend it until 2018. GOP index was introduced by Can et al. (2021b) and further improved by Can et al. (2021a). Economic growth (GDP) and energy consumption (EC) are measured by GDP per capita and per capita (kg of oil equivalent) respectively. The data and variables description is provided in **Table 1**.

Estimation Strategy

The empirical methodology of the study consists of seven steps described in **Figure 2**. The particulars of each step are provided in the subsequent subsections.

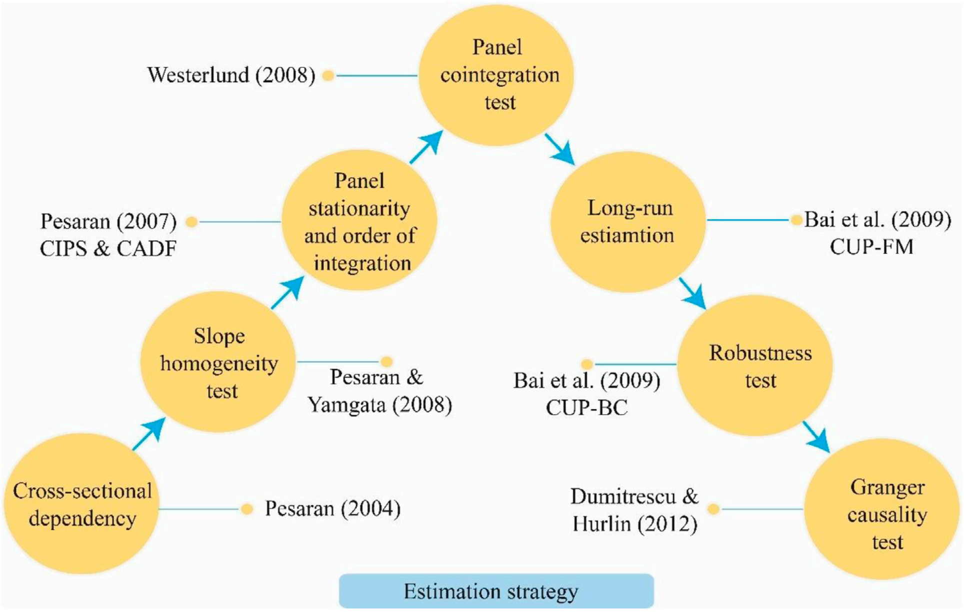

FIGURE 2 | Empirical estimation methods.

Cross-Sectional Dependence Test

In recent years, economies have been interrelated through several social, economic, and cultural channels. Therefore, the integration of economic development and the political system usually leads to interdependences, which could adversely affect the first-generation estimators' reliability. This study uses the (Pesaran, 2004) CD test to know about the possible interdependence in our data because this is necessary to choose suitable estimators for providing robust and reliable estimates. The test statistics for CD are given below.

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \tag{2}$$

Where $\hat{\rho}_{ij}$ represent the pair-wise residual correlation.

Slope Homogeneity Test

Further, the issue of slope heterogeneity may arise in panel data analysis because countries have varying rates of innovation and economic and demographic structure. Thus, to counter the issue of slope heterogeneity, the Pesaran and Yamagata (2008) method is used. The equation for this test can be written as:

$$\Delta_{ASH} = (N)^{\frac{1}{2}}\left(\frac{2k(\mathrm{T}-k-1}{T+1}\right)^{-\frac{1}{2}}\left(\frac{1}{N}S-k\right) \tag{3}$$

$$\Delta_{ASH} = (N)^{\frac{1}{2}}\left(\frac{2k(\mathrm{T}-k-1}{T+1}\right)^{-\frac{1}{2}}\left(\frac{1}{N}S-k\right) \tag{4}$$

Δ_{ASH} illustrates the adjusted delta tilde and Δ_{SH} indicates the delta tilde.

Panel Unit Root Tests

The conventional unit root test namely Fisher-ADF, Levin-Lin-Chu (LLC), Choi test, and Im, Pesaran, and Shin do not perform effectively in the presence of slope heterogeneity and CD. Therefore, in order to solve this problem, this article uses the second-generation unit root test of Pesaran (2007) (CIPS and CADF methods) to observe the stationary properties of the studied variables. The test equation is given as:

$$\Delta ZA_{i,t} = \varphi_i + \varphi_i X_{i,t-1} + \varphi_i \overline{ZA}_{t-1} + \sum_{l=0}^{p}\varphi_{il}\Delta\overline{ZA}_{t-1} + \sum_{l=0}^{p}\varphi_{il}\Delta ZA_{i,t-1} + \mu_{it} \tag{5}$$

The averages of the cross-section are $\overline{ZA}_{t-1}$ and $\Delta\overline{ZA}_{t-1}$, respectively. The CIPS test statistics are as follows:

$$CIPS = \frac{1}{N}\sum_{i=1}^{n}CDF_i \tag{6}$$

Panel Cointegration Tests

Before estimating the long-term parameters, the cointegration between the studied variables should be examined. We utilize a panel cointegration test developed by Westerlund (2008). This method has more power due to its flexibility to counter CD through common factors. It permits stationary regression in its assessment. The Durbin–Hausman can be given as follows:

$$DH_g = \sum_{i=1}^{n}S_i(\phi_i + \phi_i)^2\sum_{t=2}^{T}\hat{e}^2_{it-1} \tag{7}$$

TABLE 2 | Test results of CD.

Variable	Test stat	Prob	Corr	Abs(corr)
CO_2	4.272*	0.000	0.349	0.485
FIN	5.672*	0.000	0.463	0.530
TI	6.697*	0.000	0.547	0.547
GO	1.107	0.268	0.090	0.292
GDP	10.558*	0.000	0.862	0.862
EC	3.053*	0.002	0.249	0.743

*Note: The symbol * represents the 1% significance level.*

$$DH_p = S_n(\phi + \phi)^2 \sum_{i=1}^{n}\sum_{T=2}^{T} \hat{e}_{it-1}^2 \tag{8}$$

Long-Run Estimation

In the presence of FIN, technological innovation, and green openness, the Continuously Updated Fully Modified (CUP-FM) technique is used to investigate the long-run relationship between FIN and environmental quality. Furthermore, as a robustness test, this paper utilizes the Continuously Updated Bias-Corrected (CUP-BC) approach. These estimation methods perform better than conventional estimation techniques like DOLS, FMOLS, and DSUR. The FMOLS and DOLS provide robust results against the endogeneity and residual correlation problem but assume that cross-sections are independent. In contrast, DSUR can be used to counter the issue of CD but has limitations in not handling the serial correlation and endogeneity. Therefore, this article employs the CUP-BC and CUP-FM estimation techniques of Bai et al. (2009), which are robust to CD, slope heterogeneity, serial correlation, and endogeneity problem. The test equation can give as:

$$\widehat{B}cup, \widehat{F}cup = argmin \frac{1}{nT^2} \sum_{i=1}^{n} (y_i - x_i\beta)' M_F (y_i - x_i\beta) \tag{9}$$

Panel Granger Causality Test

Although the long-run estimation results provide significant information about the long-run effects of variables on CO_2, the causal relationship may also be important for policy measures. The current study uses the D and H (2012) causality test to examine the causal connection among variables. The test equation is given as.

$$G_{i,t} = \phi_i + \sum_{j=1}^{p} \lambda_i^j G_{i,t-j} + \sum_{j=1}^{p} \gamma_i^j T_{i,t-j} \tag{10}$$

RESULTS AND DISCUSSION

Before initiating the formal empirical analysis, we examine the CD and slope heterogeneity among the selected variables. **Table 2** depicts the outcome of the CD and rejects the null hypothesis of cross-sectional independence. The BRICS countries have a variety of economic and financial agreements, and they trade significantly with one another. Therefore, these countries are strongly interconnected, which is evident from the CD test results.

TABLE 3 | slope heterogeneity test results.

Test	Value	*p*-value
$\tilde{\Delta}$	3.996*	0.000
$\tilde{\Delta}_{adjusted}$	5.471*	0.000

*Note: The symbol * represents the 1% significance level.*

TABLE 4 | Panel unit root test results.

Variable	CADF		CIPS	
	Level	First-difference	Level	First-difference
CO_2	−1.397	−3.610*	−1.146	−2.403**
FIN	−2.002	−3.281*	−1.823	−3.045*
TI	−1.559	−3.087*	−1.289	−3.087*
GO	−1.098	−3.909*	−1.098	−3.909*
GDP	−1.502	−3.360*	−1.951	−3.753*
EC	−2.141	−3.427*	−1.857	−3.656*

*Note: The symbol * and ** represent 1 and 5% significance levels, respectively.*

TABLE 5 | Westerlund (2008) panel cointegration test.

	Value	*p*-value
DH_g	−2.018**	0.022
DH_P	−1.590***	0.056

*Note: The symbols ** and *** represent 5 and 10% significance levels, respectively.*

Despite strong integration, BRICS countries have a varying rate of technological innovation and demographic and economic structure that may lead to slope heterogeneity problems leading to biased estimates. In **Table 3**, the Pesaran and Yamagata (2008) test outcome indicates the presence of country-specific heterogeneity in our panel dataset of BRICS countries.

After checking the CD and slope heterogeneity, the stationary properties of the variables are investigated using CADF and CIPS tests. The outcomes in **Table 4** show that variables have unit root problems at the level; however, after taking the first difference, all variables became stationary.

After checking the stationarity properties, the panel cointegration test was used in this study, and the findings are exhibited in **Table 5**. The Westerlund (2008) cointegration test shows that the test results of the panel (DHp) and group (DHg) values are significant at the 5 and 10% level. Thus, the findings indicate the presence of a cointegration relationship among variables.

After performing these initial investigations, the CUP-FM and CUP-BC methods were used to estimate long-run elasticities in this study, and **Table 6** summarizes the findings. The coefficient of financial inclusion (FIN) is significant and presents a positive relationship with carbon emission. Numerically, a 1% raise in FI increases CO_2 emissions by 0.159% in the long run. This result shows that improved financial access in BRICS countries could enable citizens to purchase large-ticket products such as air

TABLE 6 | Long-run estimation results.

Variables	CUP-FM		CUP-BC	
	Coefficients	T Stats	Coefficients	T Stats
FIN	0.159*	2.815	0.165*	3.161
TI	−0.062**	−1.879	−0.070**	−2.277
GTO	−0.073*	−3.847	−0.061*	−3.621
GDP	0.174*	3.698	0.177*	4.071
EC	0.339*	6.469	0.355*	7.210

*Note: * and ** depict 1 and 5% significance level, respectively.*

conditioners, automobiles, and other electronic devices, which can raise energy demand resulting in environmental pollution. Our results portray that the FIN strategies seem ineffective in these countries and lack synergies between climate change policies and financial inclusion initiatives. Our findings coincide with that of Le et al. (2020); Hussain et al., 2021), Rehman et al. (2022), and Qin et al. (2021). However, these estimates contradict the result of Renzhi and Baek (2020) and Du et al. (2022) who claim that FIN can be used as a mitigating instrument to curb environmental degradation.

The results further indicate that technological innovation (TI) shows a negative relationship with carbon emissions. The significant negative coefficient unfolds that TI reduces CO_2 emissions in BRICS countries i.e., a 0.062% reduction in CO_2 emissions can be attained by a 1% increase in TI. This result suggests that technological innovation plays an important role in promoting environmental sustainability in BRICS countries. This is plausible because technological innovation creates a more sustainable industrial structure and improves environmental quality (Cheng et al., 2021). Our findings correspond to those of Ahmad et al. (2020), Danish and Ulucak (2021), and Erdogan (2021). However, these results are not in conformity with Santra (2017), who reported a positive connection between technological innovation and environmental degradation.

Similar to technological innovation, the coefficient of green openness (GTO) indicates a negative relationship with carbon emissions. Further, green trade decreases CO_2 emissions in the BRICS nations with an elasticity of 0.073, suggesting that increasing green trade by 1% will curb emissions by 0.073%. This implies that the import and export of green products seek less energy consumption and thereby exert minimal pressure on the environment. Additionally, it implies that international trade

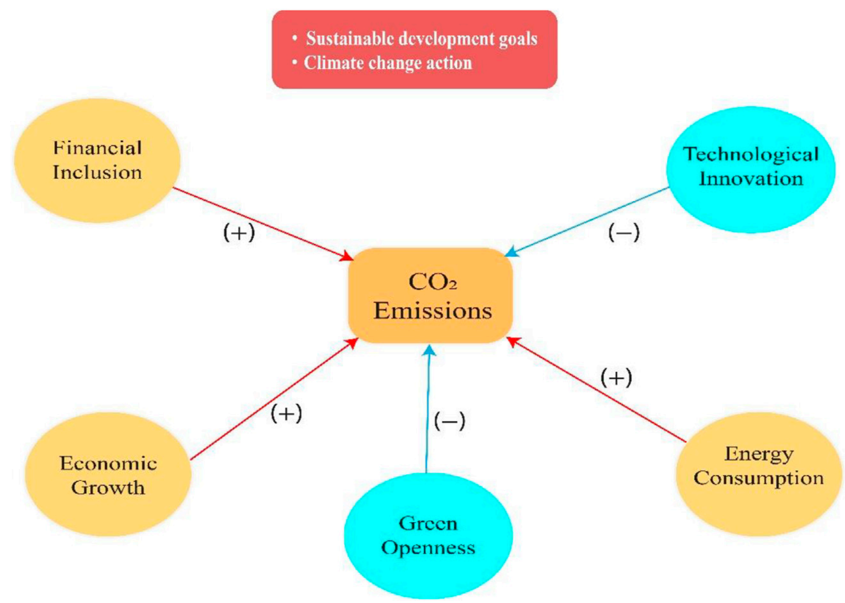

FIGURE 3 | Long-run results.

TABLE 7 | Panel Granger causality test results.

Variables	CO_2	FIN	TI	GTO	GDP	EC
CO_2	— —	3.121* (0.002)	2.282** (0.022)	1.932*** (0.053)	2.064** (0.039)	3.590* (0.000)
FIN	1.260 (0.208)	— —	9.563* (0.000)	2.316** (0.020)	7.474* (0.000)	1.137 (0.255)
TI	0.616 (0.538)	2.50** (0.012)	— —	2.639* (0.008)	2.500** (0.012)	1.450 (0.147)
GTO	1.052 (0.293)	2.140** (0.032)	3.590* (0.000)	— —	1.823*** (0.069)	1.579 (0.114)
GDP	2.359** (0.018)	3.313* (0.000)	3.268* (0.001)	5.244* (0.000)	— —	3.439* (0.000)
EC	1.801*** (0.072)	1.863*** (1.035)	1.741*** (0.082)	1.372 (0.170)	4.724* (0.000)	— —

*Note: *, **, and *** depict the significance level at 1, 5, and 10%, respectively. ( ) contain the* P-values.

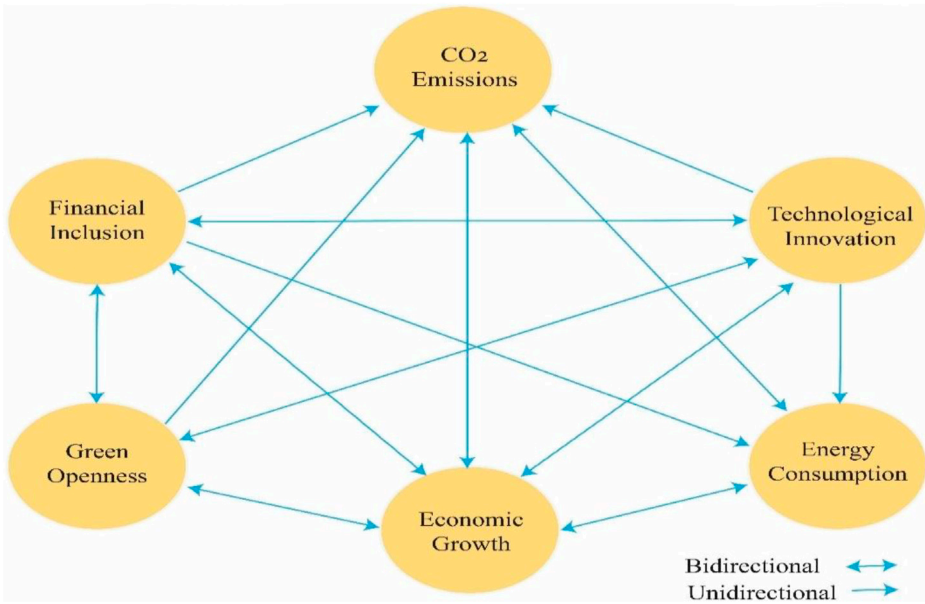

FIGURE 4 | Panel Granger causality results.

through green products contributes significantly to improving environmental quality in BRICS countries. As a result of this condition, the countries can enhance their green trade while protecting environmental quality. This finding supports the view of Can et al. (2021a), who document that green openness abates environmental degradation in OECD countries.

Further, the findings demonstrate that GDP poses a positive effect on environmental degradation. Statistically, a 0.174% increase in CO_2 emissions is caused by GDP. There are several main reasons for this result. Firstly, over the last two decades, the BRICS countries have experienced remarkable development, their per capita GDP (constant $) grew from US$ 5524.98 to US$ 8067.03 during 2004–2018. It portrays that economic expansion in BRICS countries is attained at the cost of environmental quality. Secondly, the prime reason for increasing emissions in BRICS countries is the reliance on conventional energy sources. This conclusion is similar to the findings given by Ahmed et al. (2021) for G7 countries, Ahmed et al. (2020) for China, and Shahbaz et al. (2013) for Indonesia. The results contradict the findings of Salahuddin et al. (2016), who indicated that GDP has no significant long-run and short-run impact on CO_2 emissions in OECD economies. Also, this result opposes the finding of Ozcan et al. (2020), who indicated a negative relationship between economic growth and CO_2 emissions.

Finally, in the BRICS countries, energy consumption (EC) was found to intensify CO_2 emissions. Numerically, a 1% expansion in EC can raise the CO_2 emissions by 0.339%. This means that energy use creates environmental pressure on the BRICS nations. These findings are reasonable because these nations depend on traditional energy sources to meet their increasing energy demand, and non-renewable energy (e.g., oil, coal, and gas) meets approximately 86 percent of total energy demand. These results coincide with earlier studies of (Rahman and Kashem, 2017) for Bangladesh and (Ulucak et al., 2020) for OECD economies. The long-run estimation results from CUP-FM and CUP-BC are graphically presented in **Figure 3**.

Following the long-run elasticity evaluation, the Dumitrescu and Hurlin (2012) panel Granger causality test is used. The outcomes in **Table 7** depict the unidirectional causal linkage running from financial inclusion, technological innovation, and green openness to CO_2 emissions. This means that any policy associated with financial inclusion, technological innovation, and green openness will have an impact on CO_2 emissions. The results depict that bidirectional causality exists between technological innovation and financial inclusion. Thus, an increase in technological innovation will also boot financial inclusion and vice versa. We also found bidirectional causality between green openness, technological innovation, and financial inclusion. The results further indicate the bidirectional causal association between energy use, economic growth, and CO_2 emissions. Economic growth, energy consumption, and emissions all have a strong link, according to these findings. Therefore, it will be challenging for BRICS countries to curb CO_2 emissions without affecting energy consumption and economic growth. The panel Granger causality results are given in **Figure 4**.

CONCLUSION AND POLICY IMPLICATIONS

During the last two decades, financial inclusion and technological innovation have dramatically augmented the accessibility and affordability of financial services and contributed to economic development; however, their environmental implications cannot be overlooked. Limited studies assess the relationship between financial inclusion and environmental degradation; however, research integrating financial inclusion and technological innovation in the same environmental policy framework is still scant. In this context, the impact of financial inclusion, technological innovations, green openness, GDP, and energy consumption on CO_2 emissions in BRICS countries is investigated. This study relied on advanced empirical estimation methods, such as CUP-FM and CUP-BC for long-run empirical estimation, which counter the issue of slope heterogeneity and CD. According to the empirical study, financial inclusion, economic growth, and energy consumption all increase CO_2 emissions. In contrast, technological innovation and green openness decrease CO_2 emissions. Further, according to the findings, economic development and energy consumption both intensify environmental degradation. The causal outcomes reveal that CO_2 emissions are caused by financial inclusion, technical innovation, and green openness, but not the other way around. Further, technological innovation, green openness, and financial inclusion Granger cause each other.

These results have significant policy implications for improving environmental quality in BRICS countries. Firstly, to address the negative impact of financial inclusion on CO_2 emissions, policymakers should integrate financial inclusion with climate change policies at the local, national, and regional levels. Further to reverse the trend, policymakers should expand the access and inclusiveness of green finance to individuals, micro, small and medium-sized enterprises in a more accurate direction, enabling them to adopt environmental sustainability actions.

Secondly, policies should be designed to increase the number of patents as technological innovation positively impacts environmental sustainability. Furthermore, the government should allocate more funds and offer subsidies and tax benefits to support research and development activities. Thirdly, to achieve carbon neutrality goals, policymakers should expand the market of ecologically beneficial products. To do this, inter-government long-term agreements on the trade of green products and reducing tariffs could be initiated for the betterment of environmental quality. Fourthly, since economic growth is found to be associated with environmental degradation, the BRICS countries should redesign their economic development policies. The BRCIS economies should adopt a sustainable production and consumption pattern that will aid in the achievement of the Sustainable Development Goals (SDG-8 and 13). Finally, energy consumption is a significant factor in environmental damage. This means that the existing energy consumption policies in BRICS countries need to be restructured. To fulfill the economic requirements, the BRICS countries rely significantly on fossil fuels and non-renewable energy. Notably, assisting various organizations in exploring clean energy sources and investing in clean energy innovation will be preferred options to achieve Sustainable Development Goals (SGD-7).

The scope of this article is limited to BRICS countries and only a limited number of variables are considered for a short period of 2004–2018. An in-depth study on the direct and indirect impact of financial inclusion on environmental quality can be conducted by adding its interaction terms with different variables. Also, the impact of financial inclusion on various environmental indicators can be studied and comparison can be made for interesting findings.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

MA: Conceptualization, data curation, formal analysis, visualization, writing original draft. ZA: Conceptualization, Writing original draft. YB: writing—review, and editing. GQ: writing—review and editing, supervision. JP: writing—review, and editing, funding acquisition. JO: supervision, project administration, writing—review, and editing.

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A Step Towards a Green Future: Does Sustainable Development Policy Reduce Energy Consumption in Resource-Based Cities of China?

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Undoubtedly, resource-based cities (RBCs) have significantly contributed to the socio-economic development of China; however, energy consumption intensified due to this development. Reducing energy consumption in RBCs and transforming the energy structure of RBCs are major challenges. To promote the energy structure transformation of RBCs, the Chinese government has introduced the Sustainable Development Policy for Resource Cities (*SDPRC*), but the effectiveness of *SDPRC* is still unclear. Therefore, this study uses the difference-in-difference (DID) approach to explore the impact of *SDPRC* on energy consumption scale (*ECS*) and energy consumption intensity (*ECI*) in RBCs based on panel data of 280 cities from 2006 to 2019. Firstly, the empirical results indicate that the implementation of SDPRC significantly reduces energy consumption in RBCs. The findings unfold that the inverted U-shaped relationship between SDPRC and *ECS*, while the effect on *ECI* has a certain lag, which is significant from the second year, and its impact increases persistently with the advancement of the policy. The stability test also verifies our conclusion. Secondly, the heterogeneity results show that the effect of *SDPRC* implementation varies across RBCs in different regions and development stages. Thirdly, the impact mechanism test result shows that controlling pollutant emissions and getting rid of resource dependency are important ways to reduce energy consumption in RBCs. However, the implementation of *SDPRC* does not promote the rationalization and transformation of industrial structure in RBCs. Based on the findings, policy recommendations are proposed for energy transformation and sustainable development of RBCs.

Keywords: sustainable development, energy consumption, resource-based cities, difference-in-difference, China

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1 INTRODUCTION

With the increasing energy demand and climate problems, the transformation and sustainable development of resource cities has become a contemporary issue worldwide. RBCs are cities where the exploitation and processing of natural resources such as minerals and forests are the leading industries (Martinez-Fernandez et al., 2012). The RBCs play a pivotal role in the economic development of an economy (Wang et al., 2022). Industrialization and rapid economic growth have led to resource depletion, air pollution, and ecological deterioration (Gonzalez-Garcia et al., 2018). Besides that, poor industrial structure, insufficient innovation, and low productivity of enterprises negatively affect economic growth (Ndlovu and Inglesi-Lotz 2020; Ahmad and Zheng 2021; Xing et al., 2021). The energy industry is the backbone of China's economic development. China has become the world's largest energy consumer, and the total energy consumption is still climbing (He et al., 2017). According to the Global Energy Statistics Yearbook 2020, China's energy intensity is 1.15 higher than the United States, 1.62 than Japan, 1.75 than the European Union, and twice the world average. RBCs are predominantly responsible for higher energy intensity because of excessive reliance on natural resources, and conventional industrial structure leads to higher energy consumption and energy structure transformation difficulties, and other issues (Li S et al., 2021).

Some scholars recently proposed paths for RBCs transformation to promote sustainable development, such as increasing investment in renewable energy and low-carbon technologies, building a diversified energy structure, optimizing industrial structure, and actively promoting industrial extension and substitution (Jiao et al., 2020; Stephenson et al., 2021). In response to the critical situation in RBCs, the Chinese government has introduced a series of policies, among them the Sustainable Development Plan of Nation RBCs, 2013-202 (*SDPRC* hereafter) announced by the State Council in 2013. The main aim of this policy is to promote the transformation of the energy mix and sustainable development of RBCs. Although 7 years have passed since the SDPRC was enacted, the current literature is silent on how SDPRC impacted RBCs' energy consumption and the mechanisms of its impact?

The common methods used in studies exploring policy effects include Synthetic Control Method (Chen et al., 2022), Difference in difference (Fang et al., 2021), Regression Discontinuity Design (Salti et al., 2022), and Instrumental Variable Methods (Caselli and Reynaud, 2020). The DID method explores the effect of policy implementation by capturing the difference in changes between the Treatment group and Control group before and after policy implementation, which can avoid endogeneity problems to a large extent and get more accurate results. Qiu et al. (2021) explored the impact of low-carbon city pilot policies on urban green total factor productivity; Zhang and Wang (2021) investigated the impact of carbon trading on economic output and carbon reduction in China's industrial sector. Therefore, this study uses the DID method to investigate the impact of *SDPRC* on energy consumption in RBCs.

We consider the SDPRC as a quasi-natural experiment on the selected panel data of 280 cities from 2006to 2019. To do this, two-way fixed-effects regression using the DID method is employed to estimate the impact of *SDPRC* implementation on energy consumption in RBCs and performed the stability tests on the results to verify the findings. We explore the differences in the impacts of SDPRC implementation in different types of RBCs from two perspectives: spatial and developmental stages, explore the mechanisms of SDPRC impacts on energy consumption in RBCs, and finally propose targeted suggestions for the transformation and sustainable development of RBCs.

The remainder of this paper is structured as follows. **Section 2** presents the literature review and policy background, **Section 3** presents the methodology and data source, **Section 4** comprises the results and discussion, **Section 5** sums up the conclusion and policy implications.

2 LITERATURE REVIEW AND POLICY GROUND

2.1 Literature Review

2.1.1 Studies on Resource-Based Cities

Research on RBCs is mainly divided into theoretical studies and transformation studies. Firstly, Lucas and Tepperman (1971) extended the four-stage theory by arguing that RBCs also go through the recession and closure stages. Based on these theories, Auty and Warhurst (1993) believe that RBCs have a resource curse phenomenon. He further highlighted that countries or regions with abundant natural resources would gradually lose the economic dividends and benefits from early resource extraction as the resources are depleted. The study on RBCs transformation has recently become a hot research topic among scholars. Xiao et al. (2021) measure the eco-efficiency of RBCs after the financial crisis by using a two-stage DEA model that includes both government and industrial sectors. The results show that eco-efficiency in RBCs is positive, and governance efficiency is positively associated with production efficiency. Likewise, Liu et al. (2021) used the improved TOPSIS method to assess the transformation effect of RBCs. Their findings show that the transformation efficiency of the vast majority of cities is between 0.4 and 0.8, and the transformation efficiency of all four economic regions is increasing, with the best transformation effect in the eastern region and the worst in the northeastern region. Yang et al. (2019) constructed a green development evaluation index system to assess the green development level (GDL) of mineral RBCs (MRBCs) from three perspectives, i.e., social, economic, and environmental. They concluded that the GDL of most MRBCs shows a good trend, but there are still 25% of cities whose performance is difficult to reach the expected effect, and the GDL of MRBCs shows significant variability between regions, decreasing from East to west. Long et al. (2013) integrated the intra- and inter-regional comparative advantages into a two-dimensional matrix model to select RBC alternative industries. The results show that stricter criteria correspond to a smaller total number of alternative industries. Taking Jiaozuo City as an example, rubber manufacturing, non-ferrous metal smelting, and machinery manufacturing have significant comparative advantages, and different types of RBCs should carry out industrial transformations according to their characteristics.

2.1.2 Studies on Energy Consumption

Concerning energy structure transformation research, Guilhot (2022) examined the energy policy over 40 years (1981–2020) in China. The results show that China's energy policy before the 21 century focused on energy efficiency and energy security, while the current energy policy is more concerned with low-carbon energy transition and energy system diversification. Shahbaz et al. (2022) assessed the relationship between economic growth, research and development (R&D) spending, and energy consumption based on Chinese economic data from 1971 to 2018. Their empirical outcome disclosed a positive association between economic growth and energy consumption. However, there is a significant negative relationship between R&D expenditures and energy consumption. Similarly, Xin-gang and Jin (2022) explored the relationship between industrial restructuring, energy consumption, and economic growth at aggregated and decomposed levels using the least-squares and panel vector error models. The results showed that renewable energy consumption's impact on economic growth is much lesser than coal and electricity consumption. Likewise, Amoako and Insaidoo (2021) examined the association between foreign direct investment (FDI) and energy consumption in Ghana from 1981 to 2014. The findings revealed that although FDI is positively correlated with energy consumption, FDI in Ghana has not yet resulted in energy-saving benefits.

2.1.3 Studies on Sustainable Development Policy

Likewise, *SDPRC* has attracted the attention of many scholars after its enactment. Fan and Zhang (2021) explored the impact of the policy on the transformation of RBCs after its implementation. The results showed that the program's implementation caused a positive impact of 19.6, 55.4, and 74.5% on RBCs' economic, social, and ecological transformation, respectively, but did not significantly impact the sustainable use of resources. Li Q et al. (2021) investigated the influence of the policy on the industrial transformation, and it was found that the implementation of *SDPRC* significantly reduced the share of secondary industry output in GDP and resource dependence in RBCs, and this impact was more significant in western cities.

2.1.4. Literature Gap

Although there has been an increasing number of studies on energy consumption in recent years, most have focused on the national and regional levels, and few studies have been conducted on energy consumption in resource-based cities. Due to the differences in research subjects and econometric techniques, there is no consensus on the impact aspects of energy consumption. At the same time, past studies on RBCs mainly focused on green development, industrial structure transformation, and eco-efficiency, but the research on energy-related issues in RBCs is still blank. In addition, no literature discusses the impact of SDPRC on energy consumption in RBCs. It would be more helpful to formulate corresponding policies for different stages to achieve synergistic governance in energy consumption.

Given the motivation of the study, this study contributes to the literature in the following ways. Firstly, this study explores the impact of *SDPRC* on energy consumption in RBCs using the DID method, which further enriches the relevant research on energy-related concerns in RBCs. Secondly, the impact mechanism of *SDPRC* on energy consumption in RBCs is explored from three perspectives: (1) pollution emission, (2) industrial institution rationalization, and (3) resource dependence. Thirdly, this study examines the impact of *SDPRC* on energy consumption scale (*ECS*) and energy consumption intensity (*ECI*) in RBCs from spatial and development stages perspectives to provide precise policy suggestions for the transformation of RBCs.

2.2 Policy Background

The transformation and sustainable development of RBCs has become a serious problem faced by many countries around the world, especially developing countries and emerging countries. Among them, China is experiencing rapid urbanization and industrialization. Thus, developing economic and social construction and ecological, environmental protection in a benign and coordinated manner has become an urgent problem in China. China's RBCs are large in number and widely distributed. As important strategic bases for energy resources in China, they have contributed significantly to the economic and social development of China. However, the problems of unbalanced, uncoordinated, and unsustainable domestic economic development are prominent, and resource depletion and environmental problems are becoming increasingly severe. How to deal with the contradiction between resource development and ecological protection is the sustainable development of RBCs has become an urgent problem to be solved. To this end, the Chinese government has launched a series of policies and measures to promote green innovation in RBCs, including the *SDPRC* promulgated by the State Council 2013, which established a list 262 of RBCs. They classified them into growth cities (31), mature cities (141), declining cities (67), and regenerative cities (23) according to their characteristics and development stages. The policy establishes the general concept, objectives and guarantees measures for the sustainable development of RBCs. This consists of a pattern of coordination between urban resource development and economic and social development, ecological and environmental protection, and transforms the original economic development mode of resource cities, which relies excessively on resources and establishes a sound long-term mechanism to promote sustainable development RBCs.

3 MATERIAL AND METHODS

3.1 Method

DID is one of the most commonly used methods in recent years to investigate policy effects by capturing the differences in changes between the treatment and control groups before and after policy implementation (Qiu et al., 2021). To investigate the impact of *SDPRC* on energy consumption in resource cities, we construct the DID model as follows.

$$EC_{it} = \alpha_0 + \alpha_1 \times treat_{it} \times time_{it} + \alpha X_{it} + \varepsilon_{it} \tag{1}$$

In **Eq. 1**, EC_{it} indicates the energy consumption of i city in t year. We further divide EC_{it} into energy consumption scale (*ECS*) and energy consumption intensity (*ECI*). $treat_{it}$ as an individual dummy variable representing the cities in the

TABLE 1 | Energy conversion factor.

Energy type	Coal (ton)	Natural gas (m^3)	Power	Liquefied petroleum gas
Conversion factor	0.7146	1.3300	1.2290	1.7143

TABLE 2 | Variable, measurement, and source.

Variable		Symbol	Measurement	Source
Control variable	Energy consumption scale	lnECS	Total energy consumption	China city statistical yearbook
	Energy consumption intensity	ECI	The ratio of total energy consumption to GDP	
	Economic development	lnECO	GDP per capita	
	Industrial structure	IND	The ratio of secondary industry output to tertiary industry output	
	Foreign direct investment	FDI	The ratio of foreign direct investment to GDP	
	R&D intensity	RI	The ratio of science and technology expenditure to public finance expenditure	
	Environmental governance	EG	The frequency of environmental words in local government work reports	Prefectural government work report
	Green technology innovation	lnGTI	Number of green patent applications	National intellectual property database
Mechanism variable	Pollutant emission	PE	Combined Pollutant emission index	Manual calculation
	Rationalize the structure of production	RSP	Industrial structure rationalization index	
	Resource dependence	RD	Percentage of employees in the secondary industry	China city statistical yearbook

experimental group in *t* year as 1, and other cities as 0; $time_{it}$ is a time dummy variable bounded by the year of policy implementation before implementation year is defined as 0, and other years are defined as1. X_{it} is a set of control variables with observable effects on energy consumption. The cross term $treat_{it} \times time_{it}$ represents the dummy variable for RBCs after policy implementation, and its coefficient α_1 is the core coefficient of interest, capturing the net effect of *SDPRC* on energy consumption. The policy treatment effect reflects the effect of policy on energy consumption in the treatment and control groups difference, and according to our hypothesis, this coefficient should be negative. There is a significant downward trend or slowdown in energy consumption growth rate in RBCs after the policy implementation. ε_{it} denotes the random error term. Because this paper is based on a panel dataset of cities, city fixed effects and time fixed effects are added to construct a two-way fixed effects model

$$EC_{it} = \alpha_0 + \alpha_1 \times treat_{it} \times time_{it} + \alpha_3 X_{it} + u_i + \lambda_t + \varepsilon_{it} \quad (2)$$

In **Eq. 2**, u_i and λ_t represent individual fixed effects and time fixed effects, respectively.

3.2 Description of Variables

3.2.1 Dependent Variable

There have been numerous studies on the determinants of energy consumption, and these studies used different proxies to measure energy use (Dingbang et al., 2021; Wang and Gong, 2022; Xue et al., 2022). By following the study of Feng et al. (2019), we calculated the energy consumption of cities as follows.

$$ECS_{\mathrm{i}} = \sum EC_i \times \eta_i \quad (3)$$

In **Eq. 3**, ECS_i denotes the scale of urban energy consumption; EC_i denotes the total amount of energy consumed in category i; η_i denotes the conversion factor of energy in category i into standard coal. The specific conversion coefficients of each type of energy and standard coal are shown in **Table 1**.

ECI is the main indicator reflecting energy consumption level and energy saving and consumption reduction and is used to examine the changes in economic structure and energy use efficiency. In this study, energy consumption per unit of GDP, the ratio of *ECS* to GDP, is used to measure energy intensity. In order to eliminate the effect of price fluctuations, GDP was deflated on a 2006 annual basis. **Table 2** shows the measurements and sources of the variables.

3.2.2 Independent Variable

According to the list of RBCs published by *SDPRC*, we construct RBCs (109) as the treatment group and non-RBCs (171) as the control group. In this paper, the interaction term of the dummy city variable (*Treat*) and the policy variable (*Time*) is defined as the independent variable (*Treat*Time*). *Treat is the* city dummy variable, which is defined as RBCs by *SDPRC* as 1 and non-RBCs as 0; *Time* is the time dummy variable, and given that the year of *SDPRC* implementation is the end of 2013, the occurrence point of the policy is positioned 2014 as implementation year, before the year is defined as 0, and after the year is defined as 1.

3.2.3 Control Variable

According to existing studies (Shen et al., 2020; Fu et al., 2021), although DID method can solve part of the endogeneity problem. In order to reduce the estimation bias caused by omitted variables, the following variables were chosen to control the model.

- Level of economic development (ECO). Many studies have demonstrated that economic growth is the essential driver of energy consumption and that the economic development of a city or region and energy consumption are closely related (Ahmad et al., 2021). Considering the differences in population size among cities, the logarithm of GDP per capita is used in this paper to measure economic development and to eliminate the effect of price fluctuations; GDP per capita is deflated on a 2006 annual basis.
- Industrial structure (IND). Differences in industrial structure usually cause differences in energy consumption, and it is necessary to adjust the industrial structure, reduce the energy-intensive industrial structure, and achieve a positive interaction between industrial and energy structures (Carmona et al., 2017). The ratio of the tertiary industry to secondary industry represents the industrial structure. It is crucial that RBCs increase the proportion of tertiary industries and reduce the proportion of secondary industries, so the larger the ratio indicates that the industrial structure has been upgraded.
- Foreign direct investment (FDI): Many studies have found that energy efficiency and emissions reduction can be expensive because of high R&D costs, more and more developing economies are considering *FDI* as an important tool to improve energy policies and develop emission reduction technologies (Amoako and Insaidoo, 2021). This paper uses the ratio of *FDI* to GDP to reflect the level of *FDI*.
- R&D intensity (RI). It is widely believed that R&D activities are a vital factor influencing energy consumption. Therefore, this study uses the ratio of Science and Technology expenditure to public finance expenditure to reflect R&D intensity.
- Environmental governance (EG): the different attitudes of local governments towards environmental governance often lead to different degrees of leniency in the introduction of policies, which in turn result in differences in local energy consumption. Concerning the study of Chen et al. (2018), the frequency of environment-related terms (low carbon, environmental protection, PM2.5, emission reduction, energy consumption) appearing in the work reports of prefecture-level municipal governments and their weight were selected to reflect the level of environmental governance of prefecture-level municipal governments.
- Green Technology Innovation (GTI): As a key driver of sustainable economic development, green technology innovation plays an essential role in reducing energy consumption and advancing energy structure transformation, and the energy industry's shift to innovation-driven development will be the future trend (Jiang et al., 2020). According to the International Patent Classification Green Inventory (IPC Green Inventory) classification number launched by WIPO in 2010, each city's green patent application data are retrieved and used to measure green technology innovation.

3.2.4 Mechanism Variables

The following variables were selected to explore the path of SDPRC influencing energy consumption in RBCs.

- Pollutant emission (PE): Fossil energy generates large amounts of SO_2, soot, and other pollutants during the combustion process, and it has been well documented that the level of pollutant emission in a region is closely related to the level of energy consumption. In this paper, regarding Domazlicky and Weber (2004), the comprehensive pollutant emission index is chosen to measure the pollutant emission of each city.
- 1) The unit pollutant emissions of each city are linearly normalized. This paper mainly calculates three types of pollutants: wastewater, SO_2, and soot.

$$UE_{ij}^{s} = \frac{UE_{ij} - \min\left(UE_j\right)}{\max\left(UE_j\right) - \min\left(UE_j\right)} \tag{4}$$

Where UE_{ij} is the pollutant emissions per unit output value of pollutant *j* in city *i*, max(UE_j) and min(UE_j) are the maximum and minimum values of each indicator in all cities, and UE_{ijs} is the standardized value of the indicator.

2) The proportion of pollutant emissions varies greatly from city to city, and the intensity of emissions of different pollutants also varies greatly. The formula calculates the adjustment factor:

$$W_j = \frac{UE_{ij}}{\overline{UE_{ij}}} \tag{5}$$

UE_{ij} is the city average of unit output emissions of pollutant *j* during the sample period.

3) Calculate the pollutant emission intensity of each city. PE_i is the environmental regulation intensity of city *i*.

$$PE_{\mathrm{i}} = \frac{1}{3}\sum\nolimits_{i=1}^{3} W_j UE_{ij}^{s} \tag{6}$$

- Rationalization of industrial structure (RSP): In the past, the rapid economic development of RBCs have relied on large inputs of production factors and large consumption of energy, and a series of unsustainable problems accompany such a development model, so the rationalization and transformation of the industrial structure of RBCs are essential to achieve sustainable economic growth. We use the index rationalization of industrial structure to measure the level of industrial structure rationalization of cities (Xin-gang and Jin, 2022). In this paper, we utilized the Thiel index to measure the degree of industrial structure rationalization of each prefecture-level city, which has the excellent property of measuring the structural deviation of different industries in

TABLE 3 | Descriptive statistics of the variables.

Variable	N	Mean	S.D	Min	Max
lnECS	3982	4.3976	1.2156	1.8473	6.9523
ECI	3982	0.0191	0.0258	0.0007	0.1224
lnECO	3982	10.5145	0.6800	9.0755	11.8556
IND	3982	1.3129	0.4748	0.4988	2.6592
FDI	3982	0.0638	0.1490	0.0001	0.7363
RI	3982	1.3940	1.2309	0.1536	5.2912
EG	3982	0.0052	0.0021	0.0017	0.0105
lnGTI	3982	5.3923	1.4391	1.0986	6.6120
PE	3982	0.1653	0.2823	0.0000	1.3657
RSP	3982	0.2671	0.1936	0.0106	0.7482
RD	3982	43.8911	13.6170	17.5000	72.2000

Note: This table shows the sample size (N), mean, standard deviation (S.D), minimum (Min), and maximum(Max) values for 280 cities from 2006 to 2019.

TABLE 4 | Correlation test of control variables.

Variables	lnECO	RD	EG	lnGTI
lnECO	1			
IND	−0.016			
FDI	0.499***			
RI	0.614***	1		
EG	0.339***	0.210***	1	
lnGTI	0.713***	0.671***	0.281***	1

*** p< *0.001*, ** p< *0.01*, * p< *0.05*.

terms of output and employment and the different economic status of each industry. The specific calculation formula is.

$$RSP_{i,t} = \sum_{m}^{3} y_{i,m,t} \ln\left(\frac{y_{i,m,t}}{l_{i,m,t}}\right), m = 1, 2, 3 \tag{7}$$

Where $y_{i,m,t}$ represents the proportion of regional GDP in period t of industry m *in* region i; $l_{i›m›t}$ represents the proportion of industry m in region i in total employment in period t. The industrial structure Thayer index reflects the output value structure and employment structure of the three key industries. If the value is 0, the industrial structure is at the equilibrium level; if not 0. In terms of industrial structure, the industrial structure is unreasonable, and it is deviating from equilibrium.

- Resource dependence (RD): Currently, the secondary industry is still the pillar industry on which RBCs rely for survival and development and is often used to measure the level of resource dependence, regarding Li Q et al. (2021). The proportion of employees in the secondary industry indicates the degree of resource dependence.

3.3 Data Source

The empirical analysis is conducted on the RBCs of China at the prefecture-level and above. Based on the data available, we utilize the panel data from 2006 to 2019 for 280 prefecture-level cities (109 RBCs and 171 non-RBCs) to assess the influence of sustainable development policies on energy consumption in RBCs. The data retrieved from China City Yearbook, China Statistical Yearbook, and Statistical Yearbooks of Cities, and the few missing data were interpolated to make up for them. To eliminate the effect of price fluctuations, GDP is deflated on a 2006 annual basis according to the price index of each province. In the empirical process, this paper take the natural logarithm of *ECS*, *ECO*, and *GTI* to attenuate the heteroskedasticity (Fan and Zhang, 2021). Descriptive statistics of the variables are shown in **Table 3**.

TABLE 5 | VIF test.

Variable	VIF	1/VIF
lnGTI	2.67	0.374239
RI	2.3	0.43394
lnECO	2.28	0.437717
FDI	1.92	0.520757
EG	1.16	0.859841
IND	1.01	0.992929
Mean VIF	1.89	0.603237

TABLE 6 | Baseline regression results.

Variables	(1)	(2)	(3)	(4)
	ECS	ECI	ECS	ECI
treat*time	−0.1055***	−0.0068***	−0.0795***	−0.0046***
	(0.0248)	(0.0006)	(0.0250)	(0.0006)
lnECO			0.2906***	−0.0065***
			(0.0366)	(0.0009)
IND			−0.0413**	−0.0002
			(0.0186)	(0.0005)
FDI			−0.5599***	0.0706***
			(0.1612)	(0.0041)
RI			−0.0193*	0.0017***
			(0.0112)	(0.0003)
EG			1.0758***	−0.0205**
			(0.3709)	(0.0093)
lnGTI			0.1005***	0.0008***
			(0.0127)	(0.0003)
Constant	3.7350***	0.0104***	0.7205**	0.0698***
	(0.0236)	(0.0006)	(0.3553)	(0.0090)
Observations	3,783	3,783	3,783	3,783
R-squared	0.692	0.492	0.708	0.552
Number of cities	280	280	280	280
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	No	No	Yes	Yes

Note: No control variables were added in columns (1) (2), and control variables were added in columns (3) (4).
***p < *0.001*, **p < *0.01*, *p < *0.05*, *Standard errors in parentheses.*

4 EMPIRICAL RESULTS AND DISCUSSION

4.1 Variable Multicollinearity Test

Table 4 shows the results of correlations analysis. The outcome indicates that the maximum correlation coefficient is 0.713 (level of economic development and green technology innovation), and most of the variables have correlation coefficients less than 0.6.

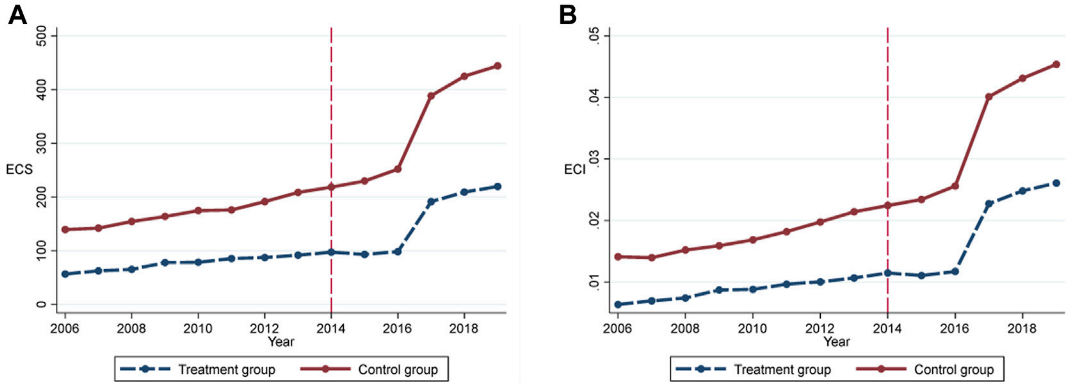

FIGURE 1 | Time trend of *ECS* **(A)** and *ECI* **(B)** between treatment group and control group.

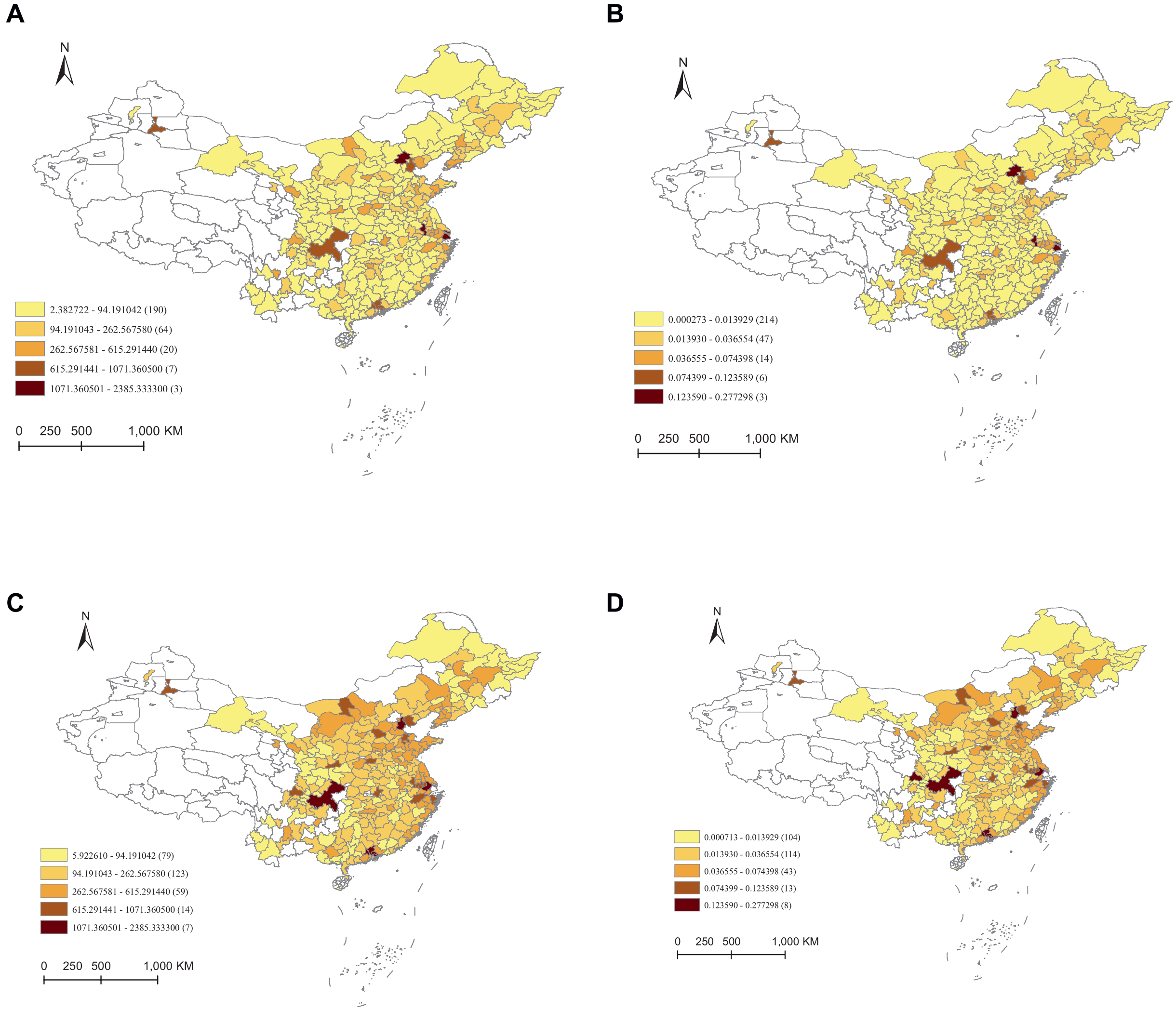

FIGURE 2 | Spatial distribution of *ECS* **(A,C)** and *ECI* **(B,D)** in 2006–2014 and 2014-2019.

Therefore, the control variables do not have a strong correlation. **Table 5** shows the results of the variance inflation factor (VIF) test. The maximum VIF value was 2.67 (*lnGTI*), which is much smaller than 10. Therefore, the multicollinearity of variables could be ignored.

4.2 Parallel Trend Test

Before using the DID method, the key step is to make a common trend assumption, which requires that ECS and ECI of the Treatment and Control groups have parallel trends before *SDPRC*. **Figures 1A,B** show the time trends of *ECS* and *ECI* from 2006 to 2019, respectively, and it can be seen from the figure that before the 2014 years, the Treatment group and Control group both had consistent trends in *ECS* and *ECI*. However, it is difficult to distinguish which category of cities has a greater impact on energy consumption by implementing the policy based on the time trend graph alone, which we will further discuss in the empirical evidence below.

In addition, **Figure 2** show the spatial distribution of *ECS* and *ECI* of cities, (a), and (b) for *ECS* and *ECI* before the policy implementation (2006–2014), and (c), and (d) for *ECS* and *ECI* after the policy implementation (2015–2019), respectively. From the spatial distribution of *ECS* and *ECI* before and after the policy, we can see that the *ECS* and *ECI* of most cities are still on the rise in the 5 years after the policy, which may be because most cities are still in the development stage and still need a large amount of energy consumption to support the rapid economic development. At the same time, the spatial distribution map also reflects another problem: there are significant differences in *ECS* and *ECI* between cities. Furthermore, energy consumption varies significantly between cities in different geographic locations, which may affect our empirical results.

4.3 Baseline Regression Results

First, this study estimates the parameters of the benchmark model based on **Eq. 2** using the DID method based on the panel data of 280 cities over 2006-2019, and **Table 6** shows the regression results. It can be seen that the coefficients in columns (1)–(4) are all negative and significant at 1% level, indicating that the total *ECS* and *ECI* of RBCs decreased or slowed down after the implementation of *SDPRC* compared to non-RBCs. This result indicates that *SDPRC* is playing an important to reduce energy consumption and promoting energy structure transformation in RBCs.

The coefficients of *ECO* are significant at a 1% level with the values of 0.2096 and -0.0065. Numerically, a 1% increase in *ECO* leads to a 0.2906% increase in *ECS* and a 0.065% decrease in *ECI*. The reason may be that a large amount of energy consumption still accompanies the rapid economic development of the city, but the low-carbon transformation of the energy structure has been promoted in parallel, making the energy consumption intensity has gradually tended to be decoupled from the economic development, which is also consistent with the study of Tang et al. (2018).

The coefficients of *IND* are significantly negative with the values of -0.0413 and -0.0002. The results portray that optimizing industrial structure significantly reduces *ECS*, but the effect on *ECI* is not significant. It indicates that the focus of controlling energy consumption in RBCs in the future should still be on industrial structure adjustment and optimization. We also test the role of industrial structure rationalization in reducing energy consumption in the subsequent impact mechanism test.

The coefficients of *FDI* are -0.5599 and 0.0706, and both pass the significance test at the 1% level. *ECS* decreases 0.5599% when FDI goes up by 1% and an increase of 0.0706% in *ECI*. It indicates that as the level of *FDI* increases, the energy consumption of RBCs decreases, but the energy consumption intensity increases instead. These findings indicate that while expanding the scale of *FDI*, foreign and domestic enterprises do not adopt uniform energy conservation and emission reduction policies. It can be concluded that FDI is allocated towards energy-intensive industries. It caused a negative correlation between *FDI* and *ECI*. Our findings are in agreement with the findings of (Yue et al., 2011).

The results further show that for every 1% increase in *RI*, *ECS* decreases by 0.0193%, and *ECI* increases by 0.0017%. Referring to past studies (Huang et al., 2021), R&D investment intensity usually reduces total energy consumption by acquiring advanced energy-saving and emission-reducing technologies and equipment. The coefficient of *ECS* is negative, which is also the same as most previous studies conclude that the increase in *RI* reduces the scale of energy consumption. However, unlike the findings of past studies, the increase in *RI* leads to a simultaneous increase in *ECI*. Exploring the reason for this may be that resource-based urban industries are still dominated by steel and petrochemicals, and R&D intensity often fails to have a significant impact on these industries with high pressure on energy conservation and emission reduction and low production efficiency (Luan et al., 2019).

For every 1% increase in *EG*, *ECS* increases by 0.0758%, and *ECI* decreases by 0.0205%, indicating the current government program has reduced the *ECI* to some extent has not stopped the rising trend of energy consumption. Although the level of environmental governance is improving, it is not sufficient to offset the large amount of energy consumption brought about by the rapid development of the city; and there is often a lag between the formulation and implementation of policies, which leads to the fact that *ECS* is not significantly inhibited by environmental governance (WU et al., 2020).

The coefficients of *lnGTI* are 0.1005 and 0.0008, and both pass the significance level test. It indicates that green innovation does not mitigate energy consumption growth; contrary to green technology, innovation suppresses energy consumption in cities (Khattak et al., 2022). The reason for these findings may be because this paper chooses green invention patents to measure urban green technology innovation, and patents, as a form of green input, may have a certain lag from being converted into output.

4.4 Time Trend Analysis

To further explore the effect of *SDPRC* over time, we construct the dummy time variables *pre*(n) and *post*(n) before and after the policy, the policy implementation year 2014 as the base year:

TABLE 7 | Results of the parallel trend analysis.

Variables	(1)	(2)
	ECS	ECI
pre5	0.0995*	0.0033**
	(0.0514)	(0.0013)
pre4	0.1168*	0.0027
	(0.0646)	(0.0017)
pre3	0.0998	0.0023
	(0.0645)	(0.0017)
pre2	0.0536	0.0009
	(0.0647)	(0.0017)
current	0.0123	-0.0003
	(0.0647)	(0.0017)
post1	-0.0456	-0.0016
	(0.0645)	(0.0017)
post2	-0.0828	-0.0032*
	(0.0646)	(0.0017)
post3	-0.0387	-0.0066***
	(0.0647)	(0.0017)
post4	0.0020	-0.0073***
	(0.0645)	(0.0017)
post5	0.0203	-0.0079***
	(0.0647)	(0.0017)
Constant	3.6963***	0.0091***
	(0.0309)	(0.0008)
Observations	3,783	3,783
R-squared	0.693	0.498
Number of cities	280	280
City FE	Yes	Yes
Year FE	Yes	Yes
Control variables	Yes	Yes

*Note: ***p < 0.001, **p < 0.01, *p < 0.05, Standard errors in parentheses.*

current, the pre-policy time dummy variable as *pre*(n) (n = 1,2,3,4,5), the post-policy time dummy variable as *post*(n) (n = 1,2,3,4,5) To eliminate the effect of policy lag, we exclude the *pre*1 and add the interaction term of the resource-based city dummy variable ($treat_{it}$) and the time dummy variable to the model for regression. **Table 7** represents the regression results.

When *ECS* is the dependent variable, the coefficients of the interaction term before the policy implementation (*pre*2-*pre*5) are positive. After the policy implementation (post1-post3), the interaction term coefficients are all negative but insignificant. The absolute values of the coefficients after the implementation are inverted U-shaped, reaching a maximum in the second year. The coefficients of *post*4 and *post5* become positive again, indicating that the implementation of *SDPRC* did cause a small but insignificant decrease in *ECS* in RBCs. The effect reached best after 2 years, but the effect has disappeared since the fourth year after implementation.

When *ECI* is the dependent variable, the coefficients of the interaction terms are positive before the policy and negative after the implementation. The coefficients become significant from *post*2, and the absolute values increase year by year, indicating the policy lag's impact on the *ECI* of RBCs after the implementation. The effect of policy implementation gradually improves over time, *ECI* is significantly inhibited by this compound.

4.5 Heterogeneity Test

The previous results show that *SDPRC* significantly reduces energy consumption in RBCs. To further explore the impact of *SDPRC* on energy consumption in RBCs, we examine the heterogeneity of RBCs, which may have heterogeneity in the impact of *SDPRC* implementation due to certain differences in geographic location and economic development level. Therefore, the paper explores the heterogeneity of their spatial differences and development stage differences.

4.5.1 Spatial Heterogeneity

Table 8 shows that all coefficients are negative except for the coefficient of energy consumption scale in the western region, which passed the significance test, indicating that the implementation of *SDPRC* has a certain degree of suppression effect on energy consumption in RBCs in the central and eastern regions.

When *ECS* is the dependent variable, the effect of *SDPRC* is more vigorous in East than Central and West regions (i.e., East > Central > West). However, when *ECI* is the dependent variable, the effect of *SDPRC* is strong in the East than in the West and Central regions (i.e., East > West > Central). It indicates that *SDPRC* has a more obvious effect on energy consumption reduction in the eastern region. On the one hand, cities in the central and western regions are inland, with closed transportation, backward innovation capacity, and brain drain, and urban development still relies on high-energy-consuming and high-polluting enterprises. Many traditional industries have outdated infrastructure and low productivity. Therefore, since the policy has been implemented, cities in the central and western regions still face problems such as lagging policy execution and difficulties in transformation. On the other hand, in the transformation of RBCs, because the policy implementation has brought an industrial transfer to central and western cities, most negative environmental externalities and pollution-induced welfare losses are borne by cities in the middle and west. This result agrees with the finding of Wang et al. (2022).

4.5.2 Growth-Stage Heterogeneity

SDPRC classifies RBCs into four types according to their resource security capacity and economic development stage: growing, mature, declining, and regenerating. Growing cities are in the rising stage of resource development, while Mature cities have a stable resource with a substantial resource security capacity. Declining cities deplete resources and have sharp conflicts between economic development and the ecological environment. Regenerating cities are gradually becoming less reliant on resources and stepping into the path of sustainable development. Therefore, the implementation of *SDPRC* may have heterogeneous impacts on RBCs in different development stages.

Table 9 shows the regression. The coefficients of the interaction terms are negative, and most of them are significant, except for the positive coefficient of the interaction term in column (1). The coefficient of the *ECS* in growing cities is positive, and the reason for this may be that growing cities are

TABLE 8 | Regression results in different regions.

Variables	Eastern		Central		Western	
	(1)	(2)	(3)	(4)	(5)	(6)
	ECS	ECI	ECS	ECI	ECS	ECI
treat*time	−0.2174***	−0.0085***	−0.1351***	−0.0027***	0.0331	−0.0045***
	(0.0419)	(0.0014)	(0.0381)	(0.0007)	(0.0559)	(0.0014)
Constant	4.2961***	0.0161***	3.4530***	0.0065***	3.3686***	0.0084***
	(0.0349)	(0.0012)	(0.0368)	(0.0007)	(0.0551)	(0.0014)
Observations	1,357	1,357	1,476	1,476	950	950
R-squared	0.722	0.602	0.699	0.506	0.671	0.388
Number of cities	99	99	108	108	73	73
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*Note: ***p < 0.001, **p < 0.01, *p < 0.05, Standard errors in parentheses.*

TABLE 9 | Regression results in different economic development.

Variables	Growth type		Mature		Declining		Regenerative	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ECS	ECI	ECS	ECI	ECS	ECI	ECS	ECI
treat*time	0.2778***	−0.0053***	−0.0366	−0.0068***	−0.4150***	−0.0114***	−0.2595***	−0.0010
	(0.0537)	(0.0016)	(0.0303)	(0.0008)	(0.0404)	(0.0013)	(0.0524)	(0.0016)
Constant	3.7904***	0.0124***	3.7665***	0.0113***	3.8687***	0.0125***	3.9087***	0.0133***
	(0.0275)	(0.0008)	(0.0257)	(0.0007)	(0.0251)	(0.0008)	(0.0266)	(0.0008)
Observations	2,486	2,486	3,084	3,084	2,611	2,611	2,487	2,487
R-squared	0.732	0.501	0.713	0.520	0.725	0.493	0.725	0.516
Number of cities	181	181	229	229	191	191	181	181
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Note: ***p < 0.001, **p < 0.01, *p < 0.05, Standard errors in parentheses.*

Table 10 | Robustness test results of other policy impacts.

Variables	Low carbon pilot		Twelfth five-year plan		Action plan	
	(1)	(2)	(3)	(4)	(5)	(6)
	ECS	ECI	ECS	ECI	ECS	ECI
treat*time	−0.1020***	−0.0066***	−0.1117***	−0.0105***	−0.0910***	−0.0069***
	(0.0281)	(0.0007)	(0.0384)	(0.0011)	(0.0319)	(0.0009)
Constant	3.7361***	0.0104***	3.7415***	0.0105***	3.7598***	0.0109***
	(0.0238)	(0.0006)	(0.0270)	(0.0007)	(0.0207)	(0.0006)
Observations	2,968	2,968	2,147	2,147	2,716	2,716
R-squared	0.694	0.487	0.759	0.546	0.669	0.503
Number of cities	280	280	280	280	280	280
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*Note: ***p < 0.001, **p < 0.01, *p < 0.05, Standard errors in parentheses.*

rapidly growing and are resources are still being developed. Therefore, the impact of policy does not offset the energy consumption required for rapid growth development. The coefficients of the interaction terms for the remaining three types of cities are all negative, implying that SDPRC has reduced the energy consumption of all three types of cities. The coefficients for mature cities are all negative and pass the significance test at the 1% level, indicating that *SDPRC* significantly reduces energy consumption in mature cities. The coefficient of the interaction term for declining cities is negative and high in absolute value, indicating that *SDPRC* suppresses the energy consumption of declining cities, and the effect is more significant among the four types of cities. The problems faced by declining cities, such as resource depletion and ecological and environmental pressure, are still serious, so it is urgent to reduce energy consumption and improve the energy structure. The

TABLE 11 | Counterfactual test of *ECS*.

Variables	(1)	(2)	(3)	(4)	(5)
	2006–2012	2006–2011	2006–2010	2006–2009	2006–2008
2007	0.0163	0.0155	0.0133	0.0056	0.0061
	(0.0293)	(0.0296)	(0.0289)	(0.0291)	(0.0302)
2008	0.0075	0.0034	0.0006	−0.0063	
	(0.0255)	(0.0246)	(0.0245)	(0.0269)	
2009	0.0077	−0.0065	0.0053		
	(0.0429)	(0.0415)	(0.0383)		
2010	0.0111	0.0103			
	(0.0343)	(0.0353)			
2011	−0.0397				
	(0.0250)				
Constant	3.7327***	2.0753***	2.0294**	1.7476	0.0689
	(0.0170)	(0.6900)	(0.8928)	(1.3680)	(1.7280)
Observations	1,870	1,599	1,326	1,053	782
R-squared	0.450	0.415	0.335	0.281	0.303
Number of cities	280	280	280	280	280
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

*Note: ***p < 0.001, **p < 0.01, *p < 0.05, Standard errors in parentheses.*

TABLE 12 | Counterfactual test of *ECI*

Variables	(1)	(2)	(3)	(4)	(5)
	2006–2012	2006–2011	2006–2010	2006–2009	2006–2008
2007	0.0010	0.0008	0.0007	0.0005	0.0007
	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0006)
2008	−0.0003	−0.0004	−0.0004	−0.0000	
	(0.0003)	(0.0003)	(0.0003)	(0.0007)	
2009	0.0010	0.0009	0.0004		
	(0.0011)	(0.0011)	(0.0007)		
2010	−0.0008	−0.0010			
	(0.0013)	(0.0013)			
2011	−0.0007				
	(0.0005)				
Constant	0.0303***	0.0248***	0.0221***	0.0240***	0.0131
	(0.0112)	(0.0093)	(0.0075)	(0.0072)	(0.0200)
Observations	1,870	1,599	1,326	1,053	782
R-squared	0.132	0.089	0.063	0.052	0.057
Number of cities	280	280	280	280	280
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

*Note: ***p < 0.001, **p < 0.01, *p < 0.05, Standard errors in parentheses.*

absolute value of the interaction term coefficient (column8) for regenerative cities is the smallest and insignificant among the four types of cities, indicating that the policy implementation does not significantly impact their energy consumption intensity. It shows that regenerative cities are gradually getting rid of their dependence on resources, continuously optimizing their energy structure, and stepping into a virtuous track of sustainable economic development. These results indicate that the impact of *SDPRC* differs significantly between different types of cities. Therefore, targeted energy structure transition strategies should be proposed for the development stages and characteristics of different types of cities.

4.6 Robustness Test

4.6.1 Impacts of Other Policy

Previously, we explored the impact of *SDPRC* on energy consumption in RBCs from 2006 to 2019; the Chinese government also issued some policies to promote energy transition in cities over this period. Considering that these policies may also affect energy consumption in cities, we tested the robustness of the empirical results by changing the study window. Three other policies are announced (i.e., 2010, 2012, and 2017) for low-carbon cities' transformation. The 12th Five-Year Plan (2011–2015) put forward new requirements for low-carbon urban transformation and ecological protection. The Action

TABLE 13 | Regression results of mechanism analysis.

Variables	(1)	(2)	(3)
	PE	RSP	RD
treat*time	−0.1594**	−0.0028	−1.8970***
	(0.0758)	(0.0054)	(0.3558)
Constant	4.5158***	0.6189***	−22.6995***
	(1.0780)	(0.0770)	(5.0565)
Observations	3,783	3,783	3,783
R-squared	0.009	0.041	0.251
Number of cities	280	280	280
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

*Note: ***p < 0.001, **p < 0.01, *p < 0.05, Standard errors in parentheses.*

Plan for the upgrading and transformation of coal power energy conservation (2014–2020) (hereafter referred to as the Action Plan) put forward a new plan for energy structure transformation that the eastern, central, and western regions are required to complete the transformation and upgrading of coal-fired power plants by 2020, 2017, 2018. To eliminate the impact of the above policies, the years in which the above policies were implemented are removed in turn and then regressed, and **Table 10** shows the regression results.

The results unveil that the coefficients of the interaction terms corresponding to the three policies are negative after changing the time window and passing the significance level test. It means that the previous empirical results do not change significantly, which means that the reduction in urban energy consumption is indeed caused by the implementation of *SDPRC*, proving the robustness of the initial results.

4.6.2 Counterfactual Test

To further eliminate the interference of other random factors and ensure the robustness of the baseline results. We perform counterfactual tests by varying the time of policy implementation on this basis by following the study of (Li S et al., 2021). We set the year of *SDPRC* implementation to 2007, 2008, 2009, 2010, 2011, set 5 different policy implementation intervals, and again used the DID method for estimation. **Table 11**; **Table 12** show the regression results with *ECS* and *ECI* as dependent variables. We can see from the consequence that the coefficients of interaction term of *ESC* and *ECI* as dependent variables are insignificant, indicating that the assumed year of *SDPRC* does not influence the dependent variable, suggesting that the change in energy consumption in RBCs is indeed caused by *SDPRC* implementation rather than by random factors.

4.7 Mechanism Analysis

Based on the previous regression results, the implementation of *SDPRC* significantly reduces energy consumption in RBCs. A city's environmental pollutant emission level, industrial structure rationalization transformation, and resource-dependent degree are often closely related to its energy consumption level. *SDPRC* may affect the city's energy consumption by controlling pollutant emission, industrial structure rationalization transformation, resource-dependent, and other channels, so we choose *PE*, industrial structure rationalization index, and resource-dependent degree as dependent variables and construct the following model.

$$Mechanism_{it} = \alpha_0 + \alpha_1 treat^{*}time + u_i + \lambda_t + \varepsilon_{it} \quad (8)$$

$Mechanism_{it}$ represents the impact mechanism variables (*PE, RSP, RE*), $treat_{it}$ is a dummy variable for RBCs, $time_{it}$ is a time dummy variable for policy implementation, u_i and λ_t represent the individual city effect and time effect, respectively, and ε_{it} is a random disturbance term.

The results of **Table 13** show that the coefficient of *PE* is −0.1594, and it passes the 5% significance level test, which indicates that *SDPRC* reduces the pollution level in RBCs. The coefficient of *RD* is −1.897, which indicates that the *SDPRC* limits the employment of secondary industries and indicates that controlling pollutant emissions and getting rid of resource dependence are indeed important ways to reduce energy consumption in RBCs. However, the coefficient of *RSP* is −0.0028, which indicates that *SDPRC* did not promote the rationalization and transformation of industrial structure in RBCs. Exploring the reason, it may be due to the early crude development of RBCs. The industrial structure is still dominated by the secondary industry represented by high pollution and high energy consumption, and there are still some difficulties and lags in the transformation of industrial structure compared with non-RBCs.

5 CONCLUSION AND POLICY IMPLICATIONS

5.1 Conclusion

This study uses *SDPRC* as a quasi-natural experiment to explore the impact of *SDPRC* on energy consumption in RBCs by using the DID method based on panel data of 280 cities from 2006 to 2019. Furthermore, we examine the spatial and development stage heterogeneity of RBCs, and finally, we also explore the mechanism of *SDPRC's* influence on energy consumption in RBCs. Based on the empirical analysis, we conclude that: (1) The implementation of *SDPRC* significantly reduces energy consumption in RBCs, where the effect on *ECS* has an inverted U-shaped distribution, with the effect peaking in the second year; the effect on *ECI* has a lag, starting significantly in the second year, and the effect increases incrementally as the policy advances. Subsequent stability tests with other policy effects and counterfactual tests also validate the baseline findings. (1) The consequences of the heterogeneity test show that: spatially, the implementation influence of *SDPRC* is more strong in eastern regions "Eastern > Central > Western" for *ECS* as the dependent variable, and "Eastern > Western > Central" for *ECI* as the dependent variable. Therefore, the implementation effect of *SDPRC* is most obvious in the eastern cities; in terms of the development stage, the implementation effect of *SDPRC* is "declining > regenerating > mature > growing" with *ECS* as the dependent variable, and the implementation effect is "declining > regenerating > mature > growing" with *ECI* as the dependent variable. Therefore, the effect of *SDPRC* implementation is most obvious in declining cities. The heterogeneity results indicate that the implementation effect of *SDPRC* differs among RBCs in different spatial and developmental stages, so targeted transformation suggestions should be made according to the characteristics of RBCs. (3) The results of the mechanism test show that both controlling pollutant emissions and getting rid of resource dependency are important ways to reduce energy consumption in RBCs. However, *SDPRC* does not contribute to the rationalization and transformation of industrial structure in RBCs.

However, this paper has some limitations. First, the discussion of energy consumption only focuses on the end consumption, and future studies will try to analyze from multiple perspectives such as renewable and non-renewable energy, clean energy, and dirty energy. Second, due to the unavailability of data, our data are available until 2019, and as the availability of relevant data increases in the future, we will supplement the data in future studies to obtain more accurate results. In future studies, we will explore more variables that affect energy consumption and control them in order to get more accurate results.

In our future research, we will explore the more comprehensive impacts of sustainable development policy on RBCs, such as sustainable development capacity and resource and environmental carrying capacity. We will also further explore the energy structure to provide more references for RBCs to achieve sustainable development.

5.2 Policy Implications

Based on the above research consequences and in the light of the actual situation of RBCs in China, we propose the policy recommendations to provide references and lessons for RBCs to achieve energy transition and sustainable development.

1) RBCs should develop a circular economy, switch the driving force of economic growth, gradually eliminate their dependence on resources, and adopt sustainable business models to focus on the transformation of RBCs in the future. After fully considering their geographical location, social culture, resource endowment, and other conditions, local governments need to develop a development model that meets their characteristics. Growing cities are in the rising stage of resource development and economy, and while developing, they should pay attention to reasonably determining the intensity of resource development to achieve circular and sustainable development. It is also imperative to continue improving the efficiency and quality of economic development in regenerative cities,
2) Develop clean energy and improve energy utilization efficiency. As a fundamental component of a sustainable energy system, new and sustainable energy must be developed. From the spatial point of view, efforts should continue to be made to improve the backward production capacity of RBCs in central and western China further to promote the improvement of their energy utilization efficiency and ease the pressure of energy consumption brought by economic growth. From the perspective of the development stage, growing cities should regulate the order of resource development, reasonably determine the intensity of resource development, and create a strategic succession base of resources with their characteristics; mature and declining cities should focus on accelerating the comprehensive management of hidden disasters such as abandoned pits and sinkholes and restoring the ecological environment.
3) Government departments should accelerate industrial restructuring and actively plan the layout of new industries. Improve the ability of original innovation, integrated innovation and re-innovation of introduction, digestion, and absorption, improve the quality and grade of products in traditional industries, and cultivate and grow high-tech industries and strategic emerging enterprises. It is imperative that growing cities speed up the implementation of industry support plans upstream and downstream and improve the deep processing of resources. Industrial clusters and leading enterprises should be located in mature cities, as well as industrial chains and pillar-type replacement industries. In declining cities, it is essential to develop replacement industries to enhance sustainable development capacity. In addition, regenerating cities should further optimize the industrial structure, accelerate the transformation and upgrading of traditional industries, and cultivate new momentum for development.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: The datasets used or analyzed in this study are publically available (http://www.stats.gov.cn/tjsj/ndsj/2021/indexeh.htm) and can also be accessible from the corresponding author on demand.

AUTHOR CONTRIBUTIONS

HZ: Conceptualization, Methodology, Software, Data curation, Formal analysis, Visualization, Writing-Original Draft. XS: Review and editing, Supervision, Funding acquisition. MA: Writing, review and editing, Supervision.YL: Data curation, review and editing. CX: Data curation, review and editing.

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Can Market-Oriented Environmental Regulation Tools Improve Green Total Factor Energy Efficiency? Analyzing the Emission Trading System

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Undoubtedly, green total factor energy efficiency plays a pivotal role in achieving energy conservation, emission reduction, and green development goals. China mainly used command-based environmental regulation tools to enhance the green total factor energy efficiency in the early stage. Later, under the new trend of market-oriented reform, the Chinese government introduced market-oriented environmental regulation tools such as carbon rights. However, the effectiveness of market-oriented environmental regulation tools is still unclear. Therefore, this study investigates the impact of market-oriented environmental regulation tools on green total factor energy efficiency by using the data of 265 cities in China. For this purpose, yearly data from 2003 to 2017 are employed using the difference-in-difference method. The empirical results unveil that the emission trading system can significantly improve green all factor energy efficiency. In addition, the heterogeneity analysis shows that the emission trading system is conducive to improving energy efficiency in resource-based cities. Based on the results, this study provides policy enlightenment for market-oriented environmental regulation tools to promote green development according to the local conditions.

Keywords: market-oriented environmental regulation tools, emission trading system, green total factor energy efficiency, difference-in-difference method, energy efficiency

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1 INTRODUCTION

Improving green total factor energy efficiency is an important issue that needs to be solved urgently to realize green development in China's economy from the stage of high-speed growth to the stage of high-quality development. In recent years, China has achieved remarkable results in promoting the reform of energy conservation and consumption reduction as well as green development. The proportion of coal consumption in total energy consumption has declined from 72.8% in 2011 to 56% in 2021. However, coal consumption is still dominant in the primary energy mix and, at the same time, the total carbon dioxide emission has not yet peaked. In addition, the power consumption of China's GDP is about 0.6 kWh/US$, which is far higher than the world average of 0.2 kWh/US$. Under increasing pressure on the ecological resources and environment, improving green all factor energy efficiency is an inevitable choice. The energy sector is mainly liable for environmental degradation (Khan et al., 2021,2022). The role of energy is indispensable to attaining economic development; however, it also adversely affects the environmental quality and is mainly responsible for climate change. Green total factor energy efficiency is one of the easiest and most cost-effective ways to reduce energy usage and combat climatic changes. In the early stage, China mainly focused on command-based environmental regulation tools. Later, China gradually explored market-oriented environmental regulation tools with transaction modes such as emission rights, water rights, and energy rights.

The traditional analysis holds that environmental regulation may reduce energy efficiency in the short term by imposing pollution control costs. In contrast, the "Porter Hypothesis" holds that environmental regulation improves energy efficiency by promoting innovation (Porter and Linde, 1995). The principle of market-oriented environmental regulation tools comes from the "Coase Theorem." The existing literature always uses the emission trading system as a "quasi-experiment" to evaluate whether the environmental regulation policy immediately affects the environmental quality (Lambie, 2010; Calel and Dechezleprê tre, 2016; Zhang et al., 2017; Chen and Chen, 2019). However, they ignore the critical role of energy in promoting energy conservation and emission reduction by market-oriented environmental regulation and have not yet involved the impact of market-oriented environmental regulation on energy conservation and green production efficiency. Based on the specific perspective of green total factor energy efficiency, this study expands the institutional dividend of market-oriented environmental regulation tools for the first time. This research puts green total factor energy efficiency in the impact analysis scope of market-oriented environmental regulation system, which makes up for the lack of comprehensive measurement and analysis. Meanwhile, it also makes up for the lack of empirical tests on market-oriented environmental regulation tools and urban green total factor energy efficiency in the existing literature to a certain extent.

2 LITERATURE REVIEW

2.1 Environmental Regulation and Total Factor Productivity

The relationship between environmental policy and total factor productivity has been controversial in academia. For instance, Gray and Shadbegian (2003) found that mandatory environmental regulation negatively impacts the total factor productivity of the industry. Likewise, Lanoie et al. (2008) found that the additional cost due to increased environmental regulation intensity adversely affects the total factor productivity in the short term. In contrast, Hamamoto (2006) found that environmental regulation leads to an increase in R&D expenditure, which leads to the growth in productivity in Japan's manufacturing sector. Similarly, Testa et al. (2011) confirmed that flexible environmental regulation poses a significant and positive effect on the proportion of R&D investment, increasing the production efficiency. Tang et al., (2015), Rubashkina et al. (2015) and Li and Chen (2016) found that industrial production increased due to the impact of environmental policies. In the production process of enterprises, when environmental regulation improves the environmental performance, it will inevitably affect the activities such as resource redistribution, capital investment, and technological innovation, and ultimately affect the total factor productivity (Hering and Poncet, 2014; Feng and Ye, 2015; Hancevic, 2016; Albrizio et al., 2017). Ren et al. (2019) believed that implementing emission trading in areas with high environmental law rules can effectively improve the total factor productivity. Tang et al. (2020) identified optimal transition timing from command-and-control policies to market-based policies by analyzing the trade-off between the abatement cost and innovation compensation effects of environmental regulations.

2.2 Emission Trading System

The research on the effect of emission rights policy mainly focuses on environmental performance, economic performance, and technological innovation. Betsil and Hoffmann (2011) believed that when designing the total volume control and trading system, the most controversial issue is how to allocate licenses and how to conduct free distribution or auction. On the one hand, the research conclusions of some scholars support the policy effect of emission trading. For instance, Schleich and Betz (2004) found that the emission permit trading system positively impacts the emission reduction of small- and medium-sized enterprises. The enterprises involved in emissions trading have a relatively greater possibility of environmental innovation (Schleich et al., 2009; Anderson and Di Maria, 2010 et al., 2009; Lin and Sun, 2016; Lu et al., 2020). On the other hand, some scholars believe that the effect of emission rights policy is limited. Borghesi et al. (2015) found that implementing the European emissions trading system (EU-ETS) has limited policy effect due to loose quota issuance. Li and Wen (2016) believed that the role of the market mechanism makes the emission reduction effect of emission trading in pilot areas significant. Stein (2019), Cheng et al., (2015) and Zhou et al., (2020) believed that emission trading has no significant emission reduction effect in the pilot areas. Still, it is undeniable that there are long-term economic and environmental dividends. Shi and Li (2020) found that the emissions trading system reduces the energy consumption per unit GDP by increasing marketization, the relationship between government and market, developing the degree of factor market, and improving the green total factor energy efficiency by green innovation.

Based on the above literature, we can conclude that the research on the impact of market-oriented environmental regulation tools on green total factor energy efficiency is limited. Therefore, this study focuses on the samples of 265 cities in China to examine the impact of market-oriented environmental regulation tools on green total factor energy efficiency, and thus, expands the current literature by analyzing the heterogeneous effect of market-oriented environmental regulation in different types of cities at different periods. Based on the above considerations, this study selects emission trading representative of market-oriented environmental regulation tools. It takes cities under the pilot provinces of the emission trading system as the research samples to conduct an in-depth analysis. Additionally, a series of robustness tests on the impact

TABLE 1 | Description of variables.

Variable	Symbol	Measurement	Source
Green total factor energy efficiency	Gtfpe	Calculated by the SBM Malmquist Luenberger index method	CESY
Population density	Density	Obtained by dividing the city's population by the administrative area	CUSY
Industrial structure	Structure	Proportion of the added value of the secondary industry in the regional GDP	CUSY
Per capita GDP	pgdp	The city's GDP is divided by the city's total population	CUSY
Total energy consumption	Energy	Obtained by using night light data simulation measurement	NOAA
Sulfur dioxide emission	SO_2	Representative pollutant emission level	CESY
R&D and innovation capability	Innova	Number of invention patents represents the city's R&D and innovation ability	SIPOC

Note. CESY, China Energy Statistics Yearbook; CUSY, China Urban Statistical Yearbook; NOAA, National Oceanic and Atmospheric Administration; SIPOC, State Intellectual Property Office of China.

TABLE 2 | Descriptive statistics of the main variables.

Variable	Observation	Mean	Std.dev	Minimum	Median	Maximum
Gtfpe	3,815	0.963	0.412	0.237	0.891	6.217
SO_2	4,106	5.587	5.725	0.001	4.126	68.303
Smoke	4,106	3.198	11.682	0.003	1.825	511.372
Effluents	4,106	0.711	0.916	0.001	0.0.453	9.061
Indensity	4,106	5.648	0.809	1.662	5.812	7.513
Structure	4,106	0.421	0.102	0.075	0.424	0.853
lnpgdp	4,106	8.406	0.719	6.013	8.415	13.782
lninnova	4,106	3.691	1.582	0.000	3.506	10.693

mechanisms and path of emission trading system on green total factor energy efficiency are carried out and further investigate the heterogeneous effect of urban resource endowment.

3 RESEARCH DESIGN

3.1 Data Sample

In 2007, China's Ministry of Finance and the Ministry of ecological environment approved 11 provinces to carry out the pilot emission trading system. They set up emission trading centers, marking the formal institutionalization and standardization of China's market-oriented environmental regulation tools. This study considers the panel data of 265 cities from 2003 to 2017 as the research sample. Following the study by Shi and Li (2020), this research sets 2008–2017 as the implementation year of the emission trading system and sets 2003–2007 as the period before the introduction of the system. In the division of the experimental group and the control group, the cities under the jurisdiction of 11 provinces implementing emission trading are the experimental group. The cities under the jurisdiction of the other 20 provinces are used as a control group during the empirical analysis.

3.2 Variable Definition and Data Description

The main explanatory variable is the green total factor energy efficiency (Gtfpe). Following the study by Liu et al. (2017), we used capital, labor, and energy as inputs and GDP as the desired output; the industrial sulfur dioxide (SO_2), the emissions of industrial smoke and dust, and industrial wastewater (effluents) are regarded as undesirable outputs. The SBM Malmquist Luenberger index method is used to calculate each city's green total energy efficiency. **Table 1** shows the variable measurement, symbol, and data sources of the study variables.

The control variables mainly include population density, industrial structure, per capita gross regional product (pgdp), total energy consumption, sulfur dioxide emission (SO_2), and R&D and innovation capability. The descriptive statistics of the study variables are given in **Table 2**. The mean value of green total factor energy efficiency (Gtfpe) is 0.963, the standard deviation is 0.412, the minimum value is 0.237, the median value is 0.891, and the maximum value is 6.217. This indicates significant differences in the energy efficiency among cities during the study's sample period.

3.3 Identification Strategy and Model Setting

This study uses the difference-in-difference (DID) method to estimate the impact of the emission trading system on green total factor energy efficiency. The DID method is a commonly used method for evaluating policy effects. Referring to the research of Wang and Dong (2019) and Shi and Li (2020), the design model is as follows:

$$\mathrm{Gtfpeit} = \alpha_0 + \alpha_1 \mathrm{Experiment}_{it} \times \mathrm{post}_{it} + \beta \mathrm{Control}_{it} + \gamma_t + \theta_i + \mathrm{Province}_j \times \mathrm{Year}_t + \varepsilon_{it}. \tag{1}$$

In **Eq. 1**, i, t, and j denote the city, year, and province, respectively. The symbol Gtfpeit is the explained variable indicating the efficiency of green total factor energy, while the experiment is a city grouping variable. The pilot city of the

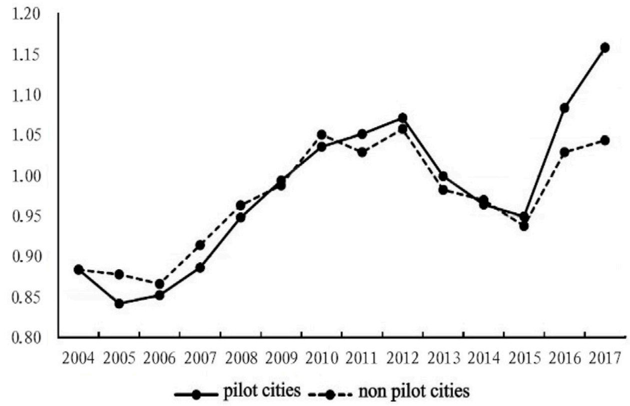

FIGURE 1 | Mean change in the green total factor energy efficiency in pilot and non-pilot cities.

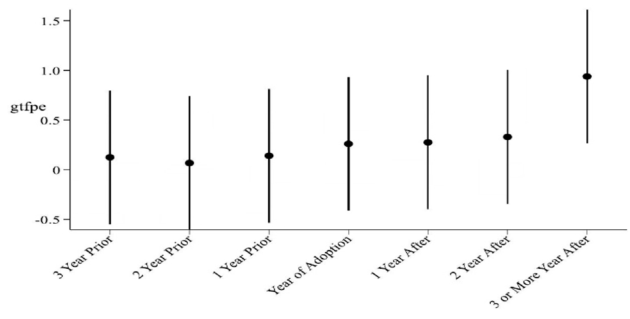

FIGURE 2 | Parallel trend test. Note: The *X*-axis represents the time before and after implementing the emission trading system. The Year of Adoption represents the year in which the emission trading system is implemented. The first 3 years are expressed in Prior, and the last 3 years and above are described in After.

TABLE 3 | Regression results of the DID model: emission trading system and energy efficiency.

	Gtfpe
Experiment × post	0.912** (0.437)
cons	−1.938* (1.132)
N	3,815
Adj-R^2	0.419

*Note: The values in parentheses are standard errors. ***, **, and * represent the significance levels of 1, 5, and 10%, respectively.*

emission trading system in *t* year is denoted as 1, and the non-pilot city is 0. The symbol postit is a time group variable, which is 1 in 2008–2017 and 0 in 2003–2007; Controlit is the control variable group; γt is the time fixed effect; and θi is the urban fixed effect that does not change with time. Moreover, Provincej × Yeart is the individual time effect of provinces, intended to control the influence of unobservable factors of cities over time on the estimation results. The symbol εit represents the random error term.

4 EMPIRICAL RESULTS AND ROBUSTNESS TEST

4.1 Analysis of the Time Trend Chart of Energy Efficiency Change

This study draws on the changing trend of green all factor energy efficiency in pilot cities and non-pilot cities with emission trading systems. **Figure 1** compares the changing trend of the two indicators in the experimental and control groups, and can intuitively reflect the effect of emission trading policies on regional energy efficiency. Before 2010, the green total factor energy efficiency of non-pilot cities was significantly higher than that of pilot cities. However, since 2008, the green all factor energy efficiency of pilot cities increased rapidly and surpassed the non-pilot cities in 2010. In general, the efficiency of pilot cities is stable above the non-pilot cities. So it can be preliminarily considered that the improvement of green total factor energy efficiency in pilot cities relative to the non-pilot cities around 2008 is likely to be induced by the emission trading system.

4.2 Regression Results of the Difference-in-Different Model: Emission Trading System and Energy Efficiency

In order to verify the conjecture obtained from the time trend chart, this study uses the DID method to test it empirically. The sample period is divided by the year of policy implementation, and the system effect is statistically analyzed by comparing the average processing effect before and after policy implementation. The results are shown in **Table 3**. The city, year, and province×year effects are controlled, and the control variables such as population density and industrial structure are introduced. After implementing the emission trading system, compared with the non-pilot cities, from the regression results, the green total factor energy efficiency values of the pilot cities have effectively been improved at a significance level of 5%.

4.3 Precondition for the Application of the Difference-in-Different Model: the Parallel Trend Test

The important premise of using the DID method is that the experimental and control groups should agree with the assumption of a parallel trend. Before the pilot implementation of the emission trading system, the green total factor energy efficiency maintains a relatively stable change trend. Specifically, consider 2008, the pilot year of the emission trading system, as the base year. OLS-DID regression is carried out separately for the explained variables in the first 3 years and the last 3 years and above the base year. The regression results show that the experiment×post coefficient of green total factor energy

TABLE 4 | Emission trading system and energy efficiency: estimation of instrumental variables.

	First stage regression	Second stage regression
—	Experiment × post	Gtfpe
iv × post	0.049*** (0.001)	—
Experiment × post	—	0.136*** (0.040)
cons	0.517 (0.329)	−1.721*** (0.377)
Control	Yes	Yes
Year	No	No
City	Yes	Yes
N	3,815	3,815
Adj-R^2	0.382	0.167
F value of the first stage	28.531	—

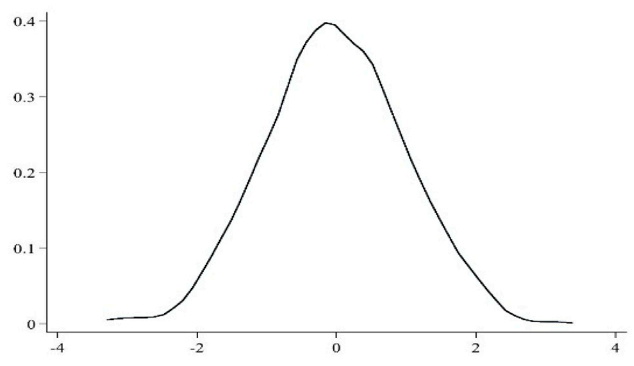

FIGURE 3 | The x-axis represents the t value of the ‘experiment × post’ coefficient, Y-axis represents its corresponding p-value.

TABLE 5 | Emission trading system and energy efficiency: PSM-DID model estimation.

	Gtfpe
Experiment × post	1.156** (0.527)
cons	−0.682 (0.816)
Control	Yes
Year	Yes
City	Yes
Province × Year	Yes
N	3,195
Adj-R^2	0.428

efficiency is not significant in the 3 years before the pilot of the emission trading system. Meanwhile, the regression coefficients are nearly 0, indicating no significant difference between the pilot and non-pilot cities before 2008, which accords with the assumption of a parallel trend. Furthermore, **Figure 2** shows that from the dynamic effect of the parallel trend test, after the third year (after 2011), the green total factor energy efficiency has a significant improvement trend. Meanwhile, it indicates a time lag of about 3 years in the emission trading system based on green total factor energy efficiency.

4.4 Overcoming Endogenous Problems: the Instrumental Variable Method

The selection of pilot cities may be affected by other potential factors, which may interfere with the estimation results of the DID method and affect the accuracy of the results. Therefore, based on the study of Cai et al. (2016), the instrumental variable method is used to overcome the influence of endogenous problems as much as possible. Specifically, based on Shi and Li (2020), the air circulation coefficient is selected as the instrumental variable and included in the pilot cities in the emission trading system. Moreover, meteorological and geographical conditions determine the air circulation coefficient, which can accord with the exogenous hypothesis of instrumental variables.

The estimation results of the instrumental variables are shown in **Table 4**. The instrumental variable is denoted by iv, which represents the natural logarithm of the annual mean value of the air circulation coefficient of the sample city. In the first stage of regression, the coefficients of the interaction item iv × post of instrumental variables and time variables are significant, and the *F*-values are greater than 10. The results show that the instrumental variables accord with the correlation conditions. In the second stage of regression, the interaction term experiment × post is still significant, indicating that the emission trading system can still significantly improve green total factor energy efficiency after eliminating endogenous problems.

4.5 Robustness Test

4.5.1 Placebo Test

In order to further eliminate the influence of other unknown factors and ensure the accuracy of the research conclusions, a placebo test is used. Specifically, this study conducted 500 samples in all 265 cities and randomly selected 100 cities as the virtual experimental group each time and the other cities as the control group for regression. The kernel density distribution plot of the explained variables in **Figure 3** shows that the absolute value *t* of most sampling estimation coefficients is within 2, and the *p*-value is greater than 0.1, indicating that the emission trading system has no significant effect on these 500 random samples. Therefore, the conclusion of this study can pass the placebo test.

TABLE 6 | Heterogeneity of the impact of the emission trading system on energy efficiency.

	Gtfpe				
	All resource-based city	**Growing resource-based city**	**Mature resource-based city**	**Declining resource-based city**	**Renewable resource-based city**
Experiment × post	0.091*** (0.031)	0.582*** (0.173)	0.071* (0.042)	0.012 (0.067)	0.126*** (0.049)
cons	−1.412*** (0.266)	−0.228 (0.875)	−0.919*** (0.236)	−2.698*** (0.503)	−1.312*** (0.293)
Control	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes
Province × Year	No	No	No	No	No
N	1,539	172	851	315	201
Adj-R^2	0.235	0.463	0.143	0.451	0.537

4.5.2 Propensity Score Matching-Difference-in-Difference Estimation

The sample of this study covers 265 cities across the country. There are significant differences among the sample cities, which may affect the consistency of the estimator and leads to biased results. Therefore, the propensity score matching method (PSM) is used to match the cities of the experimental group and the control group with the control variables as the identification characteristics of the sample points used for regression. The findings in **Table 5** show that the emission trading system significantly improves the green total factor energy efficiency of the pilot cities, indicating that the conclusions obtained in this study are still robust.

4.6 Heterogeneity Analysis: Heterogeneous Impact of Different Types of Resource-Based Cities

The total factor energy efficiency of most resource-based cities is in a state of nonefficiency, and there are significant differences among different types of resource-based cities. China's sustainable development plan for resource-based cities (2013–2020) has established 262 resource-based cities that are divided into four types, growing, mature, declining, and renewable resource-based cities, according to the abundance of resources. **Table 6** reports the results of the heterogeneous impact of the emission trading system on different types of resource-based cities from the perspective of green total factor energy efficiency.

The emission trading system has the most pronounced effect on improving the green total factor energy efficiency in the growing resource-based cities, followed by renewable and mature types. It has no significant impact on the declining types. The possible reason is that in growing resource-based cities, the pressure on environmental protection is slight, and there is a net inflow of labor and capital. As a result, the energy exploitation and total factor energy efficiency are mostly increasing. After experiencing the development stage of high pollution and high energy consumption, renewable resource-based cities have become more aware of cleaner production technology and energy efficiency. The energy utilization and pollution emission of mature resource-based cities are relatively stable. Meanwhile, the technical difference between enterprises is relatively small, resulting in less impact of emission trading system on improving green all factor energy efficiency. With the gradual depletion of energy resources, the production costs of various enterprises increase, and the outflow of labor and capital, resulting in generally low investment in cleaner production technology, and the emission trading market is likely to be stagnant. Therefore, the emission trading system has no significant impact on the green all factor energy efficiency of declining resource-based cities.

5 RESEARCH CONCLUSION AND POLICY IMPLICATIONS

5.1 Research Conclusion

This study considers 265 cities from 2003 to 2017 as a research sample to investigate the impact of market-oriented environmental regulation tools, especially the emission right system, on green total factor energy efficiency using the DID model. The main conclusions are as follows: after a series of robustness tests such as the parallel trend test, instrumental variable method, random sampling simulation test of the experimental group, and PSM method, it is found that the emission trading system significantly improves the green all factor energy efficiency. It is found from heterogeneity analysis that the emission trading system is generally conducive to improving energy efficiency in resource-based cities. The improvement effect of green all factor energy efficiency on the emission trading system is of growing type, renewable type, and mature type from large to small, and the impact on declining type is not significant.

5.2 Policy Implications

From the new perspective of green total factor energy efficiency, this study analyzes in-depth the impact of market-oriented environmental regulation tools, especially on the emission trading system. Additionally, this research discusses the heterogeneity of resource-based cities, providing a targeted empirical basis and policy enlightenment for further improving the emission trading system's energy conservation and consumption reduction as well as the green development effect. Thus, the following policy implications are desirable based on the empirical results.

Market-oriented environmental regulation tools should fully play their role in market-oriented attributes and provide good market trading platforms, intermediary organizations, and legal support for trading subjects, especially in dealing with the synergy between the government and the market in implementing the trading system. The government should not intervene in implementing the trading system but provide necessary trading market supervision, especially paying attention to the design of the cross-regional trading system. At the same time, it should create a good business environment and encourage social capital to participate in transactions. The government should strengthen environmental administrative supervision, increase the monitoring frequency and intensity of pollution sources, and ensure the accurate collection of emission information.

The key link for improving the green total factor energy efficiency is to build an enterprise R&D innovation system. For cities with coal as the main energy consumption structure, we should highlight the R&D investment or technology introduction of clean coal utilization technology by the innovation fund and gradually reduce the proportion of coal consumption in energy consumption. Meanwhile, for cities with advantages in renewable energy development, fiscal, tax, and financial policies supporting the development of emerging industries can be comprehensively applied to provide necessary policy support for the renewable energy power generation industry. The focus should be on the development of high-tech industries and we should strive to eliminate the dependence of economic development on high energy consumption and high pollution industries to improve the green all factor energy efficiency.

The market-oriented environmental regulation tools have a heterogeneous impact on the green total factor energy efficiency. Different pilot cities have significant differences in their economic development, innovation level, energy structure, and other factors, and the implementation effects of environmental regulation tools are significantly different. Therefore, each transaction pilot city cannot adopt the same standard when formulating the policies. It should carry out the transaction pilot construction "according to local conditions" to recognize its particularity to improve the efficiency of green development.

The improvement of green total factor energy efficiency has always been a key area of green transformation and development of the industry. Although the current market-oriented environmental regulation tools had a positive impact, steps to improve the enthusiasm of the main participants in the trading market to a greater extent should be paid more in-depth attention. Including how to build a cross-regional trading market and overcoming the energy rebound effect are important theoretical and practical issues worthy of discussion in the future.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

XW: Conceptualization, data curation, formal analysis, visualization, writing—original draft. ST: writing—original draft and editing. MA: supervision, writing—review, and editing. YB: writing—review, project administration, and editing.

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Financial Risk, Renewable Energy Technology Budgets, and Environmental Sustainability: Is Going Green Possible?

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Since the industrial revolution, countries have been facing the issue of climate change and environmental degradation. It is widely believed that the investment in research and development of renewable energy can play a pivotal role in fighting against climate change. However, the financial risk also increases, which can influence renewable energy technology R&D budgets and environmental sustainability. Nevertheless, the current literature is silent on the linkage between financial risk, renewable energy technology budgets, and environmental quality. Against this backdrop, this article attempts to explore the dynamic linkage between financial risk, renewable energy technology budgets, and ecological footprint under the Environment Kuznets Curve (EKC) framework in Organization for Economic Cooperation and Development (OECD) countries. For this purpose, yearly data from 1984 to 2018 is employed using the advanced panel data estimation methods that address the slope heterogeneity and cross-sectional dependence issues. The results indicate that improvement in the financial risk index significantly decreases footprints, and renewable energy technology budgets also promote environmental sustainability. Economic globalization poses a significant negative effect on the ecological footprint, while energy consumption adds to the footprint. Moreover, the findings validated the EKC hypothesis in OECD countries. In addition, a unidirectional causality is detected from financial risk to renewable technology energy budgets, while bidirectional causality exists between financial risk and ecological footprint, and between financial risk, and economic growth. Based on the empirical findings, policy suggestions are presented to promote environmental sustainability.

Keywords: financial risk, renewable energy technology budgets, environmental sustainability, OECD, CS-ARDL

INTRODUCTION

Undoubtedly, climate change is posing adverse effects on human life and the environment in every region. Decades of persistent efforts by the international community and environmentalists resulted in certain agreements and commitments to tackle the growing environmental challenges. In this context, the United Nations member nations agreed to pursue Sustainable Development Goals (SDGs) that offer guidance to solving various important global challenges (UN, 2021). All 17 SDGs are vital for safeguarding the foundations of life and supporting human prosperity; however, goal 13, which seeks immediate actions to address climate change, provides the foundation of sustainable development. This goal is closely linked with all other 16 goals that are important to pursue sustainable development.

The Paris Agreement was an important initiative to combat climate change and keep the global temperature increase below 2°C. The importance of the Paris Agreement cannot be denied; however, the commitments from all the signatories are insufficient to fulfill its objectives since the emissions level is not expected to change by 2030. Moreover, the global temperate level can reach 1.5°C by early 2030 and even 2°level by 2050 (Almond et al., 2020). On the other hand, most nations are facing the issue of reducing biocapacity against the massively increasing ecological footprint (EF) (Mohammed et al., 2021), which indicates that resource consumption is augmenting and Earth's regenerative capacity is plummeting (GFN, 2021). Under such a situation, it becomes necessary to explore some new dimensions and factors that could influence climate change and EF.

Economic progress has long been considered the primary driver of environmental pollution (Alvarado et al., 2021b). Evidently, growth in almost every economy is fueled by energy (Alvarado et al., 2019), and the energy structure of most countries is constituted of fossil energy up to a great extent (Kanat et al., 2021; Oláh et al., 2021; Štreimikienė, 2021; Hussain et al., 2022b). Hence, it is not surprising that growth levels are closely knotted with environmental pollution (Ahmed et al., 2021a). However, the growth of nations and environmental deterioration association is generally discussed under the Environment Kuznets Curve (EKC) framework, which explains that environmental pollution upswings only at primary levels of growth, and growth beyond a specific level, can stimulate clean technologies, ecological laws, innovation, energy efficiency, etc. that can alleviate the rising level of environmental pollution (Alvarado et al., 2021a; Ahmad et al., 2022; Ali et al., 2022; Hussain, 2022). Thus, renewable technology budgets (RTB) are among the necessary factors that could lessen the destructive environmental repercussions of growth. RTB are among the basic elements of innovation in green energy, and providing global access to low-cost electricity, which is the target seven of SDGs, needs more investments in wind, solar, thermal, and other clean sources of energy. Boosting the innovation through RTB can produce some green technologies, which will augment renewables' share in the total energy mix, and lower the dependence on coal, gas, and oil (Ahmed et al., 2021b).

Hence, this research uncovers the impacts of renewable technology budgets (RTB), and financial risks (FR) on environmental deterioration in the OECD nations. Ensuring the energy transition of economies entails investments from governments in the form of RTB as well as from the private sector. In this context, the financial risk levels of economies are expected to affect cleaner investments, and thus, the production of green energy can be significantly influenced by risk levels. In addition, FR of economies can decrease economic stability, climate protection preferences, and environmental regulations (Xue et al., 2022), which in turn can escalate EF. On the contrary, stable economic systems with fewer risks are beneficial for maintaining a persistent level of RTB and consistent environmental policies, which in turn can lessen pollution levels.

To apprehend the FR and RTB effects on EF, this study selected the sample of OECD because this group of nations has a massive 60% contribution to global GDP. Alongside, these countries are committed to reducing fossil energy and boosting clean energy since around 50% of the world's clean energy is utilized by OECD (BP, 2021). The OECD nations are among the fastest-growing economies that emit around 35% of the world's emissions (Majeed et al., 2022). In addition, the majority of member countries in the OECD group are dealing with high ecological deficits (GFN, 2021). Moreover, this group of countries is famous for its significant investment in cleaner technologies and carbon control research. Also, FR in the OECD group has significantly increased over the last 2 decades (ICRG, 2021).

Based on this background, this study complements the literature in several ways. Firstly, this study investigates the impact of the financial risk index on the ecological footprint in OECD countries. Secondly, this study integrates the financial risk index and renewable energy technology budgets into one framework to probe their impact on ecological footprint. No existing research has combined these three indicators together for environmental policies; thus, this study makes a unique contribution under the specific background of OECD. Lastly, this study employed the CS-ARDL method that handles cross-sectional dependence, endogeneity, and heterogeneity in data. Apart from this, the causal analysis at the end of the study is performed to disclose the causal flow among variables.

LITERATURE REVIEW

Since the UN climate conference (COP21) in Paris in 2015, countries are committing to becoming carbon neutral in the coming few decades. Allocation of financial resources towards renewable energy technological innovation is considered a viable way to reduce the dependence on fossil fuels and, at the same time, fulfill the dream of carbon neutrality. However, countries are facing internal and external challenges such as trade friction, anti-globalization trends, health-related issues (Covid-19 pandemic), and financial risk, which are increasingly influencing investment decisions that may affect climate-related goals. Consequently, the influence of financial risk on environmental quality has gained little consideration from academia and found contradictory results. For instance, Zhang and Chiu (2020) used the data of 111 nations from 1985 to 2014 to analyze the non-linear impact of country risk (i.e., economic, political risk, and financial) on CO_2 emissions. Their results illustrated that financial risk monotonically escalates environmental degradation across panel countries. On the contrary, Zhang (2011) reported that financial stability increases the CO_2 emissions in China. Nevertheless, Ozturk and Acaravci (2013) underlined that financial stability does not pose a significant impact on emissions in the long term. Recently, Zhao et al. (2021) disclosed that financial risk increases CO_2 emissions directly but also indirectly influences technological innovation.

Growing global concern about the devasting effect of fossil fuel energy use (e.g., coal, oil, and gas) on the environment has prompted many countries to shift their energy structure towards renewable energy sources. Indeed R&D in the renewable energy sector can be a viable way to boost its share in the primary energy mix and promote green growth (Alvarado et al., 2021a; Hussain et al., 2022a). For instance, the study of Shahbaz et al. (2018) underlines that energy research innovation significantly enhances environmental quality in France. They further highlighted that financial stability is an absolute prerequisite for energy innovation and improving environmental quality. Similarly, Jin et al. (2017) also reported that technological advancement in the energy sector curbs ecological degradation and documented the inverted U-shaped association between GDP and pollution in China. Similarly, another study was carried out by Baloch et al. (2021) in the context of OECD countries between 1990 and 2017. They concluded that the energy budget promotes environmental sustainability, and the inverted U-shaped association exists between GDP and emissions n OECD economies.

In recent empirical work, Altıntaş and Kassouri (2020) investigated the influence of energy technology expenditures on environmental degradation in 12 EU economies from 1985 to 2016. Their empirical findings show that energy budgets significantly promote environmental sustainability while positive shocks in budgets reduce emissions; however, negative shock does not affect carbon footprint. In contrast, Ahmad et al. (2021) studied the asymmetric and symmetric linkage between RTB and CO_2 in the United States from 1985 to 2017 using the ARDL method. The author disclosed that RTB do not pose a significant effect on emissions. Moreover, positive or negative changes in RTB could not significantly impede CO_2 emissions in the United States. Yang et al. (2022) studied the impact of RTB on environmental quality in G-7 countries from 1985 to 2019 and found that RTB decrease CO_2 emissions.

Conversely, Jordaan et al. (2017) claimed that energy technology investments are heavily weighted toward fossil fuels which increase emissions in Canada and hinder climate-related commitments. The author suggested that regional policies should be aligned with federal climate change policies to curb emissions and enhance clean energy innovation in Canada. Similarly, Koçak and Ulucak (2019) studied the influence of energy R&D expenditures on environmental quality in 19 OECD member countries from 2003 to 2015. Their empirical results revealed that the energy R&D disbursements for energy efficiency and fossil fuel have an escalating impact on CO_2, while renewable R&D expenditures did not influence CO_2 emissions.

Based on the review of the literature, we can deduce the following aspects. Firstly, few studies examined the linkage between financial risk and ecological quality and demonstrated inconsistent conclusions. Besides, the possible association between financial risk, RTB, and EF is unexplored. Secondly, the literature is silent on how financial risk Granger causes RTB. Thirdly, the current literature extensively used carbon (CO_2) emissions as an indicator of environmental sustainability. While discussing the climate change goal, focusing merely on CO_2 emissions cannot provide a holistic view. Lastly, previous studies used the first-generation estimation methods and ignored panel data's problems, such as CD and slope heterogeneity, which may affect the estimator's consistency and lead to biased results. Against this backdrop, this study fills this gap and investigates the dynamic linkage between financial risk, RTB, and ecological footprint in OECD countries under the EKC framework.

MATERIAL AND METHODS

This study developed the following model to analyze the dynamic linkage between financial risk, RTB, and ecological footprint under the EKC framework.

$$\begin{aligned} ln\,EF_{it} = \alpha_0 + \beta_1\, ln\,GDP_{it} + \beta_2\, ln\,GDP_{it}^2 + \beta_3\, ln\,FR_{it} + \beta_4\, ln\,RTB_{it} \\ + \beta_5\, ln\,EG_{it} + \beta_6\, ln\,EC_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

In **Equation 1**, the dependent variable is the ecological footprint (EF). Explanatory variables included the GDP and GDP^2 indicating the economic growth per capita (constant 2010$) and its quadric term. Financial risk index (FR) is the core explanatory variable, which is established based on five indicators, i.e., 1) total foreign debt as % of GDP, 2) exchange rate stability, 3) current account as a percent of exports of goods and services, 4) international liquidity, and 5) debt service as % of EGS. The renewable energy research and development budgets (RTB) are in million $ (2020 prices and PPP). Economic globalization (EG) is a broad index based on financial and trade globalization, while E.C. denotes the primary energy consumption per capita (gigajoule). α_0 and ε_{it} denote intercept and residual term, respectively. Lastly, t and i depict time dimension and country, respectively.

This paper used the data of 18 OECD countries from 1984 to 2018 for empirical analysis. As for as the data sources are concerned, the data of EF is obtained from GFN (2021). The financial risk data is obtained from the International Country Risk Guide database (ICRG, 2021). The data of RTB is acquired from IEA (2022). The data of the economic globalization index is sourced from the KOF Swiss Economic Institute developed by Gygli et al. (2019). The data on energy consumption and GDP are attained from BP (2021), and WDI (2021), respectively. All selected variables are transformed into their natural logarithm form before empirical estimation. **Table 1**

TABLE 1 | Variable's description.

Variable	Symbol	Measurement	Source
Ecological footprint	EF	Global hectares per capita	GFN (2021)
Economic Growth	GDP	Per capita (constant 2010US$)	WDI (2021)
Financial risk	FR	Financial risk rating index—0 (High) → 50 (low)	ICRG (2021)
Renewable energy technology budget	RTB	Million US$ (2020 prices and PPP)	IEA (2022)
Economic globalization	EG	Index based on financial and trade globalization	Gygli et al. (2019)
Energy consumption	EC	Primary energy consumption (Gigajoule per capita)	BP (2021)

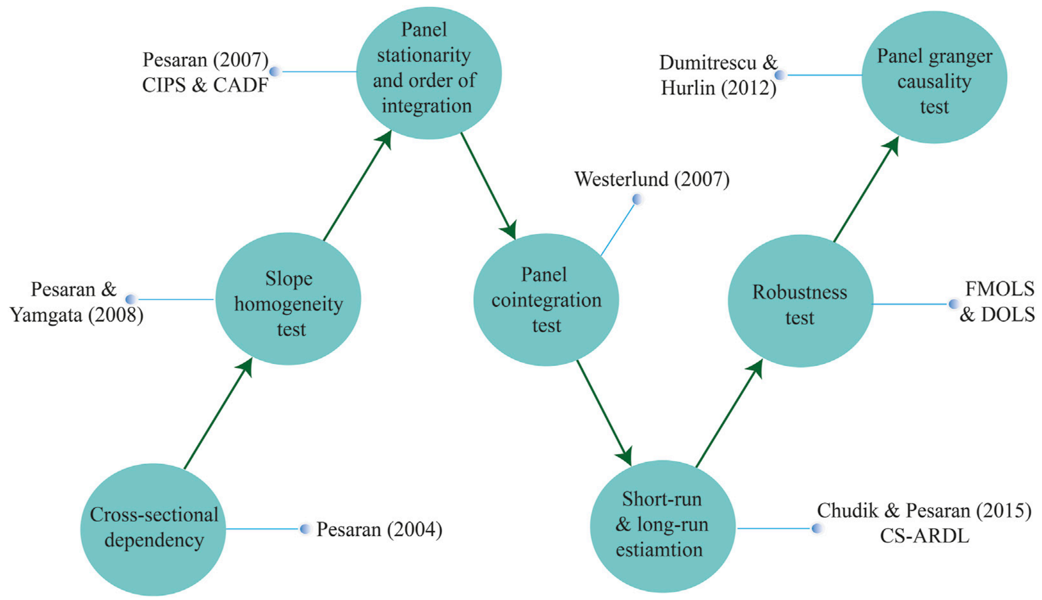

FIGURE 1 | Panel empirical estimation process.

depicts the details of variables used in this study for empirical analysis.

This article used advanced estimation methods for empirical assessment, primarily based on the following steps. The OECD economies are high-income countries and extremely integrated through social, economic, and political ways. Thus, it is crucial to consider the cross-sectional dependence (CD) issue among study variables because ignoring CD can lead to erroneous and invalid estimates. This research employed the CD test of Pesaran (2004) for this purpose. These economies share common traits in many ways; however, also differ in some aspects, such as geographical structure, culture, and allocation of funds towards RTB. Thus, ignoring slope heterogeneity may yield biased estimates. This study utilized the slope homogeneity test established by Pesaran and Yamagata (2008). Next, this study examines the stationarity characteristics of selected variables using the CIPS and CADF unit root test of Pesaran (2007). After primary analysis, the subsequent proposed step is to inspect the long-term equilibrium relationship, which is investigated by using the cointegration test (Westerlund, 2007). Afterward, we analyze the short-run and long-run relationship using the CS-ARDL method of Chudik and Pesaran (2015). The FMOLS and DOLS methods are utilized for robustness checks. Lastly, the causal flow among variables is examined using the Dumitrescu and Hurlin (2012) Granger causality method. **Figure 1** shows the estimation strategy visually.

RESULTS AND DISCUSSION

The descriptive statistics of the study variables are given in **Table 2**. The results indicate that the mean values of GDP, RTB, and energy consumption are high, while the standard deviation of these variables is also high as compared to other variables. The ecological footprint range between 2.60 and 11.20 global hectares per capita in the sample countries. **Figure 2** demonstrates the spatial distribution of ecological footprint in OECD for 2018, indicating that Canada, Australia, and United States have the highest per capita EF, while the United Kingdom and Spain have the lowest EF in the selected OECD countries. The financial risk rating index ranges between 26 and 50, with a mean value of 41.138. **Figure 3** shows the risk rating index in OECD countries for the year 2018. The mean value of RTB is 101.816 while it ranges between 198.182 and

TABLE 2 | Descriptive statistics.

Variables	Observations	Mean	Std. Dev	Minimum	Maximum
EF	630	6.168	1.530	2.600	10.429
GDP	630	42,252.876	15,078.916	12,288.434	91,964.258
FR	630	41.138	5.153	26.00	50.00
RTB	630	101.816	198.172	0.547	2638.454
EG	630	70.248	10.671	38.837	89.566
EC	630	205.104	85.643	52.877	444.047

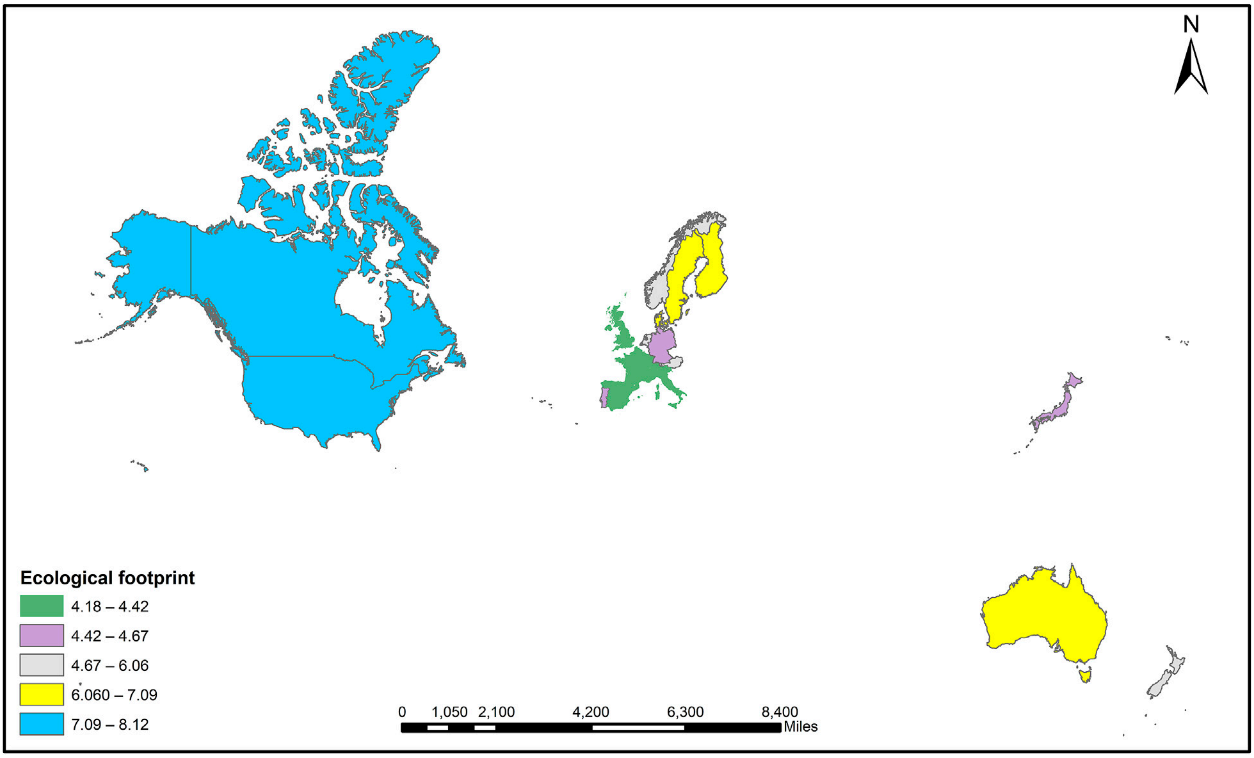

FIGURE 2 | Spatial distributions of ecological footprint per capita in 2018. Data Source: GFN (2021).

2638.45 million US$, and it ranges between **Figure 4** depicts the trends in renewable energy technology budgets from 1984 to 2018, indicating that the United States and Japan have allocated more budgets towards energy research and development as compared to other OECD member economies.

Table 3 represents the variance inflation factor (VIF) test result. The maximum value of VIF is 2.31 of *ln*GDP, while the average value of all the variables is less than 5. Therefore, the multicollinearity of variables could be ignored.

Table 4 represents the findings from the CD test and homogeneity test. The outcome disclosed that all the variables rejected the null hypothesis of cross-sectional independence at a 1% significance level. In addition, the value of correlation ranges between 0.42 and 0.96, indicating that all variables are related. The findings from the slope heterogeneity test depict the presence of heterogeneity in slope parameters, which is apparent from the delta and delta_adjusted values. Hence, the issues of CD and slope heterogeneity need to be considered while performing the further empirical estimation.

Considering the existence of CD, and slope heterogeneity in panel countries, we employed the latest unit test of CADF and CIPS. The findings in **Table 5** indicates that FR, RTB, EG, and EC have unit root problem at the level in the CIPS test. Interestingly, except for RTB, all the variables show similar outcomes in CADF. In conclusion, the study variables have mix order of integration; however, all become stationary after taking the first difference. Thus, we can proceed with further investigation for the long-run cointegration relationship. The findings from the Westerlund cointegration test are presented in **Table 6**, indicating that there is a long-run stable relationship between ecological footprint as the dependent variable and financial risk and RTB as explanatory variables in the presence of some control variables.

After confirmation of cointegration in the model, we can proceed to investigate the short and long-term association

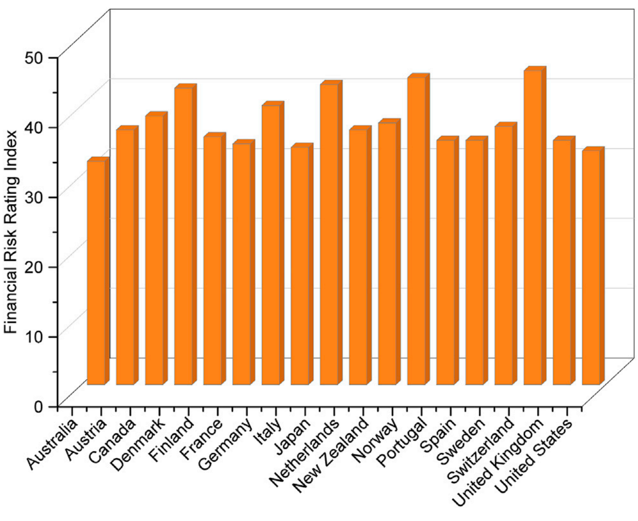

FIGURE 3 | Financial risk rating index of OECD economies for the year 2018. Data source: ICRG (2021)

TABLE 3 | VIF test results.

Variable	VIF	1/VIF
*ln*GDP	2.31	0.432
*ln*FR	1.23	0.815
*ln*RTB	1.19	0.839
*ln*EG	1.65	0.606
*ln*EC	1.54	0.650
Mean VIF	1.58	—

TABLE 4 | Cross-sectional dependency and slope homogeneity test.

Variables	Stat	Prob	Abs (Corr)
Pesaran (2004) Cross-Sectional Dependency Test Results			
*ln*EF	24.507***	0.000	0.420
*ln*GDP	69.205***	0.000	0.946
*ln*GDP^2	69.203***	0.000	0.946
*ln*FR	47.660***	0.000	0.655
*ln*RTB	42.142***	0.000	0.589
*ln*EG	68.760***	0.000	0.940
*ln*EC	31.273***	0.000	0.537
Pesaran and Yamagata (2008) slope heterogeneity test			
$\tilde{\Delta}$	16.894***	0.000	—
$\tilde{\Delta}_{adjusted}$	19.234***	0.000	—

*Notes: *** depicts the significance level at 1%.*

between financial risk, RTB, economic globalization, energy consumption, and EF under the EKC framework. The CS-ARDL is utilized for this purpose, and the findings are shown in **Table 7**. The coefficient of GDP is significant in the short and long term, with the value of 0.803, and 0.423, respectively. The positive impact of GDP on EF portrays that OECD countries have compromised their environmental quality over economic growth. The rapid development in OECD countries has intensified resources and energy consumption leading to higher ecological degradation (Chen and Lei, 2018). The coefficient of GDP square is negative in the short-run and long-run with the value of −0.030 and −0.015, respectively. The coefficient values of GDP and GDP square validated the presence of the EKC hypothesis in OECD countries. These results indicate that environmental-related

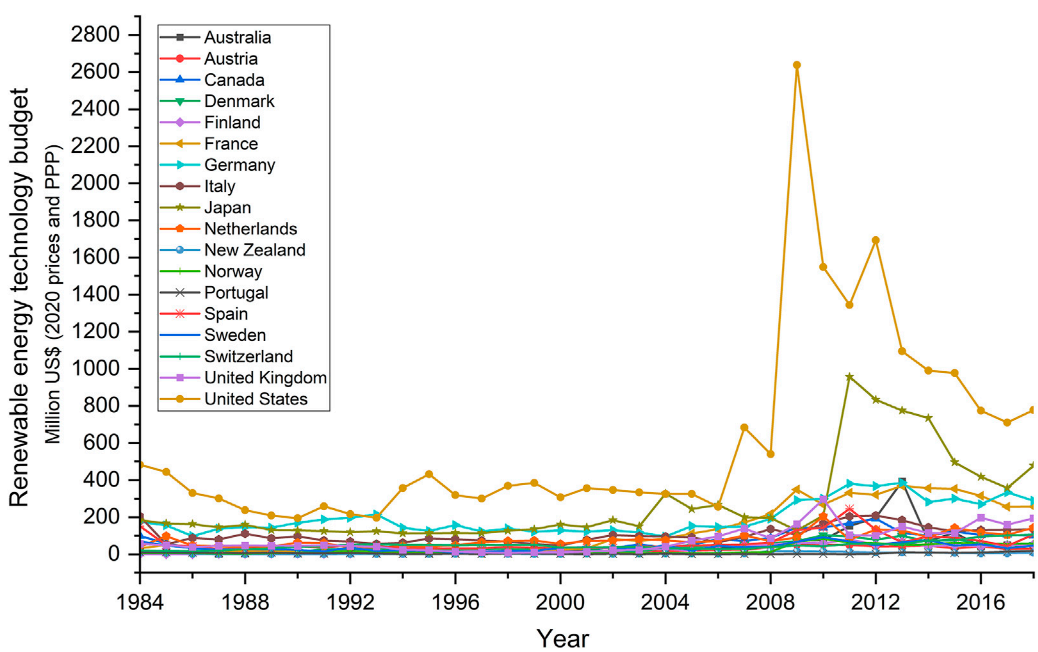

FIGURE 4 | Trends in renewable energy technology budget in OECD countries from 1984 to 2018. Data source: IEA (2022)

TABLE 5 | Unit root test results.

Variable	CIPS		CADF	
	Level	First-Difference	Level	First-Difference
*ln*EF	−2.073	−5.832***	−1.960	−4.300***
*ln*GDP	−1.578	−3.205***	−2.418	−3.055***
*ln*GDP^2	−1.563	−3.222***	−2.390	−3.036***
*ln*FR	−3.199***	−5.976***	−2.621***	−4.892***
*ln*RTB	−3.118***	−5.748***	−2.285	−4.640***
*ln*EG	−2.633***	−5.409***	−2.667***	−4.244***
*ln*EC	−2.513***	−5.978***	−2.250**	−5.128***

*Note: *** and ** depict the significance level at 1% and 5%, respectively.*

TABLE 6 | Westerlund cointegration test results.

Statistic	Value	Z-value	*p*-Value
G_t	−3.856***	−5.947	0.000
G_a	−14.040	−0.092	0.463
P_t	−17.374***	−7.001	0.000
P_a	−15.579***	−2.700	0.004

*Note: *** depicts the significance level at 1%.*

TABLE 7 | Short-run and long-run test results.

	Coefficient	Standard Error	Z-value	*P*-value
Short-run results				
*ln*GDP	0.803***	0.226	3.550	0.000
*ln*GDP^2	−0.030***	0.011	−2.640	0.008
*ln*FR	−0.015*	0.008	−1.930	0.053
*ln*RTB	−0.009*	0.006	−1.700	0.089
*ln*EG	−0.021**	0.009	−2.400	0.017
*ln*EC	0.297**	0.130	2.290	0.022
ECM (-1)	−0.835***	0.060	−13.890	0.000
Long-run results				
*ln*GDP	0.423***	0.120	3.520	0.000
*ln*GDP^2	−0.015***	0.006	−2.640	0.008
*ln*FR	−0.009**	0.004	−2.110	0.035
*ln*RTB	−0.005*	0.003	−1.730	0.084
*ln*EG	−0.011**	0.005	−2.310	0.021
*ln*EC	0.159**	0.069	2.300	0.022

*Note: ***, **, and * indicate the significance level at 1%, 5%, and 10%, respectively.*

TABLE 8 | FMOLS and DOLS test results (Robustness check).

Variable	FMOLS		DOLS	
	Coefficient	T-statistic	Coefficient	T-statistic
*ln*GDP	2.048***	3.631	3.943***	2.814
*ln*GDP^2	−0.092***	−3.464	−0.184***	−2.809
*ln*FR	−0.107***	−3.661	−0.151***	−2.592
*ln*REB	−0.009**	−2.549	−0.023***	−3.353
*ln*EG	−0.419***	−9.973	−0.297***	−3.059
*ln*EC	0.703***	23.495	0.603***	10.072

*Note: *** and ** depict the significance level at 1% and 5%, respectively.*

policies in OECD economies are going in the right direction, as income will decrease environmental degradation after reaching a certain point. These findings are consistent with Ahmad et al. (2020) for emerging economies, Yang et al. (2021) for and Xue et al. (2022) for France.

Concerning the effect of our core explanatory variable, the findings show that controlling the financial risk increases the ecological quality in OECD economies in the short and long term with the coefficient value of −0.015, and −0.009, respectively. According to ICRG financial risk index, a high score of the financial risk index (near 50) indicates less risk, while a low score (near 0) specifies the higher risk. Financial risk can affect the allocation of green finance and climate-related policies and inevitably lead to economic and social disorder. In contrast, lower financial risk enhances financial development and can enable countries to boot the investment towards green finance and achieve carbon neutrality. Our outcome is contrary to the findings of Zhao et al. (2021), who found that financial risk leads to environmental degradation in 62 developing countries.

The results further suggest that RTB pose a negative and significant effect on EF in the short and long term with the coefficient values of -0.009, and -0.005, respectively. Our findings support the idea that government policy support for innovation in the renewable energy sector can play a pivotal role in environmental sustainability. This finding links to the fact that OECD countries are increasing their efforts for energy transition, which is evident from their RTB increase from 93.39 million USD (2020 prices and PPP) to 168.20 over 1984–2018 with an average growth rate of 1.70%. However, the growth rate is quite low; thus, policymakers should put more effort to boost investment in renewable energy research and development activities in order to stimulate environmental sustainability. This result is similar with Altıntaş and Kassouri (2020), and Yang et al. (2022). However, it contradicts Ahmad et al. (2021), who reported that RTB does not significantly affect EF in the United States.

The findings indicate that ecological globalization (E.G.) pose a positive and significant effect on EF in the short-run and long-run with the coefficient value of −0.021 and −0.011, respectively. The mitigating effect of EG on footprint indicates that OECD countries benefit from globalization to enhance their environmental quality. Economic globalization enables countries to trade environmentally friendly products and attract investment for green projects. Our results oppose the results of Ahmad et al. (2021) for emerging countries, Wang et al. (2021) for G-7, and Rudolph and Figge (2017) for 146-panel countries. Lastly, energy consumption increases environmental degradation as indicated by the positive coefficient in the short and long term with the value of 0.297 and 0.159, respectively. This estimate is consistent with many studies that describe the detrimental environmental effects of energy consumption, for example, Danish and wang (2019) for the NEXT-11, Dogan et al. (2019) for and Shahzad et al. (2021) for the United States. The destructive effect of energy consumption is reasonable because fossil fuel energy dominates the total energy mix of OECD, i.e., oil 35.97%, natural gas 29.89%, and coal 10.87% (BP, 2021).

This study opted for the FMOLS and DOLS tests to reconfirm the long-run results. The findings given in **Table 8** endorse the

TABLE 9 | The DH non-causality test results.

Variables	lnEF	lnGDP	lnFR	lnRTB	lnEG	lnEC
lnEF	— —	7.334***[0.000]	3.204***[0.001]	8.231***[0.000]	3.469***[0.001]	5.758***[0.000]
lnGDP	2.404**[0.014]	— —	2.054**[0.040]	3.474***[0.000]	7.144***[0.000]	2.144**[0.032]
lnFR	2.276**[0.023]	10.875***[0.000]	— —	1.643[0.100]	7.663***[0.000]	2.485**[0.013]
lnRTB	1.902*[0.057]	15.594***[000]	4.746***[0.000]	— —	9.310***[0.000]	4.224***[0.000]
lnEG	0.595 [0.551]	2.143**[0.032]	3.766***[0.000]	0.390[0.695]	— —	1.166[0.243]
lnEC	2.705***[0.001]	11.235***[0.000]	5.222***[0.000]	9.506***[0.000]	3.874***[0.000]	— —

*Note: ***, **, and * indicate the significance level at 1%, 5%, and 10%, respectively.*

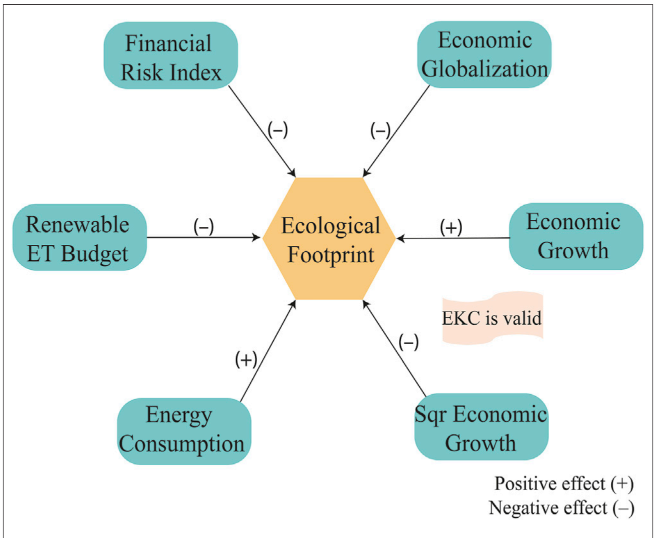

FIGURE 5 | Visual representation of long-run results based on CS-ARDL FMOLS, and DOLS.

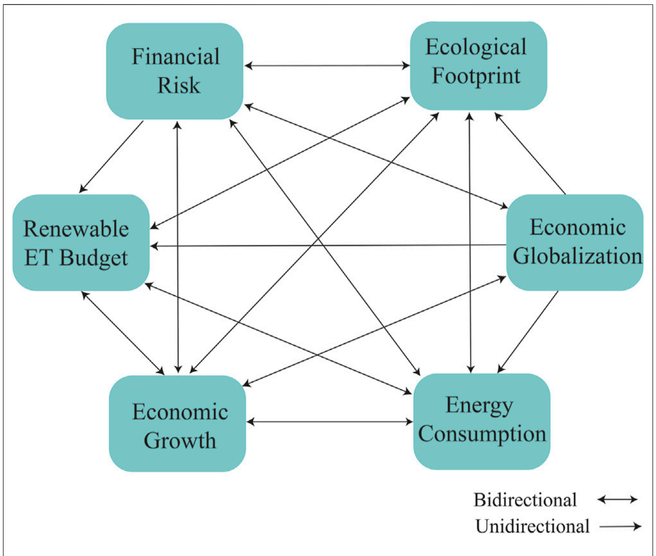

FIGURE 6 | Visual representation of panel granger causality test results.

CS-ARDL results inferring that our estimations are stable and authentic. Although the coefficient values of FMOLS and DOLS are slightly high from CS-ARDL, on the whole, the coefficient signs (i.e., positive or negative) of the regressors are consistent. Moreover, the long-run results are visually presented in **Figure 5**.

Finally, to examine the causal flow among studied variables, this study employed Dumitrescu-Hurlin causality, and the results are given in **Table 9**. Our study underlines the existence of causality from financial risk to RTB. This relationship has not been highlighted in the earlier studies. These results indicate that financial risk can, directly and indirectly, cause environmental deterioration through RTB. Thus, controlling financial risk can play a pivotal role in promoting RTB and ecological sustainability in OECD countries. Besides, a bidirectional causal relationship exists between RTB and ecological footprint. Thus, any policy changes in RTB will affect ecological footprint and vice versa. A similar casual association is also observed between GDP-RTB, and FR-GDP. In summary, controlling financial risk not only influences RTB and GDP but also environmental sustainability in OECD countries. Moreover, the panel granger test results are visually presented in **Figure 6**.

CONCLUSION AND POLICY IMPLICATIONS

Conclusion

This study empirically analyzed the dynamic linkage between financial risk, RTB, and EF in the presence of economic globalization and energy consumption under the EKC framework for OECD countries from 1984 to 2018. This study utilized Pesaran's (2004) and Pesaran and Yamagata's (2008) estimation methods to check the CD and slope heterogeneity among the variables. The CADF and CIPS tests of Pesaran (2007) and Westerlund, (2007) are employed to check the stationarity properties and long-run equilibrium relationship between the variables, respectively. The long and short-run relationships were examined using the CS-ARDL method of Chudik and Pesaran (2015), and FMOLS and DOLS are applied for robustness check. Afterward, Dumitrescu and Hurlin (2012) Granger causality test is employed to report mutual causal directions.

The empirical results unveiled that the model is suffering from the issue of slope heterogeneity and CD. The unit root tests' findings show that variables have mix order of integration, and all are stationary at the first difference. The cointegration test result indicates the existence of an equilibrium association among the selected variables. The CS-ARDL results disclosed that the financial risk index is negatively correlated with EF, indicating that controlling financial risk enhances environmental quality in OECD countries. The results further unfold that RTB and economic globalization are negatively associated which implies that an increase in RTB and economic globalization will reduce the EF. Energy consumption intensifies EF and EKC is verified between income and EF. The panel causality results denote the unidirectional causality from financial risk to RTB, while bidirectional causality is detected between financial risk-EF and financial risk-GDP.

Policy Implications

The results of this study have important policy implications for OECD countries. Firstly, improvement in the financial risk index mitigates EF. Thus, it is beneficial for OECD nations to consider financial risk when making climate-related policies. Also, steps should be taken to boost the investment in renewable energy research and development. Besides that, economic globalization is negatively associated with EF; therefore, OECD countries should reduce trade barriers and encourage businesses to promote environmentally friendly globalization. Moreover, energy consumption was found to have a positive impact on EF in OECD economies, indicating that policies related to energy usage in these economies need careful monitoring. The government should facilitate firms and organizations for green technological transformation and increase the share of cleaner and renewable energy sources which can lead to the achievement of SDG-7.

This study explores the dynamic linkage between financial risk, RTB, and ecological footprint in OECD countries. Future studies can not only probe this nexus in other countries but also include more variables in the model, such as fiscal policies, technological innovation, human capital, etc.

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

MA: Conceptualization, data curation, formal analysis, writing original draft. ZA: Writing original draft, writing—review, and editing. BG: writing—review, and editing, funding acquisition. JO: supervision, project administration, writing—review, and editing.

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ORIGINAL RESEARCH
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How Green is the Economic Complexity in the Central and Eastern European Union Countries?

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The paper analyses the association between economic complexity and openness to trade green products in eleven Central and Eastern European Union (EU) countries over the period of 2003–2016. The study uses the "green openness index" as it is framed by the Beta Akademi Social Science Lab in order to explain the progress in the productive structure of the European economies. In a panel data approach comprising of eleven EU economies, other explanatory variables of economic complexity are included: financial development, research and development (R&D) expenditures, and number of patents. The methodological approach includes: testing cross-sectional dependence of considered variable and second generation test for stationarity check. Cointegration on long run is verified by Westerlund test and estimation of regression coefficients uses FMOLS and DOLS models. Finally the causality relationship between economic complexity and explanatory variables is tested with Dumitrescu-Hurlin test. Empirical results show that Economic Complexity Index (ECI) is positively associated with green openness index (GOP), financial development, R&D expenditures and number of patents in the examined panel of countries. A validated causality relationship is running from green trade to economic complexity and from economic complexity to financial development and number of patents. It is also revealed validated bidirectional causality between R&D expenditures and ECI. Policy implications are also provided.

Keywords: economic complexity, green openness index, financial development, patents, R&D expenditures

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INTRODUCTION

The present paper intends to explore the link between economic complexity and green economy by examining the influence on economic complexity of the green trade in the Eastern and Central European countries.

Economic complexity has gained the interest of researchers as a result of revival of industrial policy (more complex products), the growth of artificial intelligence (embedded in manufactured products) and development of endogenous growth theory (based on the assumption that growth is based on the increase of knowledge) (Hidalgo, 2021). The concept of economic complexity is based on the idea of a production function that connects economic inputs and outputs (Hidalgo, 2021) and requires productive knowledge, consisting of human and social capital and advanced production technologies. Dynamics of economic activities and their geographical distribution can be studied using techniques derived from the complexity theory, complex systems, computer sciences and networks (Observatory of Economic Complexity, OEC). In order to explain and understand international differences in development outcome, based on data on the geography of economic activities, the concept of economic complexity express the one's country capabilities (human and social capital, institutions, technology) that generates a certain level of sophistication of exported products. The complexity of economies is generated by the complexity of locations (cities, regions, countries) and that of economic activities (products, technologies, industries) present in them (Observatory of Economic Complexity, OEC). The Economic Complexity Index introduced by Hidalgo and Hausmann (2009) summarizes factors that are 'optimal to explain the geography of multiple economic activities' (Hidalgo, 2021).

In the current young literature on economic complexity, a set of studies are discussing its drivers such as: high-tech exports, financial development, number of patents, foreign direct investment, human capital, institutional quality and fiscal policies, (i.e., Antonietti and Franco, 2021; Innocenti et al., 2021; Bahar et al., 2020; Khan et al., 2020; Kannen, 2020; Nguyen et al., 2020; Lapatinas, 2019, Lapatinas et al., 2019a, Lapatinas et al., 2019b; Sweet and Eterovic Maggio, 2015; Erkan and Yildirimci, 2015; Zhu and Fu, 2013) and its impact on environment (Neagu and Teodoru, 2019; Neagu, 2020; Yilanci and Pata, 2020; Ahmad et al., 2021; Rafique et al., 2021a; Ikram et al., 2021; Majeed et al., 2021; Nathaniel, 2021; Adebayo, 2022; Adebayo et al., 2022). But we know very little about channels for reducing this impact (i.e., investment in clean and environment-friendly technologies, use of renewable energy). Findings of recent studies suggest the followings: enhanced renewable energy technology budgets (Ahmed et al., 2022) for mitigating pollution induced by the increase of products complexity; more renewable energy generation and efficient use of human capital would led to the improvement of economic complexity (Rafique et al., 2021a); national policies towards products sophistication hold the potential to solve ecological problems (Ikram et al., 2021); the clean energy and renewable energy in industry is a tool for improvement of exports quality and pollution mitigation (Wang et al., 2021); policies towards products diversification induce the growth of renewable energy demand in the economy (Shahzad et al., 2021b).

Given the fact that the level of products sophistication and the required structural changes in industry are contributing to the increase of pollution, analyzing the effect of trading with green products on economic complexity would offer the opportunity to identify the potential to reduce its environmental impact. This is quite important for emerging economies that have not achieved a certain level of development along with appropriate institutional and technological factors allowing to curb the environmental pressures, as it is revealed for the case of well developed and complex economies (i.e., Can and Gozgor, 2017, Neagu, 2020; Neagu and Neagu, 2022).

The concept of green economy was coined by United Nations Environmental Programme (UNEP) within the Green Economy Initiative (GEI) (https://unep.org) launched in 2008, as an economy with reduced environmental risks and scarcities and an improved human well-being and social equity, in other words, green economy is one which is "resources efficient, low carbon and also, socially inclusive." Over the past years the concept has became a priority for governments in many countries within the global efforts for climate change mitigation and how to shape the global economy in a more sustainable way. Green economy focused on the synergies between the economic and environmental pillars of sustainable development. As an economic current model, the green economy can be supported through incentives of investment in green energy sources and technologies, developing new industries and markets for green products as well as by promoting the resource and energy efficiency in all economic and social activities. In the context of green economy, there is no agreement on a standard definition of green products. They are generally classified as environment-friendly goods, that resulted from production using cleaner technologies or products that cause less environmental damage (World Bank, 2008). Eurostat (2009) defines environmental products as goods and services that "measure, control, prevent, restore, minimize and prevent the environmental damage (to air, water and soil)."

The paper intends to put together these two perspectives (economic complexity and green economy) in order to reveal their connections in a panel approach including eleven Central and Eastern European countries, analyzing the association between economic complexity and the openness to green trade.

The CEE countries were chosen to be examined due to several reasons: 1) a specific dynamics of economic complexity in the last decades: positive values in an ascending trend; 2) as European Union (EU) Member States they are struggling in different catching-up strategies to reduce the income and development gap compared with Western developed countries and achieve intra-EU convergence; 3) as emerging economies, they experience higher growth rates compared to Western countries and manage an expanding financial sector meant to support their development and trade openness; 4) they assumed to achieve in 2030 a reduction of CO_2 emissions to 40% of the 1990 level and a share of renewable energy of 27% in the energy sources (European Union, 2018), as well as carbon neutrality targets by 2050 within the European Green Deal (Skjaerseth, 2021).

The present study is motivated by several aspects: 1) the concern of countries to increase their economic complexity, found as accurate predictor of income (Hausmann et al., 2014); 2) the newly introduced index of green trade would suggest a potential channel for more sophisticated products without generating increasing levels of pollution; 3) the emergence of green economy principles in many countries (including CEE countries) in the context of the climate change pressure, environmental degradation, natural resources depletion and international commitments of governments for sustainability and carbon neutrality.

To the best of authors' knowledge, this is the first paper analyzing the impact of 'green products' on economic complexity within Central and Eastern European economies. The paper uses the index of green openness product (GOP) newly introduced by Can et al. (2022); Can et al. (2021) in order to express level of a country's openness to green trade. The present study embraces two new paradigms of current economic context that are in the focus of recent debates of scholars, and academics: economic complexity and green economy. The paper is also placed among the very few studies dealing with the newly issued green openness index. Another contribution of the paper consists of the enriching the scarce literature on the factors enabling economic complexity, by adding a new one, that of trading with green products, in the basket of sophisticated products that give the complexity level of an economy. It is also worth to be mentioned that, apart of other studies, bidirectional causality between R&D expenditures and economic complexity is reported.

The paper is structured as follows. After introduction, the recent relevant literature is reviewed in **section 2**; data and methodology of the paper are exposed in **section 3**. **section 4** describes the results and **section 5** consists of discussion. The last section is dedicated to conclusions and policy implications.

A BRIEF LITERATURE REVIEW

Given the aim of the paper to explore a new driver of economic complexity, namely, trade of environment-friendly goods expressed by the green openness index, the review of current literature will discuss studies focused on the determinants of economic complexity. Nevertheless, economic complexity presumes structural changes in the economy with consequences on energy demand, resources development and allocation, and large effects on environment, economy and society. In other words, we will discuss the drivers of economic complexity along with its consequences. This approach is useful to better understand the connection between the two concepts: economic complexity and green economy.

The literature on economic complexity is 'young' (Hidalgo, 2021) and also, a limited number of recent studies are dedicated to the drivers of economic complexity. The following factors of economic complexity were identified: high-tech exports, intellectual property system, financial development, foreign direct investment, birthplace, Internet usage, fertility rate, institutional quality, fiscal policy (taxation), research and development (R&D) expenditures.

Erkan and Yildirimci (2015) found that a low share of high-tech exports is correlated with a reduced level of economic complexity in the case of Turkey over the period of 1993–2013.

Sweet and Eterovic Maggio (2015) found that stronger intellectual property systems would lead to higher levels of economic complexity in 94 countries from 1965 to 2005. This effect is present in countries with an initial above-average level of development and economic complexity.

Nguyen et al. (2020) investigated the impact of financial development and number of patents on economic complexity in a panel of 52 middle-income and high-income economies. They found a long-run cointegration relationship between number patents, financial development and economic complexity. They also revealed a bi-directional causality explanatory variables and economic complexity.

Foreign direct investment (FDI) was identified in some studies of the recent literature as a driver of economic complexity. FDI induced a greater level of economic complexity in a panel of 117 countries from 1995 to 2016 and specifically knowledge-intensive green field projects caused economic complexity in developed countries (Antonietti and Franco, 2021). Khan et al. (2020) identified a long-run bidirectional relationship between inward FDI and economic complexity in China from 1985 to 2017. Similar results regarding the positive impact of FDI on economic complexity were reported by Zhu and Fu (2013) in their study developed for 171 countries. Kannen (2020) found that FDI in tertiary sector has a significant positive effect on economic complexity in 63 developed and developing countries over the period of 2005–2014.

Another identified driver of economic complexity is the birth place of individuals. Thus, a higher diversity in the birth place of immigrants can boost economic complexity through an increasing diversification of the host country's export basket (Bahar et al., 2020).

It is also proved that economic complexity is associated with the fertility change across Italian provinces (Innocenti et al., 2021) and the Internet usage (Lapatinas, 2019).

Appropriate fiscal policies are necessary for the development of sophisticated products. The level of labor taxation influences the level of complexity: economies with higher taxation tend to produce simple products. Furthermore, capital taxes have a negative impact on economic sophistication and this effect is stronger in developed countries (Lapatinas et al., 2019a).

Vu (2021) provides evidence on the positive effects of institutional quality on economic complexity for 115 economies. He suggests that institutions can affect economic complexity by promoting innovative entrepreneurship, developing productive capabilities through incentives for human capital accumulation, and the allocation of human resources towards productive activities, as previously reported by Zhu and Fu (2013). Human capital accumulation is seen also as a driver of economic complexity by Hausmann et al. (2007). Human capital and R&D investment are important sources of indigenous knowledge creation and directly contributes to the exports upgrading of countries (Zhu and Fu, 2013).

The relationship between economic complexity and environment is more studied; authors are focused on several dimensions and expressions of pollution (i.e., ecological footprint, CO_2 emissions, GHG emissions) generated by economic complexity, or environmental quality measures (i.e., environmental performance index) linked to the level of sophistication of products.

Very recent studies provide evidence in support of a harmful effect of economic complexity increase on environment. For example, Adebayo (2022) found that economic complexity hinders the quality of environment in Spain using a novel wavelet coherence technique based a dataset covering the period of 1970Q1 and 2017Q4. Similar results were reported in the case of MINT economies (Mexico, Indonesia, Nigeria and Turkey) by Adebayo et al. (2022) who revealed that the increase of economic complexity led to the CO_2 emissions growth over the period of 1990–2018. On the contrary, Ahmed et al. (2022) found that economic complexity has a mitigating effect on ecological footprint in for G7 countries from 1985 to 2017.

A higher economic complexity is associated with increased environmental degradation, and this poses huge challenges to be overcome by countries related to ensure the environmental sustainability (i.e., Adebayo, 2022; Adebayo et al., 2022; Ahmad et al., 2021; Ikram et al., 2021; Majeed et al., 2021; Nathaniel, 2021; Rafique et al., 2021a; Shahzad et al., 2021a; Neagu, 2020; Yilanci and Pata (2020); Neagu and Teodoru, 2019).

Moreover, the harmful impact on environment depends on the stage of development as Dogan et al. (2019) highlighted and the effect is higher in lower and higher middle income countries while in high-income economies is limited. Similar findings were reported by Ahmad et al. (2021) in emerging economies. It is also suggested that increasing the share of renewable energy sources in the energy mix would and reducing fossil fuel use will have as result decreasing levels of environmental degradation. In the context of our research, energy policies in the examined countries meant to enhance the use of renewable energy sources in industry along with pricing strategies stimulating the abandon of fossil fuels would be beneficial for the environment. This would counteract the negative impact of an increased economic complexity on the environment.

On the other hand, Romero and Gramkow (2021) proved that economic complexity can be associated with less carbon emission due to the type of technologies involved in the manufacturing process. In this line, several studies report that economic complexity can induce a raise of environmental performance (expressed through the Environmental Performance Index) (i.e., Boleti et al., 2021; Lapatinas et al., 2019b). Moreover, Ahmed et al. (2022) found that economic complexity had a positive contribution to reduce environmental deterioration expressed by ecological footprint in G7 countries from 1985 to 2017. In line with these findings, Wang et al. (2021) revealed that exports quality led to decreasing levels of CO_2 emissions in the case of leading complex economies, as well as Dogan et al. (2021) in the case of 28 OECD countries for 1990–2014.

Further, there are other studies providing evidence in support of the validation of Environmental Kuznets Curve model in the presence of economic complexity as explanatory variable (i.e., Neagu and Neagu, 2022; Chu, 2021; Chu and Le, 2021; Pata, 2021; Neagu, 2019; Can and Gozgor, 2017) suggesting that it is possible to curb the environmental pressure, mainly in developed countries. In the early stages of structural transformation of economy, the economic complexity induces increasing levels of pollution until a threshold. Further, the use of advanced and cleaner production, along with economic and social factors, and an appropriate institutional framework will induce a reduction effect on environment and curb the environmental pressure.

Some recent studies are focused on the link between economic complexity and renewable energy. For example, Shahzad et al. (2021b) provide evidence on support of idea that policies towards product diversification have as result positive effects on renewable energy demand in emerging as well as developed economies (G-7 and E-7 countries) in the period of 1990–2017. They also identified a nonlinear relationship between export diversification and renewable energy. The study of Rafique et al. (2021b) revealed that economic complexity has a positive impact on renewable energy demand in G7 and E7 countries.

Finally, we identified only two studies using the newly introduced green openness index in the analysis of the association between income and environmental degradation. Can et al. (2021) tested the role of green openness index on environmental sustainability using the Environmental Kuznets Curve (EKC). They identified the validity of the EKC hypothesis in 35 OECD countries. The new introduced variable is found as an essential factor of the reduction of environmental deterioration (expressed by ecological footprint) and could be seen as useful tool to achieve carbon neutrality targets. The study of Can et al. (2022) revisits the trade-environment nexus for 31 OECD countries over the period of 2007 and 2017, provides evidence in favor of the EKC hypothesis and reveals that the presence of green products in trade reduces the ecological footprint.

Summarizing the above assertions, we can conclude that the determinants of economic complexity still remain an under-explored topic. Even the link between economic complexity and environment is in the focus of more studies, the multifaceted phenomenon of complexity in economy and environment call for further investigation and analysis. As regards to the relationship between economic complexity and renewable energy, only two studies could be mentioned as well as regarding the green trade and environment. The present paper aims to cover these gaps and to use the newly introduced index of green trade in a new, non-explored until now, analysis of its potential association with economic complexity. Thus, our research's contributions consist of connecting the two concepts (economic complexity and green economy) and enriching the scarce literature on economic complexity drivers with a new factor (green trading).

DATA AND METHODOLOGY

Data

The present study aims to analyze the impact of green products on economic complexity in eleven Central and Eastern European countries (Bulgaria, Czech Republic, Croatia, Hungary, Estonia, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia) for a time span running from 2003 to 2016.

The level of the relative knowledge intensity of one's country economy is expressed by the economic complexity index (ECI), calculated by Observatory of Economic Complexity (OEC) (Simoes and Hidalgo, 2011). The values of this index are computed based on data connecting locations to the activities that are present in them (OEC).

The Economic Complexity Index expresses the productive structure of a country by computing data regarding diversity (number of activities of a location) and ubiquity of an activity (number of location where is present) (Hidalgo and Hausmann, 2009; Hidalgo, 2021).

In the economic complexity a perspective, countries have their own capabilities to manufacture products but also, they are connected to other countries in order to ensure the capabilities they need to produce them. It results a network in which countries are connected to their available capabilities and products to the capabilities they require. Further, a product can be exported by several countries while a country can export products that are made based on capabilities deriving from other countries. It results bipartite networks connecting countries to their exported products. The mathematical representation is an 'adjacency matrix, M_{cp}' (Hidalgo and Hausmann, 2009). The complexity K_c of a location c and the complexity K_p of an activity p are defined as a function of each other. In other words, "the complexity of a location is a function of the activities that are present in it and vice versa" (Hidalgo, 2021).

The Economic Complexity Index (ECI) is computed as follows (Hausmann et al., 2014):

$$ECI_c = \frac{K_c - mean(K_c)}{std(K_c)} \tag{1}$$

According to the work of Can et al. (2022), the Green Openness Index, 2022 (GOP) of a country is calculated as follows:

$$GOP_{i,t} = \left(\frac{GRNX_{i,t} + GRNM_{i,t}}{GDP_{i,t}}\right) \cdot 100 \tag{2}$$

where: $GRNX_{i,t}$ denotes the present value of green products exported by a country i to the world at time t, $GRNM_{i,t}$ stands for the present value of green products imported by the country i (from the world) at time t. $GDP_{i,t}$ represents the total value of produced goods (Gross Domestic Product) in a country i in current year t.

The index is computed for the European Union (EU) countries for the period of 2003–2016 based on the items included in the OECD's Combined List of Environmental Goods (CLEG) (introduced by Sauvage, 2014) covering 255 environmental products.

In the CLEG[1] list are included basket represents a combination of three lists: the 'Friends' List[2] issued the World Trade Organization (WTO) (WTO, 2009); a modified Plurilateral Agreement on Environmental Goods and Services (PEGS)[3] list released by OECD (Sauvage, 2014); and Asia -Pacific Economic Cooperation (APEC) (APEC, 2012).

[1]The environmental themes under consideration for the goods and services included in the CLEG list are: air pollution control, cleaner, and resource efficient production and technologies, environmentally preferable products (i.e., based on end use or disposal features), heat and energy management, environmental monitoring, analysis and assessment equipment, natural resource protection, noise and vibration abatement, renewable energy, solid and hazardous waste management as well as recycling systems, clean up or remediation of soil and water, potable water management and waste water management.

[2]This list includes 154 products circulated by the members of the "Friends' Group" (Canada, the European Union, Japan, Korea, New Zealand, Norway, Switzerland, Chinese Taipei, and United States).

[3]The initial PEGS list was introduced by OECD in 2010, at the Summit of G-20 countries.

GOP time series were extracted from BETA Akademi Social Science Research Lab (section of the European Union countries).

Methodology

The following econometric model will be used in our study:

$$ECI_{i,t} = \beta_0 + \beta_1 \cdot \ln GOP_{i,t} + \beta_2 \cdot \ln FinDev_{i,t} + \beta_3 \cdot \ln R\ \&\ D_{i,t} + \beta_4 \cdot \ln PT_{i,t} + \varepsilon_{i,t} \tag{3}$$

where: i denotes the country, t means time, ECI represent the Economic Complexity Index, GOP represents the Green Openness Index, FinDev is the Financial Development Index, R&D represents Research and Development Expenditures, PT is the Number of Patents; β_0, β_1, β_2, β_3, β_4 are regression parameters, and $\varepsilon_{i,t}$ is the error term.

In order to ensure the robustness of our results we will introduce a set of control variables. Thus, **Eq. 3** will have the following form:

$$ECI_{i,t} = \beta_0 + \beta_1 \cdot \ln GOP_{i,t} + \beta_2 \cdot \ln FinDev_{i,t} + \beta_3 \cdot \ln R\ \&\ D_{i,t} + \beta_4 \cdot \ln PT_{i,t} + \beta_5 \cdot X_{i,t} + \varepsilon_{i,t} \tag{4}$$

where: $X_{i,t}$ represents a vector of three control variables: Human Capital (HC), Gross Capital Formation (GCF) and Foreign Direct Investment (FDI).

Given the aim of the study to investigate the impact of green trade openness on economic complexity, our core explanatory variable is GOP. Other independent variables are introduced in the model following the results of Nguyen et al. (2020) regarding financial development and number patents as drivers of economic complexity. R&D expenditures were also included in the model due to the fact economic complexity is based on productive knowledge (human and social capital, technologies) that could be enhanced through appropriate investment in research—development and innovation activities. As control variables, gross capital formation expresses the physical resource (endowment) required in the production of goods, foreign direct investment and human capital are mentioned in several studies as enabler factors of products sophistication (i.e., Nguyen at., 2020, Zhu and Fu, 2013; Hausmann et al., 2007).

Name of variables and their sources are displayed in **Table 1**.

The econometric strategy will include the following the steps: 1) cross-sectional dependence test for the variables under examination; 2) if the dependency is identified, stationarity of variables will be checked using second-generation unit root tests (CIPS and PESC-ADF); 3) their long-run cointegration relationship is tested with Westerlund test; 4) we estimate the long-run parameters with panel Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) models; 5) we identify the direction of the causal relationship between variables with Dumitrescu and Hurlin (2012) test.

The cross-sectional dependence among variables is checked using the Pesaran (2004) CD test. The null hypothesis of no cross-sectional dependence assumes that the correlation of disturbances between different cross-sections is zero: $H_0\ \rho_{ij} = corr(u_{it}, u_{jt}) = 0$, for $i \neq j$, while the alternative hypothesis states that it exists $i \neq j$ for $\rho_{ij} = corr(u_{it}, u_{jt}) \neq 0$

TABLE 1 | Variables and their sources.

Acronym	Name	Explanation	Source
Variables of interest			
ECI	Economic Complexity Index	A measure of the capacity an economy to connect locations (e.g., countries, cities, regions) to the economic activities (e.g., products, technologies, industries) present in them	Observatory of Economic Complexity (OEC)
GOP	Green Openness Index	The share of the total present value of exported and imported green goods (as % of GDP)	BETA Akademi Social Science Research Lab
FinDev	Financial Development Index	An aggregate of Financial Institutions index (banking sector development) and Financial Markets Index (market capitalization)	International Monetary Fund (IMF)
R&D	Research and Development Expenditures	Research and development expenditures (as % of GDP)	World Bank
PT	Total Patents, by residents	Patent application filed through the Patent Cooperation Treaty procedure or with a national patent exclusive rights for an invention	World Bank
Control variables			
HC	Human Capital index	Human Capital Index, based on years of schooling and returns to education (Feenstra et al., 2015)	Penn World Tables 9.1
GCF	Gross Capital Formation	Share of Gross Capital formation in GDP (Feenstra et al..,2015)	Penn World Tables 9.1
FDI	Foreign Direct Investment	Foreign Direct Investment net inflows as % of GDP	World Bank

The test statistic is computed by:

$$CD = \sqrt{\frac{2}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} T_{ij}\hat{\rho}_{ij} \rightarrow N(0,1)\right) \tag{5}$$

where: $\hat{\rho}_{ij}$ denotes the correlation coefficients of the residuals, N and T denote the countries and the years of observation, respectively.

The null hypothesis of no cross-sectional dependence is rejected if the values of Prob are lower than 0.05.

When the cross-serial correlation across the panel is identified, efficiency of estimated results may decrease (Phillips and Sul, 2003). Therefore, in order to ensure reliable and accurate results, we apply second generation unit root tests (Pesaran, 2007), namely, the cross-sectionally ADF (PES-CADF) and the cross-sectional augmented IPS (Im, Pesaran, Shin, 2003) (CIPS) for variables' stationarity testing.

The cross-sectionally Augmented Dickey-Fuller (CADF) test consists of standard Dickey-Fuller (DF) regressions augmented with cross-sectional averages of lagged levels and first difference series of the *i*-th cross-section in the panel (Pesaran, 2007):

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + \delta_i \bar{y}_{t-1} + \sum_{j=0}^{k}\delta_{ij}\Delta\bar{y}_{i,t-j} + \sum_{j=0}^{k}\Delta y_{i,t-j} + \varepsilon_{it} \tag{6}$$

where: $\bar{y}_{t-1} = \frac{1}{N}\sum_{i=1}^{N} y_{i,t-1}$, $\Delta\bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{it}$, α_i is constant, k specifies the lag, $t_i(N,T)$ is the t-statistic of the estimated ρ_i in the above equation, computed by individual ADF statistics.

The CIPS test computes the average of individual CADF statistic values for individual cross-sections:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} t_i(N,T) \tag{7}$$

where: $t_i(N,T)$ is the CADF statistic for the *i*-th cross-section unit.

The null hypothesis of homogeneous unit root states that all panel sections are non-stationary, while the alternative establishes that at least one individual section in the panel is stationary.

In order to ensure the accuracy and robustness of results in the presence of cross-sectional dependence, the Westerlund (2005) cointegration test will be applied. The test works under two assumptions of cointegration presence: in *some of the panels* or *in all the panels*. Under the first assumption (cointegration is identified in *some of the panels*) the auto regression (AR) parameter is panel specific while under the second option (*all panels are cointegrated*), the AR parameter is the same over the panels. When the *p*-value of the variance ratio (VR) statistic is under the chosen significance level the null hypothesis (of no cointegration) is rejected, the alternative hypothesis being accepted (cointegration is present at least in some panels or in all panels).

We use the panel fully modified ordinary least squares (FMOLS) and panel dynamic ordinary least squares (DOLS) methods developed by Pedroni (2001a, 2001b) in order to estimate the long-run parameters.

The panel FMOLS method is based on the following equation:

$$\begin{aligned} y_{it} &= \alpha_{it} + \delta_{it}t + \beta x_{it} + \mu_{it} \\ x_{it} &= x_{it-1} + e_i \end{aligned} \tag{8}$$

where: y_{it} is the dependent variable, x_{it} the independent variable, α_{it} denotes the constant effects, and β is the long-term cointegration coefficient.

The panel FMOS estimator is computed with the formula below:

$$\hat{\beta}^{*}_{FM} = n^{-1}\sum_{i=1}^{n}\hat{\beta}^{*}_{FM,i} \tag{9}$$

TABLE 2 | Statistical description of variables.

	ECI	lnGOP	lnFinDev	lnR&D	lnPT	lnGCF	lnFDI	lnHC
Mean	0.9296	2.1034	−1.0604	−0.1654	5.7539	−1.4369	1.2060	1.1847
Median	0.8496	2.0482	−1.0381	−0.1916	5.5567	−1.4264	1.3442	1.1724
Max	1.6918	3.0602	−0.5630	0.9419	8.4501	−0.9417	2.6188	1.3262
Min	0.0683	1.3428	−1.9521	−1.0201	2.8903	−2.2045	−2.6310	1.0680
Std. Dev	0.4248	0.4115	0.2920	0.4809	1.1936	0.2230	0.8875	0.0668

authors' computation based on EViews 12.0 software.

where: $\hat{\beta}^*_{FM}$ is the FMOLS estimation result for cross section that forms each ith section.

The panel cointegration coefficient is estimated considering the average of FMOLS coefficients in the cross sections.

The DOLS panel regression model (Pedroni, 2001b) is defined as follows:

$$y_{it} = \alpha_i + \beta_i x_{it} + \sum_{k=-K_i}^{K_i} \gamma_{it} \Delta x_{it-K} + \varepsilon_{it} \tag{10}$$

This equation is estimated for each panel cross section and then the panel cointegration coefficient is computed as average of the DOLS coefficients for each section.

The panel DOLS estimator is calculated as below:

$$\hat{\beta}^*_D = n^{-1} \sum_{i=1}^{n} \hat{\beta}^*_{D,i} \tag{11}$$

We use the test developed by Dumitrescu and Hurlin (2012) in order to identify the direction of causality between the variables.

Under the null hypothesis (of no causality from x to y):

H0: $\beta_i = 0$ for $\forall i = 1, \ldots, n$; $\beta_i = \beta_i^{(1)}, \beta_i^{(2)}, \ldots, \beta_i^{(3)}$

The alternative hypothesis assumes that there are $n_1 < n$ individual processes with no causality from x to y:

H1: $\beta_i = 0$ for $\forall i = 1, \ldots, n_1 \beta_i \neq 0$ for $\forall i = n_1, n_1 + 1, n_1 + 2, \ldots, n$where: n_1 is unknown and $0 \leq \frac{n_1}{n} < 1$. When $n_1 = n$ there is no causality for any panel sections. If $n_1 = 0$ then the causality relationship is present in all sections in the panel. When $n_1 > 0$, this indicates a heterogeneous causality relationship.

The Dumitrescu and Hurlin test uses the average Wald statistic in association with the test of non causality hypothesis for $i = 1, \ldots, n$.

$$W_{n,T} = \frac{1}{n} \sum_{i=1}^{n} W_{i,T} \tag{12}$$

In the case of the null hypothesis (of non causality), each individual Wald statistic converges to a chi-squared distribution (with K degrees of freedom):

$$W_{i,T} \xrightarrow{d} \chi^2(K), \forall i = 1, \ldots, n \quad T \to \infty \tag{13}$$

When T tends to infinity, presuming that the individual residuals ε_i are independently distributed across groups, this indicates an identical distribution of individual Wald statistics.

When $T, n \to \infty$, specifically $T \to \infty$ first and then $n \to \infty$ $(T < n)$, the standardized test is defined as follows:

$$Z_{n,T} = \sqrt{\frac{n}{2K}} \left(W_{n,T} - k\right) \to n(0,1) \tag{14}$$

The homogeneous non causality hypothesis is rejected when Z-statistic is higher than the chosen critical value.

MAIN FINDINGS

The descriptive outline of variables under examination is displayed in **Table 2**. The values of Economic Complexity Index (ECI) are positives for all considered countries and the whole period of time, indicating that these locations have a complexity that is larger than the average location. The averages values are close to 1 and maximum to 1.7 that indicates a good position of the considered countries in the international rankings of ECI where the most complex economies record values around 2.5.

The results of the cross-sectional dependence test are shown in **Table 3**. We notice that the cross-sectional dependence is identified in all variables' series, for a statistical threshold of 5%.

The statistics of both unit root tests (PES-CADF and CIPS) displayed in **Table 4** indicates that the considered variables are not stationary at their level, but they are integrated at their first level [I (1)] for a statistical significance threshold of 5%.

Table 5 shows the cointegration results using the Westerlund test. The values of prob. are lower than 0.05 that indicates the presence of a cointegration relationship on the long run between the examined variables under both assumptions ("some panels are cointegrated" and "all panels are cointegrated"). We conclude that the long-run stability link exists between ECI, lnGOP, lnFinDev, ln R&D, and lnPT and also when the control variables (lnGCF, lnHC, and lnFDI) are added.

The estimation of the FMOLS and DOLS models illustrates positive elasticities of explanatory variables with the dependent variable. ECI is positively associated with lnGOP, lnFinDev, lnR&D, and lnPT (our variables of interest) for a statistical significance of 1% in both models (**Table 6**). This suggests that an increase in the level of explanatory variables (lnGOP, lnFinDev, lnR&D, and lnPT) is associated with a higher level of economic complexity. The relationship is maintained when the control variables (lnGCF, lnHC, and lnFDI) are added, indicating

TABLE 3 | Results of cross-sectional dependence test.

	ECI	lnGOP	lnFinDev	lnR&D	lnPT	lnGCF	lnFDI	lnHC
Breusch-Pagan LM	554.42*	389.10*	286.39*	346.55*	160.42*	317.27*	128.43*	757.09*
Pesaran Scaled LM	47.61*	31.855*	22.06*	27.79*	10.05*	25.00*	7.00*	66.94*
Bias corrected Scaled LM	47.19*	31.43*	21.63*	27.37*	9.62*	24.58*	6.57*	66.51*
Pesaran CD	22.97*	18.40*	12.24*	11.80*	2.26**	16.91*	9.07*	27.51*

$*p < 0.01$; $**p < 0.05$.
authors' computation based on EViews 12.0 software.

TABLE 4 | Results of unit root tests.

Variable	PES-CADF test		CIPS test	
	z (t-bar)		CIPS statistic	
	constant	constant and trend	constant	constant and trend
ECI	−0.936	1.892	−0.607	−2.087
ΔECI	−5.402*	−2.513*	−3.698*	−3.101*
lnGOP	−2.480*	1.406	−1.735	−1.789
ΔlnGOP	−4.449*	−3.358*	−3.192*	−3.384*
lnFinDev	−1.179	−3.324*	−2.117	−3.372*
ΔlnFinDev	−6.873*	−5.104*	−3.989*	−3.968*
lnR&D	−1.502**	0.594*	−1.171**	−1.958
ΔlnR&D	−3.504*	−2.847*	−2.977*	−3.213*
lnPT	−0.967	−0.984	−2.048	−2.589
ΔlnPT	−6.216*	−4.426	−3.773*	−3.731*
lnGCF	−2.283**	−1.795**	−2.480**	−2.861**
ΔlnGCF	−4.933*	−3.421*	−3.351*	−3.405*
lnHC	−3.057*	−8.675*	−1.930	−2.338
ΔlnHC	−10.076*	−10.204*	−2.761*	−3.709*
lnFDI	−3.487*	−2.514*	−2.876*	−3.102*
ΔlnFDI	−8.342*	−6.594*	−4.472*	−4.467*

$*p < 0.01$; $**p < 0.05$; $***p < 0.1$.
Authors' computation based on Stata 15 software.

TABLE 5 | Results of Westerlund cointegration test.

Variables: ECI, lnGOP, lnFinDev,lnR&D,lnPT				Variables: ECI, lnGOP, lnFinDev,lnR&D,lnPT, lnGCF, lnHC, lnFDI			
Assumptions				Assumptions			
"some panels are cointegrated"		"all panels are cointegrated"		"some panels are cointegrated"		"all panels are cointegrated"	
statistic	*p*-value	statistic	*p*-value	statistic	*p*-value	statistic	*p*-value
2.0559	0.0019	1.7876	0.0369	3.400	0.000	3.4858	0.000

Authors' computation based on Stata 15 software.

the robustness of the results. Gross capital formation is positively associated with economic complexity and its regression coefficient is significant. The same association is identified in the case of human capital as contributor to economic complexity, but its coefficient is significant only in the FMOLS model. Foreign direct investments are negatively associated with economic complexity in the examined period of time (2003–2016) in CEE countries. This result can be explained by the short period of time included in the analysis and also by specific factors in these countries that induce a specific dynamics of FDI hindering their contribution to the sophistication level of productive structure and traded goods.

From running the Dumitrescu-Hurlin test (**Table 7**) the following causal relationships were identified between the dependent variable and explanatory variables of interest: 1) bidirectional relationship between ECI and lnR&D; 2) unidirectional causalities running from lnGOP to ECI, from ECI to FDI and from ECI to lnPT.

First of all, the association between economic complexity and green openness index is of great interest for the aim of our study. The results suggest that the share of green products in the export basket may lead to a higher complexity. Moreover, research and development expenditures represent not only enablers for increasing complexity of exported goods but also, an increase

TABLE 6 | Results of regression estimation.

	Dependent variable ECI			
	Explanatory variables: lnGOP, lnFinFev, lnR&D, lnPT		Explanatory variables: lnGOP, lnFinFev, lnR&D, lnPT, lnGCF, lnHC, lnFDI	
	FMOLS	DOLS	FMOLS	DOLS
lnGOP	0.3563*	0.3790*	0.4906*	0.3581*
lnFinDev	0.2847*	0.3234*	0.0818*	0.1353**
lnR&D	0.1889*	0.2947*	0.1868*	0.2826*
lnPT	0.0728*	0.0922*	0.1429*	0.1445*
lnGCF			0.5388*	0.4953*
lnHC			0.0976**	0.2925
lnFDI			–0.1198*	–0.0940*
R-squared	0.9436	0.7368	0.8312	0.8207

*p < 0.01; **p < 0.05.

Authors' computation based on EViews 12.0 software.

TABLE 7 | Dumitrescu-Hurlin causality test.

Null hypothesis	z-bar	*p*-value	z-bar tilde	*p*-value
lnGOP does not Granger -cause ECI	6.1271	0.0000	2.2447	0.0248
ECI does not Granger -cause lnGOP	1.4016	0.161	0.5326	0.5943
lnFinDev does not Granger- cause ECI	1.8924	0.0584	0.8531	0.3936
ECI does not Granger -cause lnFinDev	11.0190	0.0000	4.5322	0.0000
lnRD does not Granger -cause ECI	5.5653	0.0000	1.9820	0.0475
ECI does not Granger -cause lnRD	8.0601	0.0000	3.1486	0.0016
lnPT does not Granger -cause ECI	3.9694	0.0000	1.2358	0.2165
ECI does not Granger cause lnPT	3.6308	0.0000	1.9886	0.0467

Authors' computation based on Stata 15 software.

in economic complexity generates a higher demand for more research and development activities, as productive capabilities. Inversely, the level of sophistication of exported products can stimulate the financial development and the increase of patents' number in the countries under examination.

DISCUSSION

Our empirical results reveal that the presence of green products in trade (imports and exports basket) could be considered as an enabler of the complexity level of Central and Eastern European economies. Generally, green products are based on cleaner technologies with a reduced impact on environment and also resource and energy efficient. This is also a general principle guiding the green economy. Increase of trade with green products would generate a beneficial impact on environmental quality (Gao and Zheng, 2017; Guo et al., 2017). In this way, the detrimental effect of economic complexity on environment (i.e., greenhouse gas emissions, CO_2 emissions and ecological footprint) reported by some studies (e.g., Can and Gozgor, 2017; Lapatinas et al., 2019b; Neagu and Teodoru, 2019; Dong et al., 2020; Dogan et al., 2021; Romero and Gramkow, 2021; Adebayo, 2022; Adebayo et al., 2022; You et al., 2022). Can et al. (2022) reported that Environmental Kuznets Curve (EKC) is valid in a sample of 31 OECD countries over the period of 2007–2017. The variable 'green openness index' was found to have a positive impact on reduction of environmental degradation. They also suggest that trading green goods is a powerful tool for attaining carbon neutrality targets in the examined countries.

Our results could be linked to the findings of Shahzad et al. (2021a) who provided evidence in support of the idea that policies directed towards product diversification have positive effects on renewable energy demand in emerging as well as developed economies (G-7 and E-7 countries) in the period of 1990–2017. This issue could be further analyzed, in the context of using the green openness index linked to economic complexity.

In spite of the detrimental effect on environment, the increase of economic complexity has beneficial effect on growth (i.e., Tachella et al., 2018; Chavez et al., 2017; Özgüzer and Binatli, 2016; Cristelli et al., 2015; Poncet and de Waldemar, 2013; Bustos et al., 2012; Felipe et al., 2012) and income distribution (i.e, Lee and Vu, 2020; Hartmann et al., 2017). Thus, our findings suggest that growth of green trading would generate higher levels of income and narrowing the income gap in the examined countries.

We revealed that financial development is stimulated by the increase of economic complexity and the causality runs from ECI to financial development in CEE countries. This is different from the results of Nguyen et al. (2020) (for 52 middle-income and high-income economies) revealing bidirectional causality between financial development and economic complexity. It is also different from the findings of Ahmed et al. (2022) who identified a causality running from financial development to ECI in the case of G7 countries.

Economic complexity is found to be positively associated with the number of patents issued by residents in the examined countries, that is in line with the conclusions of Sweet and Eterovic Maggio (2015) stating that stronger intellectual property rights system could engender higher levels of economic complexity. The identified causality from ECI to number of patents is in contrast with the conclusions of Nguyen et al. (2020) who reported an inverse direction of this causal relationship.

We identified a bi-directional relationship between R&D expenditures and ECI. Increase of the R&D expenditures leads to higher economic complexity as well as, inversely, a higher level of sophistication of exported products stimulates the investment in R&D activities. Basically, economic complexity is the expression of a country's innovative output; specifically, it embeds technological innovation and R&D investment which may generate less pollutant industrial processes and more energy efficiency. The impact of economic complexity on environment would be less detrimental if countries would adopt enhanced renewable energy technology budgets, as it is suggested by Ahmed et al. (2022). Due to the fact that green products are inducing higher levels of economic complexity, green production capabilities must be developed in order to implement green production systems (as suggested Mealy and Teytelboym, 2020) and this could be possible through enhanced investment in R&D and human capital development.

The findings of the present study reveal that: 1) a new determinant of economic complexity is validated, trading with green products, being added to those identified in the current scarce literature; 2) R&D activities, as basis for sophistication level of products, are found to be statistical significant for increase of economic complexity; 3) higher levels of economic complexity would stimulate financial development and increase of patents' number. In light of these results, the paper's theoretical implications could be as stated as follows: 1) the connection between economic complexity and green economy is highlighted and offers a potential area for further analysis and research; 2) it is revealed the essential role of R&D activities not only for creating the necessary capabilities for more sophisticated products but also is also for introducing advanced green technologies in the production process and to use renewable energy sources; 3) the corroboration of results to the findings of Shahzad et al. (2021b) and Rafique et al. (2021b) regarding the link between economic complexity and renewable energy, allows us to emphasize the fact that the effect of green trading on economic complexity is twofold: increasing levels of products sophistication (that generates higher level of income, according to Hausmann et al., 2014) and stimulating the renewable energy demand (that is less pollutant) and 4) given the fact that countries tend to converge to the level of income induced by the sophistication of their productive structure (Hausmann et al., 2014), analyzes of the possibilities to increase their economic complexity will be of great interest for academics, researchers and policy makers.

The present paper is a starting research on which further analyzes can be built, for example, on specific channels of economic complexity inducing less pollution in the economy and promoting green economy (e.g., green growth and economic complexity; productive knowledge in the green economy). It is also worthy to be mentioned the potential of green openness index to be used in further research on economic complexity to discover driving factors for the presence of green products in the basket of sophisticated products, as highlighted Can et al. (2022).

CONCLUSIONS AND POLICY IMPLICATIONS

The aim of the paper was to assess the association between green openness index, financial development, R&D expenditures, number of patents and economic complexity index in eleven Central and Eastern European countries. The findings show that green openness index is statistically validated as a driver of economic complexity in the considered countries over the period of 2003–2016. As reported by Nguyen et al. (2020), financial development and number of patents are positively associated with economic complexity. Moreover, the extension of financial sector and the number of patents are positively influenced by the level of sophistication of exported products.

The paper reports also another driving factor of economic complexity namely, R&D expenditures, as a proxy for investment in activities generating productive knowledge required to increase the level of sophistication of exported products. Moreover, the empirical results show that investment in R&D is stimulated by higher levels of economic complexity. In this virtuous circle, the necessary productive knowledge generated by the R&D investment serves as input for the productive structure and the evolving sophisticated productive output will stimulate the demand for more investment in R&D.

The increase of economic complexity (as a contributor to economic growth) put a new challenge for all countries: additional concern related to environmental sustainability must be placed in the center of economic and energy policies, if countries aim to increase their complexity level (Neagu, 2021). Moreover, as suggested by Rafique et al. (2021b) economic complexity may be seen as a 'political factor stimulating the energy transformation and greener energy demand'. Specific economic policy measures must be designed regarding the selection of more green goods and services in the sophisticated products basket.

The paper's results must be viewed in the specific context of the countries under examination. Central and Eastern European countries are experiencing an ascending trend of their economic complexity, accompanied by an accelerated economic growth and concerns related to environmental degradation resulted from intense economic activities.

Based on the above findings, policy makers from CEE countries must be focused on strategies to expand the share of the green products in their export baskets. This would generate beneficial effects for environmental quality and make progress towards reduced carbon emission economies. Given the fact that several papers revealed the negative effect of economic complexity on environment (e.g., Neagu and Teodoru, 2019; You et al., 2022), the paper highlights the fact that an increase of economic complexity based on green trade will have a lower detrimental effect on environment compared to the non-green trade.

The paper's findings are encouraging in the examined countries the design of public policies meant to stimulate the green basis of the production process. First, orientation of R&D investment towards green and clean technologies may generate a positive effect on economic complexity accompanied with less environmental damage. The CEE countries have the example of developed countries (e.g., G7 countries) of enhanced renewable energy technology budgets as suggested by Ahmed et al. (2022). Second, specific policies are needed to extend the productive capabilities (knowledge basis, qualitative human capital, technology development) ensuring higher economic complexity (i.e., more public investment in education sector and opportunity for highly skilled human capital, especially for green development; more financial private and public support for investment in science, innovation and R&D, production based on less resources-intensive). Concrete policy measures are required in order to reduce the tariff and non-tariff barriers for green products (as highlighted by Can et al. (2021)). Development of green technologies requires intense investment in R&D and innovation activities. Extension of green technologies will help to meet the climate change targets (share of global carbon emissions). As Paramati et al. (2020) found for OECD countries, green technology is a major factor in reducing the carbon emissions.

These policies must be complemented by appropriate energy policies. A special attention must be given to the increase of renewable energy share in the energy consumption mix as well as to diversification of sources (i.e., solar, wind, biomass), through diverse policy instruments: grants and loans, and fiscal measures (incentives, subsidies, energy tax allowance or exceptions, reduced VAT, and refunds). Another direction for energy policies must be focused in an adequate energy policy mix allowing for reducing levels of carbon intensity and stimulating the transition to low-carbon economy.

Further, in order to finance, implement and enhance technological progress needed for higher economic complexity, a well developed financial sector is essential. Therefore, national policies aiming to sustaining the financial and banking sector have an important role. Credit opportunities for greener companies or green products development provided by the financial and banking sector would be beneficial for enhancing the countries' capabilities to improve the complexity of their productive structure. Directly linked to the financial sector, the legal framework and governance quality in the examined countries it is also important. For example, a careful monitoring of environmental regulations implementation and overcome of weaknesses in governance, such as corruption, less democracy or less accountability must be included among the governamental policy objectives.

The EU Recovery and Resilience Facility (2021) provides the opportunity to shape national priorities (i.e., National Recovery and Resilience Plans) to be financed, under two general objectives: 'green' and 'digital' transition. Governments from CEE countries have the opportunity to claim, under national coherent strategies, grants and loans, based on macroeconomic results, meant to help them catch-up in terms of economic complexity, intra- EU convergence and green economy development.

As limitations of the study, we mention the short period of time considered for analysis due to the availability of time series for the newly introduced green openness index. As new time series will be computed, the analysis will be extended to new periods of time and new countries.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

ON designed the research, collected data, analyzed them revised sections: Data, Methodology, Main Findings and Discussion. M-IN wrote and revised Introduction, Main Findings, processed and revised data with EViews and Stata 15, BG wrote and revised Introduction, Literature Review, Discussion and Conclusions.

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A Path Towards Green Revolution: How do Environmental Technologies, Political Risk, and Environmental Taxes Influence Green Energy Consumption?

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Enhancing green energy consumption is the most important strategy to achieve environmental goals and control global temperature rise. Unquestionably, political intuitions make decisions for developing environmental technologies and imposing environmental taxes for phasing out fossil fuels and achieving energy transition. Therefore, this study explores the role of environmental technologies, political risk, and environmental taxes in green energy consumption considering the potential impacts of population density and economic growth in G7 countries. Second-generation tests are applied for analyzing the long-run equilibrium connection and stationarity features. Finally, the CuP-FM and CuP-BC estimators are applied for assessing long-run linkage and Dumitrescu-Hurlin causal test is applied to reveal causal flow among variables. The estimates uncovered that enhancing environmental technologies and environmental taxes upsurges the consumption of green energy. Reducing political risk in G7 countries also boosts green energy consumption. Economic growth is evidenced to stimulate the consumption of green energy, while population density limits the consumption of green energy. Moreover, environmental technologies and political risk Granger cause green energy utilization, while a feedback relationship exists between environmental taxes and green energy usage. Based on the results, this study suggests that G7 countries should allocate more funds to accelerate innovation in environmental technologies and, at the same time, reduce the political risk to boost green energy consumption.

Keywords: environmental technologies, green energy consumption, economic growth, environmental taxes, G7 countries

INTRODUCTION

Environmental deterioration instigates global warming by interrupting the carbon cycle, and thus, environmental institutions and governments across the world strive to control environmental deterioration (Ahmed et al., 2021a; Awosusi et al., 2022). Scholars have identified energy consumption, mainly gas, oil, and coal, as the leading contributor to environmental deterioration and global warming (Wang et al., 2019; Alvarado et al., 2021; Murshed et al., 2021). Although the negative environmental consequences of energy usage are well documented, such adverse effects do not undermine the importance of energy since energy is a major requirement for sustaining economic activities and accomplishing economic progress (Kanat et al., 2021; Oláh et al., 2021; Štreimikienė, 2021; Can et al., 2022).

The world has apprehended that achieving sustainable growth entails upgrading the energy mix of nations. In this context, reducing fossil fuels combustion and eventually phasing out their usage will be a key strategy to pursue sustainable growth (Mohammed et al., 2021; Xue et al., 2022). In this regard, the Sustainable Development Goal (SDG) 7 sets the target for ensuring global access to sustainable clean energy by 2030 for sustainable growth (UN, 2021). Undeniably, enhancing the supply of sustainable green energy and driving its consumption requires expanding the clean energy infrastructure, which needs technological upgrading (Krzymowski, 2020). Environmental technologies can curb the overall consumption of energy by boosting energy efficiency, which can ultimately decrease the adverse impacts of energy (Hussain et al., 2020; Oláh et al., 2020; Ahmad et al., 2022). In addition, environmental technologies can drive the production of sustainable energy, including wind, bioenergy, solar, geothermal, etc., which will enhance the share of green energy, reduce energy insecurity, and stimulate sustainable growth (Széles et al., 2019; Ahmad et al., 2021b; Buturache and Stancu, 2021). Thus, enhancing environmental technologies can be a practical and effective strategy for realizing energy transition.

Alongside this strategy, environmental taxes levied on energy-related emissions are among critical policy instruments for pollution control, which can discourage fossil fuel combustion and expand green energy consumption. Developed nations introduced environmental taxes in 1980, and since then, various reforms were also introduced to maximize the benefits of such taxes (Shahzad, 2020). Environmental tax is a useful strategy to reduce the economic feasibility of fossil fuels since such tax upsurges the prices of fossil energy making them more expensive for consumers as well as producers. Consequently, individuals and businesses are encouraged to adopt modern technologies and alternative fuels, which in turn reduce emissions (Aydin and Esen, 2018; Sabishchenko et al., 2020).

Environmental taxes are among the critical fiscal policy instruments which can influence energy structure and climate targets. Also, the role of environmental technologies cannot be ignored in energy transition strategies. Nevertheless, the effectiveness of both these factors depends on the performance of political institutions, which formulate strategies for energy transition and pollution control. Poor institutional quality with high political risk can lead to corruption and bad governance, which can hinder the implementation of climate-related policies. Producing environmental technologies and making strategies to boost environmental quality are dependent on the quality of institutions in a country (Dasgupta and De Cian, 2018). An effective intuitional framework can ensure persistent growth with less environmental pollution (Rizk and Slimane, 2018).

According to Shahzad (2020), empirical evidence regarding the effectiveness of environmental taxes in energy transition and pollution control is meager. Ahmad et al. (2021c) suggest that past investigations on political institutions' role in pollution control present inconclusive results. This study uncovers the impacts of environmental taxes, environmental technologies, and political risk on green energy utilization in G7 nations due to several reasons. Consumption of energy is closely connected with economic progress, and in this context, G7 countries make a substantial 46% contribution to the total global GDP (Ahmed et al., 2020). These seven nations utilize almost 30% of the total global energy and generate approximately 25% of energy-related emissions. In addition, in G7, green energy constitutes almost 20% of total electricity generation in 2020 (IEA, 2021). The highly developed group of seven strives to raise green energy consumption to limit environmental pollution and boost sustainable growth. Thus, this study will determine the effectiveness of environmental taxes and environmental technologies in green energy utilization by considering the role of political risk.

Unlike previous studies, this research unfolds the influence of environmental taxes, environmental technologies, and political risk on green energy utilization. Previous panel studies have not explored environmental taxes, environmental technologies, political risk, and green energy nexus in G7. In doing so, this study employed the CuP-FM and CuP-BC estimation techniques to estimate the long-run relationship among variables. These methods can tackle the common panel data issues like cross-sectional dependence, residual correlation, heteroscedasticity, fractional integration, and endogeneity. In addition to the long-run investigation, causal associations among selected variables were also investigated.

LITERATURE REVIEW

There is consensus in the economics literature that the development and use of green energy can be a viable way of curtailing environmental degradation. Although green energy is rapidly increasing worldwide, the share in the primary energy mix is still minimal. Technological progress is believed to enhance green energy use, but their association has scarcely been investigated and mostly leans towards their positive side. For instance, Alam and Murad (2020) studied the linkage between technological progress, economic growth, trade openness, and green energy use in OECD economies from 1970 to 2012. Their findings revealed that technological progress, economic growth and trade openness significantly influence green energy use in the long run across OECD countries. However, the short-run results show mixed results. The author concluded that the short-term dynamics vary due to differences in trade openness and technological progress in OECD countries. Likewise, Khan et al. (2020) studied the impact of environmental technologies on total and disaggregated energy use in G-7 countries from 1995 to 2017. Their results revealed that environmental innovation significantly and negatively influences the total energy use while positively related to green energy use in G-7 countries. Vural (2021) also reported the positive impact of technological innovation and economic growth on green energy in selected Latin American countries.

In contrast, Bamati and Raoofi (2020) investigated the impact of technological progress on green energy by using the developing and developed country's data. Their results unveiled that technological progress and economic growth mainly drive green energy in developed countries, while technological progress cannot explain green energy dynamics in developing countries. Khan et al. (2021) concluded that technological progress not only enhances emissions and total energy use but also negatively impacts renewable energy consumption in 69 Belt and Road Initiative countries.

Besides that, political risk factors have gained substantial research interest from the perceptive of green energy consumption. Brunnschweiler (2010) highlighted that green energy projects benefit from effective governance, sound regulatory framework and overall political stability like other investment projects. Moreover, some studies found that political instability and corruption influence environmental policies and green energy investments (Fredriksson and Svensson, 2003; Junxia, 2019; Uzar, 2020). Mahjabeen et al. (2020) suggested institutional stability and technological advancement for the green energy transition and achieving SDGs. Su et al. (2021) studied the impact of political risk and environmental technologies on green energy use in OECD countries from 1990 to 2018. Their outcome disclosed that political risk and environmental technologies significantly stimulate green energy use in OECD countries.

Studies related to environmental taxes mainly focus on their role in carbon emissions mitigations (Shi et al., 2019; Shahzad, 2020; Doğan et al., 2022; Rafique et al., 2022; Yunzhao, 2022), while little attention has been paid to its impact on green energy use. Acemoglu et al. (2016) suggested that environmental regulation can boost the green energy sector growth and lower emission in developed countries, which ultimately leads to the accomplishment of SDGs. Bashir et al. (2021) studied the impact of environmental taxes and regulations on green energy use in 29 OECD countries from 1996 to 2018. They concluded that environmental regulations impede green energy use in these economies. They further propose that OECD countries should focus on implementing their environmental strategies and, at the same time, promoting environmental technologies will be a viable option to promote the green energy industry. Similarly, Carfora et al. (2021) concluded that the environmental tax burden negatively impacts the green energy investment in EU countries.

MATERIAL AND METHODS

Data Specification

This article uses the panel time-series data from 1994 to 2018 to investigate the impact of environmental technologies, political risk, and environmental taxes on green energy consumption in G7 countries. The dependent variable is the green energy consumption (per capita kWh), and the data is obtained from Ritchie and Roser (2020). The explanatory variables include the environmental technologies (patents related to environmental-related technologies) retrieved from the OECD database OECD (2022). Political risk ranking index (based on 12 indicators) accessed from ICRG (2021). Economic growth (per capita constant 2010$) and population density (People per square kilometer square of land) are obtained from WDI (2021). Data on environmental taxes (environmentally related tax revenue) are obtained from the OECD (2022). This study constructed the empirical model as follows:

$$LGR_{it} = \beta_1 LERT_{it} + \beta_2 LPR_{it} + \beta_3 LETA_{it} + \beta_4 LGDP_{it} + \beta_5 LPD_{it} + \varepsilon_{it} \quad (1)$$

Where in **Eq. 1** t is the time dimension, and i represent the cross-sections for OECD economies. The description of the study variables is given in **Table 1**.

Estimation Methods

In recent literature, the analysis of panel data is initiated by performing cross-sectional dependence (CD) estimation because, in recent decades, nations are closely knotted in various trade agreements, and assumptions like cross-sectional independence are far from reality. To reveal CD in G7 data, this work utilized one of the popular methods (CD test) introduced by Pesaran (2004). The test's equation is articulated below.

$$CTD = \sqrt{\frac{2d}{p(p-1)}}\left(\sum_{i=1}^{p-1}\sum_{j=i+1}^{p}\hat{A}_{ij}\right) \quad (2)$$

In **Eq. 2**, CTD refers to the CD test, p indicates sample size, d depicts time and $\hat{A}_{ij}$ signifies pair-wise serial correlation. In addition, the G7 panel has diverse features in terms of variables, such as ERT, GE, PR, ET, and GDP; therefore, overlooking the possibility of heterogeneity may produce misleading conclusions. Hence, to reveal the heterogeneity in the selected panel, the popular test of Pesaran and Yamagata (2008) is applied. This method computes the adjusted delta ($\tilde{\Delta}_{DAD}$) statistics by using the following equation.

$$\tilde{\Delta}_{DAD} = (n)^{\frac{1}{2}}\left(\frac{2K(t-K-1)}{t+1}\right)^{-\frac{1}{2}}\left(\frac{1}{n}\tilde{z}-K\right) \quad (3)$$

In addition, the delta ($\tilde{\Delta}_D$) stat is produced through the following equation.

$$\tilde{\Delta}_D = (n)^{\frac{1}{2}}(2K)^{-\frac{1}{2}}\left(\frac{1}{n}\tilde{z}-K\right) \quad (4)$$

The null hypothesis for both statistics describes slope homogeneity, and thus, heterogeneity of slope entails its rejection. This analysis is meant to assist in choosing the most suitable estimators for further investigation. In this context, tracing independence and homogeneity of slope parameters requires adopting the first-generation tests; however, this was not the case in our analysis. Thus, this work made use of the second-generation techniques.

TABLE 1 | Variables, data source, and measurement.

Variable	Symbol	Measurement	Source
Green energy	LGR	Green energy is measured by Renewable energy consumption per capita (kWh)	Ritchie and Roser, (2020)
Environmental technologies	LERT	Environmental related technologies patents	OECD, (2022)
Political risk	LPR	Political risk rating index based on 12 indicators	ICRG, (2021)
Environmental taxes	LETA	Environmentally related tax revenue	OECD, (2022)
Economic growth	LGDP	Economic growth per capita (constant 2010$)	WDI, (2021)
Population density	LPD	People per square kilometer (km^2) of land	WDI, (2021)

The investigation for apprehending the order of integration is performed by utilizing the CADF and CIPS tests. These two tests familiarized by Pesaran (2007) are applied considering the rejection of homogeneity and independence in the previous tests.

$$\Delta m_{i,t} = \alpha_i + \varphi_i m_{i,t-1} + \varphi_i \overline{CZ}_{t-1} + \sum_{l=0}^{p} \varphi_{il} \Delta \overline{CZ_{t-1}} + \sum_{l=0}^{p} \varphi_{il} \Delta m_{i,t-1} + \mu_{it} \tag{5}$$

Where α symbolizes the intercept, m shows the calculated variable, p symbolizes lag length, and $\overline{CZ}_{t-1}$& $\Delta\overline{CZ_{t-1}}$ describes the cross-sectional average. The $\overline{CZ}_{t-1}$& $\Delta\overline{CZ_{t-1}}$ presented in **Eq. 5** is utilized further for computing the CIPS stat. These renowned test are considered robust in the absence of homogeneity and independence.

Afterward, the long-run equilibrium connection is estimated by using the Westerlund (2008) approach that produces a group stat (DH_g) along with a panel stat (DH_p) through the use of the Durbin–Hausman principle. The investigation of cointegration under this test requires a non-stationary response variable along with stationary or non-stationary regressors. This test is popular for datasets with independence and heterogeneity concerns.

Bai et al. (2009) familiarized the CuP-FM & BC tests with the striking features of handling autocorrelation, CSD, endogeneity, and mixed integration levels. Consequently, scholars in environmental economies literature prefer these two tests over many other available tests. As the dataset of G7 exhibits long-run equilibrium association, the coefficients for the long-run are computed by using these two tests. Additionally, the FMOLS test is also utilized owing to the fact that it counters issues like autocorrelation and endogeneity in panel datasets using the lags and leads options.

In the end, the analysis for calculating the long-run elasticities is aided with Granger causality analysis by using the test of Dumitrescu and Hurlin (2012). The long-run estimation alone is not enough for practical policy suggestions. Thus, the knowledge of the direction of causal flow is important to suggest policy implications.

RESULTS AND DISCUSSION

This study uses the CD test proposed by Pesaran (2004) to evaluate the independence or dependence among selected variables in OECD countries. The result is shown in **Table 2**, which supports the existence of a cross-section within our dataset.

TABLE 2 | CD test results.

	Stat	Prob	Abs (Corr)
LGR	8.794***	0.000	0.665
LERT	21.556***	0.000	0.941
LPR	8.380***	0.000	0.370
LETA	8.008***	0.000	0.494
LGDP	17.979***	0.000	0.785
LPD	12.361***	0.000	0.630

**** <1%.*

TABLE 3 | slope heterogeneity test results.

Test	Value	*p*-Value
$\tilde{\Delta}$	9.972***	0.000
$\tilde{\Delta}_{adjusted}$	12.093***	0.000

**** <1%.*

TABLE 4 | Unit root test results.

Variable	CIPS		CADF	
	Level	First-difference	Level	First-difference
LGE	−1.935	−5.365***	−1.466	−4.073***
LERT	−3.616***	−4.685***	−3.655***	−3.844***
LPR	−2.949***	−4.935***	−1.892	−3.288***
LETA	−1.194	−4.051***	−1.386	−2.581**
LGDP	−1.300	−2.942***	−1.682	−3.641***
LPD	−1.197	−3.520***	−1.507	−3.730***

**** <1%, **<5%.*

Considering the issue of slope homogeneity, this study used Pesaran and Yamagata (2008) estimation method. The results in **Table 3** show that the model has a heterogeneous slope and ignoring this can affect the consistency of the estimator.

The results of CIPS in **Table 4** show that data of environmental technologies and political risk have unit root problems at the level, while green energy, environmental taxes, economic growth, and population density are significant at first difference. The results from CADF indicate that only environmental technologies suffer from stationarity issues at the level, but all the variables show stationarity at first difference.

The results from the Westerlund (2008) panel cointegration test in **Table 5** indicate that the study variables have a long-run equilibrium relationship, which is evident from of DH_g and DH_p

TABLE 5 | Westerlund (2008) panel cointegration test.

	Value	*p*-Value
DH_g	−2.045**	0.022
DH_P	−1.590*	0.056

** <5%, *<10%.

TABLE 6 | Long-run estimation results.

Variables	CuP-FM		CuP-BC	
	Coefficients	T Stats	Coefficients	T Stats
LERT	0.012***	5.083	0.011***	5.144
LPR	0.008***	3.678	0.009***	3.867
LETA	0.024***	9.686	0.022***	9.516
LGDP	0.050***	20.456	0.052***	21.183
LPD	−0.050***	−20.345	−0.049***	−20.739

*** <1%.

values. This enables us to estimate the long-run cointegration relationship.

Table 6 represents the CuP-FM and CuP-BC results, indicating that the coefficient value of environmental technologies is statistically significant and positive at a 1% significance level. This indicates that environmental technologies increase green energy consumption in G7 countries. The findings portray that the environmental technologies support the renewable energy transition. The results can be justified on the ground that G7 countries are among the high-income countries and the leading player in innovation related to environmental technologies. The result of our study coincides with Alam and Murad (2020) for OECD and Vural (2021) for selected Latin American countries but opposes the findings of Khan et al. (2021), who concluded that innovation leads to impeding green energy in BRI countries.

The results further indicate that the improvement of the political risk rating index leads to enhance green energy consumption in G7 countries. These results indicate that green energy consumption increases due to investment profile up-gradation, socio-economic, maintaining democratic accountability, and most importantly, the governance stability conditions in G7 countries. These factors positively contribute to boosting green energy consumption. The result of our study coincides with Mahjabeen et al. (2020), and Su et al. (2021).

On the other hand, the coefficient value of environmental taxes is statistically significant and positive at a 1% significance level. This implies that increases in environmental taxes boost the green energy consumption in G7 countries. These results are justifiable because environmental taxation discourages fossil fuel combustion and encourages individuals and businesses to adopt energy-efficient technologies and expand green energy consumption in G7 countries. Many economists agree that environmental tax is a key tool for fighting climate change. Environmental taxes discourage anti-ecological behavior, internalize the negative externalities, motivate companies to innovate technologies, promote energy-saving, and expand the use of green energy sources. Our results coincide with Acemoglu et al. (2016), who concluded that environmental regulation and taxes could boost green energy sector growth and curtail environmental degradation. However, our results are similar to the findings of Bashir et al. (2021), and Carfora et al. (2021), who found that environmental tax not only impedes green energy consumption but also negatively impacts green energy investment.

TABLE 7 | Robustness test - FMOLS.

Statistic	Coefficient	Standard error	T-Value	*p*-Value
LERT	1.003***	0.034	29.039	0.000
LPR	0.077***	0.023	3.392	0.000
LETA	1.805***	0.017	103.273	0.000
LGDP	3.669***	0.035	103.374	0.000
LPD	−4.232***	0.006	−635.909	0.000
R-squared	0.912			
Adjusted R-squared	0.905			

*** <1%.

The results further unveiled that the coefficient value of economic growth is statistically significant and positive at a 1% significance level. This implies that an increase in GDP increases the green energy use in G7 countries. Since these economies are high-income countries, they can allocate more financial resources for green energy projects. Hamburger and Harangozó (2018) highlighted that high-income countries could offer more opportunities to enhance green energy than low-income countries. Burke (2010) also disclosed that countries move toward green energy sources with the increase in their income level. Our results oppose the findings of Godawska (2021), who concluded that economic growth adversely affects green energy production in Visegrad countries.

The coefficient value of population density is statistically significant and negative at a 1% significance level. The transformation from fossil fuel to green energy is linked to the availability of land and population density. However, the land use aspects differ in G7 countries. For instance, Japan has a high population density per square kilometer of land with 347.13, following the United Kingdon with 274.71 people per square kilometer. Canada has large land with a low density of 4.13 people per square kilometer, but the challenges vary greatly, like the sun does not always shine, and the wind does not always blow.

In order to reconfirm the results of CuP-FM and CuP-BC, this study adopted the FMOLS method, and the results are shown in **Table 7**. The results validate the earlier findings as environmental technologies, political risk, environmental tax, and economic growth have a positive impact on green energy consumption, while population density negatively impacts green energy consumption in G7 countries.

This study employed the panel Granger causality test to examine the causal flow between variables. The findings shown in **Table 8** indicate the unidirectional causality from environmental technologies and political risk to green energy. In contrast, bidirectional causality exists between environmental taxes and green energy use. Economic growth granger causes

TABLE 8 | Dumitrescu-Hurlin panel causality tests.

Null hypothesis	W-Stat	Zbar-Stat	Prob	Conclusion
LNET does not homogeneously cause LGE	4.023***	4.553	0.000	LNET→LGE
LGE does not homogeneously cause LNET	7.067	1.335	0.181	
LPR does not homogeneously cause LGE	2.681**	2.459	0.014	LPR→LGE
LGE does not homogeneously cause LPR	1.590	0.757	0.449	
LETA does not homogeneously cause LGE	4.106***	4.683	0.000	LETA↔LGE
LGE does not homogeneously cause LETA	2.706**	2.498	0.013	
LGDP does not homogeneously cause LGE	2.587**	2.313	0.021	LGDP↔LGE
LGE does not homogeneously cause LGDP	2.655**	2.418	0.016	
LPD does not homogeneously cause LGE	4.702***	5.614	0.000	LPD→LGE
LRE does not homogeneously cause LPD	2.067	−0.189	0.849	

*** <1%, **<5%.

green energy use and the other way round. Population density granger causes green energy use but not the other way round.

CONCLUSION AND POLICY IMPLICATIONS

This study investigates the impact of environmental technologies, political risk, and environmental taxes on green energy consumption, considering the potential impacts of population density and economic growth in G7 countries from 1994 to 2018. This study employed second-generation tests for analyzing the long-run equilibrium connection and stationarity features. The findings from CuP-FM and CuP-BC unveiled that environmental technologies and environmental taxes promote green energy consumption in G7 countries. The improvement in the political risk index and economic growth stimulates green energy consumption, while population density negatively affects the green energy use in these countries. The panel causality test indicates the unidirectional causality from environmental technologies, political risk, and population density to green energy use. Environmental taxes and economic growth have bidirectional causality with green energy use.

Our results have substantial policy implications for the G7 countries in terms of green energy transition and environmental sustainability policies. Our findings conclude that raising innovation in environmental technologies boosts renewable energy use. Thus, G7 countries should allocate more financial resources to research and development of environmentally friendly technologies. The government should provide subsidies for environmental innovation and discourage fossil fuel usage. The policymakers should provide easy access to credit at a lower rate to businesses engaged in research and development activities. At the same time, they should facilitate industries to switch from traditional to eco-friendly technologies and motivate them to use green energy rather than fossil fuel. The political risk rating index positively impacts green energy use in G7 countries. Thus the policymaker should further promote the investment profile up-gradation, and improve democratic accountability and governance to boost green energy consumption in G7 countries.

This study is limited to the G7 countries and a limited number of variables are considered for a short period of 1994–2018. In future investigations, one may conduct similar studies in developing countries by introducing the role of fiscal decentralization and human capital.

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

GP: Conceptualization, methodology, data collection, empirical analysis, writing original draft. FM: Writing—review, and editing, Supervision. ZA: Conceptualization, writing original draft. JO: writing—review, and editing, Funding acquisition. EH: Writing—review, and editing.

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Supply Chain Finance and the Sustainable Growth of Chinese Firms: The Moderating Effect of Digital Finance

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Sustainable development is crucial to the survival and healthy development of enterprises, which is closely related to their financing situation. Supply chain finance is an effective way to improve and enhance the financing situation by easing financing constraints and reducing financing costs. As an important source of supply chain short-term financing, trade credit plays an important role in enterprise production and circulation. Taking Chinese listed companies from 2011 to 2020 as samples, this paper studied the impact of trade credit on sustainable growth and its internal mechanism. Furthermore, we analyzed the moderating effect of digital finance development on the influence of trade credit on sustainable growth. It is found that receiving trade credit benefited firms' sustainable growth. Furthermore, study found that receiving trade credit has a greater positive impact on the sustainable growth of enterprises in regions with higher levels of financial development, high-tech industries, state-owned enterprises and small enterprises. Whereas, the provision of trade credit had an obvious inhibiting effect on the sustainable growth of enterprises in the regions with low level of financial development, non-high-tech industries, private enterprises and small enterprises. The results of the influencing mechanism showed that receiving trade credit promoted firm's sustainable growth by "agency cost reducing effect," while providing trade credit inhibited firm's sustainable growth by "forcing effect." In addition, the development of digital finance weakens the positive impact of trade credit financing on enterprises' sustainable growth but strengthens the negative impact of providing trade credit on sustainable growth. From the perspective of sustainable growth, this paper explained the role of trade credit financing in alleviating the financing dilemma of enterprises, which is urgently needed by most emerging economies pursuing high-quality development. Therefore, in order to give full play to the role of trade credit financing, the government should actively create a good credit environment. At the same time, the government should vigorously develop digital finance to enhance its ability to serve the real economy.

Keywords: supply chain finance, trade credit, sustainable growth, mandatory effect, digital finance

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1 INTRODUCTION

Growth is the eternal theme of the enterprise, and whether sustainable growth can be achieved is related to the fate of the enterprise's future development. In the context of the global financial crisis and the pursuit of economic recovery and sustainable growth, the economic growth model based on sustainable growth is proposed to achieve sustainable growth. Sustainable growth refers to the realization of ecological balance and economic and social development on the premise of coordinated development between the speed and scale of economic and social development and the ecological environment. The concept of agricultural and environmental sustainability refers to minimizing the degradation of natural resources while increasing crop productions (Abbas et al., 2022). Currently, fertilizers account for about half of the total input energy in maize production in Pakistan (Abbas et al., 2020), and reducing overuse of farm inputs is a potential sustainable crop production strategy (Abbas et al., 2021). The real economy is the mainstay of sustainable growth. The sustainable growth of enterprises refers to that in the process of pursuing survival and development, enterprises should not only achieve their business objectives but also maintain their continuous profitability, and ultimately ensure the long-term prosperity of enterprises. The realization of sustainable growth goals is conducive to improve enterprises' ability to create wealth, increasing employment, improving the quality of economic growth and social and economic value (Xiao and Wang, 2004), which is of great significance to promote the healthy development of real economy. In the process of economic transformation from high-speed growth stage to high-quality development stage, how to realize the sustainable growth of enterprises and inject sustainable impetus into the high-quality development of China's real economy has become an important issue. Therefore, it is of great theoretical and practical significance to explore the factors affecting the sustainable growth of enterprises to prevent the financial risks of enterprises and promote the healthy development of entity enterprises. The production and operation of enterprises need funds, and the financing capacity determines the sustainable growth prospects of enterprises. Due to the existence of credit rationing, enterprises are often excluded from the traditional financial system due to their weak conditions, and indirectly obtain limited financial services. In addition, the direct financing channels of equity and creditor's rights are not perfect. The current financing problem is still the key factor restricting the sustainable development of Chinese enterprises.

Supply chain finance is a professional field of commercial bank credit business, but also a financing channel for enterprises, especially small and medium-sized enterprises. It is a financing model that can provide flexible financial products and services, and a systematic financing arrangement for all members of the supply chain. Supply chain finance is a series of technology-based business and financing processes that link transaction buyers, sellers and financing institutions with the aim of easing corporate financing constraints, reducing financing costs, and optimizing working capital (Tang and Zhuang, 2021). Supply chain financing types include bank credit financing and trade credit financing (Tang et al., 2017). Under the trade credit financing mode, enterprises often transfer credit to the upstream and downstream enterprises in the supply chain in the form of short-term credit. But bank credit financing makes it difficult for enterprises to obtain loans because of harsh lending conditions. Therefore, trade credit financing is more common and important for enterprises, and is more conducive to supply chain coordination (Chang and Rhee, 2011). As an important source of short-term financing in the supply chain, trade credit financing plays a role in accelerating capital turnover and lubricating production and circulation in industrial development, which is of great significance to short-term financing for enterprises in a vulnerable position in the supply chain (Liang et al., 2016). Therefore, this paper discusses the impact of trade credit based on supply chain finance on firm's sustainable growth.

Trade credit is a kind of direct finance which is born in the entity enterprise. Companies can alleviate short-term capital shortages by occupying capital from upstream and downstream enterprises, thus reducing financing problems. In particular, the advantages of convenient financing and fewer restrictions are favored by more and more enterprises. Studies have confirmed that more than 65% of American enterprises and 75% of British enterprises use trade credit as a financing method in the production and sales process (Atanasova and Wilson, 2003). Moreover, the contribution of trade credit financing to economic development is no less than that of bank credit (Ge and Qiu, 2007). Trade credit financing can realize higher resource allocation efficiency than bank loan (Shi and Zhang, 2010). Therefore, especially for the immature financial development of China, the use of trade credit is of great significance to realize the sustainable growth of enterprises.

Digital finance is a new financial mode in which traditional financial institutions and Internet companies use digital technology to realize financing, payment, investment and other financial activities (Huang and Huang, 2018). Traditional financial development is the foundation of digital financial development, the better traditional finance develops, the faster digital finance develops (Wang et al., 2021). Trade credit financing is an effective supplement to traditional finance and plays an alternative financing role. Therefore, it is necessary to further subdivide the impact of trade credit on sustainable growth under different levels of financial resources. Based on this, this paper further analyzes the impact of trade credit on sustainable growth of enterprises at different levels of digital finance development.

Compared with the article of Huang et al. (2019), our research contributes to the literature in three aspects. Firstly, this paper discusses the impact on the sustainable growth of enterprises from the dual perspective of trade credit supply and demand. It enriches the research perspective of the influencing factors of enterprises' sustainable growth and provides theoretical support for enterprises' sustainable growth policy formulation at the level of trade credit. Secondly, it enriched the research on the economic effect of trade credit and confirmed the influence mechanism and intermediary effect of trade credit on sustainable growth. More importantly, it discusses the moderating effect of digital finance development on trade credit and sustainable growth, and expands related research on trade credit from the perspective of regional financial development.

The remaining article is structured as: We first review the literature and develop our hypotheses in **Section 2**. **Section 3** describes the data, variable and model. **Section 4** presents the empirical results of how trade credit affects the sustainable growth of enterprises and discusses the moderating effect of digital finance development. Conclusions are provided in the final section.

2 LITERATURE REVIEW AND RESEARCH HYPOTHESES

China's financial system is dominated by bank loans, but there is a mismatch of financial resources. Enterprises' production and operation are short of capital sources and the efficiency of resource allocation is low for a long time, which is not conducive to sustainable growth of enterprises and seriously hinders the economic development process (Sui, 2017; Zhou et al., 2021). The emergence of trade credit financing can effectively make up for the deficiency of traditional finance. In the case of imperfect financial market development, insufficient supply of credit resources and limited financing channels for enterprises, trade credit assumes the supplementary function of financing and is an important external financing channel for enterprises (Sun et al., 2014). Enterprises facing financing constraints that are more inclined to replace traditional bank loans with trade credit (Zhang, 2019), and trade credit can achieve greater scale efficiency than traditional bank loans (Shi and Zhang, 2010). Fisman and Love (2003) found that in regions with relatively slow financial development, the growth rate of industries dependent on trade credit was higher. Trade credit is a kind of credit behavior frequently occurring in supply chain enterprises. It is a kind of informal financing, widely existing in the business activities of enterprises. On the one hand, enterprises obtain funds through deferred payment, advance collection and other ways to solve the problem of short-term capital shortage and reduce financing constraints. Thus, the efficiency of enterprise resource allocation can be improved (Elahi et al., 2018b) to promote the efficient investment (Tian, 2019; Liu et al., 2021; Elahi et al., 2022), and profitability and performance of system can be improved (Elahi et al., 2018a; Gao, 2019). On the other hand, the use of trade credit can add certainty to the inflow and outflow of cash. The production and operation environment of enterprises is improved, more funds will be invested in R&D and innovation activities, which is of great significance to improve market competitiveness and production efficiency (Liu et al., 2022). Therefore, trade credit financing has a positive impact on the sustainable growth of enterprises.

The separation of ownership and management leads to serious principal-agent problems between shareholders and management, which may lead to "short-sighted behavior" of management. As a result, resource allocation efficiency is low for a long time, which is not conducive to the sustainable growth of enterprises (Chen and Tang, 2006). Compared with other creditors, trade creditors have advantages in information acquisition, customer control and property recovery (Du, et al., 2021). Therefore, it can better play the supervision function of creditors and restrain agency behavior, thus effectively reducing agency cost and improving investment efficiency (Liu and Guan, 2016). Moreover, as a short-term liability, trade credit can limit managers' pursuit of profitable financial assets (Du et al., 2021). Therefore, industrial investment will be promoted and R&D investment and innovation activities of enterprises will be improved (Xu and Zhu, 2017; Xiao et al., 2021; Zhao et al., 2021; Rathnayake et al., 2022), and ultimately promote the sustainable growth of enterprises. At this point, trade credit, as a short-term liability, may affect the sustainable growth of enterprises by reducing agency costs. Therefore, we propose the first hypothesis of this paper, namely hypothesis 1.

Enterprises provide trade credit also bear credit risks. If customers intentionally occupy corporate funds, trade credit will become a malicious default to obtain corporate liquidity at a lower cost (Fabbri and Menichini, 2010). Such behavior will squeeze enterprise resources, lead to limited operating cash flow, increase operating risks, and thus adversely affect the sustainable growth of enterprises. Firstly, the role of the firm in providing liquidity may increase the risk of overdue collection and capital chain disruption, thus affecting overall efficiency (Wu et al., 2021). Secondly, providing trade credit means giving up the opportunity to earn interest income, resulting in opportunity costs. At the same time, the provision of trade credit also increases the cost of credit management. In particular, companies spend more time and money closely monitoring the flow of customers' funds. Finally, the provision of trade credit also means that enterprises have tax obligations before they get the cash flow of sales revenue, leading to the outflow of tax funds and the reduction of internal funds of enterprises, thus hindering sustainable growth. Li and Song (2021) found that the "compulsory credit" formed by debt default that was not conducive to the development of enterprises. Therefore, trade credit may be a kind of "mandatory credit," and malicious breach of contract increases market transaction costs, operational risks and resource allocation costs (Chen et al., 2016). Thus, it increases the uncertainty of enterprise production and operation and seriously hinders the sustainable growth of enterprises. To sum up, the provision of trade credit increases the risks and costs of enterprises, produces a "mandatory effect," and has a negative impact on the sustainable growth of enterprises. Therefore, we propose hypothesis 2.

There are obvious regional differences in China's economic development. Higher development level of traditional finance, there will be more perfect the financial system, and the level of credit issued by banks will also higher. The use of trade credit financing will further increase the capital of enterprises and reduce financing constraints. Thus, the guarantee of funds ensures the normal operation of production and management and promotes the sustainable growth of enterprises. In highly developed financial areas, the use of trade credit plays a "icing on the cake" role for enterprises. In areas with low level of financial development, the financial system is imperfect and financing channels for enterprises are limited (Sheng, 2021; Sun, 2021). The provision of trade credit increases the cost and management risk of enterprises, and the production environment deteriorates further, which is not conducive to improve the sustainable growth level of enterprises.

Similarly, the response to trade credit varies by industry. High-tech industrial enterprises are characterized by high skills, high investment and high risk. They have difficulty in financing and are highly dependent on external capital (Zhang and Hu, 2020; Elahi et al., 2021). However, traditional financial institutions pay more attention to hard assets that can be secured when lending, which makes it difficult for high-tech enterprises to obtain financing from banks and they have to turn to other financing channels for financing. At this point, trade credit financing can effectively solve this problem. It can improve the capital environment of enterprises, improve the level of investment in R&D, and then promote the sustainable growth of high-tech industry enterprises. At the same time, it is worth noting that high-tech enterprises themselves are facing strong competitive pressure and are keener to carry out innovative activities to compete for market position (Zhu et al., 2019). In addition, the government's policy support for high-tech enterprises makes it easier for them to obtain government innovation subsidy funds. Therefore, the provision of trade credit has little effect on inhibiting innovation and has limited ability to reduce the level of sustainable growth. As a result, the negative impact of the provision of trade credit is more obvious in non-high-tech enterprises than high-tech enterprises.

China's financial resources are badly mismatched. Compared with private companies, state-owned enterprises are more favored by the credit sector. The better relationships with governments tend to give them access to bigger credit lines, longer loan maturities and lower interest costs. Despite their significant contribution to economic development, private enterprises are often excluded from the formal financial system due to their lack of effective collateral assets, unsecured records and poor credit histories, making it difficult for them to obtain the financial services they need. At this time, the emergence of trade credit as an informal financing method is beneficial to the development of private enterprises. It can increase the external financing channels of private enterprises and promote the sustainable growth of enterprises. There is also an empirical fact that state-owned enterprises are obliged to shoulder the burden of government policies, including some of the construction of projects in the form of overinvestment. State-owned enterprises often suffer from excessive investment and overcapacity (Liu et al., 2018), and low investment efficiency. However, the phenomenon of providing trade credit occupying their funds will reduce excessive investment behavior. As a result, state-owned enterprises can allocate capital more efficiently and invest more efficiently, thus promoting sustainable growth. Namely, the provision of trade credit significantly promoted the sustainable growth of state-owned enterprises.

There exists "scale discrimination" in the allocation of financial resources in China. Small enterprises are small in scale, lack of effective asset guarantee, and have low quality of external information disclosure. Therefore, it is difficult for them to obtain traditional bank credit. As an informal financing mode, trade credit has positive impact on the sustainable growth of small enterprises. However, due to their low market position, small enterprises are often forced to provide trade credit to large enterprises, resulting in their capital encroachment. Moreover, it is difficult for small enterprises to obtain external capital, leading to a high possibility of capital chain fracture. Therefore, the provision of trade credit has a greater negative impact on the sustainable growth of small businesses. Therefore, we propose hypothesis 3 about heterogeneity.

Whether the use of trade credit can promote the sustainable growth of enterprises is also closely related to digital finance. With the application of digital technology, digital finance occupies a considerable position in China's modern financial system and has a significant impact on China's economic development. Digital finance has financial attributes and does not change the essence of financial services. However, different from traditional finance, digital finance can cover customers that are difficult to be covered by traditional finance, cover more long-tail groups, and improve the convenience and availability of financial services (Chen et al., 2021). China's financial system is dominated by commercial banks. In areas with low level of digital finance development, enterprises rely more on traditional bank loan financing mode. With the improvement of the development level of digital finance, Internet finance, online lending and other network services continue to occupy the traditional banking business (assets, liabilities, and intermediate business). The development of digital finance makes traditional financial institutions compete with each other for market share, actively carry out digital transformation, and constantly improve the efficiency and quality of financial services (Wu, 2015). Therefore, the financing difficulty of enterprises is reduced (Tang et al., 2020), thus weakening the positive impact of informal finance-trade credit financing on sustainable growth.

In areas with a high level of digital finance development, online services such as Internet financial products are increasing. As the real economy is struggling and inefficient, enterprises invest more money in online financing in pursuit of higher short-term returns and profit maximization. The development of the real economy was not given much attention. Moreover, the financial products chosen may face higher risks, for example, some Internet loan asset-backed securities are highly leveraged. Chen and Ye (2016) found that the interest rate fluctuations of online loans have agglomeration and risk accumulation effects. Loan market has strong risks, but market participants have weak awareness of risk identification and are prone to temptation of high returns. One of the most direct evidences of the negative impact of the development of digital finance is the explosive phenomenon of P2P products. It reduces the possibility for enterprises to recover capital, including principal and interest, resulting in credit risk, resulting in a shortage of capital flow needed for production and operation. Thus, the development of digital finance reinforces the negative impact of the provision of trade credit on sustainable growth. In summary, our assumptions are given as follows:

Hypothesis 1: Receiving trade credit has a positive impact on sustainable growth, which may be achieved through a channel of reducing firm's agency costs.

Hypothesis 2: The provision of trade credit is not conducive to the sustainable growth of enterprises.

Hypothesis 3: The impact of trade credit on sustainable growth has obvious regional differences and enterprise characteristics differences.

Hypothesis 4: The development of digital finance weakens the positive effect of obtaining trade credit financing on sustainable growth of enterprises, while strengthens the negative effect of providing trade credit on sustainable growth.

3 MATERIALS AND METHODS

In this stage, sample data, variable definitions and econometric models used in this paper are introduced in three sections respectively.

3.1 Data and Sampling

This paper takes listed non-financial companies in China from 2011 to 2020 as research samples. To eliminate the effects of variable outliers, we also winsorize all main continuous variables at 1% level. The main financial data obtained from the China Stock Market and Accounting Research Database (CSMAR), the property of ownership indicators is derived from CCER China Economic and Financial Database. The data of digital finance index come from "The Peking University Digital Financial Inclusive Index of China (PKU-DFIIC)" released by Peking University Digital Finance Research Center, which has been widely used by Chinese scholars. Grouped variable-financial development level data were obtained from China Statistical Yearbook.

3.2 Definitions of Variables

3.2.1 Sustainable Growth

The dependent variable "sustainable growth of firm," denoted as SGR. Chinese scholars found that sustainable growth rate refers to the maximum sales growth rate that an enterprise can achieve without increasing external equity funds (Guo and Guo, 2002). Most of the existing literature adopts the sustainable growth model proposed by Higgins (1988) and Van Horne (1988). In this paper, the model constructed by Higgins is used to calculate the dependent variable in the basic regression. It is explained the sustainable growth rate as the maximum sales growth rate an enterprise can achieve without exhausting its resources, which is a balanced growth and reveals the financial factors that restrict the growth of an enterprise. In a robustness test, we used Van Horne' model to calculate the sustainable growth rate, emphasizing the target value of sustainable growth.

3.2.2 Trade Credit

This paper studies trade credit from the perspective of supply and demand, which can be divided into "access to trade credit" (AP) and "provision of trade credit" (AR). Among them, the independent variable AP is measured as the sum of accounts payable, notes payable and advance receivable scaled by total assets, and AR is measured as the sum of notes receivable, accounts receivable and prepayments scaled by total assets (Lu and Yang, 2011; Liu, 2021).

3.2.3 Digital Finance

We adopt the PKU-DFIIC as a proxy variable to measure the level of digital finance of each city, which is compiled by a joint research team composed of the Peking University Digital Finance Research Center and Ant Financial Group. The data, which started in 2011 and is updated until 2020, can effectively measure the development of digital finance in China (Guo et al., 2020). In the analysis, we not only use aggregate index (Fin) to describe the digital finance level of each city, but also use first-level indicators including coverage_breadth (B), usage_depth (D), and digitization_level (S). In order to avoid the influence of excessive value and improve the fitting of regression, we take logarithm of digital finance index.

3.2.4 Control Variables

According to the existing literature on the sustainable growth of enterprises, control variables including return on total assets (ROA), leverage ratio (LEV), net fixed assets (FA), dividend distribution ratio (DDR) and enterprise size (SIZE) are selected. The specific meaning of each variable is presented in **Table 1**.

3.3 Econometric Model

3.3.1 Basic Regression Model

Benchmark model was used to estimate the impact of trade credit on the sustainable growth of enterprises (Fisman and Love, 2003).

$$SGR_{it} = \alpha_0 + \alpha_1 AP_{it} + \alpha_2 Control_{it} + \alpha_3 \sum year + u_i + \varepsilon_{it} \quad (1)$$

$$SGR_{\mathrm{it}} = \beta_0 + \beta_1 AR_{it} + \beta_2 Control_{it} + \beta_3 \sum year + u_i + \varepsilon_{it} \quad (2)$$

Here subscripts i and t respectively represent individual enterprise and year. SGR represents sustainable growth of enterprise. AP and AR represent the acquisition and provision of trade credit, respectively. Control represents the control variables that may affect the sustainable growth of an enterprise. U is the individual effect of the enterprise, which is used to control the characteristics of the enterprise that do not change with time and cannot be observed. In addition, we control for year. ε is the random error term of the model.

3.3.2 Mediating Effect Model

To further explore the potential mechanism of trade credit financing affecting sustainable growth of enterprises, this paper refers to the mediation effect test model proposed by Wen and Ye (2014) to test whether trade credit can promote sustainable growth of enterprises by reducing agency costs.

$$SGR_{it} = \gamma_0 + cAP_{it} + \gamma_1 Control_{it} + u_i + \varepsilon_{it} \quad (3)$$

$$AG_{it} = \gamma_0 + aAP_{it} + \gamma_1 Control_{it} + u_i + \varepsilon_{it} \quad (4)$$

$$SGR_{it} = \gamma_0 + c' AP_{it} + bAG_{it} + \gamma_1 Control_{it} + u_i + \varepsilon_{it} \quad (5)$$

AG is the selected intermediary variable-agency cost. Other variables are defined in the same way as **Eqs 1**, **2**.

TABLE 1 | The definitions of the main variables.

Variables	Definitions
SGR	Higgins' sustainable growth rate can be expressed by the formula: SGR = P*A*T*R, P is profit margin (net profit scaled by operating income), A is asset turnover (operating income scaled by total assets), T is leverage factor (total assets scaled by beginning-of-period equity), and R is earnings retention rate
SGR1	Van Horne's sustainable growth rate can be expressed as follows: SGR = P*A*T_0*R/(1-P*A*T_0*R), P is profit margin (net profit scaled by operating income), A is asset turnover (operating income scaled by total assets), T_0 is leverage factor (total assets scaled by end-of-period equity), and R is earnings retention rate
AP	The sum of accounts payable, notes payable and advance receivable scaled by total assets
AR	The sum of notes receivable, accounts receivable and prepayments scaled by total assets
Fin	The development level of digital finance
ROA	The ratio of net profit to total assets
LEV	Financial leverage, represented by the ratio of total debt to total assets
FA	Net fixed assets, measured logarithmically by the amount of net fixed assets
DDR	Dividend distribution ratio, measured by the ratio of cash dividends per common share to earnings per share
SIZE	The size of the firm, measured by the natural logarithm of total assets
AG	Agency costs, calculated as the ratio of overhead to operating revenue
SOE	Dummy variable, which equals the value 1 if the firm is a state-owned, and 0 if the firm is private
JR	Level of financial development, expressed by the ratio of total deposits and loans in RMB of financial institutions to GDP

3.3.3 Moderating Effect Model

To further analyse the relationship between trade credit and sustainable growth of enterprises in the external environment of digital finance development, this paper sets the following moderating effect model for empirical analysis. The main method to judge whether the moderating effect exists or not is to verify the significance of interaction coefficient. In this study, it can be achieved by judging whether the interaction coefficients (δ_3 *and* θ_3) between digital finance and trade credit is significant.

$$SGR_{cit} = \delta_0 + \delta_1 AP_{cit} + \delta_2 Fin_{ct} + \delta_3 Fin_{ct} * AP_{cit} + \delta_4 Control_{cit} + \delta_5 \sum year + u_i + \varepsilon_{cit} \tag{6}$$

$$SGR_{cit} = \theta_0 + \theta_1 AR_{cit} + \theta_2 Fin_{ct} + \theta_3 Fin_{ct} * AR_{cit} + \theta_4 Control_{cit} + \theta_5 \sum year + u_i + \varepsilon_{cit} \tag{7}$$

Subscript *c* stands for city. Fin represents the development level of digital finance. The definitions of other variables are the same as above.

4 RESULTS AND DISCUSSION

In this stage, firstly, the statistical characteristics of the data are briefly analyzed. Secondly, we first analyze the effect of trade credit on sustainable growth of enterprises, including baseline regression, heterogeneity analysis and robustness analysis, and then analyze the mechanism of trade credit on sustainable growth. Finally, the moderating effect of digital finance development is analyzed. In addition, in the regression results of all our tables, standard errors are reported in parentheses, with *, **, and ** indicating statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE 2 | Descriptive statistics.

Variables	N	Mean	Standard deviation	Minimum	Maximum
SGR	25,591	0.083	0.082	–0.037	0.457
AP	18,466	0.169	0.117	0.003	0.543
AR	22,872	0.183	0.122	0.002	0.554
Fin	25,554	5.303	0.420	3.987	5.773
ROA	26,853	0.047	0.047	–0.107	0.208
LEV	26,853	0.413	0.206	0.051	0.925
FA	25,614	0.289	0.307	0.000	1.869
DDR	26,845	20.061	1.712	15.230	24.771
SIZE	26,853	22.094	1.278	19.661	26.120

4.1 Descriptive Statistics

The descriptive statistics are presented in **Table 2**. The minimum value of SGR is −0.037, while the maximum value is 0.457, indicating that there are significant differences in sustainable growth among enterprises. The minimum AP value is 0.003 and the average value is 0.169, the minimum value of AR was 0.002 and the average value was 0.183, indicating that the use of trade credit by some enterprises has not reached the average level. After taking the logarithm, the minimum value of Fin is 3.987, and the maximum value is 5.773, indicating that there are obvious differences in the development of digital finance among regions. Other variables are also different in different degrees, which lays a foundation for this study. It is worth noting that when the sustainable growth of an enterprise is negative, it indicates that the company's current operating efficiency and financial policies are unreasonable. When this situation occurs, enterprises should make adjustments in time to reverse the adverse situation.

Before the multiple regressions, we report the Pearson correlation matrix in **Table 3**. The correlation between AP and SGR is significantly positive, which provides preliminary evidence that access to trade credit can help to improve the sustainable growth of enterprises. The AR is also positively

TABLE 3 | Correlation matrix.

	SGR	AP	AR	Fin	ROA	LEV	FA	DDR	SIZE
SGR	1.000								
AP	0.108***	1.000							
AR	0.069***	0.352***	1.000						
Fin	−0.035***	0.074***	0.065***						
ROA	0.629***	−0.120***	0.005	−0.018***	1.000				
LEV	0.043***	0.517***	0.047***	−0.032***	−0.359***	1.000			
FA	−0.079***	0.057***	−0.210***	0.060***	−0.109***	0.349***	1.000		
DDR	−0.304***	−0.072***	−0.057***	0.025***	0.023***	−0.188***	0.032***	1.000	
SIZE	0.029***	0.224***	−0.158***	0.128***	−0.122***	0.520***	0.734***	−0.022***	1.000

TABLE 4 | Benchmark regression results: Trade credit and sustainable growth.

Variables	(1) SGR	(2) SGR	(3) SGR	(4) SGR
AP	0.039*** (0.01)	0.044*** (0.01)		
AR			−0.014** (0.01)	−0.016** (0.01)
ROA	1.576*** (0.02)	1.541*** (0.02)	1.561*** (0.01)	1.532*** (0.01)
LEV	0.050*** (0.00)	0.041*** (0.01)	0.061*** (0.00)	0.054*** (0.00)
SIZE	0.015*** (0.00)	0.026*** (0.00)	0.012*** (0.00)	0.023*** (0.00)
FA	−0.012*** (0.00)	−0.010*** (0.00)	−0.010*** (0.00)	−0.009*** (0.00)
DDR	−0.054*** (0.00)	−0.054*** (0.00)	−0.055*** (0.00)	−0.054*** (0.00)
Constant	−0.102*** (0.02)	−0.366*** (0.02)	−0.055*** (0.02)	−0.302*** (0.02)
N	18,654	17,634	23,036	21,839
R^2	0.480	0.490	0.493	0.503
Code	Control	Control	Control	Control
Year	No	Control	No	Control

correlated with SGR. Sustainable growth (SGR) is positively correlated with return on total assets (ROA), leverage ratio (LEV) and enterprise size (SIZE), and negatively correlated with net fixed assets (FA) and dividend distribution ratio (DDR).

4.2 Basic Regression Results

The Hausmann test results indicate that the fixed effects model should be used. The fixed effect regression results after controlling the influence of other variables are shown in **Table 4**. As can be seen from columns (1) and (2) of the **Table 4**, the regression coefficient between the AP and SGR is positive and significant at 1% level. That is, the acquisition of trade credit significantly promotes the sustainable growth of enterprises, and hypothesis 1 is partially verified. The possible explanation is that the access to trade credit effectively alleviates the financial pressure of enterprises and alleviates the financing constraints. The financial situation of enterprises is improved, the level of R&D investment of enterprises is increased, the market competitive advantage is enhanced, and the sustainable growth of enterprises is promoted. There is a significant negative correlation between the AR and SGR in columns (3) and (4), indicating that the provision of trade credit has a negative impact on the sustainable growth of enterprises, which verifies hypothesis 2 proposed in this paper. This may be because the provision of trade credit increases the cost of enterprises, and the situation of capital occupation is not conducive to the guarantee of normal production and operation in the later period. That is, the provision of trade credit has a "mandatory effect," which is not conducive to the improvement of enterprises' sustainable growth ability. In the analysis of control variables, ROA, LEV, and SIZE are positively correlated with the sustainable growth of enterprises, while FA and DDR are negatively correlated with the sustainable growth of enterprises. By comparing the results of columns (1), and (2), (3) and (4), it can be seen that the impact of trade credit on sustainable growth is more obvious after year is controlled, so two-way fixed effect model is adopted in the subsequent regression.

4.3 Heterogeneity Analysis

In hypothesis 3, we assume that there are obvious regional differences and firm characteristics differences in the impact of trade credit on firm sustainable growth. Therefore, we test the hypothesis in the empirical part.

4.3.1 Heterogeneous Impact on Areas With Different Levels of Financial Development

Table 5 reports the regression results. In column (1) of **Table 5**, the coefficient of AP is significantly positive, while the coefficient in column (3) is not significant. The promoting effect of AP on SGR is more obvious in the regions with higher level of financial development. In column (2) of **Table 5**, the coefficient of AR is negative but not significant, and that in column (4) is significantly negative. The inhibition effect of AR on SGR is more obvious in enterprises in low level of financial development. The results were as expected.

TABLE 5 | Heterogeneity analysis: Level of financial development.

Variables	Areas with high financial development level		Areas with low financial development level	
	(1) SGR	(2) SGR	(3) SGR	(4) SGR
AP	0.055*** (0.01)		0.015 (0.01)	
AR		−0.002 (0.01)		−0.027*** (0.01)
ROA	1.614*** (0.02)	1.582*** (0.02)	1.481*** (0.02)	1.504*** (0.02)
LEV	0.061*** (0.01)	0.062*** (0.01)	0.029*** (0.01)	0.051*** (0.01)
SIZE	0.022*** (0.00)	0.021*** (0.00)	0.030*** (0.00)	0.024*** (0.00)
FA	−0.010*** (0.00)	−0.010*** (0.00)	−0.010*** (0.00)	−0.009*** (0.00)
DDR	−0.049*** (0.00)	−0.050*** (0.00)	−0.059*** (0.00)	−0.058*** (0.00)
Constant	−0.275*** (0.03)	−0.259*** (0.03)	−0.420*** (0.03)	−0.311*** (0.03)
N	9,972	12,393	7,872	9,689
R^2	0.520	0.521	0.475	0.496
Code	Control	Control	Control	Control
Year	Control	Control	Control	Control

TABLE 6 | Heterogeneity analysis: High-tech and non-high-tech industries.

Variables	Enterprises in high-tech industry		Non-high-tech industry enterprises	
	(1) SGR	(2) SGR	(3) SGR	(4) SGR
AP	0.080*** (0.02)		0.037*** (0.01)	
AR		−0.018 (0.01)		−0.016** (0.01)
ROA	1.388*** (0.03)	1.394*** (0.03)	1.586*** (0.02)	1.580*** (0.02)
LEV	0.0180 (0.01)	0.052*** (0.01)	0.052*** (0.01)	0.062*** (0.00)
SIZE	0.028*** (0.00)	0.022*** (0.00)	0.027*** (0.00)	0.024*** (0.00)
FA	−0.013*** (0.00)	−0.013*** (0.00)	−0.009*** (0.00)	−0.008*** (0.00)
DDR	−0.050*** (0.00)	−0.051*** (0.00)	−0.055*** (0.00)	−0.055*** (0.00)
Constant	−0.321*** (0.06)	−0.211*** (0.05)	−0.402*** (0.03)	−0.342*** (0.02)
N	3,978	5,410	13,656	16,429
R^2	0.462	0.495	0.503	0.512
Code	Control	Control	Control	Control
Year	Control	Control	Control	Control

TABLE 7 | Heterogeneity analysis: Division of enterprise ownership.

Variables	State-owned enterprises		Private enterprises	
	(1) SGR	(2) SGR	(3) SGR	(4) SGR
AP	0.053*** (0.01)		0.048*** (0.01)	
AR		0.035*** (0.01)		−0.049*** (0.01)
ROA	1.533*** (0.03)	1.518*** (0.02)	1.522*** (0.02)	1.533*** (0.02)
LEV	0.047*** (0.01)	0.061*** (0.01)	0.040*** (0.01)	0.057*** (0.01)
SIZE	0.025*** (0.00)	0.019*** (0.00)	0.026*** (0.00)	0.023*** (0.00)
FA	−0.009*** (0.00)	−0.005*** (0.00)	−0.011*** (0.00)	−0.012*** (0.00)
DDR	−0.053*** (0.00)	−0.053*** (0.00)	−0.055*** (0.00)	−0.055*** (0.00)
Constant	−0.370*** (0.04)	−0.323*** (0.04)	−0.322*** (0.03)	−0.234*** (0.03)
N	6,200	7,211	10,209	12,802
R^2	0.472	0.477	0.498	0.519
Code	Control	Control	Control	Control
Year	Control	Control	Control	Control

4.3.2 Heterogeneous Impact on Different Industries

Table 6 reports the regression results by industry type. The coefficients of AP in columns (1) and (3) of **Table 6** are positive at the 1% significance level, indicating that the acquisition of trade credit has a positive impact on the sustainable growth of enterprises in high-tech and non-high-tech industries. Further, the comparison of coefficients shows that the promotion effect is more obvious in high-tech enterprises. In column (4) of **Table 6**, the coefficient of AR is significantly negative, while the coefficient in column (2) is not significant. The provision of trade credit significantly inhibits the sustainable growth of non-high-tech enterprises, but has no significant effect on high-tech enterprises.

TABLE 8 | Heterogeneity analysis: Division of enterprise size.

	Large-scale enterprise		Small-scale enterprise	
	(1) SGR	(2) SGR	(3) SGR	(4) SGR
AP	0.019 (0.02)		0.099** (0.05)	
AR		−0.010 (0.02)		−0.105*** (0.03)
ROA	1.860*** (0.07)	1.719*** (0.04)	1.443*** (0.06)	1.455*** (0.06)
LEV	0.064** (0.03)	0.018 (0.02)	−0.040 (0.03)	0.015 (0.02)
SIZE	0.032** (0.01)	0.034*** (0.01)	0.074*** (0.01)	0.069*** (0.01)
FA	−0.004 (0.00)	−0.007** (0.00)	−0.022*** (0.00)	−0.021*** (0.00)
DDR	−0.032*** (0.00)	−0.039*** (0.00)	−0.046*** (0.01)	−0.047*** (0.01)
Constant	−0.658** (0.28)	−0.587*** (0.14)	−1.125*** (0.18)	−1.021***
N	2,249	3,405	4,223	4,461
R^2	0.686	0.661	0.399	0.399
Code	Control	Control	Control	Control
Year	Control	Control	Control	Control

4.3.3 Heterogeneous Impact on Enterprises With Ownership

Table 7 reports the regression results for the differentiation of business ownership. In columns (1) and (3) of **Table 7**, the coefficient of AP is positive at the significant 1% level, indicating that access to trade credit has a positive impact on the sustainable growth of enterprises regardless of the nature of ownership. Further comparison of the coefficients showed that this effect is more obvious in state-owned enterprises. In column (2) of **Table 7**, the coefficient of AR is positive at the significant level of 1%, indicating that the provision of trade credit has a positive impact on the sustainable growth of state-owned enterprises.

4.3.4 Heterogeneous Impact on Enterprise Size

Divide the top 25% of the size of the enterprise into small enterprises and the bottom 25% into large enterprise. **Table 8** reports the results of the regression by firm size. In column (3) of **Table 8**, the coefficient of AP is positive at the significant level of 5%, indicating that access to trade credit has a positive impact on the sustainable growth of small enterprises. In contrast, in column (1) of **Table 8**, the coefficient of AP is not significant. As an alternative financing, trade credit plays an important role in increasing financing sources of small enterprises, effectively alleviating the dilemma of insufficient funds, reducing the negative impact of credit discrimination. Thus improving their sustainable growth level. Moreover, the coefficient of AR is significantly negative at the 1% level. The result verified hypothesis.

4.4 Robustness Tests

4.4.1 Measure of Substitution Variable

Since the measurement method of variables will produce bias to the results, we refer to Chen and Ma (2018) measurement of trade credit. AP is measured as the sum of accounts payable, notes payable and advance receivable scaled by operating cost, and AR is measured as the sum of notes receivable, accounts receivable and prepayments scaled by operating income. Regression results are shown in Columns (1) and (2) of **Table 9**. The sustainable growth rate calculated by Van Horne is used to measure the dependent variable in this paper, and the results are listed in columns (3) and (4) of **Table 9**. The above regression coefficients were expected and significant. The results of variable substitution show that the conclusions of this paper are still robust after the measurement methods of trade credit and sustainable growth are replaced.

4.4.2 Substitution Regression Method

To further test the robustness of our empirical results, we change regression method to help establish the causality. We use DIFF-GMM to investigate the impact of trade credit on the sustainable growth of enterprises (Yang et al., 2020). The first order lag of SGR was added into the DIFF-GMM model as an explanatory variable. The results of DIFF-GMM regression are shown in columns (5) and (6) of **Table 9**. The regression results show that the sustainable growth of the previous period is significantly positively correlated with the sustainable growth of the current period. This means that the sustainable growth of enterprises is affected by its own inertia, showing a strong self-cumulative effect. The results in the table show that AP is positively correlated with SGR, while AR is negatively correlated with SGR. The results are robust.

4.4.3 Management of Endogeneity Problem

Finally, we used the idea of controlling endogenous problems to perform robustness tests. There may be a reverse causality relationship between trade credit and sustainable growth, which leads to the bias in the research results of this paper. The omission of variables in model selection may also lead to endogeneity. Therefore, two-stage instrumental-variable regression model is used to alleviate the endogeneity problem. In this study, the selection of instrumental variables draws on the ideas of Yu (2013) and Zhang et al. (2020). Details are as follows: the mean value of AP calculated by province and industry (PIAP) and first-order lag of AP (LAP) are used as instrumental variables of AP, and the mean value of AR calculated by year and industry (SNAR) and first-order difference of AR (DAR) are used as instrumental variables of AR.

TABLE 9 | Substitution variables and regression methods.

Variables	Substitution argument		Substitution dependent variable		DIFF-GMM	
	(1) SGR	(2) SGR	(3) SGR1	(4) SGR1	(5) SGR	(6) SGR
L.SGR					0.514** (0.25)	0.640*** (0.07)
AP	0.005*** (0.00)		0.046* (0.02)		0.113** (0.05)	
AR		−0.004*(0.00)		−0.024**(0.01)		−0.401*** (0.13)
ROA	1.552*** (0.02)	1. 529*** (0.01)	1.545*** (0.05)	1.805*** (0.05)	1.632*** (0.07)	1.705*** (0.07)
LEV	0.054*** (0.00)	0.055*** (0.00)	−0.011 (0.02)	0.012 (0.01)	0.009 (0.03)	0.096*** (0.02)
SIZE	0.025*** (0.00)	0.023*** (0.00)	0.067*** (0.00)	0.070*** (0.00)	0.049*** (0.00)	0.034*** (0.00)
FA	−0.010*** (0.00)	−0.009*** (0.00)	0.003 (0.00)	0.002 (0.00)		−0.001 (0.00)
DDR	−0.052*** (0.00)	−0.053*** (0.00)	−0.082*** (0.00)	−0.117*** (0.01)	−0.054*** (0.01)	−0.058*** (0.00)
_cons	−0.333*** (0.02)	−0.292*** (0.02)	−1.462*** (0.07)	−1.492***(0.07)		
N	16,870	20,848	16,995	21,075	8,893	12,518
R^2	0.493	0.508	0.130	0.134		
Code	Control	Control	Control	Control		
Year	Control	Control	Control	Control		
AR (1)					0.010	0.000
AR (2)					0.427	0.217
Hansen					0.154	0.266

Note: AR (1), AR (2), and hansen test all show p *values.*

TABLE 10 | Regression results of instrumental variables.

Variables	(1) AP	(2) AR	(3) SGR	(4) SGR
AP			0.192*** (0.03)	
AR				−0.109*** (0.02)
PIAP	0.212*** (0.07)			
LAP	0.369*** (0.02)			
DAR		0.468*** (0.01)		
SNAR		0.380*** (0.03)		
ROA	0.086*** (0.02)	0.135*** (0.02)	1.598*** (0.04)	1.598*** (0.03)
LEV	0.215*** (0.01)	0.088*** (0.01)	0.031** (0.01)	0.100*** (0.01)
SIZE	−0.009*** (0.00)	−0.007*** (0.00)	0.020*** (0.00)	0.011*** (0.00)
FA	−0.004** (0.00)	−0.010*** (0.00)	−0.006*** (0.00)	−0.007*** (0.00)
DDR	0.001 (0.00)	−0.002 (0.00)	−0.046*** (0.00)	−0.048*** (0.00)
N	11,915	16,426	11,915	16,426
R^2			0.543	0.575
Kleibergen-paap rk LM statistic	308.65 (0.000)	715.74 (0.000)		
Kleibergen-paap rk Wald F statistic	233.32 (11.59)	1027.75 (11.59)		
Hansen J statistic			2.186 (0.139)	1.265 (0.261)

Note: LM and F parentheses report critical values at the 15% level. Hansen shows the p *value in parentheses.*

The 2SLS regression results are reported in **Table 10**. It can be clearly seen from columns (1) and (2) in **Table 10** that there are no weak instrumental variables, under-recognition and over-recognition problems, indicating that instrumental variables are effective. In addition, in columns (3) and (4), the coefficients are in line with expectations and significant, confirming that the results are still robust.

4.5 Test of Influence Mechanism

We used the mediating effect model to verify the influencing mechanism by referring to the current common practice of scholars. The selection of intermediary variable-AG index refers to the research of Liu (2021). The mediation effect proportion was calculated by ab/c. The mediating effect mechanism results are reported in **Table 11**. In column (2) of **Table 11**, AP is negatively correlated with AG, indicating that obtaining trade credit reduces the agency cost of enterprises. In column (3) of **Table 11**, AG is negatively correlated with SGR,

TABLE 11 | Analysis of AP influence mechanism.

	(1) SGR	(2) AG	(3) SGR
AP	0.041*** (0.01)	−0.447*** (0.04)	0.038*** (0.01)
AG			−0.006*** (0.00)
ROA	1.566*** (0.02)	−0.771*** (0.09)	1.558*** (0.02)
LEV	0.046*** (0.01)	0.202*** (0.03)	0.048*** (0.01)
SIZE	0.015*** (0.00)	−0.084*** (0.01)	0.015*** (0.00)
FA	−0.011*** (0.00)	-0.043*** (0.00)	−0.012*** (0.00)
DDR	−0.054*** (0.00)	0.004 (0.01)	−0.054*** (0.00)
Constant	−0.120*** (0.02)	2.975*** (0.10)	−0.100*** (0.02)
N	17,634	17,492	17,477
R^2	0.473	0.062	0.474
Code	Control	Control	Control

TABLE 12 | Total digital finance index and "Broadband China" policy impact.

Variables	Impact of overall indicators		"Broadband China" strategic policy	
	(1) SGR	(2) SGR	(3) SGR	(4) SGR
AP	0.035*** (0.01)		0.019*** (0.01)	
AR		−0.011* (0.01)		−0.009* (0.00)
Fin	−0.007 (0.01)	−0.006 (0.01)		
Fin*AP	−0.017** (0.01)			
Fin*AR		−0.017** (0.01)		
DD			−0.005*** (0.00)	−0.005*** (0.00)
ROA	1.545*** (0.02)	1.534*** (0.01)	1.542*** (0.01)	1.528*** (0.01)
LEV	0.046*** (0.01)	0.056*** (0.00)	0.052*** (0.00)	0.058*** (0.00)
SIZE	0.026*** (0.00)	0.023*** (0.00)	0.015*** (0.00)	0.012*** (0.00)
FA	−0.010*** (0.00)	−0.009*** (0.00)	−0.010*** (0.00)	−0.009*** (0.00)
DDR	−0.052*** (0.00)	−0.053*** (0.00)	−0.070*** (0.00)	−0.072*** (0.00)
Constant	−0.315*** (0.05)	−0.267*** (0.04)	−0.129*** (0.01)	−0.088*** (0.01)
N	16,870	20,848	16,870	20,848
R^2	0.494	0.508	0.585	0.595
Code	Control	Control	Control	Control
Year	Control	Control	No	No

indicating that agency cost seriously hinders enterprises from improving their sustainable growth level. The coefficient of column (3) is lower than that of column (1). The above results indicate that agency cost plays a partial intermediary role in the process of obtaining trade credit to promote the sustainable growth of enterprises. The mediation effect accounts for about 6.54% of the total effect. Obtaining trade credit promotes the sustainable growth of enterprises through reducing agency costs.

The empirical findings show that providing trade credit inhibits the sustainable growth of enterprises, confirming the "mandatory effect" proposed in the theoretical part. However, since there is no suitable proxy variable for the "mandatory effect" in the existing literature, this stage only examines its effect from the division of large and small enterprises. If the provision of trade credit significantly inhibits the sustainable growth of small enterprises, but the inhibitory effect on large-scale enterprises is not ideal, or the inhibitory effect on large-scale enterprises is not as good as that of small enterprises, it means that "mandatory effect" is established. The regression results of columns (2) and (4) in **Table 8** are in line with expectations. In other words, the provision of trade credit produces a "mandatory effect" that inhibits sustainable growth of firms.

4.6 Analysis of External Environment of Digital Finance

To test hypothesis 4, we further explore the impact of trade credit on the sustainable growth of enterprises in the context of regional financial development from the perspective of digital finance. In the regression of moderating effect, digital financial data at city level were used and the data were decentralized.

4.6.1 The Impact of Total Indicators of Digital Finance

In column (1) of **Table 12**, the main effect coefficient is significantly positive, while the interaction coefficient is significantly negative. This suggests that the development of digital finance has weakened the positive impact of access to trade credit on sustainable growth. It may be that the development of digital finance has improved the degree of competition in the banking (Thakor, 2020), and thus prompted financial institutions to improve the efficiency and quality of financial services, so that enterprises can meet their loan needs more effectively. The service effect of informal finance is weakened, thus weakening the promotion effect of obtaining trade credit on sustainable growth. In column (2) of **Table 12**, the main effect coefficient is significantly negative, and the interaction effect coefficient is significantly negative. The development of digital finance has enhanced the negative impact of trade credit provision on sustainable growth. The possible reason is that with the high level of development of digital finance, enterprises are vulnerable to the temptation of high-risk and high-yield internet products. As a result, enterprises will put more money into internet financial products, which may reduce the probability of the return of investment funds. The funds needed for the development of the real economy have not been met. Thus, enhancing to the negative impact of trade credit provision on sustainable growth.

4.6.2 "Broadband China" Strategic Policy

The development of digital finance is inseparable from the construction of digital infrastructure. This paper chooses the "Broadband China" strategy pilot as exogenous policy impact, and uses the difference-in-differences model to explore the impact of trade credit on the sustainable growth of enterprises in the external environment of digital finance development. Since the "Broadband China" strategy was carried out in 3 years in 2014, 2015, and 2016, the policy implementation time was different, so the multi-period DID model should be adopted for empirical analysis. DD is the impact effect of the implementation of "Broadband China" policy. The results in columns (3) and (4) of **Table 12** show that the effect of the

TABLE 13 | The structural impact of digital finance.

Variables	(1) SGR	(2) SGR	(3) SGR	(4) SGR	(5) SGR	(6) SGR
AP	0.034*** (0.01)		0.036*** (0.01)		0.036*** (0.01)	
AR		−0.011* (0.01)		−0.011* (0.01)		−0.011* (0.01)
B	0.006 (0.01)	0.005 (0.01)				
B*AP	−0.022** (0.01)					
B*AR		−0.020** (0.01)				
D			−0.023*** (0.01)	−0.019*** (0.01)		
D*AP			−0.010 (0.01)			
D*AR				−0.017** (0.01)		
S					−0.003 (0.00)	−0.002 (0.00)
S*AP					−0.010* (0.01)	
S*AR						−0.008 (0.00)
ROA	1.545*** (0.02)	1.533*** (0.01)	1.545*** (0.02)	1.534*** (0.01)	1.545*** (0.02)	1.534*** (0.01)
LEV	0.046*** (0.01)	0.056*** (0.00)	0.046*** (0.01)	0.056*** (0.00)	0.046*** (0.01)	0.056*** (0.00)
SIZE	0.026*** (0.00)	0.023*** (0.00)	0.026*** (0.00)	0.023*** (0.00)	0.026*** (0.00)	0.023*** (0.00)
FA	−0.010*** (0.00)	−0.009*** (0.00)	−0.010*** (0.00)	−0.009*** (0.00)	−0.010*** (0.00)	−0.009*** (0.00)
DDR	−0.052*** (0.00)	−0.053*** (0.00)	−0.052*** (0.00)	−0.053*** (0.00)	v0.052*** (0.00)	−0.053*** (0.00)
Constant	−0.369*** (0.04)	−0.310*** (0.03)	−0.248*** (0.04)	−0.209*** (0.04)	−0.334*** (0.03)	−0.283*** (0.02)
N	16,869	20,847	16,870	20,848	16,870	20,848
R^2	0.494	0.508	0.494	0.508	0.494	0.508
Code	Control	Control	Control	Control	Control	Control
Year	Control	Control	Control	Control	Control	Control

implementation of "Broadband China" strategy policy is the same as that of basic regression.

4.6.3 Structured Analysis

Digital finance has three first-level indicators: coverage_breadth (B), usage_depth (D) and digitization_level (S). To further analyze which dimension of digital finance plays a more obvious role, we carry out structural analysis of digital finance. It can be clearly seen from **Table 13** that B and S weaken the promotion effect of trade credit access on sustainable growth, while D has no significant effect. In addition, by comparing the coefficients, it is found that B plays a stronger role. The larger the coverage breadth is, the more "long tail customers" are covered by financial services. The problem of financial exclusion is well solved, and the alternative financing role of informal finance is weakened. In columns (2) and (4) of **Table 13**, B and D significantly enhance the negative impact of the provision of trade credit on sustainable growth, and B plays a larger role. The above results can be further interpreted as that digital finance mainly affects the impact of trade credit on the sustainable growth of enterprises through the coverage of breadth channel.

5 CONCLUSION AND POLICY IMPLICATIONS

Financing is the key factor restricting the development of enterprises. As an important part of supply chain finance, trade credit financing plays an important role in the business activities of enterprises. This paper took Chinese listed companies as research samples to explore the impact and mechanism of trade credit on sustainable growth, as well as the moderating effect of digital finance. The results showed that access to trade credit contributes to the sustainable growth of enterprises, and this relationship is more obvious in enterprises in areas with higher financial development level, enterprises in high-tech industry, state-owned enterprises and small enterprises. The provision of trade credit significantly inhibits the sustainable growth of enterprises, and this effect is more obvious in enterprises in areas lower financial development level, enterprises in non-high-tech industries, private enterprises and small enterprises. The results of influence mechanism showed that access to trade credit has an impact on sustainable growth through reducing agency cost. Providing trade credit will produce "compulsion effect," which restricts the sustainable growth of enterprises. Further analysis showed that the development of digital finance has a moderating effect on the relationship between trade credit and enterprise sustainable growth. Specifically, the higher the development level of digital finance, the weaker the positive impact of trade credit access on sustainable growth of enterprises, and the stronger the negative impact of trade credit provision on sustainable growth. As can be seen from the above results, the effect of digital finance in serving the real economy has not been fully manifested.

The empirical results show that trade credit financing significantly promotes the sustainable growth of Chinese enterprises. Therefore, trade credit financing remains a viable alternative to corporate financing in the context of imperfect financial systems in China and other countries. In order to fully mobilize the impetus of sustainable growth of enterprises and maximize the role of trade credit financing, the government must strengthen the construction of credit, enhance the quality of contract, and realize the healthy development of trade credit. At the same time, we found that the service effect of digital finance on the sustainable growth of enterprises is not ideal. It can be seen that although China's digital finance development level is at the forefront of the world, it does not play a greater role. Therefore, governments of all countries should strengthen the construction of digital financial infrastructure, enhance the coverage of network services, fully mobilize the ability of digital finance to serve the real economy, and jointly undertake the task of high-quality economic development together with trade credit.

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

TL: Conceptualization, Supervision, Validation, Project administration, funding support and Writing-review. WL: Formal analysis, Writing-original draft, Writing-review and editing. EE: Writing-review and language polishing. XL: Logicalization, content modification, review and accountability. Conceptualization, formal analysis, writing-revise, project administration. All authors contributed to manuscript revision and approved the submitted version.

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Effect of High-Tech Manufacturing Co-Agglomeration and Producer Service Industry on Regional Innovation Efficiency

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The study discusses the effect of co-agglomeration between the producer service industry and the high-tech manufacturing industry on regional innovation efficiency. Based on data from public companies of three urban agglomerations from 2011 to 2019, we used the Data Envelopment Approach (DEA)- Banker, Charnes, Cooper (BCC) model to estimate real innovation efficiency. Results found that the industrial co-agglomeration and regional innovation efficiency have an "inverted U-shaped" relationship. The industrial co-agglomeration in regions with a low level of co-agglomeration plays an important role in expediting regional innovation efficiency than that in high-level areas of co-agglomeration. Moreover, it is confirmed that the prefecture-level cities of the three urban agglomerations have low innovation efficiency types and low collaborative agglomeration types. Yangtze and Pearl river delta urban agglomeration can promote innovation efficiency through industrial co-agglomeration. While for the industrial co-agglomeration of Beijing, Tianjin, and Hebei, the urban agglomeration has not become the main way to promote innovation efficiency. The regression results of different industry collaborative agglomeration found that the co-agglomeration of information transmission, computer services, software industries, and the high-tech manufacturing industry plays a significant role to improve innovation efficiency. Moreover, the co-agglomeration of the transportation service industry and high-tech manufacturing industry plays a relatively weak role in regional innovation efficiency. Therefore, it is suggested to formulate more adaptive and heterogeneous market policies. The paper provides an important idea for improving innovation efficiency by optimizing industrial spatial layout.

Keywords: industrial agglomeration, innovation efficiency, service industry, Yangtze river, China

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1 INTRODUCTION

The producer service industry is representative of the modern service industry. The high-tech manufacturing industry has better technological innovation ability and market competitiveness than the traditional manufacturing industry (Peng et al., 2019b; Peng et al., 2020a; Zhao et al., 2020). According to the National Bureau of Statistics data in 2020, the added value of the high-tech manufacturing industry increased by 5.9% from last year in the first ten months. It is significantly faster than the growth of industries above the designated size and continued to maintain rapid growth. Under the epidemic's impact, some high-tech enterprises have accelerated their transformation and gradually transformed into a combination of online and offline. In the context of the current economic transformation, the integrated development between producer services and high-tech manufacturing can better represent the direction of economic development and industrial structure optimization in China (Peng et al., 2019b; Tu et al., 2019; Zheng et al., 2020; Peng et al., 2021a). In addition, according to the data of the "China Enterprise Innovation Capability Ranking 2020″, the invention patents applied by the top 1000 high-tech enterprises took possession of 62.9% of the overall number of patents applied for that year, the proportion has increased by 2.9% than last year. It is particularly valuable to explore regional innovation from the perspective of the high-tech enterprises, and one of the important ways to promote enterprise innovation is the integrated development of producer services and manufacturing, especially high-tech manufacturing (Huang et al., 2021; Wu et al., 2021; Zhao et al., 2021).

The ability of independent innovation is the top priority of long-term industrial structure adjustment (Peng et al., 2019a; Zhang H. X. et al., 2020; Peng et al., 2020c), and the improvement of innovation ability is not only due to the continuous increase of R&D investment because of the increase of innovation efficiency (Dai and Liu, 2016). Adoption of technology is important for the sustainability and efficiency of the ecosystem (Elahi et al., 2019c; Elahi et al., 2021a). Regarding innovation efficiency, previous studies have focused on its influencing factors, including environmental regulation, ownership structure, equity allocation, and industrial agglomeration (Elahi et al., 2020; Elahi et al., 2021b; Elahi et al., 2022). Among them, around the proposition of the relationships between the industrial agglomeration and innovation efficiency, the early study was mainly the perspective of producer service industry agglomeration (Wang et al., 2019; Peng et al., 2021b; Zhong et al., 2021). Some scholars believed that the diversification of the producer service industry agglomerated in the eastern region and large and medium-sized prefecture level cities. The promotion of innovation efficiency is obvious, and the rise of specialized agglomeration is obvious in the western and middle regions and small cities (Yang and Bao, 2019). Specialization agglomeration will help improve the innovation efficiency of the manufacturing industry in the area (Shen et al., 2019; Zhang et al., 2019; Tu et al., 2020; Peng et al., 2021d). Most scholars agreed that the promotion influence of industrial agglomeration on innovation efficiency is more obvious (Peng et al., 2020b; Wang et al., 2021; Zhang et al., 2021). This research perspective emphasizes the effect of industrial agglomeration, but industrial agglomeration does not reflect the co-agglomeration relationship between industries, and the conclusions that focused on the effect of different industrial agglomeration on innovation efficiency are inconsistent.

In the last decade, with the continuous development of the manufacturing industry and the producer service industry, the upstream and downstream relationship between the manufacturing industry and the producer service industry in the same industry chain has become more obvious. The innovation environment and innovation cost have an impact, and then the incentives for the formation of innovation efficiency are also emerging (Amiti, 2001; Weterings and Boschma, 2009; Zhong et al., 2020). Consequently, the industrial co-agglomeration has gradually become an advanced stage of industrial agglomeration (Wang and Sun, 2020), and its impact on innovation efficiency has also become a current research hotspot. Many Chinese scholars agreed that the promotion effect of the two industries' co-agglomeration is obvious (Hua et al., 2021). Furthermore, some scholars have studied the effect of industrial co-agglomeration on industrial enterprise innovation and regional innovation. In various studies, it is found that the industrial co-agglomeration has increased the technological innovation of manufacturing enterprises (Liu et al., 2019). However, the selection of indicators is often limited by factors such as enterprise characteristics and local policies. Furthermore, it is reported that the level of urban innovation will continue to improve with the deepening of industrial co-agglomeration, but it will be affected by urban and industry heterogeneity (Peng et al., 2021c; Zhang et al., 2022; Zhao et al., 2022) (Liu et al., 2019). The promoting effect of industrial co-agglomeration on urban innovation decreased in Eastern, Central, and Western regions (Wang and Mu, 2020). However, different from the research conclusions of the above scholars on agglomeration and co-agglomeration, some scholars believed that in the initial period of industrial agglomeration, the crowding effect dominated and inhibited economic development (Sun et al., 2013). Other scholars agreed that the agglomeration of producer services has no obvious effect on regional innovation and that there is a nonlinear relationship between co-agglomeration and regional innovation capabilities. The manufacturing industry mainly promoted regional innovation through effective interaction with local human capital (Ni and Li, 2017; Sheng et al., 2019). Most previous studies focused on the industry, enterprise, and macro-regional levels; however, did not emphasize regional innovation efficiency. The research on the high-tech manufacturing industry is important for innovation-driven development. In the context of today's domestic circular economy, the co-agglomeration effect of producer services and high-tech manufacturing should not be ignored. Therefore, the current study explored the action path of the two industries' co-agglomeration on innovation efficiency. Moreover, we integrated the micro data of all enterprises to measure the innovation efficiency of the regions.

The article consists of several sections. **Section 1** deals with the introduction. **Section 2** describes the theoretical framework of the study and research hypotheses. **Section 3** relates to research methods. **Section 4** presents the results and discussion. **Section 5** provides the main findings of the study with policy implications.

2 THEORETICAL FRAMEWORK AND HYPOTHESES

2.1 The Impact Mechanism

With the enhancement of the co-agglomeration relationship, the competition effect, cooperation effect, spillover effect, and learning effect gradually appeared and promoted enterprise innovation, and improved enterprise innovation efficiency (Xie and Wu, 2017).

2.1.1 Competitive Effects

The product market in agglomeration areas is very competitive (Chen and Hu, 2008). Due to the early completion of innovation, enterprises will break the original profit distribution pattern, putting the enterprises behind the R&D in a disadvantageous position or even facing a choice of survival. These enterprises will increase the enthusiasm of technical R&D personnel through the implementation of rewards and punishment. It improves the level and ultimately promotes the efficiency of enterprise innovation.

2.1.2 Cooperation Effect

It is often difficult for a single enterprise to maintain the supply of knowledge, and technology required for innovation. It is more inclined to seek cooperation with related enterprises to obtain new ideas or product technologies, and co-agglomeration of industries provides convenience for such cooperation. When companies in the industry know each other well enough, they have established a foundation of trust, which reduces the risk and uncertainty of cooperation and makes it easier to improve innovation efficiency (Xie and Wu, 2017).

2.1.3 Spillover Effect

By sharing R&D infrastructure, knowledge, and information service systems, the enterprises in the industrial co-agglomeration area are conducive to improving the utilization efficiency of software and hardware facilities in the region, producing a "1 + 1>2″ collaborative innovation effect, reducing production costs in the R&D process and saving technical consulting services between enterprises and other time to improve the fault tolerance rate in the innovation process.

2.1.4 Learning Effect

The learning effect is reflected in the exchange and cooperation of personnel and technology between enterprises, and co-agglomeration reduces the cost of such frequent contacts and provides a suitable environment. Alfred Marshall believes that synergistic gathering in the same space will promote more knowledge spillover. Enterprises themselves continue to accumulate experience and knowledge in the process of innovative products, and form an efficient conversion of knowledge and technology through the learning-by-doing effect, thus continuously spawning new research results.

An excessive co-agglomeration will lead to a shift from scale effect to crowding effect. When the scale of the industry is too large and exceeds the environmental economy and market load, the agglomeration area will experience environmental degradation, infrastructure shortages, and rising living costs. In addition, there will be vicious competition among enterprises to compete for resources, breaking the trust established before, and the "restriction effect" of cooperative R&D is strengthened (Li and You, 2018), and the imbalance of factor ratio leads to non-economics, and inhibiting innovation. The negative externality of industrial co-agglomeration is also reflected in the "path dependence effect". The long-term development of enterprises in the low-end value chain will hinder the diffusion and transformation of technology, thereby inhibiting the efficiency of innovation.

It can be seen from the above analysis that industrial co-agglomeration can improve the efficiency of regional innovation. The industrial co-agglomeration in the region attracts a large number of related high-tech enterprises to enter, thereby reducing the search cost and communication cost of enterprises, and it is inevitable for enterprises to exchange and cooperate in the process. As an important part of regional innovation efficiency, enterprise innovation efficiency can more deeply analyze the ways that affect regional innovation efficiency, but excessive co-agglomeration will influence the opposite direction of innovation efficiency. Therefore, the co-agglomeration of producer services and high-tech manufacturing maybe has a nonlinear relationship. When the level of co-agglomeration is below a specific threshold, increasing the level of co-agglomeration will promote innovation efficiency, and when the level of industrial collaborative agglomeration exceeds this level. When a specific threshold is reached, innovation will be inhibited. Thus, the paper proposes the following assumptions on the impact of industrial co-agglomeration on innovation efficiency.

Hypothesis 1. Industrial co-agglomeration and regional innovation efficiency may exist in an "inverted U-shaped" relationship.

2.2 The Impact Mechanism of the Co-Agglomeration

There are certain differences in the industry characteristics and functional positioning of the sub-sectors of the producer service industry. Therefore, the externalities generated by the co-agglomeration of different types of producer services and high-tech manufacturing industries affect innovation efficiency, especially for innovation efficiency from the micro perspective of high-tech enterprises may produce different results. The co-agglomeration of transportation, warehousing, and postal industries and high-tech manufacturing is conducive to promoting the factors of mobility and reducing the search cost and time cost of enterprises, which may imply an increase in regional innovation efficiency (Lv and Yuan, 2020). The development of high-tech manufacturing and the R&D innovation of enterprises are much more dependent on capital than traditional industries, and the financial industry has functions such as risk management, supervision, and incentives. Therefore, the co-agglomeration of the financial industry and high-tech manufacturing is likely to a large extent. Promote the innovation of high-tech enterprises, thereby greatly improving the efficiency of regional innovation (Lv and Yuan, 2020). Both industries are more closely related to high-tech manufacturing. According to Wang et al. (2019), it is found that the degree of co-agglomeration and correlation between industries may have different effects on total factor productivity. Therefore, the given assumptions can be written as:

Hypothesis 2. Heterogeneous industries of producer services and co-agglomeration of high-tech manufacturing have a positive moderating effect on innovation efficiency, but the effects are different.

In addition, the co-agglomeration of producer services and high-tech manufacturing requires certain social and economic conditions in the region and is affected by local policies and macroeconomic environment, and the three major urban agglomerations have differences in economic level, factor endowment, and resource allocation. It not only leads to differences in the level of co-agglomeration between sub-sectors of producer services and high-tech manufacturing but also may lead to differences in their impact on innovation efficiency. Since the reform and opening up, regional economic development has shown remarkable regional characteristics. From South to North, the three major urban agglomerations have successively become the new highlands of China's economic growth. The three major urban agglomerations have attracted a large number of talented and skilled workers from underdeveloped areas to gather spontaneously due to their superior economic development environment, large development space, and high wage levels. Due to their proximity to ports, transportation costs and transaction costs are low, the business environment is convenient, it is easy to form resource agglomeration, and attract huge external incremental resources. The entry of high-quality foreign capital has stimulated regional industrial integration, and the growth rate of the high value-added tertiary industry, especially the modern service industry represented by the producer service industry has gradually surpassed the secondary industry. The demand for human capital and the gathering of industries and talents have further stimulated the improvement of the technological level of the three major urban agglomerations. However, of the differences between urban agglomerations, the Yangtze River Delta and Pearl River Delta urban agglomerations also contain a large number of high-tech enterprises and traditional manufacturing industries. Except for Beijing and Tianjin, Beijing, Tianjin, and Hebei have smaller industrial scales and are more affected by government policies (Liu, 2020). Therefore, we can write a hypothesis as:

Hypothesis 3. The co-agglomeration of two industries in different urban agglomerations may have different results on innovation efficiency.

3 MATERIAL AND METHODS

3.1 Source of Data Collection

From 2011 to 2019, the data of public companies were collected from the CSMAR database and WIND database of Guotaian. The record is derived from the 'China Urban Statistical Yearbook' and 'China High-tech Industry Statistical Yearbook'. According to the data integrity and availability, the research period of this paper began in 2011, and the cities with serious data missing were excluded. Finally, 743 listed companies' annual observations in 43 prefecture-level cities were obtained. The missing data were supplemented by mean interpolation.

3.2 Construction of Statistical Model and Definitions of Variables

3.2.1 Statistical Model

In the previous literature, it is found that the co-agglomeration level of producer services and high-tech manufacturing and regional innovation efficiency is not a simple linear relationship. When a variable reaches a certain value, it will show a nonlinear relationship. Therefore, this paper discusses when the two are related, the square term of the level of industrial co-agglomeration is added, and the following prefecture-level, city-level panel model is set to test the impact of the co-agglomeration of producer services and high-tech manufacturing on regional innovation efficiency:

$$eff_{it} = \beta_0 + \beta_1 Coagg_{it} + \beta_2 Coagg_{it} \times Coagg_{it} + \beta_3 Contr_{it} + u_i + u_t + \varepsilon_{it} \tag{1}$$

where eff is amount to regional innovation efficiency, Coagg is the amount to the level of industrial co-agglomeration, and contr is the amount to other control variables, including enterprise age, financial leverage, enterprise scale, government subsidies, and corporate cash flow. u_i and u_t represent the fixed effect of city and year, respectively. ε_{it} is the residual term which is assumed to be normally distributed at zero mean value and constant variance (Elahi et al., 2019a; Elahi et al., 2019b; Elahi et al., 2020).

3.2.2 Definitions of Variables

According to a new economic growth theory, the accumulation of human capital can generate incremental returns, and increase the returns of other input factors, thereby increasing the total returns to scale. Therefore, the DEA-BCC model under the condition of variable returns to scale is selected to break through the constraints of a small feasible domain that is established, and the innovation efficiency eff is measured with the help of pure technical efficiency PTE. It should be paid attention to using the DEA-BCC method to measure innovation efficiency. It still needs the input and output indicators of enterprise innovation. The research results of Chen et al. (2012) and Liang et al. (2015) proved that listed companies did not disclose new products. For the sales revenue data, this paper selects the number of technical personnel and R&D expenses of listed companies in the region as input indicators to reflect the labor and capital input of innovation efficiency respectively and chooses the number of patent applications of listed companies in the region as the output indicator of innovation efficiency. Since the contribution of capital input to output is not only reflected in the current period, the capital stock of R&D funds is estimated by referring to the estimation formula of R&D capital stock (Wu, 2008).

$$K_{i,t} = E_{i,t-1} + (1 - \delta)K_{i,t-1} \tag{2}$$

where K represents the capital stock of R&D expenditures, E represents the price-adjusted R&D expenditures, and δ is the depreciation rate of the capital stock of R&D expenditures. The R&D capital stock is directly set at 15% based on the experience of

TABLE 1 | Definitions and summary statistics of variables.

Variables	Number of observations	Mean	Standard deviation	Minimum	Maximum
Innovation efficiency	387	0.392	0.306	0.027	1
Level of collaborative agglomeration	387	2.978	1.317	1.04	11.41
Firm age	387	10.071	3.686	2	22
Financial leverage	387	0.515	0.186	0.131	2.414
Size of enterprise	387	15.304	1.855	11.622	20.993
Public subsidy	387	9.714	1.945	3.714	14.563
Enterprise cash flow	387	0.049	0.04	-0.129	0.249

previous papers. The capital stock of R&D expenditures in the base period is estimated using the following formula:

$$K_{i0} = E_{i0} / (g + \delta) \tag{3}$$

The initial year of estimation is extended to 2007, where g is the average growth rate of R&D expenditure.

3.2.2.1 Core Explanatory Variables

Following the study of Lv and Yuan (2020), the industrial synergy agglomeration exponent refers to the measurement method, and the synergy agglomeration exponent is constructed as follows:

$$magg_i = \left(\frac{E_{mi}}{E_m}\right) \Big/ \left(\frac{E_i}{E}\right) \tag{4}$$

$$psagg_{\mathrm{i}} = \left(\frac{E_{psi}}{E_{ps}}\right) \Big/ \left(\frac{E_i}{E}\right) \tag{5}$$

$$Coagg_i = 1 - \frac{|magg_i - psagg_{\mathrm{i}}|}{(magg_{\mathrm{i}} + psagg_i)} + (magg_i + psagg_i) \tag{6}$$

where $magg_i$ represents the location entropy exponent of high-tech manufacturing in region i, $psagg_i$ represents the location entropy exponent of producer services in region i. $\mathrm{E_{mi}}$ *and* $\mathrm{E_{psi}}$ represents high-tech manufacturing and producer services in region i, respectively. $\mathrm{E_m}$ *and* $\mathrm{E_{ps}}$ represents the national employment in high-tech manufacturing and producer services, respectively, E_i is the total employment in i region, and E is the total national employment. $Coagg_i$ represents the co-agglomeration exponent of producer services and high-tech manufacturing in region i. The larger the value of $Coagg_i$, the higher the level of co-agglomeration of the two industries in the region, and vice versa. The number of employees in high-tech manufacturing in each city is apportioned according to the proportion of each city's GDP in the province's GDP. It can reflect the heterogeneity of the co-agglomeration level of each city.

3.2.2.2 Control Variables

Following Zhang et al. (2020b), we selected the control variables. The selected control variables included the age of the company (Age), expressed as the year of the current year - the year of the company's listing +1; financial leverage (Fle), expressed as total liabilities and total assets. The scale of the enterprise (Scale), expressed in the total assets of the enterprise, and taking the natural logarithm; government subsidies (Gg), expressed in the total government subsidies to the enterprise, and taking the natural logarithm; enterprise cash flow (Cash), expressed as the ratio of net operating cash flow to total assets. The definitions of variables are given in **Table 1**.

4 RESULTS AND DISCUSSION

4.1 Summary Statistics of Variables

After eliminating the missing samples, all samples include 743 listed companies in 43 prefecture-level cities in 9 years of micro-data summation, which is a balanced panel (**Table 1**). Specifically, the average value of regional innovation efficiency is 0.392. The maximum value of the collaborative agglomeration level is 11.41, and the minimum value is 1.04. It shows that the degree of collaborative agglomeration and regional innovation efficiency of producer services and high-tech manufacturing industry between different cities are quite different. Enterprise maximum age is 22, and the minimum is 2. The maximum financial leverage is 2.414, indicating areas where leverage is high. The maximum value of government subsidies is 14.563, and the minimum value is 3.714, indicating that there are great differences in government support in different regions.

4.2 Regression Analysis of Overall Samples

To examines the stability of the estimated coefficients of the core explanatory variables and the control variables, the core explanatory variables, the control variables, and the square term of the core explanatory variables are gradually added to the regression equation. The results are given in **Table 2**. Statistical models 1 and 2 respectively, test the relationship between industrial collaborative agglomeration and regional innovation efficiency without introducing control variables. Statistical model 3 based on model 2, controls the region and year double fixed effect. Statistical model 4, based on model 1 at the same time added the level of collaborative agglomeration and its square term. Statistical model 5 is added to the control variables to examine the relationship between innovation efficiency and collaborative agglomeration level and its square term. Considering that the existence of missing variables or other uncontrollable factors may lead to deviations in the results, and the regression fitting degree of the double fixed effect model is better than that of the mixed regression, the regression estimation results of the statistical model (3) are mainly discussed below. The independent variables of panel data are tested by autocorrelation

TABLE 2 | Results of regression.

Variables	Innovation efficiency (1)	Innovation efficiency (2)	Innovation efficiency (3)	Innovation efficiency (4)	Innovation efficiency (5)	VIF
Coagg	0.038*** (0.014)	0.051*** (0.015)	0.023*** (0.008)	0.094*** (0.026)	0.059*** (0.022)	1.14
Age	—	−0.007* (0.004)	0.020 (0.015)	—	0.019 (0.015)	1.09
Fle	—	0.250*** (0.078)	−0.002 (0.053)	—	−0.007 (0.053)	1.18
Scale	—	−0.062** (0.031)	−0.363*** (0.034)	—	−0.359*** (0.034)	9.10
Gg	—	0.024 (0.027)	0.030* (0.016)	—	0.030* (0.016)	8.81
Cash	—	−0.166 (0.467)	−0.345* (0.187)	—	−0.351* (0.187)	1.06
Coagg × C oagg	—	—	—	−0.006** (0.002)	−0.003* (0.002)	—
Xtserial	—	—	Prob > F = 0.000	—		—
City	No	No	Yes	Yes	Yes	—
Year	No	No	Yes	Yes	Yes	—
Constant	0.281*** (0.044)	0.903*** (0.245)	5.410*** (0.549)	0.172*** (0.055)	5.271*** (0.553)	—
R^2	0.026	0.08	0.861	0.806	0.862	—

*Standard errors are given in the parentheses. * * *, * * and * represent level of significance of parameters at 1%, 5% and 10%, respectively.*

and multicollinearity test. The results show that there is no multicollinearity problem between variables, and the original assumption that there is no first-order autocorrelation is rejected.

In terms of core explanatory variables, whether or not the control variables are added, the regional innovation efficiency coefficient is significantly positive. It means that the moderate co-agglomeration of the two industries will positively promote regional innovation efficiency. Through statistical model 4 and model 5, it is found that the coefficient of the Coagg square term is always negative. It indicates that the industrial co-agglomeration and regional innovation efficiency exist in an "inverted U-shaped" relationship, which supports the theoretical hypothesis of this paper. With the improvement of industrial collaborative agglomeration levels, the diffusion of knowledge and technology is accelerating. Compared with enterprises outside the collaborative agglomeration area, enterprises in the collaborative agglomeration area are more likely to achieve new technological breakthroughs through low-cost learning and resource sharing. However, the market and space are limited. When the degree of regional collaborative agglomeration exceeds the load capacity of the region, the scarcity of resources will lead to the rise of production factor prices, and directly increase the production cost and R & D cost of enterprises (Li and You, 2018). Moreover, the enterprises in a fixed distance long-term cooperative relationship, excessive dependence on knowledge in the collaborative agglomeration area, may lead to technological innovation throughout the region is locked in a relatively backward stage. Because the risk of imitation is far lower than independent R & D, enterprises will continue to reduce R & D investment to avoid uncertainty, thereby inhibiting the improvement of regional innovation efficiency. The results are according to **Hypothesis 1**.

In terms of the age control variable, the impact of enterprise age on innovation efficiency is positive. The estimation coefficient of financial leverage (Fle) is negative and not significant, debt is not a major role in affecting the efficiency of enterprise innovation. The reason for the negative coefficient is that when the enterprise is in debt operation, the high-interest burden will crowd out some of the profits accumulated by the enterprise, thus crowding out the innovation activities. Enterprise scale (Scale) is negatively correlated at the 5% level with the continuous expansion of scale. Therefore, they are unwilling to carry out innovation activities with high-risk coefficients, thereby inhibiting enterprise innovation. Government subsidies (Gg) will promote enterprise innovation. Enterprise cash flow (Cash) is negative at the level of 10%. It means higher cash flow will inhibit enterprise innovation (Meng et al., 2021). The possible reason is that when the enterprise has more funds, it may be biased towards short-term investment, thereby reducing long-term innovation investment (Zhang H. X. et al., 2020).

4.3 High and Low Levels of Collaborative Agglomeration

The levels of industrial co-agglomeration and regional innovation efficiency have an inverted U-shaped relationship. For further verification, this paper takes the average value of collaborative agglomeration water of 43 prefecture-level cities 2.98 as the boundary. We divided the three urban agglomerations into high collaborative agglomeration level areas and low collaborative agglomeration level areas and performed the regression analysis (**Table 3**). The given results in columns 1 and 3 show the impacts of regions with a high level of collaborative agglomeration and regions with a low level of collaborative agglomeration on innovation efficiency without introducing control variables, respectively. It is found that the regions with a high level of collaborative agglomeration and regions with a low level of collaborative agglomeration can promote innovation efficiency regardless of whether the control variables are added, and the promoting effect of the latter is stronger than that of the former. This depicts that with the improvement of the collaborative agglomeration level, its promotion trend of innovation efficiency tends to be flat and gradually reaches saturation. The comparison of columns 2 and 4 showed that the promotion of innovation efficiency in areas with high collaborative agglomeration levels is mainly due to higher financial leverage, namely debt management. Whether high collaborative agglomeration or low collaborative

TABLE 3 | High and low levels of collaborative agglomeration.

Variables	High level of collaborative agglomeration		Low level of collaborative agglomeration	
	(1)	(2)	(3)	(4)
Coagg	0.029**(0.013)	0.019*(0.010)	0.057***(0.017)	0.031**(0.014)
Age	—	0.032(0.028)	—	0.017(0.017)
Fle	—	0.592***(0.185)	—	−0.061(0.050)
Scale	—	−0.603***(0.088)	—	−0.337***(0.035)
Gg	—	0.037(0.030)	—	0.014(0.018)
Cash	—	−0.498(0.494)	—	−0.129(0.175)
City	Y	Y	Y	Y
Year	Y	Y	Y	Y
Constant	0.343***(0.052)	9.070***(1.442)	0.218***(0.041)	5.031***(0.538)
R^2	0.777	0.864	0.832	0.890

*Standard errors are given in the parentheses. * * *, * * and * represent level of significance of parameters at 1%, 5% and 10%, respectively.*

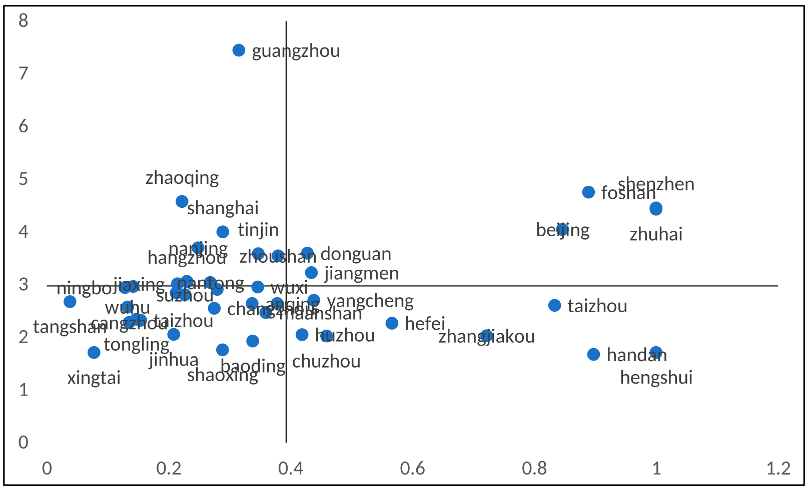

FIGURE 1 | Scatter plot.

agglomeration, the expansion of enterprise scale inhibits the increase of innovation efficiency. The possible reason is that the three major urban agglomerations, as the core hinterland of China's high-quality economic development, have better human, capital, and platform advantages, and have greater enthusiasm for R&D and innovation activities. With the continuous maturity of enterprises, the ability to cope with the market is gradually strengthened, and the competitive pressure is reduced. They are unwilling to carry out innovative activities with high-risk factors. Therefore, it will hinder the increase of real innovation efficiency.

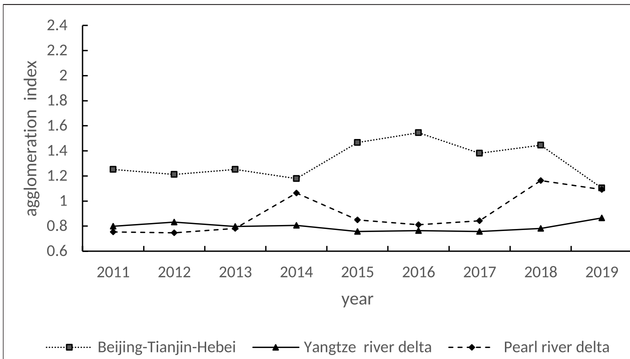

FIGURE 2 | Agglomeration of producer services.

4.4 Heterogeneity Analysis

Taking the mean value of regional innovation efficiency as the abscissa, the mean value of collaborative agglomeration water as the ordinate, and the mean value of the two as the quadrant boundary point are given in **Figure 1**. The samples in the three urban agglomerations are divided into four types. Type A is low innovation efficiency with a low collaborative agglomeration level. Type B is the high innovation efficiency with a low collaborative agglomeration level. Type C is the high innovation efficiency with a high collaborative agglomeration level. Type D is the low innovation efficiency with a high collaborative agglomeration level. Overall, most cities are still at a low level of co-agglomeration, while cities in the same urban agglomeration have different types of regions, indicating the necessity of further studying the incidence of co-agglomeration on

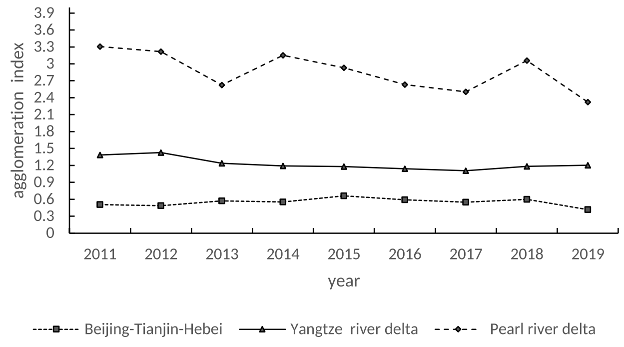

FIGURE 3 | High-tech manufacturing agglomeration.

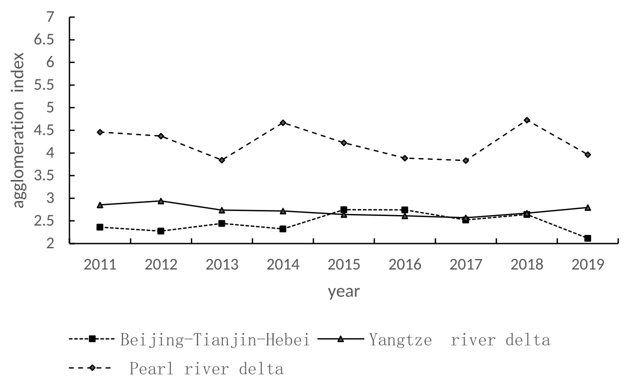

FIGURE 4 | Collaborative agglomeration of two industries.

innovation efficiency of different cities. Shenzhen, Zhuhai, Foshan, and other Pearl River Delta cities, producer services, and high-tech manufacturing industries are developing rapidly, and a large number of innovative elements are gathered. A good innovation environment makes the level of co-agglomeration and innovation efficiency at the forefront.

Similarly, **Figure 2**, **Figure 3**, **Figure 4** show the relationship between industrial agglomeration and co-agglomeration in different regions.

To further compares the internal differences between industrial co-agglomeration and regional innovation efficiency in coastal areas, the results of the regression are given in **Table 4**. The regression coefficient of industrial co-agglomeration on innovation efficiency in Beijing, Tianjin, and the Hebei region is not significant. The possible reason is that the level of co-agglomeration and innovation efficiency in Beijing and Tianjin are generally higher than those in other regions of Beijing, Tianjin, and Hebei, and have obvious comparative advantages. However, industrial collaborative agglomeration brings more competition for technology and innovation resources and has not yet formed a synergistic driving effect. The regression coefficient of innovation efficiency in the Yangtze River Delta region is significantly positive at the level of 1%. It is mainly due to government subsidies. Moreover, listed companies in the urban agglomeration need to reduce their cash flow and stop the expansion of scale to better promote regional innovation. The regression coefficient of innovation efficiency in the Pearl River Delta region is significantly positive at the level of 10%. However, due to the small sample size, the regression results of some variables may not be accurate, and there is no overstatement. By comparing the level of regional co-agglomeration, innovation efficiency, and the regression aboriginality between the two, it can be seen that the innovation efficiency of the three major urban agglomerations in Eastern China is generally improved. Compared with Shenzhen and Beijing, Shanghai's innovation efficiency is slightly insufficient, which is the same as the previous research conclusion. The results confirmed **Hypothesis 3**.

To further compare the impact of co-agglomeration on regional innovation efficiency, we divided the co-agglomeration of producer services and the high-tech manufacturing industry into five types. Transportation, warehousing and postal industry and high-tech manufacturing industry collaborative agglomeration ($Coagg_{jt}$), information transmission, computer services, and software industry and high-tech manufacturing industry collaborative agglomeration ($Coagg_{xx}$), scientific research and technology services and high-tech manufacturing industry collaborative agglomeration ($Coagg_{kx}$), financial industry and high-tech manufacturing industry collaborative agglomeration ($Coagg_{jr}$) and leasing and business services and high-tech manufacturing industry collaborative agglomeration ($Coagg_{zl}$), which are reported in **Table 5**. The

TABLE 4 | Regression results of distinguishing regions.

Variables	Beijing-Tianjin-hebei		Yangtze river delta		Pearl river delta	
	(1)	(2)	(3)	(4)	(5)	(6)
Coagg	0.027(0.041)	0.000(0.031)	0.062***(0.019)	0.047***(0.017)	0.026**(0.010)	0.020*(0.011)
Age	—	0.049**(0.019)	—	0.008(0.036)	—	0.028(0.033)
Fle	—	−0.100*(0.052)	—	0.136(0.142)	—	0.361(0.236)
Scale	—	−0.416***(0.049)	—	−0.442***(0.066)	—	−0.340**(0.148)
Gg	—	−0.011(0.029)	—	0.064**-0.025	—	−0.012(0.037)
Cash	—	−0.015(0.158)	—	−0.749**(0.352)	—	−0.156(0.728)
City	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.307***(0.083)	6.642***(0.689)	0.141***(0.053)	6.140***(1.152)	0.434***(0.046)	5.550**(2.370)
R^2	0.868	0.894	0.589	0.695	0.894	0.910

*Standard errors are given in the parentheses. * * *, * * and * represent level of significance of parameters at 1%, 5% and 10%, respectively.*

TABLE 5 | Regression results of distinguishing industrial collaborative agglomeration types.

Variables	Innovation efficiency	Innovation efficiency	Innovation efficiency	Innovation efficiency	Innovation efficiency
	(1)	(2)	(3)	(4)	(5)
$Coagg_{jt}$	0.027** (0.010)	—	—	—	—
$Coagg_{xx}$	—	0.032*** (0.011)	—	—	—
$Coagg_{kx}$	—	—	0.030*** (0.011)	—	—
$Coagg_{jr}$	—	—	—	0.032*** (0.010)	—
$Coagg_{zl}$	—	—	—	—	0.031*** (0.010)
Control	Y	Y	Y	Y	Y
City	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y
Constant	5.395*** (0.554)	5.378*** (0.551)	5.404*** (0.551)	5.342*** (0.551)	5.411*** (0.550)
R^2	0.859	0.860	0.859	0.860	0.860

*Standard errors are given in the parentheses. * * *, * * and * represent level of significance of parameters at 1%, 5% and 10%, respectively.*

TABLE 6 | Results of the robustness test.

Variables	Change variable measurement method		Tailing treatment		Adjusted sample time	One Lag phase	2SLS_IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coagg	0.003*(0.002)	0.021***(0.007)	0.029***(0.009)	0.040***(0.012)	0.032***(0.009)	0.022***(0.008)	0.062***(0.02)
Control	Y	Y	Y	Y	Y	Y	Y
City	Y	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y	Y
Constant	1.380***(0.378)	3.002***(0.473)	5.377***(0.540)	5.811***(0.513)	2.389***(0.760)	5.064***(0.569)	0.906***(0.244)
R^2	0.854	0.846	0.862	0.865	0.928	0.862	0.078
Wald inspection	—	—	—	—	—	—	445.01
unrecognizedLM	—	—	—	—	—	—	24.234 (0.0000)

*Standard errors are given in the parentheses. * * *, * * and * represent level of significance of parameters at 1%, 5% and 10%, respectively.*

results showed that the co-agglomeration of the financial industry, information transmission, computer services, and software industry, and high-tech manufacturing industry has the most prominent effect on improving regional innovation efficiency, while the co-agglomeration of transportation, warehousing, and postal industry and high-tech manufacturing industry has a relatively weak effect on regional innovation efficiency. The results satisfied **Hypothesis 2**.

4.5 Robustness Test

4.5.1 The Measurement Method of Changing Innovation Efficiency

Following the Jiang et al. (2020), the ratio of natural logarithm LN (PAT_{t+1}+1) of authorized patent number PAT of listed companies in the city i in t + 1 year to natural logarithm LN (RD_t+1) +1 of R&D expenditure of listed companies in the city i in t year is used as the first replacement exponent to measure regional innovation efficiency. Furthermore, the technical efficiency (TE) measured by the above BCC model as the second replacement exponent, the results remained unchanged (**Table 6**).

4.5.2 Tailing Treatment

Take a 1% or 5% double-tailed test, particularly 1% or 5% is the double-tailed treatment of all relevant variables, eliminate the impact of some extreme values on the study, and re-examine the two-way fixed effect regression. According to the regression results, the coefficient of regional innovation efficiency is significantly positive at the level of 5% or 1%, which is consistent with the previous results (**Table 6**).

4.5.3 Adjustment in Sample Period for 2011–2016

At present, most of the literature based on the ' China High-tech Statistical Yearbook ' has been studied by provincial data until 2016, while the sample deadline selected in this paper is 2019, and some missing data are supplemented according to relevant research methods. To avoids interfering with the empirical results of the processed data, we adjusted the sample period to 2011–2016 and re-estimated it. The research conclusion is consistent with the above, and through the regression results, it is found that government subsidies have changed from non-significant to significant and the direction of the coefficient remained unchanged. The government started to pay attention to the financial support for local enterprises over time, and become one of the factors affecting the innovation efficiency of obviousness. However, it should be noted that reasonable policies and strict subsidy standards should be formulated to avoid the occurrence of non-benign rent-seeking and other situations that lead to the suppression of innovation. The results are given in **Table 5**.

4.5.4 One-Period Lag of Control Variables

In the previous literature, the impact of input is not all the current output is alleviated by the lag of R&D expenditure, but other control variables may also have potential endogenous problems. To check the robustness of the results, all other control variables are lagged for one period and tested by two-way fixed regression. The results remained unchanged (**Table 6**).

4.5.5 Endogenous Problems

The increase in innovation efficiency will reduce the production cost of the region. Through the strengthening of communication and cooperation, the factor flow between industries leads to the formation of the industrial association effect between upstream and downstream industries, and further promotes industrial collaborative agglomeration. At the same time, to reduce the cost of learning, transportation, and trading, it will be biased toward the location of the region. Although the two-way fixed effect can reduce the impact of missing variables to a certain extent when enterprises with high innovation ability move into areas with high collaborative agglomeration. To better alleviate the endogenous errors caused by two-way causality and missing variables, this paper adopts instrumental variables to further test. According to Ji and Gu (2020), the lag phase of the core explanatory variable is used as a tool variable to estimate the two-stage least squares method. The test results are shown in column 7 of **Table 6**. The estimated coefficient of the core explanatory variable is significantly positive at the level of 10%, and the Cragg-Donald Wald F statistic 445.01 is greater than the critical value at the level of 10%, which rejected the hypothesis of weak instrumental variables. The unidentifiable LM test p-value is 0.0000, which rejected the unidentifiable hypothesis. Therefore, the selection of instrumental variables is reasonable and effective.

5 CONCLUSION AND POLICY IMPLICATIONS

This paper uses the data of listed companies in the three major urban agglomerations from 2011 to 2019 to explore the impact of the co-agglomeration of producer services and high-tech manufacturing on innovation efficiency through two-way fixed panel model. The main findings of the study can summarize as:

1) Industrial co-agglomeration can encourage innovation efficiency through multiple effects, but excessive agglomeration may also inhibit innovation efficiency. The empirical results also test the "inverted U-shaped" relationship between collaborative agglomeration and innovation efficiency. It means strengthening co-agglomeration can promote innovation efficiency when the industrial co-agglomeration is at a relatively low level.
2) The promotion effect of industrial co-agglomeration on innovation efficiency is more obvious, especially for the regions with low-level of co-agglomeration. On the one hand, differentiated policies should be implemented in regions with different situations to encourage innovation through the level of co-agglomeration of the two industries. On the other hand, to guide enterprises in regions with higher collaborative agglomeration to develop into labor-intensive or capital-intensive regions with low technological content. The gap in innovation efficiency among the three major urban agglomerations has shown a narrowing process.
3) Most regions are divided into low-level industrial agglomeration types. Therefore, it is an important way for economic development to promote innovation efficiency in different regions by coordinating the development of heterogeneous related industries. For the Yangtze River Delta and Pearl River Delta Urban Agglomeration, there is a strong complementary effect between producer services and manufacturing. Although the Beijing, Tianjin, and Hebei urban agglomeration has a lot of human capital and material capital, the siphoning effect of important cities such as Beijing and Tianjin is stronger than its radiation effect. Therefore, industrial co-agglomeration has not yet become the main way to promote innovation. The results of industry heterogeneity showed that the co-agglomeration of the financial industry, information transmission, computer services, and software industry, and high-tech manufacturing industry in producer services has the strongest influence on city innovation efficiency. While the co-agglomeration of transportation, warehousing and postal industry and high-tech manufacturing industry has a relatively weak effect on regional innovation efficiency.
4) The results of the study stress that the states should encourage and adjust the level of collaborative agglomeration among regions through fiscal and taxation policies.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

CP was responsible for the data collection and arrangement of relevant literature, data analysis, and article writing. PF and ZZ commented on the written article. EE revised the article. Moreover, FB and ZL also helped to collect data for the article.

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Empirical Decomposition and Forecast of Carbon Neutrality for High-End Equipment Manufacturing Industries

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The Chinese government focuses on the high-end equipment manufacturing industry to achieve a target of carbon neutrality. This study takes China's Bohai Rim as a case study. First, the Tapio decoupling model was used to analyze the carbon emission status of the high-end equipment manufacturing industry in the Bohai Rim. Second, LMDI was used to determine the main factors of carbon emission. Similarly, the Monte Carlo simulation predicted the time of carbon neutrality. The results found that the relationship between carbon emission and the development of the high-end equipment manufacturing industry is that of strong decoupling, but there is still a risk of "recoupling." The scale effect is the primary driving force for carbon emission reduction in the equipment manufacturing industry, followed by a structural effect and a carbon emission intensity effect. In the baseline scenario, low-carbon scenario, and technological breakthrough scenario, carbon neutrality will be achieved before 2060. The results of the study suggest that China should improve energy utilization efficiency and encourage green innovation.

Keywords: high-end equipment manufacturing industry, carbon neutrality, empirical decomposition, scenario simulation, China's Bohai Rim

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1 INTRODUCTION

In 2020, China proposed to achieve carbon neutrality by 2060. The goal of this proposal indicates that carbon emission reduction and carbon neutrality will be China's development themes for a long time. The high-end equipment manufacturing industry is a technology-intensive strategic emerging industry. It is located in the high-end link of the manufacturing industry. It has the characteristics of high added value, good growth, and a strong driving force. It acts as the engine of China's economic growth (Fan and Du, 2018). Although the high-end equipment manufacturing industry has a lower carbon emission level than other manufacturing industries, it still emits 10% of the carbon dioxide from the manufacturing industry. Therefore, reducing carbon emission to achieve carbon neutrality is the top priority.

China's Bohai Rim includes five provinces and cities, namely, Beijing, Tianjin, Hebei, Liaoning, and Shandong. It is one of the most important economic circles in China's coastal areas and the second largest place for high-end equipment manufacturing in China (Tong et al., 2019). In recent years, the development of the high-end equipment manufacturing industry in the Bohai Rim has made great progress. On the basis of maintaining traditional advantages, heavy high-tech industries are emerging. In addition, the Bohai Rim is also one of the largest carbon emission areas in China. Therefore, how to reduce the carbon emission of the high-end equipment manufacturing industry in the Bohai Rim not only contributes to achieving carbon neutrality goals, but also can provide experience and reference for high-end equipment manufacturing in other countries of the world to achieve carbon neutrality, and provide theoretical support for the environmental protection of the world.

Since the reform and opening up, the scale-expanding economic growth mode has made China the second-largest economy in the world. At the same time, China has also become the country with the largest total carbon emissions. With the gradual deterioration of climate issues such as global warming, reducing carbon dioxide emissions has become the consensus of all countries in the world, but the right to carbon emission represents a country's right to development to a certain extent (Elahi et al., 2020; Elahi et al., 2021a). Therefore, how to achieve economic growth while reducing carbon emission and environmental pollution is an important topic of academic research (Sheng et al., 2019; Odhiambo et al., 2020; Peng et al., 2021a; Peng et al., 2021b; Zhong et al., 2021).

To study carbon emission, it is necessary to identify the main influencing factors of carbon emissions, and on this basis, put forward relevant suggestions for carbon emission reduction (Peng et al., 2018; Peng et al., 2020; Zhang et al., 2020; Zhong et al., 2020; Gu et al., 2020a; Wu et al., 2021; Zhao et al., 2021). First, the continuous advancement of new urbanization has an important impact on China's carbon emissions (Gu et al., 2019; Gu et al., 2020b; Zhao et al., 2020; Wang et al., 2021). The adoption of management strategies is important to reduce environmental emissions and human health damages (Elahi et al., 2021b; Elahi et al., 2022a; Elahi et al., 2022b). Although the development of urbanization has increased the level of regional carbon emissions, urbanization can also promote carbon emission reduction by enhancing human capital accumulation and cleaner production technology. Therefore, strengthening the role of urbanization in the accumulation of human capital and the promotion of cleaner production technologies is the key method to solve the "high carbon lock-in" in the process of urbanization (Zhang et al., 2016). Second, the impact of carbon emission on economic development obeys the law of rising first and then decreasing. The key to carbon emission reduction lies in reaching the peak in advance and reducing the peak height. The adjustment of the industrial structure has reduced the regional carbon emission, which is conducive to peaking carbon dioxide emissions (Yuan et al., 2016). Financial efficiency can also affect carbon emissions. If sectors with lower carbon emissions can maximize corporate profits for financial institutions, the improvement of financial efficiency can reduce regional carbon emissions (Jing et al., 2021). Technological progress also plays a key role in the process of carbon emissions. Optimal use of resources is helpful for cleaner production and reduction of health damages (Elahi et al., 2019a; Elahi et al., 2019b; Elahi et al., 2019c). It affects energy costs, reduces energy prices, creates income effects and substitution effects of energy consumption, improves energy structure, increases the proportion of clean energy use, and ultimately reduces regional carbon emissions (Yang et al., 2019). Financial and advisory services are important to disseminate technology in the society (Elahi et al., 2018). The spatial agglomeration of the economy can affect carbon emission too. Its impact shows a significant negative relationship. At the same time, stricter environmental regulation policies and deeper regional integration development caused by economic agglomeration will also indirectly promote carbon emission reduction (Ren et al., 2020).

As an uncertainty analysis method, Monte Carlo simulation has the characteristics of comprehensiveness and flexibility, so it is widely used in the analysis of uncertain events (Shao et al., 2017). Carbon emission is regarded as a standard uncertainty event, so the use of Monte Carlo simulation can give full play to predict the future carbon emission level, thus providing an effective path for exploring carbon neutrality.

In the present article, we used the Tapio decoupling model to analyze the present status of carbon emission in the Bohai Rim. The LMDI method is used to decompose the influencing factors of carbon emission in China's high-end equipment manufacturing industry. Similarly, Monte Carlo simulation is conducted to analyze the evolution trend of carbon emission to predict the carbon neutrality of the high-end equipment manufacturing industry.

2 MATERIALS AND METHODS

2.1 Data Sources

Based on the research purpose, the data from five provinces and cities in the Bohai Rim from 2009 to 2019 were collected. Particularly, the data were collected from the China Statistical Yearbook (2010–2020), China Energy Statistical Yearbook (2010–2020), China Environmental Statistical Yearbook (2011–2020), and the statistical yearbooks of the five provinces and cities in the Bohai Rim. Some missing data were supplemented by the average value method.

2.2 Analytical Framework

2.2.1 Carbon Emission Measurement Model

Because of the lack of clear classification standards for China's high-end equipment manufacturing industry, this article refers to the "National Economic Industry Classification and Code" (GB/T 4754-2017), "Strategic Emerging Industries" (trial), and " High-tech Industry Statistical Classification Catalogue," combined with relevant literature (Huang and Zhang, 2015) and divides the high-end equipment manufacturing industry including General Equipment Manufacturing (C34), Special Equipment Manufacturing (C35), Automobile Manufacturing (C36), Railways, Ships, Aerospace and Other Transportation Equipment Manufacturing (C37), Electrical Machinery and Equipment Manufacturing (C38), Computer, Communications and Other Electronic Equipment Manufacturing (C39), and Instrumentation Manufacturing (C40).

Based on the method adopted by the Intergovernmental Panel on Climate Change (IPCC), this study uses energy consumption data from the provincial statistical yearbooks, and the models were constructed as follows:

$$CE = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{A_i} \times \mathrm{N_i} \times CC_i \times O_i \times B, \quad (1)$$

where CE is the total carbon emission of high-end equipment manufacturing in the Bohai Rim, i is the kinds of fossil energy, A_i

TABLE 1 | Decoupling situation.

Decoupling level		ΔC/C and ΔG/G	DE
Decoupling	Strong	ΔC/C < 0; ΔG/G > 0	DE < 0
	Weak	ΔC/C > 0; ΔG/G > 0	0 < DE < 0.8
	Very weak	ΔC/C < 0; ΔG/G < 0	DE > 1.2
Connection	Growth	ΔC/C > 0; ΔG/G > 0	0.8 < DE < 1.2
	Weak	ΔC/C < 0; ΔG/G < 0	0.8 < DE < 1.2
Negative decoupling	Weak	ΔC/C < 0; ΔG/G < 0	0 < DE < 0.8
	Strong	ΔC/C > 0; ΔG/G < 0	DE < 0
	Very weak	ΔC/C > 0; ΔG/G > 0	DE > 1.2

is the energy consumption, N_i is the low-energy calorific value, CC_i is the carbon emission factor provided by IPCC, O_i is the carbon oxidation factor, and B is the mass ratio of carbon dioxide molecules to carbon (3.667).

2.2.2 Tapio Decoupling Model

The Tapio decoupling model has been widely used in various fields (Petri, 2005). Since the Tapio model can accurately determine the decoupling state of a region at a certain time, this study uses the Tapio model to study the relationship between the development of high-end equipment manufacturing and carbon emission in the Bohai Rim, and the decoupling model is given as

$$DE = \frac{\Delta C/C}{\Delta G/G}, \tag{2}$$

where DE is the decoupling elasticity value, ΔC is the difference between the carbon emission of the present period and the carbon emission of the previous period, C is the carbon emission of the present period, ΔG is the difference between the total output value of the high-end equipment manufacturing industry in the Bohai Rim and the previous period, and G is the present gross output value. According to the division of the decoupling elasticity value by scholars (Liu, 2016), the relationship between high-end equipment manufacturing and carbon emission is divided into three types: connection, decoupling, and negative decoupling. The details are given in **Table 1**. Among them, a strong decoupling state means that the development of the high-end equipment manufacturing industry in the Bohai Rim is not based on energy consumption and carbon emission, and there is no direct relationship between industrial development and carbon emission. Weak decoupling and very weak decoupling indicate that as the industry develops, the negative impact of carbon emission will also increase, but the growth rate is smaller than that of economic development. The connection and negative decoupling states are both non-ideal states of carbon emission and industrial economic development.

2.2.3 LMDI Decomposition Model

This study uses the LMDI model to analyze carbon emission factors (Fu et al., 2021). The model is given as

$$C = \sum\nolimits_i C_i = \sum\nolimits_i Y\frac{Y_i}{Y}\frac{C_i}{Y_i} = \sum\nolimits_i CS_iT_i, \tag{3}$$

where C is the total carbon emission of high-end equipment manufacturing in the Bohai Rim, C_i is the carbon emission of various sub-sectors in the high-end equipment manufacturing industry, Y is the output value of the high-end equipment manufacturing industry in the Bohai Rim, Y_i is the output value of each sub-sector of the high-end equipment manufacturing industry, $S_i = Y_i/Y$ is the proportion of i industry output value in total output value, and $T_i = C_i/Y_i$ is i industry unit output value energy consumption.

Assuming 0 as the base period to the t period, the change in carbon emission can be estimated using the given function:

$$\Delta C = C^t - C^0 = \sum\nolimits_i C^tS_i^tT_i^t - \sum\nolimits_i C^0S_i^0T_i^0 = \Delta C_Y + \Delta C_S + \Delta C_T, \tag{4}$$

where ΔC_Y is the scale effect of carbon emission, indicating the difference in carbon emission due to changes in the output value of high-end equipment manufacturing; ΔC_S is the structural effect of carbon emission, indicating changes in carbon emission due to structural changes in various sub-sectors of the high-end equipment manufacturing industry; and ΔC_T is the intensity of carbon emission which indicates the change in total carbon emission due to changes in the intensity of carbon emission.

On the basis of the LMDI model, we continued using the additive decomposition model to decompose the carbon emission of high-end equipment manufacturing in the Bohai Rim, and the model is given as

$$\Delta C_Y = \sum\nolimits_i L\left(C_i^0, C_i^t\right)\ln\frac{Y_i^t}{Y_i^0}, \tag{5}$$

$$\Delta C_S = \sum\nolimits_i L\left(C_i^0, C_i^t\right)\ln\frac{S_i^t}{S_i^0}, \tag{6}$$

$$\Delta C_T = \sum\nolimits_i L\left(C_i^0, C_i^t\right)\ln\frac{T_i^t}{T_i^0}, \tag{7}$$

$$L\left(C_i^0, C_i^t\right) = \begin{cases} \dfrac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} & \left(C_i^t \neq C_i^0\right) \\ C_i^t & \left(C_i^t = C_i^0\right) \end{cases}. \tag{8}$$

2.2.4. Monte Carlo Simulation

Monte Carlo simulation is used to predict the carbon neutrality of the high-end equipment manufacturing industry in the Bohai Rim. Since the most likely variation interval and median value of a variable are known, but the shape of its probability distribution is unknown, it is assumed that each variable is a triangular distribution. Then, we used Crystal Ball to simulate each factor in the baseline scenario, low-carbon scenario, and technological breakthrough scenario to predict the specific time of carbon neutrality in the high-end equipment manufacturing industry in the Bohai Rim. The number of simulations is 500,000 times. The annual average change rate is set and refers to various policies.

TABLE 2 | Carbon emission of high-end equipment manufacturing in the Bohai Rim (10 kilo-tons).

Province	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	656	715	780	856	835	803	786	815	801	738	696
Tainjin	151	136	135	229	305	241	194	135	29	28	27
Hebei	899	1,130	1,313	920	939	935	882	908	876	838	792
Liaoning	1,217	1,459	1,576	1,696	1,850	716	610	429	267	149	109
Shandong	3,590	4,544	5,739	4,356	4,535	4,313	4,124	3,442	2,953	2,704	2,476
Bohai Rim	6,513	7,984	9,543	8,057	8,464	7,008	6,596	5,729	4,926	4,457	4,100

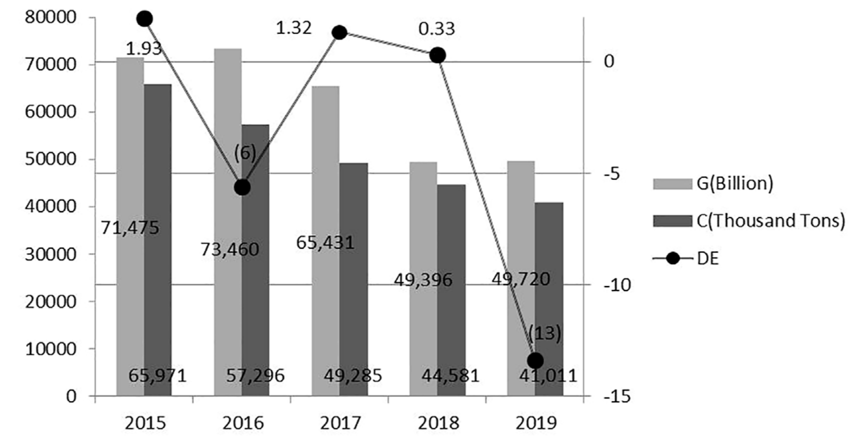

FIGURE 1 | Decoupling situation.

3 RESULTS AND DISCUSSION

3.1 Carbon Emission Status Analysis

According to the carbon emission measurement model, the carbon emission of high-end equipment manufacturing in the Bohai Rim was calculated (**Table 2**). From 2009 to 2019, the carbon emission of the high-end equipment manufacturing industry in the Bohai Rim showed an increasing trend and then reduced in the later stage. The peak of carbon emission occurred in 2011 with a total carbon emission of 95.43 million tons. From 2011 to 2019, the total carbon emission of the high-end equipment manufacturing industry in the Bohai Rim gradually decreased, with an average annual growth rate of 14.8%. From the perspective of provinces and cities, the carbon emission of the high-end equipment manufacturing industry generally presents the pattern of Shandong > Hebei > Beijing > Liaoning > Tianjin. Shandong Province contributed 60% of the total carbon emission of the high-end equipment manufacturing industry in the Bohai Rim.

3.2 Carbon Emission Decoupling Model Analysis

According to the Tapio decoupling model, this study analyzes the carbon emission decoupling effect of the high-end equipment manufacturing industry in the Bohai Rim in the past 5 years. It can be seen from **Figure 1** that since 2015, the output value (G), total carbon emission (C), and decoupling elasticity value (DE) of the high-end equipment manufacturing industry showed a decreasing trend. There was an adjustment from the weak decoupling state in 2015 to the strong decoupling state in 2019, but the decoupling state of regional carbon emission is not stable.

The carbon emission decoupling status of the high-end equipment manufacturing industry in various provinces and cities is shown in **Table 3**. It is found that by 2019, except for Shandong Province, other provinces and cities in the Bohai Rim will have reached a strong decoupling state of industrial development and carbon emission. Among them, Beijing has maintained a strong decoupling relationship between carbon emission and the development of the high-end equipment manufacturing industry in recent years. It is an advantageous area of decoupling effects in the Bohai Rim, which can provide a reference for the low-carbon development of other provinces and cities. Tianjin, Hebei, Liaoning, and Shandong have basically maintained a decoupling state; they have also crossed weak decoupling, and very weak decoupling indicates that the decoupling relationship between carbon emission and the development of high-end equipment manufacturing is not stable.

3.3 Decomposition of Carbon Emission Factors

3.3.1 Decomposition of Carbon Emission Factors in the Bohai Rim

From 2015 to 2019, the carbon emission of high-end equipment manufacturing in the Bohai Rim decreased by 28.95 million tons

TABLE 3 | Decoupling situation of the Bohai Rim.

Province	2015	2016	2017	2018	2019
Beijing	Very weak decoupling	Weak decoupling	Strong decoupling	Strong decoupling	Strong decoupling
Tainjin	Strong decoupling	Very weak decoupling	Very weak decoupling	Strong decoupling	Strong decoupling
Hebei	Strong decoupling	Weak decoupling	Weak negative decoupling	Weak negative decoupling	Strong decoupling
Liaoning	Weak negative decoupling	Weak connection	Very weak decoupling	Very weak decoupling	Strong decoupling
Shandong	Strong decoupling	Strong decoupling	Very weak decoupling	Weak negative decoupling	Weak negative decoupling
Bohai Rim	Very weak decoupling	Strong decoupling	Very weak decoupling	Weak decoupling	Strong decoupling

TABLE 4 | Decomposition of carbon emission factors in the Bohai Rim.

Bohai Rim	Changes in carbon emissions (10 kilo-tons)					
	2015	2016	2017	2018	2019	Total
ΔC	–333	–937	–800	–474	–351	–2,895
ΔCY	–252 (75.7%)	–19 (2.0%)	–291 (36.4%)	–1222 (257.8)	–395 (112.5%)	–2,179 (75.3)
ΔCS	195 (58.5%)	78 (–8.3%)	–258 (32.3%)	638 (134.6%)	170 (–48.4%)	–453 (15.6%)
ΔCT	–275 (82.6%)	–996 (106.3%)	–251 (31.4%)	1386 (–292.4%)	–127 (36.2%)	–263 (9.1%)

The values in parentheses indicate the contribution rate of each influencing factor.

of coal (**Table 4**). Among them, the carbon emission reduction caused by the scale effect of carbon emission was 21.79 million tons of coal, and the contribution rate to carbon emission reduction was 75.3%. The structural adjustment of the high-end equipment manufacturing industry reduced the carbon emission of 4.53 million tons of standard coal and contributed 15.6% to the carbon emission reduction. Changes in the intensity of carbon emission resulted in a reduction in carbon emission of 2.63 million tons of coal with a contribution rate of 9.1%.

From 2015 to 2019, the scale of the high-end equipment manufacturing industry in the Bohai Rim dropped from 7,147.5 to 4,971.9 billion yuan, and the total carbon emission also declined. It can be seen that the Bohai Rim has made significant progress in energy conservation and emission reduction in recent years. However, most of the reduction in carbon emission from high-end equipment manufacturing in the Bohai Rim region is due to the reduction in the output value, and such carbon emission reduction methods are unsustainable. Reduction of carbon emission intensity does not play an important role in the carbon emission reduction process of high-end equipment manufacturing in the Bohai Rim region. Therefore, improving the technical level and reducing the carbon emission intensity is an important way to reduce carbon emissions in the high-end equipment manufacturing industry in the Bohai Rim in the future.

3.3.2 Decomposition of Carbon Emission Factors in Provinces and Cities

3.3.2.1 Scale Effects

From 2015 to 2019, the scale effect of carbon emission has made positive contributions to carbon emission reduction except in Beijing. However, the contribution of the scale effect to carbon emission reduction is premised on the decline in the output value of the high-end equipment manufacturing industry. Among them, Shandong Province has the largest carbon emission reduction rate of 14.78 million tons. At the same time, the output value of its high-end equipment manufacturing industry has also declined the most, from a total output value of 3,480.5 billion yuan in 2015 to 1,746.4 billion yuan in 2019 (see **Table 5**

3.3.2.2 Structural Effect

From 2015 to 2019, there is regional heterogeneity in the change of carbon emissions caused by the structural effect. The adjustment of industrial structures in Beijing, Tianjin, and Hebei has increased the total amount of carbon emission. The adjustment of industrial structures in Liaoning and Shandong has promoted the reduction of carbon emissions. It is because from 2015 to 2019, the proportion of automobile manufacturing, computer communication, and other electronic equipment manufacturing in Beijing, Tianjin, and Hebei has increased. However, other sub-industries changed less, resulting in a carbon emission rise. For Shandong and Liaoning, the proportion of general equipment manufacturing, special equipment manufacturing and electrical machinery, and equipment manufacturing has dropped significantly, and consequently, the total carbon emissions have declined (**Table 6**).

3.3.2.3 Carbon Emission Intensity Effect

The reduction of carbon emission intensity in Beijing and Tianjin has promoted the decline of the total carbon emission with a contribution of 220.31% and 90.75% (**Table 7**). The reason for this phenomenon is that Beijing and Tianjin promulgate policies to improve energy efficiency. At the same time, the two cities took advantage of regional technological innovation to gradually build a green, low-carbon, and renewable energy system. However, the intensity of the carbon emission effect led Hebei, Liaoning, and Shandong to an increase in carbon emissions in the high-end equipment manufacturing industry. The contribution of carbon emission intensity in the past 5 years is –25.47%, –2.14%, and

TABLE 5 | Scale effect of carbon emission in provinces and cities.

ΔCY	2015	2016	2017	2018	2019	Total
Beijing	37.49 (214.97%)	36.58 (125.04%)	38.94 (272.72%)	26.01 (41.10%)	29.85 (71.44%)	93.89 (87.30%)
Tainjin	2.78 (5.90%)	9.91 (16.66%)	30.13 (28.60%)	2.34 (200.33%)	1.60 (228.55%)	42.10 (19.68%)
Hebei	30.49 (58.05%)	32.14 (126.95%)	107.20 (344.26%)	−88.54 (230.54%)	120.03 (258.14%)	314.11 (219.29%)
Liaoning	253.71 (237.35%)	205.57 (113.59%)	21.50 (13.34%)	20.85 (17.59%)	21.69 (54.47%)	438.61 (72.20%)
Shandong	72.69 (66.96%)	127.69 (17.00%)	214.37 (43.89%)	1182.8 (468.97%)	281.2 (126.29%)	1478 (81.07)

The values in parentheses indicate the contribution rate of each influencing factor.

TABLE 6 | Structural effect of carbon emissions in provinces and cities.

ΔC_S	2015	2016	2017	2018	2019	Total
Beijing	29.98 (171.90%)	33.45 (114.35%)	−27.38 (191.71%)	−10.09 (15.95%)	9.55 (22.85%)	35.51 (33.01%)
Tainjin	25.04 (53.10%)	6.66 (11.19%)	13.84 (13.14%)	0.50 (43.14%)	3.94 (562.15%)	22.30 (10.43%)
Hebei	80.96 (154.16%)	47.18 (186.36%)	−65.48 (210.30)	−108.30 (282.00%)	180.035 (387.18%)	134.40 (93.82%)
Liaoning	−22.20 (20.77%)	−106.75 (58.98%)	−85.82 (53.23%)	−49.05 (41.38)	82.00 (205.91%)	−181.82 (29.93%)
Shandong	80.27 (73.95%)	97.23 (12.94%)	−65.92 (13.50%)	−471.00 (186.74%)	−105.52 (47.39%)	464.93 (25.50%)

The values in parentheses indicate the contribution rate of each influencing factor.

TABLE 7 | Carbon emission intensity effect in provinces and cities.

ΔC_T	2015	2016	2017	2018	2019	Total
Beijing	−9.93 (56.93%)	−40.77 (139.38%)	−25.85 (181.00%)	−79.22 (125.15%)	−81.185 (194.29%)	−236.96 (220.31%)
Tainjin	−69.41 (147.20%)	56.26 (94.53%)	−61.37 (58.26%)	−4.01 (343.48%)	−3.04 (433.60%)	−194.1 (90.75%)
Hebei	−102.99 (196.11%)	−54.00 (213.30%)	141.54 (454.55%)	158.43 (412.54%)	−106.50 (229.04%)	36.48 (25.47%)
Liaoning	169.01 (158.11%)	131.34 (72.57%)	−96.91 (60.11%)	−90.34 (76.21%)	−100.13 (251.44%)	12.97 (2.14%)
Shandong	−261.51 (240.91%)	−976.07 (129.94%)	−208.19 (42.62%)	1401.61 (555.71%)	164.05 (73.67%)	119.89 (6.58%)

Note: The values in parentheses indicate the contribution rate of each influencing factor.

−6.58%. It caused an increase in the level of regional carbon emissions. The possible reason is that Hebei, Liaoning, and Shandong did not pay attention to improving energy utilization efficiency, and more emphasis was on adjusting the energy structure and promoting the development of clean energy, which may lead to an increase in the carbon emission intensity of high-end equipment manufacturing.

Beijing and Tianjin have obvious advantages in carbon emission reduction in the high-end equipment manufacturing industry. It is worth learning from other regions. The carbon emission reduction of high-end equipment manufacturing industries in Hebei, Liaoning, and Shandong mainly depends on the scale effect. The intensity of carbon emission has not played an important role in the process of carbon emission.

3.4 Carbon Neutrality Forecast for the High-End Equipment Manufacturing in the Bohai Rim

3.4.1 Scenario Setting

Based on the development of China's clean energy industry, the future development scenarios are set as the base scenario, the low-carbon scenario, and the technological breakthrough scenario.

3.4.1.1 Base Scenario

The base scenario refers to the high-end equipment manufacturing industry in the Bohai Rim that adheres to the present development model and carbon emission policy. Assuming that the current economic environment and technological level remain unchanged, the government will no longer issue stricter carbon emission policies. The carbon emission indicators are predicted based on the development trend in recent years. In terms of clean energy (CE), the country still adheres to the present development policy and the total output of clean energy is predicted based on the output data of recent years. At the same time, this study refers to various policies (Lin and Liu, 2010). The median value of the annual average change rate of carbon emission intensity is set to −3.43%, and then, the minimum and maximum annual average rate of change is adjusted on the basis of the median value. The potential change rate of each influencing factor under the base scenario is given in **Table 8**.

3.4.1.2 Low-Carbon Scenario

Under the low-carbon scenario, the high-end equipment manufacturing industry in the Bohai Rim has changed the traditional development model, and the industrial-scale expansion is no longer at the expense of the environment. The

TABLE 8 | Potential change rate of each influencing factor under the base scenario.

	2020–2030 (%)			2031–2040 (%)			2041–2050 (%)		
	Minimum	**Median**	**Maximum**	**Minimum**	**Median**	**Maximum**	**Minimum**	**Median**	**Maximum**
ΔCY	4.5%	5.5%	6.5%	3.5%	4.5%	5.5%	2.5%	3.5%	4.5%
ΔCS	−2.9%	−2.9%	−1.9%	−2.9%	−1.9%	−0.9%	−1.9%	−0.9%	−0.09%
ΔCT	−3.83%	−3.43%	−3.03%	−2.83%	−2.43%	−2.03%	−1.83%	1.43%	−1.03%
CE	9.2%	10.7%	12.4%	8.2%	9.7%	11.4%	7.2%	8.7%	10.4%

TABLE 9 | Potential change rate of each influencing factor under the low-carbon scenario.

	2020–2030 (%)			2031–2040 (%)			2041–2050 (%)		
	Minimum	**Median**	**Maximum**	**Minimum**	**Median**	**Maximum**	**Minimum**	**Median**	**Maximum**
ΔCY	4.5%	5.5%	6.5%	3.5%	4.5%	5.5%	2.5%	3.5%	4.5%
ΔCS	3.9%	−2.9%	−1.9%	−2.9%	−1.9%	−0.9%	−1.9%	−0.9%	−0.09%
ΔCT	−4.83%	−4.43%	−4.03%	−3.83%	−3.43%	3.03%	−2.83%	−2.43%	−2.03%
CE	10.2%	11.7%	13.4%	9.2%	10.7%	12.4%	8.2%	9.7%	11.4%

government has issued relevant policies to improve energy efficiency and reduce the intensity of carbon emissions. At the same time, the proportion of clean energy consumption in the energy consumption structure has increased, the level of energy-saving technologies has been improved, and the rate of decline in total carbon emissions has accelerated. As for the production of clean energy, the government will introduce policies to promote the development of new energy and clean energy, and the total output of clean energy production has increased. In addition, the effectiveness of policy implementation and the uncertainty of the economic environment are fully considered. The potential change rate of each influencing factor under the low-carbon scenario is given in **Table 9**.

3.4.1.3 Technological Breakthrough Scenario

With the increasingly strict carbon emission policy in China, the technological innovation activities of energy saving and emission reduction are becoming increasingly active. Technological innovation has become a necessary way to achieve carbon neutrality. On the one hand, through technological innovation, it is possible to find the potential for structural adjustment and optimization of various sub-industries of the high-end equipment manufacturing industry. On the other hand, the optimization of production processes brought by technological innovation has reduced the carbon emission intensity of various industries. At the same time, the improvement of clean energy production technology not only guarantees the safety problems in the process of clean energy production but also promotes the increase of the total amount of clean energy production. The specific change rate is shown in **Table 10**.

3.4.2 Simulation Method—Carbon Neutrality Forecast

3.4.2.1 Base Scenario

Under the base scenario, by 2049, the total carbon emission of the high-end equipment manufacturing industry in the Bohai Rim will be about 5.09 million tons. Compared with 2019, the reduction of carbon emission is 35.92 million tons and the annual carbon emission reduction is 1.1588 million tons. At the same time, the total carbon emission will decrease by about 4.52 million tons caused by the use of clean energy. Overall, the probability of achieving carbon neutrality in the high-end equipment manufacturing industry in the Bohai Rim in 2049 is 40.38%. By 2050, total carbon emissions will continue to decrease, clean energy production will continue to rise, and the probability of reaching the carbon neutrality target will increase to 81.70%. In 2051, the probability of achieving carbon neutrality in the high-end equipment manufacturing industry in the Bohai Rim will expand to 97.69%. The possibility of achieving carbon neutrality is extremely high, which is about 9 years earlier than the target. Among the influencing factors, the carbon emission intensity effect has the largest contribution to carbon neutrality. A total of 57.5394 million tons of carbon dioxide were reduced with a contribution rate of 145.93%.

3.4.2.2 Low-Carbon Scenario

Under the low-carbon scenario, compared with the baseline scenario, the carbon emissions of high-end equipment manufacturing in the Bohai Rim region are further reduced. By 2044, the total carbon emissions will be about 7.76 million tons and the carbon emissions from the use of clean energy will be about 4.10 million tons. At that time, the probability of attaining the carbon neutrality target will be about 4.35%. In 2045, the total carbon emissions will be about 5.77 million tons, while the total carbon emissions reduced by the use of clean energy will reach 4.49 million tons, and the probability of carbon neutrality will be about 49.12%. In 2046, the total amount of carbon emissions will be reduced to 3.71 million tons, while the total amount of carbon dioxide emissions reduced by the use of clean energy will reach 4.93 million tons, and the probability of achieving carbon neutrality will be 93.22%. Among the various influencing factors, the reduction of carbon emission intensity is still the biggest contributor to the realization of carbon neutrality, with a

TABLE 10 | Potential change rate of each influencing factor under the technological breakthrough scenario.

	2020–2030 (%)			2031–2040 (%)			2041–2050 (%)		
	Minimum	Median	Maximum	Minimum	Median	Maximum	Minimum	Median	Maximum
ΔCY	4.5%	5.5%	6.5%	3.5%	4.5%	5.5%	2.5%	3.5%	4.5%
ΔCS	4.9%	–3.9%	–2.9%	–3.9%	–2.9%	–1.9%	–2.9%	–1.9%	–0.9%
ΔCT	–5.83%	–5.43%	–5.03%	–4.83%	–4.43%	–4.03%	–3.83%	–3.43%	–3.03%
CE	11.2%	12.7%	14.4%	10.2%	11.7%	13.4%	9.2%	10.7%	12.4%

total carbon emission reduction of 54.75 million tons and a contribution rate of 146.78%.

3.4.2.3 Technological Breakthrough Scenario

Under the technological breakthrough scenario, because of the improvement of the production technology of the high-end equipment manufacturing industry in the Bohai Rim region and the progress of the production technology of clean energy, the realization time of carbon neutrality will be further shortened. In 2040, the probability of achieving carbon emissions is 0.039%. In 2041, the probability of achieving carbon neutrality rises to 33.50%, and it can be found that the probability of achieving carbon neutrality is still low. However, by 2042, the probability of carbon neutrality in the Bohai Rim region will increase to 97.84%, and there is great hope for achieving carbon neutrality. The technological breakthrough scenario achieves the carbon neutrality goal 4 years earlier than the low-carbon scenario and 9 years earlier than the baseline scenario, indicating that technological progress has a significant role in promoting carbon neutrality in the high-end equipment manufacturing industry in the Bohai Rim. At the same time, technological breakthroughs continued to increase the contribution of the carbon emission intensity effect, reducing carbon emissions by a total of 47.52 million tons with a contribution rate of 161.63%.

4 CONCLUSION, POLICY IMPLICATIONS, AND FUTURE RESEARCH

4.1 Conclusion and Policy Implications

In the present study, the Tapio model was used to analyze the carbon emission of high-end equipment manufacturing in the Bohai Rim (including five provinces: Beijing, Tianjin, Hebei, Liaoning, and Shandong) from 2015 to 2019. The LMDI model was used to decompose the influencing factors of carbon emissions. On this basis, combined with various policy indicators, the Monte Carlo simulation method was used to predict carbon neutrality. The main conclusions of this study are given as follows.

First, in 2019, the development of high-end equipment manufacturing and carbon emissions in the Bohai Rim region showed an ideal state of strong decoupling, but this ideal state is not stable and there is a risk of “recoupling.” From the perspective of the provinces and cities around the Bohai Sea, the carbon decoupling situation in Beijing and Tianjin is relatively good, and the ideal state of strong decoupling can be maintained. The next two provinces are Hebei and Liaoning, which have achieved strong decoupling in 2019. The carbon decoupling situation in Shandong Province is relatively poor, and it has been in a non-ideal state of negative decoupling in recent years.

Second, the result of the LMDI model finds that the scale effect is the main contributor to carbon emission reduction in the high-end equipment manufacturing industry in the Bohai Rim. The contribution rate is 75.3%. The second is the structural effect and the carbon emission intensity effect, with contribution rates of 15.6% and 9.1%, respectively. From the perspective of each province and city, except Beijing and Tianjin which use the reduction of carbon emission intensity as the main force for carbon emission reduction, the other three provinces use the scale effect as the main contributor to carbon emission reduction but such carbon reduction is unsustainable.

Third, under different scenarios, there are significant differences in the evolution path of carbon neutrality in the high-end equipment manufacturing industry in the Bohai Rim. Under the baseline scenario, the low-carbon scenario, and the technological breakthrough scenario, the carbon neutrality target is expected to be achieved ahead of schedule, and the carbon neutrality time estimated by the Monte Carlo simulation is 2051, 2046, and 2042, respectively. In each scenario, the contribution rate of carbon emission intensity to carbon neutrality is the largest and gradually increases, which are 145.93%, 146.78%, and 161.63%, respectively.

China should improve energy utilization efficiency and strengthen incentives for green innovation in high-end equipment manufacturing enterprises. The carbon emission reduction of the high-end equipment manufacturing industry in the Bohai Rim mainly depends on the scale effect, and the carbon emission intensity still has great potential to promote carbon emission reduction. Therefore, reduce the waste of energy in processing, conversion, transportation, distribution, and other terminal utilizations. Then the use of new technologies such as cloud computing and big data to establish a smart energy management system is of great importance to the high-end equipment manufacturing enterprises in the Bohai Rim. In addition, the government should guide enterprises to increase investment in energy conservation and provide enterprises with tax relief and policy subsidies to urge them to take the social responsibility for the realization of the carbon neutrality goal.

4.2 Future Research

This article gathered data from high-end equipment manufacturing in China’s Bohai Rim to research its carbon emission status and predict the time to attain the carbon neutrality goal. However, the many influencing factors affecting carbon emission and the analysis methods for carbon neutrality prediction need to be further explored. Moreover, micro-level data on carbon emissions should be considered to make a detailed and comprehensive analysis.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/**Supplementary Material**.

AUTHOR CONTRIBUTIONS

HL was responsible for the collection and arrangement of relevant literature, data analysis and article writing. EE made comments on the choice of the article title and revised the article, and ZS collected data needed for the article.

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Innovation and Recycling—Drivers of Circular Economy in EU

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In our days, a growing attention is paid to explain the influence of innovation on recycling. While many studies on this subject have been carried out, it's still needed for more investigations on measuring the effect of innovation on recycling. This paper is dedicated to measuring the intensity of the innovation influence on the recycling within EU member states. The methodology follows the next steps: visualization of data used, determining the stationarity of the time series analyzed, developing a panel model for 28 countries, applying specific statistical tests in case of the two indicators selected. After analyzing the models that resulted and applying Hausman test, the authors concluded that the regression panel with fixed effects is appropriate for our research. Thus, it is possible to show that the influence of the innovation on recycling is moderate and not instantaneous because there is manifested a lag of 2 years. In addition, the Fixed Effects model allows highlighting the heterogeneity that is present among member states. In addition, the authors concluded that the membership of the Euro Area has a positive influence on recycling and on circular economy as well. The article has several originality aspects: it took into account criteria that are not discussed very often as membership of Euro area; it has developed a model that brings quantitative aspects to describe the influence of innovation on recycling, it highlighted the heterogeneity existing among EU member states. Future research direction would be to consider including in the model some other variables as eco-investment.

Keywords: recycling, patent, fixed effects, random effects, material use rate

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1 INTRODUCTION

The latest objectives and endeavors towards a sustainable development have led to the conceptual and political promotion of new concepts such as the green growth and circular economy, as a reaction to the global recession and climate change.

The model of green economic growth presents an alternative to the conventional economic paradigm of resource exploitation, and this theory of growth involves concepts such as the sustainable use of natural resources, including greater energy and resource efficiency and improved natural capital as drivers of growth. The circular economy (CE) means the recycling of resources used in products whose life-cycle has come to an end or which have lost their usefulness to construct new objects of the same quality or even better. It is obvious that the shift towards Circular Economy involves a systemic and radical change. The historic tradition perceived socio-economic paradigm of production and consumption as a linear process, based on "*extracting, processing, manufacturing and disposing.*" In today circumstances this paradigm needs to be radically transformed in order to fulfil the objectives of the Circular Economy, namely, eliminating or reducing disposable waste as much as possible. In these circumstances, recycling is one of the main drivers of Circular Economy (EC COM., 2015).

On the other hand, innovation will play a key part in the systemic change for the economy. In order to rethink our ways of producing and consuming, and transforming waste into high value-added products as well recovering the energy incorporated into various materials (aluminum, glass etc.) there are needed new technologies, processes, services and business models to shape the future of the economy.

The relationship innovation–circular economy was the subject of many papers and models. For instance, Horbach and Rammer (2020) focused their paper on modeling how companies react within the perspective of a circular economy. The two authors considered that companies are important players for the realization of a Circular Economy (CE). The paper investigated the link between CE and firm growth and whether higher sales and employment growth emerges at the cost of worsened productivity or financial performance. The authors have used a panel model at firm-level with data of 2 years (2014 and 2016) for German companies. It resulted that all firms in Germany reported CE innovations during 2012–2014. Due to high price of energy in Germany caused by extensive use of regenerable energies, the single most important innovation activity was the reduction of energy use per unit of output. In this context process-related innovations are more frequent than product-related ones. So, out of the three main types of recycling: mechanical, energy and chemical only reducing energy consumption was the main objective for innovation.

Pieroni et al. (2019) analyzed in their paper the innovation business models for circular economy and sustainability. They systematically analyzed literature and identified 94 publications and 92 approaches (including conceptual models, methods or tools). Main findings show that business model innovation for sustainability and circularity is still fragmented. Within the models, mentioned-above we face a lack of holistic approaches covering multiple stages of innovation. As well a stronger integration between circularity and sustainability is required. The authors have proposed a unifying agenda for future research.

The topics related to reasons for non-acceptance of circular business models is also present in some research papers. Patrik Planing (2015) explored the topic of innovation acceptance/non-acceptance with the aim to develop a new conceptual framework for business to model innovation in a circular economy. As well, the author explored the reasons for consumer non-adoption of circular business models. In this context, learning about consumer motives leading to non-adoption of eco-innovation is important for removing barriers that still are in place. The paper mentioned provides support for designing better and more successful circular business models.

Other researchers have studied the way in which the innovation in the production chain influences the advances towards CE (Potting et al., 2017). The study took into account product chains from the extraction of natural resources to waste elimination. Recovering materials from discarded waste or used products often requires large amounts of energy and associated costs in additional processing. In many cases mixing of materials when discarded reduces their quality which means that very often recycled (secondary) materials do not have the same qualities as virgin raw materials so cannot be used again for the same type of product. Frequently, these recycled materials do find an application in other product chains with lower quality requirements. In a circular economy, the recovery/reuse chains are dissimilar. It is assumed that, the materials recycled from a discarded product ideally retain their original quality so that they can be used again and again in a similar product without any addition in terms of material and energy. As a result of such a logic, in the recycling process no extra natural resources are needed to manufacture the same product. In this way, discarded products no longer become waste but a raw material for a new production cycle. This ultimate circularity, in which a product chain is closed because used materials can be used over and over again is aspirational and is probably not at all feasible in practice. In most cases it is needed a supplementary input of energy or other materials.

The transition from linear model of production to a circular model is a topic of peculiar importance. In his paper, Mentink (2014) analyzed the role of innovation in transition towards a Circular Business Model. The author affirmed that: "*both 100% linear and 100% circular economies or business models do not exist due to practical limitations (friction, leakages, growth, energy losses etc.).*" This affirmation is related to the fact that all production cycles do need an input of materials, work and energy. The author mentioned the risks or barriers to implement a circular business model. It is important to know that the complexity of organization and management often increases the need for new information related to recycled materials, components and products. As it is the reality for now, the current system of legislation, consumer behavior, financing, etc. is still to the advantage of the current dominant linear models so a transition is needed.

In general, recycling serves two important purposes: 1) avoiding landfilling and incinerating so helping to reduce soil, air and water pollution and 2) valuable materials like aluminum, metal, plastic and glass are reused in other forms and not wasted. In the case of several energy-intensive materials as aluminum and glass, significant energy saving is made.

As well, it should be mentioned that in our days, it is important to minimize the waste generated and reclaim residues, as much as possible, through effective recycling. Improving the effectiveness of recycling is important and could be carried out via measures taken in various stages of recycling: collection, sorting, storage, transport, and manufacturing etc.

In all stages, one major factor that helps improving recycling is innovation. It is quite obvious that there are some conditions to be fulfilled in order to persuade consumers to change their buying behavior in favor of recycled materials. The main conditions are: the recycled product should have comparable characteristics as the product made of virgin materials and, very important, should not cost more. These conditions are not easy fulfilled; however, innovation may be a key tool to achieve them (Frone, 2017).

Therefore, considering innovation would play a major role in the new development of the circular economy, the general objective of this research is to analyze the influence of innovation on recycling. The paper has three parts, as follows: the first part is dedicated to the review of the relevant literature regarding the relationship between recycling and innovation and the influence of some other variables such as membership of Euro area. In the second part we present the research methodology, including the data sources used, indicators and research hypotheses. The third part proposes an econometric model and analyses the outcomes obtained. Finally, the authors conclude regarding the findings resulted from the econometric analysis and present some policy recommendations.

Thus, the paper could fill the gap in modelling the relationship innovation-recycling by better understanding the quantitative aspects as well as highlighting the existing heterogeneity within EU.

The main aim of this paper is to bring a contribution to the discussions concerning the influence of innovation on the recycling process, measuring this influence by statistical evidence analysis.

The research questions of the paper are the following:

1) How important is the influence of innovation on recycling within EU?
2) What is the influence of Euro membership on recycling?
3) How important is heterogeneity among EU member states?

2 MATERIALS AND METHODS

2.1 Literature Review

An important topic for science community was that of similarities and relationship between the notions sustainable development—circular economy. (Geissdoerfer et al., 2017) explained that the similarities and differences between both concepts are not so clear. So, the authors, after a special incursion in the existing literature, define the Circular Economy as: "*a regenerative system in which resource input and waste, emission, and energy leakage are minimized by slowing, closing, and narrowing material and energy loops.*" On the other hand, Sustainable Development is: "*balanced integration of economic performance, social inclusiveness, and environmental resilience, to the benefit of current and future generations.*" This is indeed a useful differentiation that can help understanding how is the Circular Economy conceptually related to sustainability. The authors found that Circular Economy is considered in many papers and research works as a condition for sustainability. As well, the beneficial relation between the two concepts can be structured into eight different relationships.

In this context, the relationship innovation—recycling was the subject of several papers and articles. For instance, a recent study (Sumrin et al., 2021) has explored major drivers. In many cases, new requirements of legislation for environmental protection and waste management have determined companies to adopt innovation as an instrument for achieving a competitive advantage. Packaging is one important area of waste management, in which firms are willing to adopt innovation. The article mentioned that irrespective of innovative technological advancement, expanding the number of global supply chains for various products has encouraged measures at the source as the utilization of smart packaging and related waste minimization solutions all along the supply process. It is well known that packaging recycling is complicated due to the multitude of packages involved but offers significant opportunities for innovation. The authors stated that innovation in packaging to facilitate recycling was not the main goal until recently. This is a new way to look at recycling innovation: taking measures at the source and not at the end of pipe. The reason for this is that recycling itself cannot cope with the entire amount of waste generated so it is important to take into account measures that could reduce at source the flow of waste. Thus, the authors consider important to better examine the innovation of packaging recycling from various perspectives such as technological capabilities, human and organizational capabilities, eco-design and innovation in packaging in order to increase its impact on waste recycling and prevention (Vence et al., 2019; Sumrin et al., 2021; Pieroni et al., 2019). The reality shows that innovations are needed more in order to minimize waste generation and to enhance the recycling process.

Other researchers have studied the way innovation influences advances in recycling (Potting et al., 2017) considering the product chains from extraction of natural resources to waste elimination for two product groups: plastic packaging and electrical and electronic equipment. Recovering materials from discarded waste or used products often requires large amounts of energy and labor so associated costs in additional processing could be significant. The conclusion of the paper highlighted a partial role allocated to technological innovation. The data shows that industrial innovation plays a role in economies that are in transitions and adopt recycling as a circularity strategy. The majority of innovations are found in a simpler form as modifications and adaptations of existing processing methods and technologies in order to meet some peculiar requirements. This procedure is known as incremental innovation (can have relatively low intensity changes in the economic system) as compared with radical innovation (can determine ample changes in the economic system by favoring the occurrence of new economic and social activities). Radical innovation is based on fundamentally new scientific knowledge. The study reveals that this form of disruptive innovation is scarcely found in the case studied.

From the research papers analyzed and other policy documents, we may report the importance of innovation in enhancing recycling. By developing innovation abilities and practices, it is possible to augment the commercial potential across all economic sectors. The second aspect worth mentioning is the fact that innovation contributes to reduce uncertainty about future market developments in EU (Pieroni et al., 2019). This will help boost investment and accelerate introduction of environmentally friendly technologies, products and services (Frone and Constantinescu, 2018).

In a real economy, the recovery/reuse chains are dissimilar. It is assumed ideally that materials recycled from a discarded product would retain their original quality so they may follow the same cycle repeatedly in a similar product without any addition in terms of materials and energy. Theoretically, in order to manufacture the same product, the recycling process would use no extra (or only a few) natural resources. This way, the discarded products no longer become waste but raw material for a new production cycle (Repp et al., 2021).

The idea regarding limits of recycling and indirect limits of circular economy is discussed by Korhonen J., et al. (Korhonen et al., 2018) in the paper *Circular Economy: The Concept and its Limitations*. The authors analyzed the concept of circular economy and discuss it from the perspective of environmental sustainability. In this framework, the authors identified six limits and barriers for the circular economy as thermodynamic limits, system boundary limits, rebound effect (Jevon's paradox, boomerang effect), limits of governance and management, etc. The thermodynamic limit for CE is derived from the writings of Nicolae Georgescu-Roegen. The authors pointed out that, according to N. Georgescu-Roegen, recycling will always need external energy. In the process of recycling will be losses of energy and materials that dissipate into the environment and cannot be recovered or the effort to recover all these will be enormous, consuming more resources that can be recovered. The conclusion of the Entropy Law is that complete recycling is not possible so a limit for recycling would occur. The paper is important for drawing attention on challenges related to CE. Authors see these six limitations and challenges as research themes and project proposals for scientists.

Another interesting viewpoint of analysis is the regional feature of innovation in the EU. The evaluation of the regional innovation degree has assembled a series of indicators used for the analysis of the macroeconomic innovation level and statistical analysis techniques and econometric classical or modern methods. Innovation represented a priority of the various EU Strategies, while the regions strengthen their position of key-actors in the process of re-ascertaining economic and social cohesion at Community level. Therefore, the authors concluded that synergy is necessary between the support instruments corresponding to innovation and social cohesion at community and regional level (Antonescu, 2015).

In order to better gather the knowledge and dissipate it, the Eco-Innovation Observatory was created as a platform for the structured collection and analysis of an extensive range of eco-innovation information, collected from across the European Union. Doranova et al. (2016) analyzed the eco-innovation performance in EU country and discussed the progress towards circular economy of EU member states.

For our article, it is of interest the way in which innovation was scrutinized. The main indicator used was the Eco-Innovation Scoreboard (Eco-IS). This indicator explains eco-innovation performance across the EU Member States using scores and indicators. The scoreboard has a complex aim of apprehending the different characteristics of eco-innovation by using 16 sub-indicators grouped into five thematic groups:

- Inputs containing investments, financial or other resources, which aim at triggering eco-innovation activities;
- Direct activities, illustrating to what extent companies, in a specific country, are active involved in eco-innovation;
- Outputs, quantifying the outputs of eco-innovation activities in terms of patents, academic literature and media contributions;
- Resource efficiency results, interpreting eco-innovation performance in the context of a country's resource efficiency and GHG emission intensity;
- Socio-economic outcomes, showing to what extent eco-innovation performance generates positive outcomes for social aspects (employment) and other economic aspects (turnover, exports).

The recent relevant interactive tool shows the results from the aggregated scoreboard for EU member states in 2019. In the current figured report, countries are clustered into three groups:

- Eco-innovation leaders, scoring Eco-IS significantly higher than the EU average; this group includes seven countries as Luxembourg (has the highest aggregate score—165), followed by Denmark, Finland (aggregate score 146 and 145), Sweden, Austria, Germany, and United Kingdom;
- Average eco-innovation performers are ten countries with scores around the EU average (aggregate score 100), ranging from 85 (Belgium) to 112 (Italy), also including: Netherlands, Spain, France, Portugal, etc.;
- Countries catching up in eco-innovation (Romania, Estonia, Poland, Greece, Malta etc.). There are eleven countries recording an aggregate score less than EU average (between 34 Bulgaria and 82 Lithuania).

In the paper *Eco-Innovation: opportunities for advancing waste prevention*, Rene van Berkel (Van Berkel, 2007) has discussed opportunities that can deliver waste prevention outcomes, broadly categorized as efficiency practices, design strategies and creativity templates. For instance, the efficiency practices could be expressed in several ways: cleaner production, waste minimization, eco-efficiency and pollution prevention. The author showed that in the industry case, efficiency improvements are related to minimizing inputs, reducing energy consumption, introducing new technologies. These actions have frequently demonstrated multiple environmental benefits coupled with commercial benefits. In this area there could be noted several positive aspects, such as: cost savings, enhanced process operability and/or better product quality (Van Berkel, 2007).

The importance of recycling in advancing circular economy is well known. A remarkable paper (Di Maio and Rem, 2015) has assigned a more robust indicator for promoting circular economy through recycling. The authors considered there was still lack of an effective key performance indicator for motivating the recycling industry. In order to solve this, the paper has proposed a new indicator named Circular Economy Index (CEI). The indicator would be calculated as the ratio of the material value produced by the recycler (market value) divided by the material value entering the recycling facility. Such an indicator could be useful but it is not clear how big would be the effort to alter the existing reporting system at the level or Eurostat and what would be the benefits of replacing the classic indicators of recycling.

Hysa E. et al. (Hysa et al., 2020) have examined the influence of several indicators on economic growth, measured by GDP. The goal was to identify the main factors, which are supportive of both sustainability and development. The authors have used a semi-log model including a panel data with fixed effects for 28 EU countries. As well, the authors included a dynamic panel of data computed using Arellano–Bond method. It is interesting to mention that the model used took into account five independent variables, such as a tax rate related to environment resources used, the recycling rate of waste, private investment and jobs, patents related to recycling and trade of recyclable materials. The results of both econometric models showed a positive correlation between selected indicators and GDP. That means all indicators have a positive influence on GDP. There could be mentioned one issue that was not solved yet by this model: the fact that some independent variables as taxes, trade, private investment and jobs are, by definition, constitutive parts of the GDP so the linkage should be positive anyhow. Another unsolved aspect of models with many independent variables is the occurrence of multicollinearity among respective variables, which implies some negative effects, such as the oversizing and/or wrong signs of estimated parameters, low Student test statistics, increasing confidence intervals etc.

The linkage among recycling and other economic indicators was analyzed also by Banacu et al. (2019). This paper discussed the implications of entrepreneurial innovation for recycling municipal waste and scrutinizes the main factors of recycling municipal waste at the European Union level. The model used was that of a linear regression to explore the influence of business expenditure on research and development (R&D), private investments, resource productivity, and environmental taxes on the recycling rate of municipal waste. The model included 27 European Union countries and a period of 8 years. In this case, the model has indicated that the business expenditure on R&D, private investments, R&D expenditures as a share of GDP and resource productivity have a direct and moderate impact on the municipal waste recycling. These four variables showed a positive and moderate effect mirrored by positive coefficients smaller than the unit. The variable Environmental Taxes showed a statistically significant effect but that value is negative meaning the impact on the waste recycling is adverse (the coefficient of that variable has a value of −0.187). This particular finding is opposed to general theory according to which environmental taxes may improve the recycling behavior of the population. In practice it is well known that the principle pays as you throw is the main instrument to reduce waste at the source so many countries have developed and implemented tariffs proportional with the quantity of waste generated.

It is important to note that some researchers (Camilleri, 2020) showed the role and status of policies and plans elaborated at EU level. These plans and policies bring an important help in diminishing the uncertainty faced by companies and population in promoting circular economy. On the opposite side, the author mentioned some of the possible challenges that could have a negative influence on the businesses' push towards a more circular activity. The reality is that advancement toward the circular economic practices is not guarantee. In many cases circularity still prove to be difficult and challenging for some industrial branches. It is well known that there are many companies maintaining the existing status quo as they still rely on linear models (Camilleri, 2019; Camilleri, 2021).

In the next period, the recycling activity will become more important in EU. One reason is the new and very ambitious Circular Economy Package promoted by EU, which includes revised legislative proposals on waste. Some of the most important targets for recycling are as follows: a common EU target for recycling 65% of municipal waste by 2035 and a common EU target for recycling 70% of packaging waste by 2030. There could be mentioned also the ambitious recycling targets for specific packaging materials: paper and cardboard: 85%; glass: 75%; plastic: 55%; wood: 30%. Also, the European Green Deal aims at revising some of these targets, in order to facilitate circularity.

2.2 Methodology and Data Sources; Theoretical Background

2.2.1 Theoretical Background

In order to detect the influence of innovation on recycling in EU member states, we used a panel data analysis. We considered two series: recycling rate (expressed by the indicator *Circular material use rate*) as dependent variable and innovation as independent variable.

At first, the series were tested whether they are stationary or not. Stationarity was determined using the Unit Root Test. Not having a unit root means that series are stationaries in levels (I (0)). If such a condition is present, there is no need to differentiate. Hence, there is no need to perform the co-integration tests. Consequently, the model will be of the OLS (Ordinary Least Squares) type.

In our case, we are going to use a panel data model in order to describe the evolution in time and across individuals (countries). E-View 11 package was the software used for all estimations. We have estimated three types of panel data models: a pooled model, a fixed effect model and a random effect model and selected the most appropriate.

In the Pooled model there are specified constant coefficients as the usual hypothesis for cross-sectional analysis; this model is the most restrictive and has a limited use:

$$\boldsymbol{Y_{it}} = \boldsymbol{\alpha} + \boldsymbol{\beta X_{it}} + \boldsymbol{u_{it}} \tag{1}$$

Where:

- Y_{it} is the dependent variable and the matrix X_{it} includes the explanatory variables;
- i represents the cross-section dimension (countries);
- t represents the time dimension;
- u_{it} is the error term.

Individual-specific effects models take into account unobserved heterogeneity along cross-sections and include it in the term α_i. If α_i correlates with the regressors X_{it}, we deal with a fixed effects model. If there is no correlation detected, we are in case of a random effect model.

A Fixed effect (FE) model allows the individual specific effects (α_i) to correlate with the regressors; this term is included in the model as intercept. The FE model is as follows:

$$Y_{it} = \alpha_i + \beta X_{it} + u_{it} \quad (2)$$

After estimating the regression outcomes, it is possible to determine the cross-sectional fixed effects for all countries included in the panel data. Therefore, each country will have a specific intercept (α_i) but the slope (β) will be the same.

The Random effect (RE) model is based on the assumption that the individual specific effects (α_i) are distributed autonomously of the regressors and is included in the error term. The RE model is as follows:

$$Y_{it} = \beta X_{it} + (\alpha_i + u_{it}) \quad (3)$$

This model considers that random effects do not correlate with the explanatory variables. A method for testing this assumption is to use the Hausman test in order to compare the fixed and random effects estimates of coefficients. If the Housman test is statistically significant (probability lower than 5%), we should use FE model. If the test is not statistically significant, we will use the RE model (Wooldridge, 2002; Baltagi, 2005).

2.2.2 Data Sources

Eurostat provides sets of data related to recycling and innovation within the Circular Economy set of indicators. Out of the 15 indicators structured in four sections we have chosen two indicators: Circular material use rate (CMUR) to stand (as proxy variable) for recycling and Patents related to recycling and secondary raw materials (called simply Patents) to stand (as proxy variable) for innovation[1].

2.2.3 Circular material Use Rate

In the last years, Eurostat developed one new indicator (circular material use rate) in order to compensate for the absence of a single summary indicator about the circularity at macro economical level. The circular material use rate (CMUR) measures the contribution of recycled materials to overall materials use. The indicator includes flows of solid materials but it does not include flows of liquids (used water).

The CMUR is defined as the ratio of the circular use of materials (U) to an indicator of the overall material use (M): CMUR = U/M and is measured in percentages.

This indicator is approximated by the amount of waste recycled excluding imported waste destined for recovery and adding exported waste destined for recovery abroad. Waste recycled in domestic recovery plants comprises the recovery operations R2 to R11—as defined in the Waste Framework Directive 75/442/EEC. The imports and exports of waste intended for recycling—i.e., the amount of imported and exported waste bound for recovery—are approximated from the European statistics on international trade in goods.

A higher value for CMUR means that more recycling is taking place and secondary materials replace primary raw materials in the economy. This way the environmental impact of extracting primary material is well diminished.

Circular Material Use Rate data are available for the period 2010–2017. For the 28 EU countries taken into account there are 224 observations with a maximum value of 29.9%, a minimum value of 1.2% and a mean of 8.6%. More details are in the **Annex 1**.

Figure 1 displays the average value of the indicator Circular Material Use Rate across 28 EU member states, in the period 2010–2017. Netherlands has the highest CMUR (26.9%); a group of leader countries (Luxemburg, Italy, United Kingdom, Belgium and France) follows, with registered average values of this indicator between 14.4 and 17.9%. Another group of countries, called average performers (Poland, Germany and Estonia), recorded average values between 10.8 and 12.4%. There are 10 catching up countries, which recorded CMUR lower than 5%. The data shows that the spread of CMUR is large; indicating that recycling is not at all uniform across EU member states.

Another perspective of the CMUR could be presented by considering the inclusion or not of a member state into the Euro area. In 2018, nine countries were not included in the Euro Area i.e.: Bulgaria, Denmark, Croatia, Czech Republic, Hungary, Poland, Romania, Sweden and United Kingdom.

States that are part of the Euro area have an average of the CMUR of 9.3%, compared with 7.0% recorded in states that are not part of Euro area (**Table 1**). The absolute difference is 2.3%, which represents 24.7% of the value recorded by states belonging to the Euro area. It is clear that member states included in the Euro area perform better in recycling.

2.2.4 Patents related to Recycling and Secondary raw Materials

Innovation will be will be analyzed through the indicator *Patents related to recycling and secondary raw materials*. The respective indicator will be called simply Patents in this article. By definition, the indicator Patents measures the number of patents[2] related to recycling and secondary raw materials. The term *"patents"* refers to patent families, which include all documents relevant to a distinct invention (e.g., applications to multiple authorities), thus preventing multiple counting. A fraction of the patent family is allocated to each applicant and relevant technology.

Eurostat provides this indicator and data are available for the period 2000–2015, from 28 EU countries. There are available 360 entries, with a maximum of 141.66 patents/year and a minimum of zero. The average value is 13.7 patents/country/year and the total number of patents registered by the 28 countries analyzed is 4,930 (for more details see **Annex 1**).

[1]https://ec.europa.eu/eurostat/data/database

[2]According to Eurostat, the attribution to recycling and secondary raw materials was done using the relevant codes in the Cooperative Patent Classification (CPC) (list of CPC codes selected) (online data code: CEI_CIE020 last update: 01/02/2020).

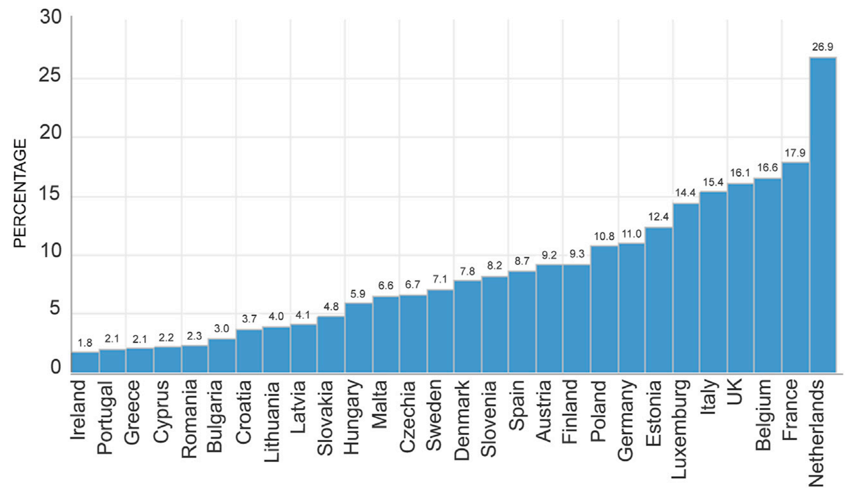

FIGURE 1 | Mean of circular material use in EU, percentage (2010–2017)/Source: own calculation with Eurostat data.

TABLE 1 | Mean of Circular Material Use Rate, by Euro area (%) (2010–2017).

Euro zone member = 0	Euro zone member = 1	Difference	%
7.0	9.3	2.3	132.9

Source: own calculation with Eurostat 2020 data.

During the period 2000–2015, most patents were registered by far in Germany (1,688 patents), followed by France (612 patents), Poland (395 patents), United Kingdom (332 patents) and Spain (308 patents). Other countries had not such a significant contribution to innovation, having registered a low number of patents (**Figure 2**).

When analyzing innovation in EU member states (2010–2015), we could deepen the perspective by aggregating countries that belong to Euro Area and others that are not yet part of it. Countries members of Euro area have recorded an average of 16.3 patents/country/year while countries which are not part have recorded 9.0 pa-tents/country/year (**Table 2**). We may notice the advance of Euro Area countries with an average of 7.3 patents/country/year.

3 RESULTS—MODEL USED

3.1 Visualization of Data Used in the Model

Data visualization is the first stage in our modelling approach by observing the graphical representation of information and data available. By using visual elements, we may have an accessible and easy way to see and understand trends, outliers and patterns in the data analyzed.

All calculations have been made on a panel data of 28 countries and a period of 2010–2017. Main statistics of the two indicators are in **Annex 1**. We have used the notation presented in **Table 3**.

Figure 3 presents the scatterplot of the two main variables *Circular material used rate* and *Patents*. In the model, for the variable Log(Patents_recycl (-2)) we have used a lag 2, assuming that the Patents variables would demonstrate their effect on CMUR at least 2 years later.

As observed from **Figure 3**, there is a relation between the two variables, represented by a regression line with a positive slope. In other words, the Circular material use rate is positively correlated with the Patents indicator. The regression line in **Figure 3** was estimated using panel OLS method. Therefore, we are going to explore this relationship.

As stated earlier, dummy variable EURO is a binary variable (1 for countries members of the Euro Area and 0 for the opposite case); **Figure 4** shows its influence on the scatterplot of the two main variables. We notice that the regression line corresponding to EURO countries is above the regression line corresponding to non-Euro countries for the entire interval considered. The slope of the regression line corresponding to the EURO area countries is 0.301 compared with the regression line on the non-EURO countries which has a smaller slope (0.2775).

3.2 Main Steps and Results

Step 1: Verifying stationarity of the panel data series

The stationarity was determined using Unit Root Test. The hypothesis H0 is: series have a unit root. We accept it if the probability is higher than 5%. If not, we reject H0. The detailed results of the Unit Root Test for both series are in **Annex 2**. The main results of the test are.

1) Series CIRCULAR_MAT_USE: the Unit Root Test using Levin-Lin-Chu (assuming common unit root process) has the probability <0.0000. As well, the test Im, Pesaran and Shin W-stat and the test ADF—Fisher Chi-square, both show a probability much lower that 5%, therefore we reject H0. We conclude the series CIRCULAR_MAT_USE has no unit root, therefore is stationary in levels.
2) Series PATENTS_RECYCL: in the case of series PATENTS_RECYCL, the Unit Root test shows that the series has no unit root, therefore it is stationary in levels. All tests performed have probabilities much lower that the threshold of

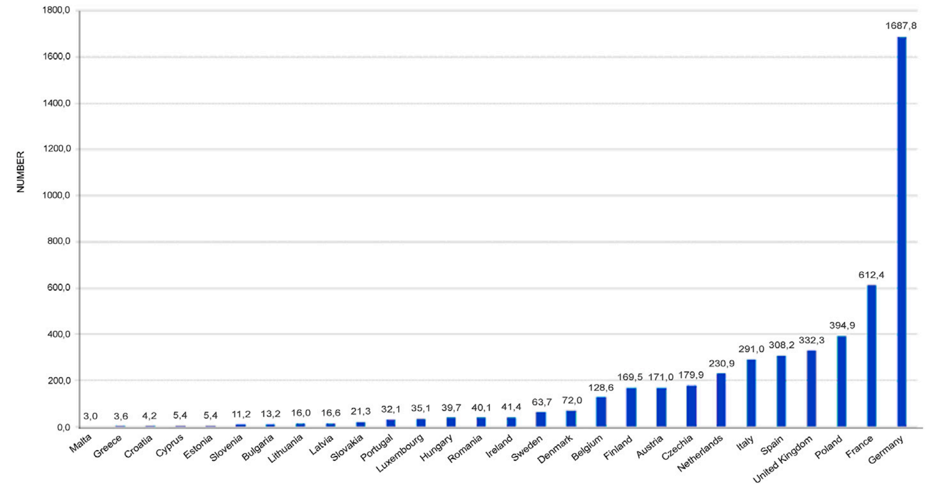

FIGURE 2 | Innovation in EU by total patents registered (2000–2015) (no.)/Source: own calculation with Eurostat data.

TABLE 2 | Mean of Patents related to recycling and secondary raw materials, by Euro area during the 2000–2015 period (no./year/country).

Euro zone member = 0	Euro zone member = 1	Difference	%
9.0	16.3	7.3	181.1

Source: own calculation with Eurostat 2020 data.

5%, therefore we reject the H0 hypothesis that the series has a unit root. We conclude that the series PATENTS_RECYCL has no unit root, therefore is stationary in levels.

Hence, both series analyzed are stationary implying that their order of integration is I (0) (stationarity in level), therefore we can find a long-term relationship between them. Consequently, the model would be estimated using OLS.

Step 2: Building the econometric model

Estimating model of panel data was carried out based on the variables:

Y_{it} = log(CIRCULAR_MAT_USE) is the dependent variable and
X_{it} = log(PATENTS_RECYCL(-2)) is the independent variable.

The model was built having natural logarithm of the raw data. This way, we are able to estimate directly the elasticity of the CMUR related to the independent variable (Patents).

We are going to estimate three models for panel regression, i.e.: Pooled OLS, Fixed effects and Random effects. **Table 4** presents the estimations of the regression coefficients and the related statistical tests.

Pooled LS Model

In case of the Pooled LS model, we have obtained the results presented in **Table 4**. The estimated coefficients of the regression are statistically significant from the Student Test point of view.

The coefficient of determination is equal to 0.31429. That means only 31.42% of the variation of the dependent variable is explained by the independent variable. We may conclude that the quality of the regression could be improved. Hence, we try to obtain an improvement of the estimation by using the method Panel EGLS (Cross-section weights) with the variant of random and fixed effects.

Random Effects Model

In case of the use of panel EGLS with random effects, we obtained parameters which are significant from the Student Test point of view (**Table 4**). We note that the quality of the regression remains quite poor. The coefficient of determination is very low (0.0348). Therefore, we consider that this model could be improved.

TABLE 3 | Variables considered and notations used.

Variable	Indicator	Notation used	Variables inside the model
Y_{it}	Dependent Variable—Circular material used rate	CIRCULAR_MAT_USE	LOG(CIRCULAR_MAT_USE)
X_{it}	Independent variable—Patents	PATENTS_RECYCL	LOG(PATENTS_RECYCL(-2))
EURO	Dummy variable	EURO	EURO

Source: own compilation.

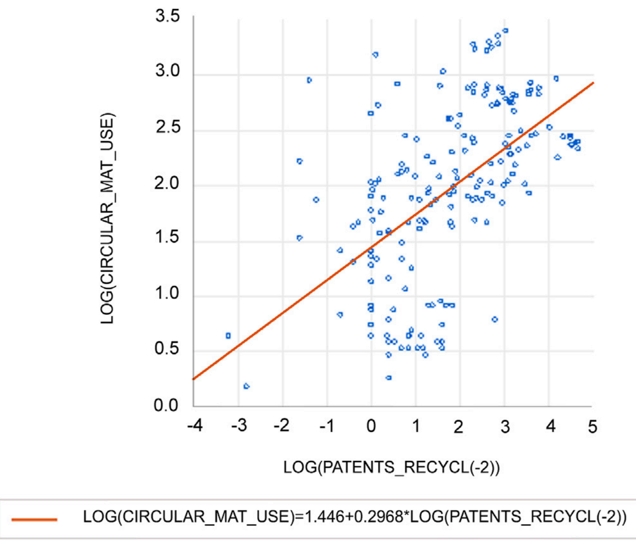

FIGURE 3 | Scatterplot of the two variables considered/Source: own calculation with Eurostat 2020 data.

Fixed Effects Model

When we used the method of panel EGLS with fixed effects, we obtained significant estimated parameters from the Student Test point of view (**Table 4**). Comparing with the previous estimations, the elasticity of the Y_i related to X_i is positive, respectively 0.0462. These results reveal that an intensification of the innovative activities, quantified by the number of patents related to the analyzed domain contributes to an increase of the rate of circular material use, but in a moderate way.

The quality of the regression is sensibly higher in comparison to the previous ones (**Table 4**). The coefficient of determination is higher than 0.99. In addition, the F-statistic is 561.02 and statistically significant. As well, FEM has better indicators as SSR and Root MSE both have the lowest values (9.87 and 0.2322) comparing with the previous models. The F-statistic is statistically significant and is highest among the models considered. Therefore, we may conclude that the FEM improved in a significant manner all good-ness-of-fit measures like F-test, SSE, root MSE and (adjusted) R^2.

As previously stated, these models showed the strength (coefficients) and the direction of influence (positive/negative) of the independent variable (patents) on the dependent variable (recycling).

Step 3. Performing Hausman test and selecting the model

We use the Hausman test to verify if the panel model with random effects is appropriate or not. Null Hypothesis (H0) is: a panel model with random effects is appropriate. As the probability given by Hausman test (p = 0.001) is much lower than 5%, we reject the H0 hypothesis (**Table 5**). We may conclude that a model with fixed effects is appropriate in our case.

The Hausman Test confirms that the Panel EGLS model with fixed effects is an appropriate form for the relationship of the rate of circular material use and the innovative activity, quantified by the number of the patents related to the recycling and secondary raw materials use.

Therefore, after comparing all the three models, we selected the model with fixed effects, i.e.:

$$\boldsymbol{Y_{it} = 1.8831 + 0.0463{*}X_{it} + [CX = F]} \qquad (4)$$

The coefficient of the X_{it} (Patents) has the value 4.626%, being sensibly lower than the unit (it signifies a slope of 2.65°). This means that a modification of the independent variable (X_{it}) by one unit has an influence on the dependent variable (Y_{it}) of 4.63%, holding all other variables constant (p < 0.0000). We consider Patents a significant predictor.

As well, we noticed a lag between the two variables; the Innovation (Patents) practically influences the dependent variable (Circular_Mat_Use) 2 years after a patent is registered. This lag accounts for all administrative and technical procedures that have to be in place before a patent effectively applies in economy. The practice confirms that a patent once registered has to proceed through various stages until it is finally applied.

The model shows us that, if the independent variable is zero (X_{it} = 0) then the dependent variable (Y_{it}) is still positive. That means, in this case, we still expect to have a positive CMUR (exp (1.8831) = 6.573%) (p < 0.0000).

While this model fits the data well, from the analysis exposed earlier regarding FE model, we may expect that the regression line for each country has different initial starting point (intercept). That is, each country may have its own initial value for CMUR, its Y-intercept, which is significantly different from those of other country but share the same slope. Therefore, next, we get country specific intercepts while the slope is the same.

As we mentioned earlier, each country will have a specific intercept (α_i) called cross-section fixed effect. The values for these intercepts are in **Table 6**.

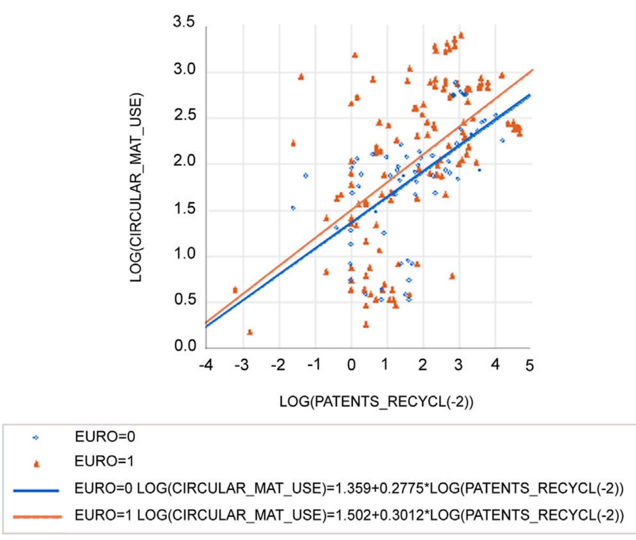

FIGURE 4 | Scatterplot of the two main variables considered and the influence of dummy variable EURO/Source: own calculation with Eurostat 2020 data.

TABLE 4 | The estimated coefficients and statistical tests of the econometric models taken into consideration.

Estimated coefficient/statistical test	Model		
	Panel OLS	Panel with random effects	Panel with fixed effects
Estimation Method	Panel Least Squares	Panel EGLS (Cross-section random effects)	Panel EGLS (Cross-section weights)
C (intercept)	1.4455	1.763137	1.883095
X_{it} = LOG(PATENTS_RECYCL(-2))	0.2968	0.078607	0.046268
t-Statistic for C coefficient	19.459	14.35009	99.34532
t-Statistic for X_{it} coefficient	9.1585	2.646272	4.525619
Probability of null hypothesis for C	0.0000	0.0000	0.0000
Probability of null hypothesis for X_{it}	0.0000	0.0088	0.0000
R-squared	0.31429	0.034869	0.990167
SSR	78.3420	12.430	9.97
Root MSE	0.6507	0.259217	0.232211
F-statistic	83.879	6.6115	561.02
Probability (F-stat)	0.000	0.0109	0.000
Cross-sections included	28	28	28
Periods included	8	8	8
Total observations	185	185	185

Source: own calculation using E-view 11.

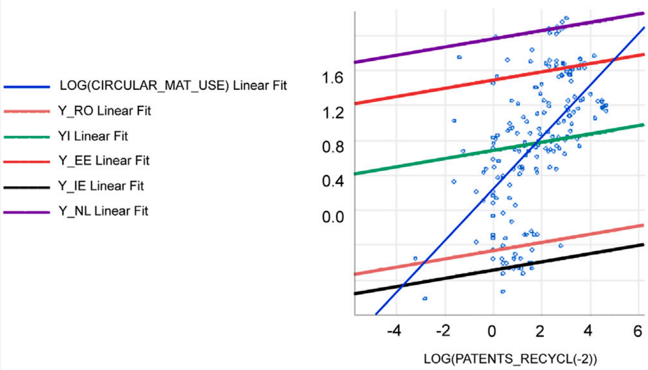

FIGURE 5 | Comparative regression lines for OLS model and Fixed Effect Model (FEM)/Source: own calculation.

The highest value for cross section effect is that of the Netherlands (1.2816), followed by France, Belgium, Estonia, United Kingdom etc. (highlighted in green). By adding the value of the coefficient C (1.8831) we obtain the intercepts for all countries. Negative intercept means that, if the independent regressor is zero (no innovation) then the recycling rate will diminish so innovation is critical to have a positive recycling rate. The intercept calculated for the 28 countries has positive values: a minimum value of 0.5172 (Ireland) and a maximum value of 3.1647 (the Netherlands). The heterogeneity of the intercept values is significant. If we calculate the coefficient of variation for the intercept values, as a measure for heterogeneity, we end up with a value of 40%.

Having cross-section effects, we could calculate and draw the regression line for each country. Because there are 28 country and it is difficult to visualize so many regression lines, we chose four countries to be represented. As well, we are going to plot the regression line resulted from the OLS panel and from the fixed effect model with cross-section weights (**Eq. 4**). **Table 7** presents the respective equations.

As can be acknowledged from **Figure 5** and how was previously stated, the FEM regression line (the green line) has a smaller slope than the OLS model (the blue line) but it has better indicators and has improved all goodness-of-fit statistics. For each individual country could be derived a regression line.

As remarked earlier, countries with negative cross section effects will have regression lines below the FEM regression line, as it is the case of the two countries (Romania and Ireland) selected as an example.

Countries with positive cross section effects will have regression lines above of the FEM regression line. It is not feasible to draw all regression line for the 28 countries analyzed.

Step 4. Introducing Dummy variable

The model described so far allows us to expand the discussion introducing the dummy variable EURO. The results are in **Table 8**.

After including the dummy variable EURO, the model will look as described in **Eq. 5**. **Table 8** presents the estimated coefficients and corresponding statistical tests.

$$\begin{aligned} \boldsymbol{LOG}\ (\boldsymbol{CIRCULAR\_MAT\_USE}) &= 1.330356 \\ &+ 0.294839 * \boldsymbol{LOG}\ (\boldsymbol{PATENTS\_RECYCL}\ (-2)) \\ &+ 0.182807 * \boldsymbol{EURO} \end{aligned} \tag{5}$$

Eq. 5 acknowledges that all coefficients are positive, meaning that all of them have a productive contribution to the dependent variable. The estimated parameter of the dummy variable EURO is statistically significant for a probability of 10% but not for 5%. The estimated parameter for the independent variable and for the intercept (C) are statistically significant for 5% probability. So, from statistically point of view the membership of Euro area has a positive influence.

TABLE 5 | Hausman test for Random Effects Model.

Correlated random effects—hausman test				
Test cross-section random effects				
Test Summary		Chi-Sq. Statistic	Chi-Sq. d.f	Prob
Cross-section random		10.851089	1	0.0010
Cross-section random effects test comparisons				
Variable	Fixed	Random	Var (Diff.)	Prob
LOG(PATENTS_RECYCL(–2))	0.039366	0.078607	0.000142	0.0010

Source: own calculation using E-view 11.

TABLE 6 | Cross-section effects (α_i) for Fixed Effect model (sorted ascending).

No.	Country	Cross-section effect	No.	Country	Cross-section effect
1	Ireland	−1.3659	15	Finland	0.0823
2	Portugal	−1.1903	16	Spain	0.1268
3	Romania	−1.1435	17	Denmark	0.1338
4	Greece	−1.0890	18	Slovenia	0.1760
5	Cyprus	−1.0790	19	Austria	0.2107
6	Bulgaria	−0.9813	20	Germany	0.3051
7	Latvia	−0.7675	21	Poland	0.3250
8	Lithuania	−0.5735	22	Luxembourg	0.6579
9	Croatia	−0.4803	23	Italy	0.6940
10	Slovakia	−0.3297	24	United Kingdom	0.7577
11	Hungary	−0.1511	25	Estonia	0.8110
12	Czech Rep	−0.1195	26	Belgium	0.8162
13	Malta	−0.0915	27	France	0.8276
14	Sweden	0.0143	28	Netherlands	1.2816

Source: own calculation with E-views 11.

TABLE 7 | Equations of the FEM model and for some countries (**Figure 5**).

Model	Intercept	Slope	Equation
Fixed effect model (FEM) (**Eq. 4**)	1.8821	0.0463	Y_{it} = 1.8831 + 0.0463*X_{it}
Panel OLS	1.4455	0.2968	Y_{it} = 1.44550 + 0.2968*X_{it}
Regression line for Romania	0.7396 = (1.8831–1.1435)	0.04627	Y_RO = 0.7396 + 0.04627*X_{it}
Regression line for Netherlands	3.165 = (1.8831 + 1.2816)	0.04627	Y_NL = 3.165 + 0.04627*X_{it}
Regression line for Estonia	2.6941 = (1.8831 + 0.811)	0.04627	Y_EE = 2.6941 + 0.04627*X_{it}
Regression line for Ireland	0,5162 = (1.8831–1,3659)	0.04627	Y_IE = 0.5172 + 0.04627*X_{it}

Source: own calculation.

TABLE 8 | The estimated coefficients and statistical tests of **Eq. 5**.

Variable	Coefficient	Std. Error	t-Statistic	Prob
C	1.330356	0.097114	13.69888	0.0000
LOG(PATENTS_RECYCL(-2))	0.294839	0.032221	9.150648	0.0000
Dummy EURO	0.182807	0.100186	1.824683	0.0697

Source: own calculations.

4 DISCUSSION AND CONCLUSION

In the endeavors to develop a low carbon, resource efficient and competitive economy and ultimately to support the sustainable development in the European Union, recycling is an important practical approach with essential contribution.

In this respect, the main objective of the paper is a theoretical and methodological grounding and analysis of the correlation of innovation and recycling required for the implementation of the circular economy in the European Union. There are also some original or less discussed aspects regarding the influence of the adoption of Euro as national currency on the performance in recycling.

The article brings new understandings regarding the relationship between innovation and recycling within EU. The 2016 report of the Eco-Innovation Observatory mentioned that innovation and CE is not homogeneous across member states. There are groups of member states: a group of leaders that have a scoring significantly higher than the EU average; a group of average performers that are countries with scores around the EU average and a catching up—group of countries—countries that recorded aggregate scores less than EU average.

Analyzing more thoroughly the two indicators selected (Circular material use rate and Patents), we found a similar pattern: uneven distribution among member states and three groups of states: leaders, average performers and catching up countries.

The step ahead made within this research is that of showing the influence of EURO membership. In case of the indicator CMUR, considered dependent variable, we found that Euro membership has a positive influence, on average, of +2.3% compared with countries that are not using Euro as a currency. Examination of the main regressor considered in the article (Patents) showed a similar pattern. There is an uneven distribution and the Euro Area membership has a positive influence on the indicator. In Euro Area, the average of the number of patents/country/years was 16.3 compared with 9.0 in case of the group of countries which are not yet members of Euro Area.

Therefore, we conclude that indicators considered have an asymmetric distribution across member states identified as leaders, average performers and catching up countries.

Furthermore, the paper provides evidence of the relationship between innovation and recycling. The model that resulted, carrying out a regression on panel data, showed the relationship between Circular Material Use Rate and Patents. The linkage is statistically significant ($p < 0.0000$) and by analyzing three similar models, the Panel Data model with fixed effects was selected as a plausible one. After comparison of the statistical values, we concluded that Fixed Effects Model (FEM) improved all goodness-of-fit measures like F-test, SSE, root MSE, and (adjusted) R^2 in a significant manner.

This paper demonstrates that the influence of the eco-innovation on recycling is moderate but it matters more when the initial status of recycling is low. If the initial status is negative then innovation is very important to bring recycling to positive values. As well, another aspect highlighted is that the influence of innovation is not instantaneous and there is a 2 years lag between the innovation inception and its implementation in practical activities, when its effects are measured by recycling rates.

From this paper could be derived some practical implication. One direction is to make more efforts to comply with the requirements of the Euro Area in order to speed up the admission of countries that still use their own currency. Of course, membership of Euro Area is not a miraculous solution but it will bring discipline, stability and financial rigor that, in turn, could add benefits in development of recycling activities.

The answer to the questions raised in the Introduction are as follows:

Answer 1: the influence of innovation on recycling is moderate with a gap of 2 years; Answer 2: the influence of the Euro area is important on recycling (+24,7%); Answer 3: the heterogeneity among member state is significant (40%)

As with the majority of studies, the design of the current article is subject to boundaries and limitations. Some of the limitations are related to available resources, since there are few prior research studies that are relevant to the topic of the article and also the statistical data are not completely available. In these circumstances, we consider as sufficient the sample of 28 countries.

For future studies it will be useful that some other explanatory variables would be used to have a better model to determine more drivers and barriers of the Circular Economy. One aspect that could be further explored is the determination of the relationship between recycling and the scoreboard defining eco-innovation as well as to explore the influence of eco-investment on the Circular Economy.

The paper has several originality aspects: it has taken into account criteria that are not so often discussed (membership of Euro Area), it has developed a model that brings quantitative values of the link between recycling and innovation. Until now, this link was analyzed so far, mainly from a qualitative point of view and less from the quantitative perspective.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://ec.europa.eu/eurostat/data/database.

AUTHOR CONTRIBUTIONS

VP and FMP conceived the study and were responsible for the design and development of the data analysis. VP and FMP were responsible for data interpretation. VP wrote the first draft of the article. DA and SF were responsible for data collection, analysis and for reviewing first draft of the article. AC and FP were responsible for general assembly of the article, English translation, template compliance and other proofreading corrections and syntax modifications.

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APPENDIX

ANNEX 1 | Descriptive statistics of the variables selected in the model.

	PATENTS_RECYCL (no./year)	CIRCULAR_MAT_USE (%)
Mean	13.69442	8.604464
Median	5.690000	7.050000
Maximum	141.6600	29.90000
Minimum	0.000000	1.200000
Std. Dev	22.80575	6.240428
Skewness	3.284577	1.107409
Kurtosis	14.49111	3.875991
Jarque-Bera	2,627.990	52.94595
Probability	0.000000	0.000000
Sum	4,929.990	1927.400
Sum Sq. Dev	186716.7	8,684.276
Observations	360	224

Source: own calculation with E-views 11.

ANNEX 2 | Results of the Panel Unit Root test.

Panel unit root test: Summary				
Series: CIRCULAR_MAT_USE				
Sample: 2000–2018				
Exogenous variables: Individual effects				
Automatic selection of maximum lags				
Automatic lag length selection based on AIC: 0 to 1				
Newey-West automatic bandwidth selection and Bartlett kernel				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin and Chu t*	–11.3075	0.0000	28	168
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	–2.62859	0.0043	28	168
ADF - Fisher Chi-square	99.0003	0.0003	28	168
Panel unit root test: Summary				
Series: PATENTS_RECYCL				
Sample: 2000–2018				
Exogenous variables: Individual effects				
Automatic selection of maximum lags				
Automatic lag length selection based on AIC: 0 to 1				
Newey-West automatic bandwidth selection and Bartlett kernel				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin and Chut*	–6,21932	0.0000	23	279
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	–3,17032	0,0008	23	279
ADF—Fisher Chi-square	73,3251	0,0000	23	279

*** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution; All other tests assume asymptotic normality.*
Source: own calculation with E-views 11.

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The Influence of Eco-Investment on E-Waste Recycling-Evidence From EU Countries

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Waste electrical and electronic equipment is the fastest growing waste stream internationally. Due to its physical characteristics, e-waste is a suitable subject for the development of recovery, repair, and recycling policies, prolonging products' life cycle for as long as possible, and is an objective pursued by the specific mechanisms of the circular economy. From the point of view of economic development models, e-waste management is one of the areas with significant potential for the implementation of the circular economy. The circular economy is analyzed through a set of 10 indicators that can be found in the Eurostat database. In this paper, we focus on the relationship between two main indicators with significance for this topic (e-waste recycling and eco-investment) and their evolution in European countries. An econometric model regarding the influence of eco-investment on e-waste recycling in EU member states will highlight the impact of circular economy indicators and the importance of promoting the reduce-reuse-recycle paradigm, especially for e-waste. A panel analysis was performed on data from European Union (EU) countries for the period (2008–2018). The analysis uses e-waste recycled per inhabitant as the determined variable and eco-investment per inhabitant as independent variable. The results of the econometric analysis performed show that, although all EU member states benefit from eco-investment, there is a group of countries that have already achieved a high capacity of e-waste recycling, while others should increase eco-investment further.

Keywords: e-waste management, eco-investment, e-waste recycling, panel regression model, fixed effects

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1 INTRODUCTION

Waste management pertaining to waste electrical and electronic equipment (WEEE) is an area with a high potential for the implementation of the circular economy. WEEE is one of the most suitable wastes for recovery, repair, and recycling, which is a main mechanism in the context of the circular economy.

The transition to the circular economy is one of the objectives stipulated in the European environmental and sustainable development policy framework. However, e-waste quantities are increasing from year to year (2% every year) due to digitization and IT&C expansion. Also, because of the international military conflict developing in North-Eastern Europe, there is a shortage of important raw materials required for electronic device production (neon, palladium). In this context, promoting the recycling and reusing of electronic devices has become more urgent and necessary than ever.

WEEE, also known as electronic waste, such as computers, TV sets, refrigerators and other household appliances, mobile phones, and electric tools, is one of the fastest growing waste streams in the world and, of course, in the European Union (EU). E-waste includes, among the parts of the discarded equipment, precious materials such as rare metals (platinum, gold), whose recycling should be improved.

E-waste contains a combination of many recyclables and hazardous components, and this is a serious concern that necessitates much attention in the future. Researchers are compelled to study the factors favorable to the progress of e-waste management.

It is important to highlight some of the most important socio-economic benefits streaming from circular e-waste management boosted by increased eco-investment.

There is a shortage of new materials for electronic device production. When recycling e-waste, all these materials can be reused (rare earths elements, platinum, cobalt, gold, and others). This is an opportunity to save raw materials from being excavated and also to reduce pollution (World Economic Forum, 2019).

E-waste can be a concerning source of pollution for the environment: discarded electronic devices can leak chemical components, polluting the soil and the groundwater. Also, countries that do not have sufficient recycling facilities for e-waste export the excess to developing countries such as India or Thailand. There, the informal e-waste recycling can be dangerous for workers, since they use rudimentary methods to dismantle the electronic devices (Purushothaman et al., 2020).

All these risks call for an increase of eco-investment in e-waste management in order to create new, safer, and greener technologies. At the same time, increasing e-waste management activities in EU countries would bring revenues and create employment in an organized and well-regulated sector of the green and circular economy (Platon et al., 2020).

The rapid growth of e-waste flow is a direct result of technological progress in the electronics industry that has led to an exponential growth in the variety and quantity of electrical and electronic equipment (EEE). E-waste management systems that are in place in EU countries are not yet able to cope with the scale of the e-waste problem, especially in new EU member countries (those joining the EU since 2004). Even if best practice has been transposed from developed member states, there is still a lack of efficiency and coherence in e-waste management.

In order to understand how e-waste management can be improved, this research focuses on finding a causality relationship between the e-waste statistical indicators and some of the other circular economy indicators analyzed at the international level. Several indicators were analyzed before establishing which one has the most significant influence on e-waste management.

The aim of this research is to determine the influence of eco-investments on the progress of e-waste management within the framework of the transition to the circular economy in the EU.

The main research objectives are to review, substantiate, and quantify the importance of eco-investment for e-waste collection, recycling, and reuse. There are also some associated collateral analysis objectives owing to the specifics of e-waste analysis, namely, the quantities of collected, recycled, and reused e-waste.

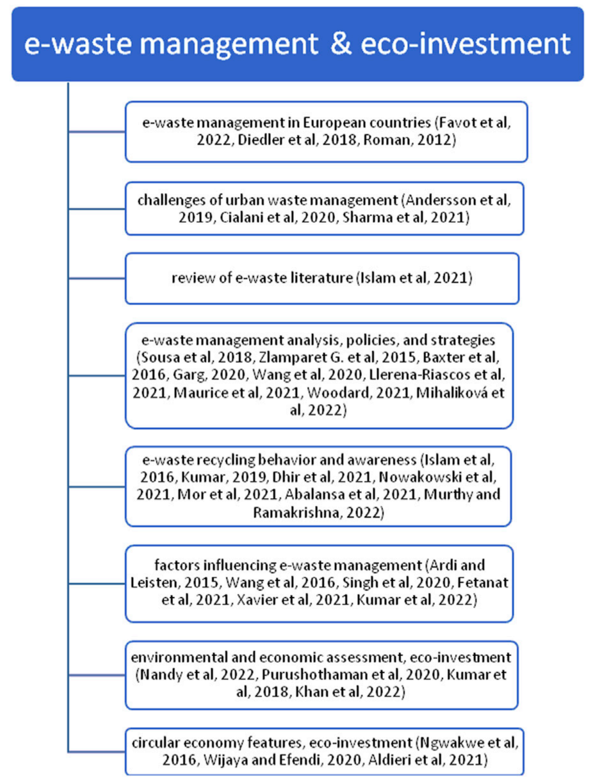

FIGURE 1 | Scientific literature development/Source: Created by the authors.

2 MATERIALS AND METHODS

2.1 Literature Review

This research examines an extremely new and modern subject. For this reason, many interesting papers can be found debating several aspects of e-waste management, as well as the necessity of investment in this economic sector. The scientific literature discusses on one hand theoretical aspects and on the other hand practical experiences from European countries and from all over the world. Our literature review focuses on EU countries' experiences but also presents experiences from other regions. **Figure 1** presents a schematic synthesis of this endeavor.

In the area of e-waste management, various papers have analyzed the respective processes and policies in order to identify the most significant factors and incentives for green development. The study of Roman (2012) is highly insightful regarding several good practices for WEEE management in Europe. This research analyzed and identified the successful experience of some European countries in the context of sustainable and efficient e-waste management, highlighting also the main issues to be tackled in a strategic sectoral approach (the legislative framework, the financing and logistic systems, the producer's responsibility, etc.).

Another most interesting and useful approach to analyzing and comparing WEEE management systems of a EU member state (Germany) and a non-EU country (Serbia) was developed by Diedler et al. (2018). The research has important insights on the most important indicators, logistics, and legal framework gaps between the European states, which impact the lower collection and recycling rate in Serbia.

Sousa et al. (2018) discussed the adjustments made by countries to EEE fees as an effect of European policy in the area of WEEE. According to the authors, there are lower EEE fees in Portugal, Poland, Greece, and Norway, and the relations with fees are largely dependent on the WEEE category.

Andersson et al. (2019) analyzed the challenges of recycling scarce metals, emphasizing that the rise in recycling rates is an industry development issue. According to the authors, this requires a strategy related to the build-up of entire value chain.

Favot et al. (2022) discussed the degree of competition/regulation in the EU WEEE recycling industry. The authors emphasized that the impact of competition on the economic performance is positive.

Kumar et al. (2022) discussed in their latest study which are the most important enablers of sustainable WEEE management. Based on the large literature review presented, the authors identified 23 enablers that facilitate the implementation of sustainable WEEE management. The study used a combination of the gray theory and DEMATEL methods (decision making trial and evaluation laboratory) in order to minimize the limitations of both methodologies. The research reached the following conclusions: the top three enablers of e-waste management are research and development capabilities, digitization, and environmental regulation.

The authors from this research team also had some previous research outcomes in this area. Garg (2020) uses the DEMATEL technique to analyze the relationship between the e-waste mitigation strategies (MS) via cause/effect analysis. According to the authors, "top management initiation and commitment towards return management" is the most important strategy for e-waste management. Fetanat et al. (2021) used a fuzzy approach, integrating also the DEMATEL method, to find the key indicators influencing the sustainability selection of CE strategies in WEEE management. According to the authors, "the profit" was the most important indicator for ranking the CE strategies.

Sharma et al. (2021) examined the challenges of electronic waste urban mining (EWUM) management. The authors use the integrated multi-criteria-decision making method (MCDM), step-wise weight assessment ratio analysis (SWARA), and weighted aggregated sum product assessment method (WASPAS). The results emphasized that socio-economic issues are the most critical issues in EWUM.

Zlamparet et al. (2015) compared the e-waste management systems in two capital cities: Beijing (China); and Bucharest (Romania). These two cities are important centers, representative of circular economy development in each country. There are some similarities as well as differences in their e-waste management. For example, they both need to improve the application of extended manufacturers' responsibility (EPR) for their products beyond the point of sale, up to end-of-product-life. As for the differences observed in the study, Romania has encouraged recycling for all WEEE categories, while China has focused on recycling only large household appliances. The conclusions of this study underline the importance of improving the policies regulating e-waste management.

Another recent study by Apostolescu et al. (2022) focused on the technologies, trends, and benefits of recovering precious metals form WEEE. They considered and analyzed several economic and environmental benefits of e-waste recycling, such as environmental and natural resource conservation, green job creation, energy saving, reducing CO_2 emissions, and landfill disposal. Their conclusions support the fact that, by recycling e-waste, precious metals may be recovered in a less costly manner (13 times cheaper) than by extraction from mines.

Baxter et al. (2016) discussed the life cycle assessment of the collection, transport, and recycling of WEEE in Norway. According to the authors, many quality aspects of WEEE recycling cannot easily be driven and regulated by policy.

Dhir et al. (2021) studied e-waste recycling attitudes and intentions. The authors used behavioral reasoning theory (BRT) and structural equation modeling, with a focus on Japanese consumers. According to these authors, "reasons for" were positively associated with attitude and intentions, while consumer values had negative associations with "reasons against."

Islam et al. (2021) used content analysis and reviewed various articles on consumer behavior regarding e-waste. The research emphasized that the consumers want important changes in e-waste management systems.

Cialani and Mortazavi (2020) analyzed the cost elasticity and marginal costs to determine if there are economies of scale for recycling urban waste in Italy. They addressed the gap in waste management demand-side aspects (reduction and discouragement of land disposal and promotion of recycling and recovery) by estimating the cost function of providing waste collection and recycling services for Italian municipalities during the years 2011–2017. The conclusions of this research paper suggested that increasing recycling rates would not substantially increase total costs for most municipalities, so recycling should be encouraged.

Maurice et al. (2021) focused on recycling strategies for increasing the recovery of chemical elements from waste printed circuit boards (WPCBs). The authors identified retrieval methods for elements that can be recovered in an environmentally friendly way.

Singh et al. (2020) investigated the drivers and barriers associated with e-waste management. The authors used a questionnaire-based survey and emphasized that the lack of awareness of environmental impact is an important problem for e-waste collection, and that the e-waste quantity and type are more important than the distance between the processing unit and the collection point.

Nowakowski et al. (2021) analyzed the use of container collection for small e-waste by individuals from the South of Poland. According to authors, there is a growing interest in the disposal of small e-waste, and a high percentage of respondents are aware of proper methods of e-waste disposal, but there is a lack of programs encouraging the population to adopt such behavior.

Mor et al. (2021) investigated the awareness level concerning e-waste management in educational institutions. The analysis was based on a questionnaire distributed among engineering students. The research showed that the awareness level regarding e-waste generation and processing was deficient, although the respondents understood the hazardous effects of e-waste.

Ardi and Leisten (2015) discussed informal operations in WEEE management systems using a system dynamics approach, focusing on India. The results emphasized the failure of formal collection and the growth of the informal sector. Llerena-Riascos et al. (2021) discussed sustainable WEEE management system policies. The authors used a system dynamics model and a mixed-integer nonlinear programming model. According to the authors, the replacement rate is an important element in increasing the performance of WEEE management systems.

Wang et al. (2020) discussed the interactions between the government and uncertified recyclers. According to the authors, the government should adopt the reward-penalty-supervision mechanism in the e-waste recycling sector. Abalansa et al. (2021) discussed the export of e-waste to developing countries. According to the authors, this activity is creating jobs, but there are some negative effects on the environment and human welfare. Woodard (2021) analyzed the level of resource leakage of recyclable and biowaste from SMEs into the household waste stream. The author presented some options to improve the management of waste from SMEs. Mihaliková et al. (2022) emphasized the relationship between public expenditure and the rate of recovery of municipal waste. According to the analysis, there is a positive influence on waste recycling from public administration expenditures related to the waste management. Murthy and Ramakrishna (2022) discussed best practices in the area of e-waste management, emphasizing the importance of policy implementation and social awareness for the sustainable and circular economy.

Various methods of analysis have been used in the literature. An important method is survey analysis, which was used by Wang et al. (2016) to investigate the factors influencing e-waste recycling behavior, with a focus on China. The indirect influencing factors were found to be environmental awareness, attitude towards recycling, perceptions of informal recycling, income and costs of recycling, and norms and publicity. Islam et al. (2016) analyzed WEEE management in Dhaka, Bangladesh, with a focus on the level of awareness, knowledge, the disposal method, and other aspects. The authors used a survey analysis and showed a low level of WEEE knowledge among households. Kumar (2019) investigated e-waste recycling behavior. The author employed a survey analysis, and the results revealed the influencing factors of e-waste recycling behavior, such as attitude, perceived control, subjective norms, and individual responsibility.

In addition to survey analysis, the following methods and models have also been used in the literature: exploratory analysis; logistic forecasting model; system dynamics; the DEMATEL method; the multi-criteria-decision making method; life cycle assessment; structural equation modeling; and content analysis. For example, Xavier et al. (2021) developed an exploratory analysis regarding e-waste management, with a focus on the American continent, to identify how legal, economic, and environmental criteria influence e-waste management options. The results indicated a direct correlation between e-waste generation and GDP.

Eco-investment, or green investment as it is often referred to in the scientific literature, concerns financial support for business practices that seek not to harm the natural environment. They are sometimes explained as socially responsible investing, encompassing environmental, social, and governance criteria. Green investments target projects or research committed to natural resource conservation, limiting pollution, or other environmentally conscious business practices. Because of its target and features, eco-investment is often found in the scientific literature analyzing innovation, eco-innovation, eco-efficiency, and sustainable development.

Khan et al. (2022) analyzed the impact of trilemma energy balance and clean energy transitions on economic expansion and environmental sustainability. According to the authors, environmental sustainability is affected by the depletion of natural resources.

Investment is an activity that usually associated with welfare, but not exclusively. As Wijaya and Efendi (2020) underlined in their paper, ensuring a good environmental condition is also important. In this context, an equilibrium must be found between profit and sustainability. This is where eco-investment comes into play, using an integrated policy system at the national or regional level. This paper presented an analysis of Indonesian laws and regulations governing the implementation of eco-investment.

Aldieri et al. (2021) proposed a systematic classification of the main circular economy features in order to identify the best intervention areas for sharing economy models and eco-innovation systems. Their three-step theoretical analysis was applied to seven particular case studies, highlighting one main conclusion: the main objective of policy makers must be increasing R&D investments focused on eco-innovations.

Ngwakwe and Ambe (2016) analyzed eco-investment as a basic condition for the eco-performance rating of a company. They stated that the "Eco-Ratio" trend analysis is significant and that it might provide a means of sustainability performance assessment for management and other interested stakeholders. Also, this type of analysis might refocus business sustainability to address ecological and social problems.

Awasthi et al. (2018) studied the connection between global e-waste generation and GDP. During their research, it became clear that there was a strong linear correlation between the analyzed indicators. The authors performed both environmental and economic assessments that showed that any kind of investment decision or market analysis must take into account the volumes of waste as well as the GDP dimension.

The study of Nandy et al. (2022) highlighted the importance of circular waste management in a green economy, focusing on the investment needs and challenges of three difficult sectors (plastics, electronics, and medical) in the context of waste

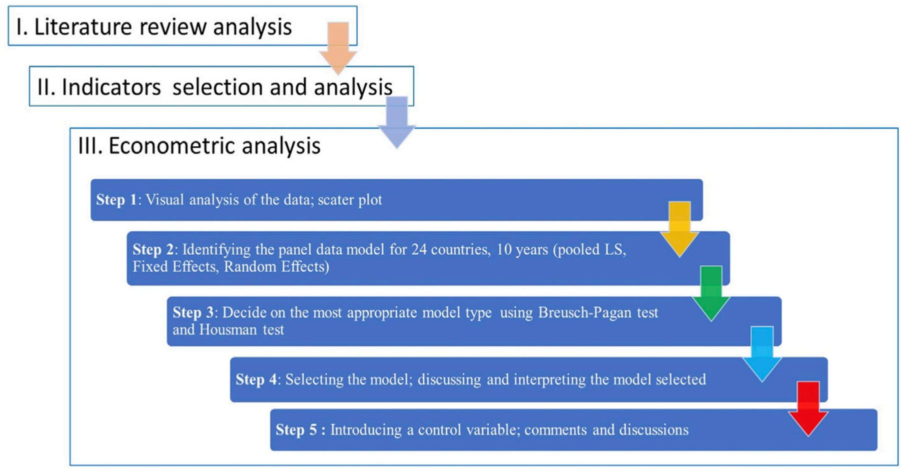

FIGURE 2 | Methodology used for modeling e-waste recycling and eco-investment in EU countries/Source: Own contribution.

management. Among the e-waste categories, the importance of the green management of portable batteries was analyzed in more detail, considering their increasing demand and that they contain precious but also potentially harmful elements (Ni-Cd, Li-Ion, Li-Po, etc.). The EU may become a leader in the sustainable management of batteries, through the creation of the "The European Battery Alliance" (EBA). This European industrial ecosystem has attracted more than €60 billion of eco-investments in 2019, creating a circular, competitive, and sustainable value chain (EU Industrial alliances).

From the research papers analyzed and the available policy documents, the importance of eco-innovation in the process of economic development is obvious. By developing eco-innovation abilities and practices, it is possible to enhance the commercial potential across all economic sectors. The second aspect that is worth mentioning is the fact that it reduces uncertainty concerning future market developments in the EU. This will help boost eco-investment and accelerate the introduction of environmentally friendly technologies, products, and services (Frone and Constantinescu, 2013).

2.2 Research Methodology

The main source of data identified for this paper's objective was the Eurostat database, which provides data collected by the European Commission regarding the quantity of WEEE collected in tons per year and also in kg per inhabitant per year.

The chosen analysis period is 2008–2018, because statistical data are available for this interval in the Eurostat database for a large majority of the 28 EU member states.

In order to develop the analysis of eco-investment's influence on e-waste management, the authors used several research methods: interrogation of available databases; comparative data analysis; data trend examination; basic desk research; processing the data; etc. Calculations were made using panel data for 24 EU member states (four member states did not provide data on investments: Irlanda, Malta, Luxembourg, and Czechia), covering a time interval between 2008 and 2018.

The main steps of the methodology used for modeling are presented in **Figure 2**.

The Eurostat database is the most important source of data regarding e-waste management in the EU. The indicators considered for this research were selected among those present in Eurostat database in different categories of interest for the analyzed subject:

- "Waste electrical and electronic equipment by waste management operations." This is a series of indicators that cover many aspects of e-waste management, from the collected e-waste to recycled and reused e-waste. This range of indicators is presented in the Environment and Energy category (https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=env_waselee&lang=en).
- "Private investments, jobs and gross value added related to circular economy sectors" is the statistical indicator used for eco-investment, which can be found in the Circular Economy indicators category of the Eurostat database, under the section Competitiveness and Innovation (https://ec.europa.eu/eurostat/databrowser/view/cei_cie010/default/table?lang=en).

In the following sections, we review these classes of indicators, taking into consideration also the several changes made in their categories and/or the reform of the indicators analyzing the process of e-waste management, followed by evolution analysis for the two main indicators used in this research, namely, e-waste recycling and eco-investment.

2.2.1 E-Waste Recycling in the EU: Evolution and Analysis

Data on WEEE available in Eurostat database are collected from EU member states and a few other countries in order to monitor compliance with the quantitative targets for the collection, preparing for reuse, recycling, and recovery of e-waste, according to the EU Directive 19/2012.

The definition of electronic equipment and of electronic waste, for the purpose of monitoring WEEE management, is as follows:

- "Electrical and electronic equipment (EEE) means equipment which is dependent on electric currents or electromagnetic fields in order to work properly as well as equipment for generation, transfer and measurement of this currents."
- "Waste electrical and electronic equipment (WEEE) represent the above-mentioned machineries that have exceeded their lifetime expectancy, also including all components, sub-assemblies and consumables, which are part of the product at the time of discarding."

The Eurostat classification, encompassing 10 major categories, was used for statistical purposes until 2018. However, since 2019, the electronic equipment has been divided into six categories: temperature exchange equipment; big screens and monitors; lamps; large household appliances and IT equipment; small household appliance and other electronic equipment; and small IT and telecommunication equipment.

There are a number of waste management operations considered by Eurostat for each of the above categories of electric and electronic equipment (EEE). The classification of these operations has also changed since 2018, expanding from six categories to nine categories: EEE placed on the market (POM); WEEE generated; WEEE collected; WEEE collection rate; WEEE preparing for re-use; WEEE recycling; WEEE preparing for re-use and recycling; WEEE recovery; and WEEE treated (in the member state, in another member state, and outside the EU).

For the purposes of this research, because the Eurostat database includes statistical updates since 2018, the authors have taken into consideration the first classification, with 10 categories of electronic equipment. For statistical purposes, a common methodology was established for the calculation of EEE weight placed on the market by each member state and for the calculation of e-waste quantity generated by weight in each member state.

In order to analyze the recovery targets, according to EU Directive 19/2012, the target achievement must be calculated for each category by dividing the e-waste weight at entry in the recovery (recycling/preparing for re-use) facility by the weight of total e-waste collected for each category, expressed as a percentage. The basic reporting unit is the company or institution performing the action (enterprises, producers, distributors, importers, local units, exporters, households, etc.) and may be different from one country to another.

All analyzed indicators—e-waste collected, e-waste treated, e-waste recycled and prepared for reuse—are expressed in kg per inhabitant based on the annual average size of the population. They are reported for every year, starting in 2005. Unfortunately, not all reporting countries have data for every year, so the analysis might have statistical gaps.

The first analyzed indicator, namely, e-waste collected, is expressed in kg per inhabitant per year. The data in **Table 1** presents a selected number of EU countries in order to show the evolution of this indicator.

The average EU level of e-waste collected has a very slightly growing trend. There are some countries with a high e-waste collection level—Sweden, the United Kingdom, France, and Germany—with numbers above the EU average. Sweden has the highest values for every year in the analyzed period, although the national trend is downwards (from 16.53 kg/inhabitant in 2009 to 14.19 kg/inhabitant in 2018).

Also, it may be noticed there are many other member states with a low e-waste collection level: Spain; Bulgaria; and Romania. The trend of these countries is upward, but the value of the indicator is below the EU average. Romania is ranked in last place in the EU regarding the e-waste collected per inhabitant in each year of the analyzed period. It must be mentioned though that the trend is ascending and the collected e-waste quantity has doubled (from 1.9 kg per inhabitant in 2009 to 3.28 kg/inhabitant in 2018).

Figure 3 presents the evolution of the e-waste treatment in the EU and some selected member states. The trends of the e-waste collected indicator can be seen here as well: the same group of countries have figures above the EU average. Sweden has the highest values for the e-waste treatment indicator, but with a downward trend (from 16.45 kg/inhabitant in 2009 to 14.19 kg/inhabitant in 2018). Germany and France are above the EU average with a slightly growing trend, and the United Kingdom has a marked trend switching (increasing until 2016 and then decreasing).

The group of countries below the EU average are also similar to those from the previous indicator: Bulgaria; Spain; and Romania. For e-waste treatment, again, Romania is ranked in last position in the EU, although the value of the indicator has significantly increased by 68.9%, from 1.8 kg/inhabitant in 2009 to 3.04 kg/inhabitant in 2018 (**Figure 3**).

Figure 4 presents the evolution of the next important indicator (e-waste recycling and preparing for reuse) in selected EU member states. The indicator follows almost the same trend as e-waste collected and e-waste treatment.

Above the EU average levels are the same four countries (Sweden, the United Kingdom, Germany, and France), although it must be mentioned that the United Kingdom did not provide data for the 2010–2013 period.

Below the EU average can be found again Bulgaria, Spain, and Romania. Although the values are on an ascending trend and the values have almost doubled in the analyzed period (from 1.51 kg/capita in 2009 to 2.72 kg/capita in 2018), Romania is again ranked in last position in the EU.

2.2.2 Eco-Investment in the EU

The statistical indicator used here to analyze eco-investment is found in the Eurostat database under the label "Private investments, jobs and gross value added related to circular economy sectors." It is found within the Circular Economy indicators and is used to monitor progress to achieve competitiveness and innovation targets.

Innovation and investments in areas such as recycling processes, industrial symbiosis, eco-design, or secondary raw materials are key elements of the transition to the circular economy. There are some specific sectors closely related to the circular economy, such as the recycling, repair, and reuse sectors. These are job-intensive economic sectors with important contributions to local employment, which is one of the most important EU circular economy goals.

TABLE 1 | Collected e-waste in some EU Countries (kg/inhabit./year)/Source: http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=env_waselee; Eurostat (2022).

Country	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
EU 28 (2013–2020)	6.9	6.9	6.7	6.8	6.06	6.2	6.91	7.99	8.02	7.84
Bulgaria	4.49	6.09	5.5	5.26	4.84	5.86	8.64	8.63	7.7	7.49
Germany	10.16	9.5	8.85	8.59	9.03	8.93	8.84	9.5	10.13	10.29
Sweden	*16.53*	*17.21*	*18.69*	*17.71*	*18.39*	*14.94*	*14.69*	*16.45*	*14.06*	*14.19*
Spain	2.96	3.39	3.29	3.38	4.49	3.98	4.97	5.38	6.16	6.85
France	6.1	6.69	7.22	7.19	7.29	7.88	9.28	10.82	11.1	12.16
Italy	8.82	9.83	9.17	8.35	7.26	5.17	5.67	5.96	6.3	6.97
Poland	2.8	2.95	3.77	4.61	4.51	4.55	5.24	6.13	6.49	6.73
Romania	1.9	1.3	1.04	1.15	1.66	1.62	2.06	2.37	2.54	3.28

Italics represents the highest values of the analysed indicator.

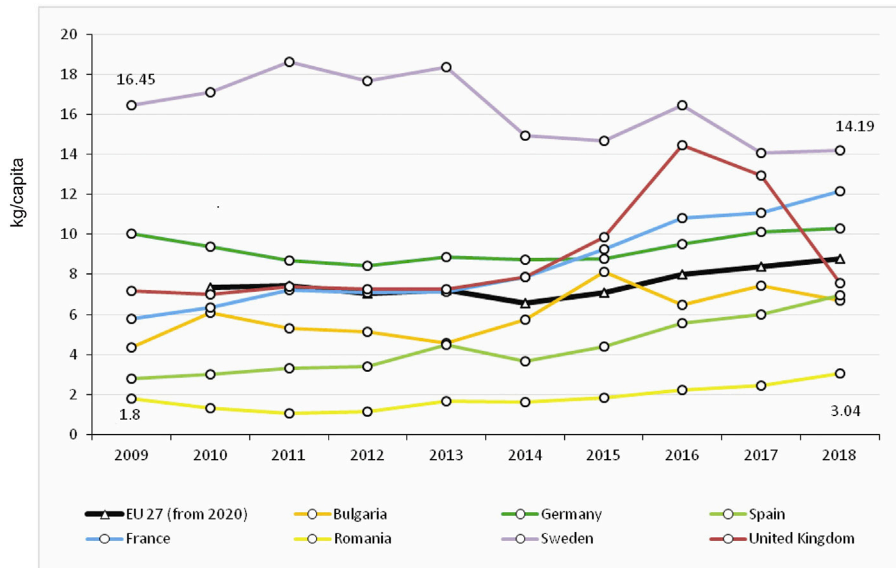

FIGURE 3 | E-waste treatment in selected EU countries, kg/capita (2009–2018)/Source: Own compilation from Eurostat data.

The indicator "Private investments, jobs and gross value added related to circular economy sectors" includes several sub-sections, namely, gross investment in tangible goods, number of persons employed, and value added at factor costs, in two main sectors (the recycling sector and the repair and reuse sector). The data presented are collected within the frame of the Structural Business Statistics and, for statistical use, the following definitions are in use.

- Gross investment in tangible goods—represents investment during the reference year in all tangible goods. Investments in intangible and financial assets are not included.
- Jobs—represents the number of persons employed, also as a percentage of total employment.
- Value added at factor costs—is the gross income from operating activities after adjusting for operating subsidies and indirect taxes.

The unit of measurement for private investments and gross value added is million euros and the percentage of GDP. For jobs, the unit of measurement is the number of persons employed and the percentage of total employment.

The eco-investment indicator has a yearly frequency of dissemination, with new data being disseminated within two years after the reference year. However, the latest available data in the Eurostat database are from 2018.

For the eco-investment evolution analysis, this research has taken into account the statistical data present in the Eurostat database for the indicator named "Gross investment in tangible goods." It is expressed in millions of euros and as a percentage of GDP. Some European countries have not provided data for this indicator.

For the analyzed period, 2008–2018, the authors chose four countries with complete data: Sweden; Germany; Spain; and Romania.

The two figures below present the situation for these countries, for the two units of measures. Spain and Sweden have average values in both graphics, both in absolute values and in percentage of GDP.

Looking at **Figure 5**, the graphic with absolute values, Germany has the highest level of eco-investment. For the percentage of GDP (**Figure 6**), Germany is in a lower position (lower than the EU average).

Although, in absolute values, Romania is ranked in last place in the EU, as percentage of GDP, the gross investment in tangible goods

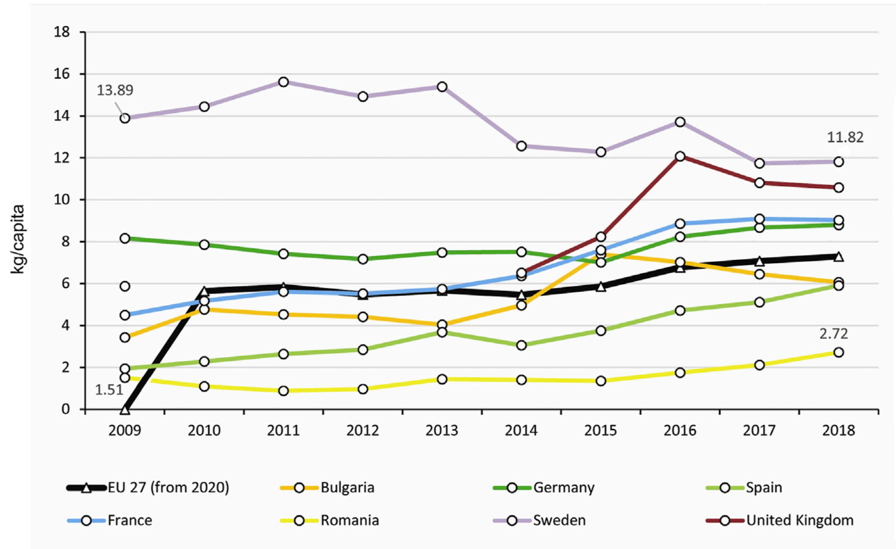

FIGURE 4 | E-waste recycling and preparing for reuse in selected EU countries, kg/capita (2009–2018)/Source: Own compilation from Eurostat data.

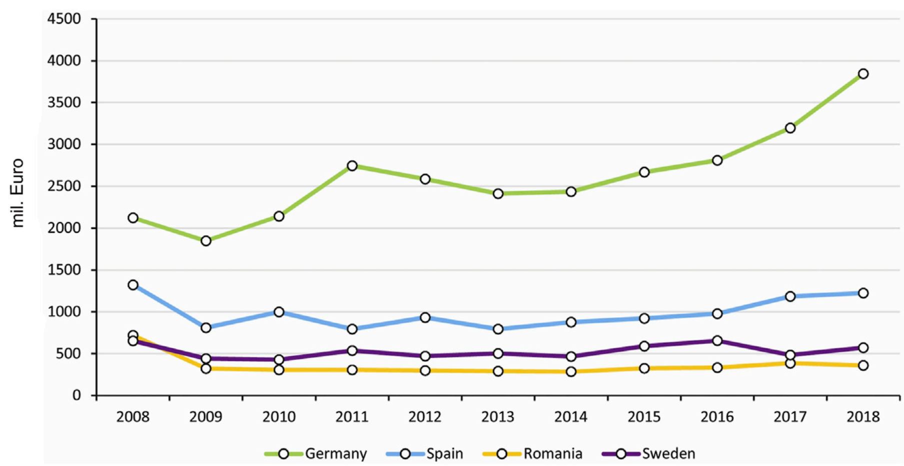

FIGURE 5 | Gross investments in tangible goods in selected European countries (million euros, 2009–2018)/Source: Own compilation from Eurostat data.

places Romania higher than the EU average and also higher than most developed European countries. The analysis thus show that numbers can be misleading: Romania seems to be in a good position relative to other EU countries; it is just has a low national GDP.

2.2.3 Econometric Analysis: Method Used

All calculations are made using panel data for 24 countries and a time frame of 10 years (2009–2018). We use the notation presented in the **Table 2**.

Step 1: Visual analysis of the data.

The first step is to draw a scatter plot (**Figure 7**) to see if there is any sort of relationship between the series selected (eco-investment and e-waste recycling).

Step 2: Identifying the model.

We estimate a model for panel regression based on **Eq. 1**.

$$Y_{it} = \alpha + \beta X_{it} + u_{it} \tag{1}$$

All estimations are carried out with the help of the EViews 11 software package. We use three types of panel data models: pooled model; fixed effect (FE) model; and random effect (RE) model.

In the pooled model, the coefficients of the two variables are specified as constant, which is the usual hypothesis for cross-sectional analysis.

Y_{it} is the dependent variable and the matrix X_{it} includes the explanatory variables. The cross-section (countries) dimension is

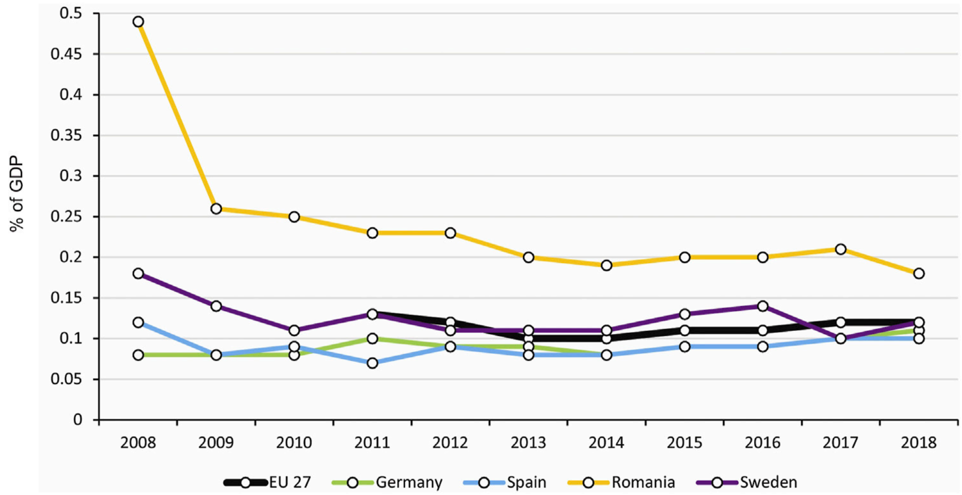

FIGURE 6 | Gross investments in tangible goods in selected European countries (percentage of GDP, 2008–2018)/Source: Own compilation from Eurostat data.

TABLE 2 | Notations used in the panel data model/Source: Own compilation.

Variables	Indicator	Notation used	Variables in model
Y_{it}	E-waste recycling (kg/inhab.)	E-waste2	E-waste2
X_{it}	Investment (€/inhab.)	Invest_recycl	Investment/capita

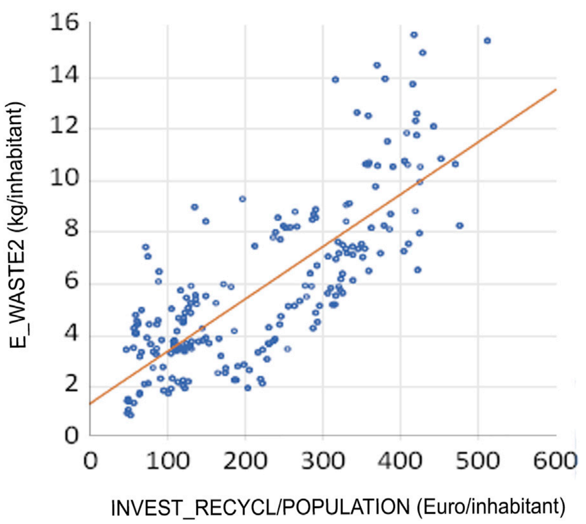

FIGURE 7 | Scatter plot of the series selected for the model (e-waste recycling and eco-investment)/Source: Own processing data from Eurostat.

represented by i, the time dimension is represented by t, and u_{it} is the error term.

Individual specific effects models take into account unobserved heterogeneity along cross-sections and include it in the term α_i. If α_i is correlated with the regressors X_{it}, we are dealing with a FE model. If the respective correlation is not detected, we are dealing with a RE model.

The FE model allows the individual specific effects (α_i) to be correlated with the regressors; this term is included in the model as the intercept. The FE model is as follows:

$$\boldsymbol{Y_{it} = \alpha_i + \beta X_{it} + u_{it}}$$

The RE model is based on the assumption that the individual specific effects (α_i) are distributed autonomously of regressors and are included in the error term. The RE model is as follows:

$$\boldsymbol{Y_{it} = \beta X_{it} + (\alpha_i + u_{it})}$$

Step 3: Selecting the most appropriate model.

In order to select the most appropriate model, first we compare the pooled model with the FE model using Breusch–Pagan test. The null hypothesis for the test (H_0) is: no effect of differences of cross-sections on the intercept. If the test rejects the null hypothesis, then we analyze the FE and RE models.

The RE estimation considers that the random effects are not correlated with the explanatory variables. A method for testing this assumption is to employ the Hausman test to compare the fixed and random effects estimates of coefficients. If the Hausman test is statistically significant (< 5%), we should use the FE model. If the test is not statistically significant, we should use the RE model (Wooldridge, 2002; Baltagi, 2005).

Step 4: Discussing and interpreting the model selected.

TABLE 3 | Breusch–Pagan test/Source: Own calculation using EViews 11.

Lagrange multiplier tests for random effects
Null hypotheses: No effects
Alternative hypotheses: Two-sided (Breusch–Pagan) and one-sided
(All other) alternatives

	Test hypothesis		
	Cross-section	**Time**	**Both**
Breusch–Pagan (0.0000)	442.3866 (0.3432)	0.898578 (0.0000)	443.2852

The last step is to discuss and interpret the model selected, as well as interpreting the heterogeneity among the countries within the model.

3 RESULTS

In this section, we present and analyze the influence of eco-investment on e-waste recycling in the EU, in the period 2009–2018, in order to observe some of the main trends and developments.

3.1 Modeling the Influence of Eco-Investment on E-Waste Recycling

The first step is to draw a scatter plot in order to visualize the possible relationship between the independent variable (e-waste recycling, kg/inhabitant) and the regressor (investment/capita, €/cap.).

As can be seen in **Figure 7**, the regression line shows that a relation between the variables is present.

The next step is to draft the pooled model as described in the **Eq. 1**. First, we perform the Breusch–Pagan test (**Table 3**). The null hypothesis is that there are no cross-section effects. As we can see, the probability is almost zero for cross-section so we reject the null hypothesis and accept the alternate hypothesis, meaning that there are random or fixed effects in our model.

The analysis continued by applying the Hausman test in order to identify the most appropriate model (FE or RE). The null hypothesis is: the RE model is appropriate.

As we can see in **Table 4**, the probability associated with the null hypothesis is zero ($p < 0.0000$), so we reject the null and accept the alternate hypothesis: the FE model is appropriate.

After applying the two tests, we conclude that a panel regression with fixed effects was appropriate, being supported by the Breush-Pagan test and the Hausman test. The estimations of the regression coefficients and the related statistical tests are presented in **Table 5**.

From **Table 5**, we conclude that coefficients of the model are statistically significant, so investment is a significant predictor. The intercept has the value of 1.245711 and it is statistically significant ($p = 0.0415 < 0.05$). The coefficient for the regressor has the value of 0.02 and is statistically significant ($p < 0.0000$). The positive value indicates that, when the independent variable increases by 10 units (€/inhab.), the dependent variable has a moderate increase of 0.2%.

We note that the FE model has an R-squared value of 0.895129, which means that the regressors explain a significant part of the variation of the dependent variable (89.5%). The *F* test has zero probability [Prob(*F*-statistic) = 0.000000], so we conclude that all coefficients in the model are different from zero and the model is valid.

The final form of the FE model is as follows:

$$\begin{aligned}\mathbf{E\_WASTE2} = \mathbf{1.2457} \\ &+ 0.\mathbf{02078{*}INVESTMENT/POPULATION} \\ &+ [\mathbf{CX = F, ESTSMPL = \}\}2009\ 2018\}\}}]\end{aligned} \quad (2)$$

Figure 8 is the graphical representation of **Eq. 2**.

The FE model accounts for heterogeneity among the 24 countries used in the analysis. **Table 6** presents the intercepts for all 24 countries within the model.

In the FE model, the slope is 0.02078 and is constant for all countries, but the intercepts are different for each country and are fixed in time. The intercept shows what the e-waste recycling (kg/capita) in a country would be when eco-investment is zero. This parameter can be interpreted as the existing recycling capacity before investment in recycling is made. For the group of 24 countries included in the FE model, the average intercept is positive (1.245 kg/capita—**Eq. 2**), meaning that without investment we still have some recycling in the group.

The situation when the intercept is negative is more complicated. There is a group of countries (Spain, Cyprus, Slovenia, and Netherlands) that have negative intercepts, meaning that without investment in recycling the quantity of e-waste recycled is negative (the stock of e-waste will increase). Latvia and Austria have intercepts near zero, so without investment the recycling quantity will not change much.

TABLE 4 | Hausman test/Source: Own calculation using EViews 11.

Correlated random effects—Hausman test
Equation: Eq_ewaste2_invest
Test cross-section random effects

Test summary		**Chi-sq. statistic**	**Chi-sq. df**	**Prob.**
Cross-section random		17.521849	1	0.0000
Cross-section random effects test comparisons				
Variable	Fixed	Random	Var (diff.)	Prob.
Investment_recycl/population	0.002529	0.000259	0.000000	0.0000

TABLE 5 | Parameters of the fixed effect (FE) model (FEM)/Source: Own calculation using EViews 11.

Dependent variable: E-waste2
Method: Panel least squares
Sample: 2009–2018
Periods included: 10
Cross-sections included: 24
Total panel (unbalanced) observations: 212

Variable	Coefficient	Std. error	*t*-statistic	Prob.
C	1.245711	0.606767	2.053030	0.0415
Investment_recycl/population	0.020780	0.002721	7.637057	0.0000
	Effects specification			
Cross-section fixed (dummy variables)				
Root MSE	1.028788	*R*-squared		0.895129
Mean dependent var.	5.843868	Adjusted *r*-squared		0.881669
SD dependent var.	3.184371	SE of regression		1.095400
Akaike info. Criterion	3.130488	Sum squared resid.		224.3816
Schwarz criterion	3.526312	Log likelihood		–306.8317
Hannan–Quinn criterion	3.290471	*F*-statistic		66.50561
Durbin–Watson stat.	0.653771	Prob. (*F*-statistic)		0.000000

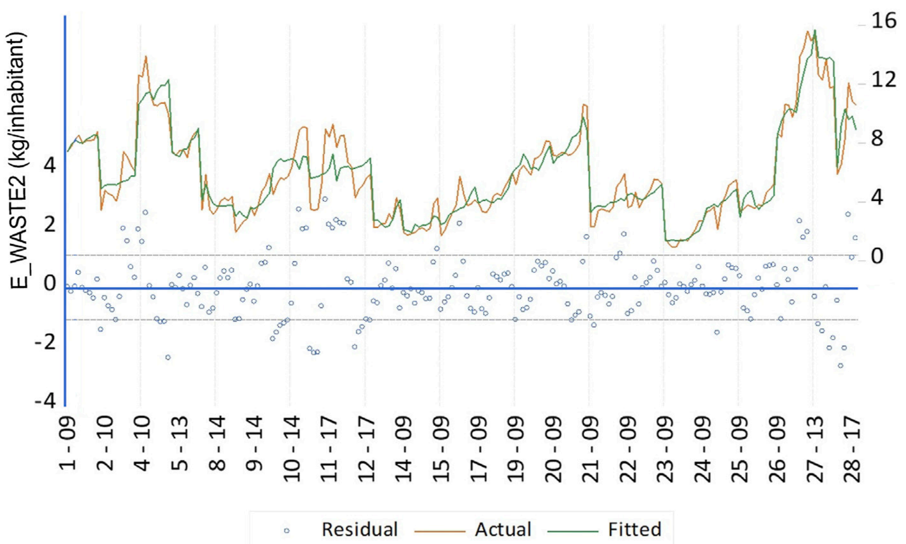

FIGURE 8 | Influence of eco-investment on e-waste recycling in the EU (kg/inhab/year, 2008–2018)/Source: Own calculation using EViews 11.

At the other end are countries like Sweden, which has the highest intercept, so it should have significant recycling capacities for e-waste (5.033 kg/capita). Sweden is followed by Belgium, Denmark, Finland, Croatia, and Bulgaria. These countries have higher values for the intercept, showing higher capacities in e-waste recycling than average. Other countries showed an intercept in the interval [1; 3 (kg/inhab.)], which means a moderate recycling capacity.

There is a group of countries (France, Germany, Italy, Romania, and the United Kingdom) with intercepts between [0; 1]. These values indicate that the capacity of recycling is still low and further investment would increase the e-waste recycling effectiveness.

The model adopted has some limits and boundaries. For instance, the negative values for the intercept could be the result of waste trade among member states. It is a reality that some countries have greater recycling capacities for electric and electronic waste, while other countries, with low capacities, just export the waste.

3.2 Introducing a Control Variable

The model presented and analyzed earlier uses only one independent variable, therefore potentially ignoring some impacts that could be important outside of the framework of eco-investment policy. To compensate for this, a control variable is included in the model to ensure that the model fits the policy practice context better. Usually, a control variable is introduced in a model in order to avoid or reduce the risk of attributing exclusive explanatory power to a single predictor.

The control variable is Internet access, which measures the spread of the Internet in the society. The indicator measures the percentage of households that have access to the Internet

TABLE 6 | Intercept for the countries within the FEM/Source: Own calculation using EViews 11.

Country	Intercept
Spain	–1.2181
Cyprus	–1.1591
Slovenia	–0.9753
Netherlands	–0.2506
Latvia	–0.0859
Austria	–0.0736
France	0.1338
Germany	0.2790
Italy	0.3017
Romania	0.3200
The United Kingdom	0.3731
Lithuania	1.1132
Poland	1.3802
Estonia	1.3945
Slovakia	1.5560
Portugal	1.8110
Hungary	2.3622
Greece	2.5237
Finland	2.5811
Belgium	2.9895
Croatia	3.1411
Denmark	3.4556
Bulgaria	3.8878
Sweden	5.0333

(2011–2020). Expanding Internet access in the society has many benefits in reducing transaction costs. At the same time, Internet access can be considered a driver for more computers, phones, TV sets, servers, modems, and other electric and electronic equipment that individuals and firms may acquire in areas that have improved Internet connections. Increasing the stock of electric and electronic equipment may have a significant impact on e-waste generated over time. It is also important to mention that Internet access may contribute to the better recycling of e-waste.

Therefore, we modify the model described in **Eq. 2** by adding the new variable Internet (%), which is provided by the Eurostat database. The outcome is presented in **Table 7**.

The model is now described by the following equation:

$$\mathbf{E\_WASTE2 = -2.07876091125 + 0.01452*INVESTMENT/POPULATION + 0.06149*INTERNET} \tag{3}$$

First, we notice that both predictors (investment and Internet) are statistically significant, and the coefficients have positive values. The intercept is negative and statistically significant. Second, we see that the coefficient for investment diminishes from 0.020 in **Eq. 2** to 0.0145 in **Eq. 3** (a decrease of 7.25%).

The R-squared value for **Eq. 2** (0.89) is close to the value for **Eq. 3** (0.90), indicating that both equations have an adequate fit. This outcome shows that, after introducing the control variable, the initial relationship (**Eq. 2**) remains at about the same level of intensity and in the same direction (positive) for the investment regressor. Therefore, we conclude that the initial relationship is valid.

3.3 Policy Suggestions

Although this was not among the primary goals of our research, the outcomes may allow us to also outline some policy suggestions.

Investment in e-waste recycling is important in building and modernizing recycling capacities. So far, the markets for e-waste recycling are fragmentated and confined around cities with a high concentration of electric and electronic equipment. Therefore, it is important to note that that policy and administrative measures do not interfere much in the e-waste market for recycling.

Moreover, some European countries already have significant capacities for e-waste recycling (Sweden, the United Kingdom, Germany, and others). Therefore, it is not appropriate and efficient for the other EU countries to develop more e-waste recycling

TABLE 7 | Introducing the Internet variable into the model/Source: Own calculation using EViews 11.

Dependent variable: E-waste_WASTE2
Method: Panel least squares
Sample: 2000–2018 if Ireland = 0 and Malta = 0 and Luxembourg = 0
And Czechia = 0
Periods included: 8
Cross-sections included: 24
Total panel (unbalanced) observations: 173

Variable	Coefficient	Std. error	*t*-statistic	Prob.
C	–2.078761	1.037862	–2.002926	0.0470
Investment_recycl/population	0.014520	0.004185	3.469855	0.0007
Internet	0.061497	0.015731	3.909297	0.0001
	Effects specification			
Cross-section fixed (dummy variables)				
Root MSE	0.939752	*R*-squared		0.906364
Mean dependent var.	5.993064	Adjusted *r*-squared		0.890439
SD dependent var.	3.079998	SE of regression		1.019477
Akaike info. criterion	3.014176	Sum squared resid.		152.7821
Schwarz criterion	3.488081	Log likelihood		–234.7262
Hannan–Quinn criterion	3.206437	*F*-statistic		56.91631
Durbin–Watson stat.	0.858951	Prob. (*F*-statistic)		0.000000

infrastructure. Instead, it is more suitable to eliminate the existing barriers that hinder e-waste trade.

Further, the use of economic instruments, such as deposit-refund or green stamps, should be expanded in order to encourage people to eliminate e-waste in a rational manner.

Last but not least, in order to reduce the quantity of e-waste, more measures are needed to reduce the amount of generated e-waste at the source.

4 DISCUSSION AND CONCLUSION

This paper has presented an extended analysis of selected circular economy indicators, namely, e-waste recycling and eco-investment, in particular EU countries. In order to analyze the recycling of e-waste, the authors presented the evolution of collected and treated e-waste. The research revealed a constant but very slow increase in all e-waste management activities. The EU trend shows a very slow increase for the analyzed period (2008–2018). The countries analyzed in this research are following slightly different trends, depending on their development level (measured by GDP): the developed countries (Sweden, Germany, France, the United Kingdom) have higher levels of e-waste collection and recycling, while the less developed countries are struggling to catch up, with very low levels of e-waste recycling (Romania, Cyprus). The eco-investment analysis also showed an increasing trend in most of the countries found in the Eurostat database for the analyzed period.

For the econometric analysis, the authors performed calculations on panel data for 24 countries and the period (2008–2018). The model was realized for two indicators: e-waste recycling (kg/inhabitant); and eco-investment (Euro/inhabitant). The four-steps analysis followed these stages: first—visual analysis of the data and drawing a scatter plot; second—identification of the proper model type to use (pooled model, FE model, RE model); third—selection of the most appropriate model for these indicators; and fourth—introducing a control variable. This was followed by the discussion and interpretation of the results.

The most appropriate model for this research was found to be the FE model, which accounts for heterogeneity among the 24 countries used in the analysis. The analysis showed what the level of e-waste recycling will be in each country with and without investments. For the 24 member states included in the FE model, the average intercept was positive (1.245 kg/inhabitant), which shows that, overall, even without eco-investment, there would still be some degree of e-waste recycling.

The analysis of heterogeneity showed that Sweden has the highest intercept value. This means that Sweden has a significant e-waste recycling capacity (5 kg/capita). Sweden was followed by Belgium, Denmark, Finland, Croatia, and Bulgaria, all of which showed high values for the intercept, indicating higher than average capacities in e-waste recycling. Other countries (Lithuania, Poland, Estonia, Slovakia, Hungary, Portugal, Greece, and Finland) showed an intercept in the interval [1; 3], which means a moderate recycling capacity. The next group of countries (France, Germany, Italy, Romania, and the United Kingdom) also had positive intercepts, but with low values, between [0; 1]. This may indicate that they have a low e-waste recycling capacity that requires further investment in order to increase e-waste recycling.

The situation is different when the intercept is negative. For Austria and Latvia, which have negative but close to zero intercepts, the results mean that no eco-investment will not greatly influence e-waste recycling. For the last group of countries with the lowest negative intercept (Spain, Cyprus, Slovenia, and Netherlands), the result means that with no investment in recycling, the quantity of e-waste recycled will decrease.

These results should be read with caution due to the fact that there is a significant e-waste trade among member states, which was not taken into account. A country may export its e-waste to a country specialized in recycling instead of investing in its own capacities. This trade could influence the final results, so future research should take this into consideration.

By introducing a control variable (Internet), it was possible to show that the selected model (**Eq. 2**) is valid. The intensity and direction of the interaction between e-waste recycling and eco-investment did not change much. Introducing the new variable (**Eq. 3**) slightly improve the overall performance indicators of the model.

This also shows that there is a robust direct correlation between the increase in eco-investment and the performance of e-waste management.

The overall results of the research show that there is a real connection between eco-investment and the e-waste recycling level in EU countries. An eco-investment increase would give a boost to e-waste collection and recycling, helping to reach the EU targets and to progress towards a more sustainable and circular economy. Future research in this direction is needed, as e-waste quantities are increasing rapidly due to the penetration of Internet technologies and eco-investment having a much slower growth rate. Further, the importance of other indicators, such as eco-innovation and e-waste trade, should be considered to expand this research.

DATA AVAILABILITY STATEMENT

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

AUTHOR CONTRIBUTIONS

AC and VP conceived the study and were responsible for the design and development of the data analysis. VP and SF were responsible for data interpretation. AC wrote the first draft of the article. MS and RM were responsible for data collection, analysis and for reviewing first draft of the article. DA and SF were responsible for general assembly of the article, English translation, template compliance and other proofreading corrections and syntax modifications.

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Imported intermediates, technology spillover, and green development: Evidence from Chinese firms

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Firms are critical stakeholders to achieve sustainable development. Thus, corporate environmental performance is a subject of broad concern. In an era of globalization, the relationship between trade and environment is hotly debated. One of the central questions is—will imported intermediates contribute to pollution abatement? Using Chinese firm-level data from 2000 to 2013, the article measures the technology spillover of imported intermediates and empirically tests the inhibitory effect and influence mechanism on pollution intensity with a fixed effects model and an instrumental variable approach. We find that: 1) the technology spillover directly increases innovation and indirectly affects innovation by importing diversity. Imported intermediates empower firms with insufficient innovation to control pollution. However, the incentive effect declines when innovation gradually improves. 2) The technology spillover diffuses along the industrial chain. Downstream firms benefit from the diffusion and thus have lower pollution intensity than upstream firms. 3) The technology spillover contributes to the end-of-pipe emission reduction. Also, it improves energy efficiency and promotes source governance. Furthermore, the environmental benefits of imported intermediates differ along a number of dimensions including sourcing countries, firm ownership, and location. Thus, we pinpoint a new channel concerning trade-induced technique effect. Meanwhile, our results confirm the rationale of liberalization and facilitation policies for imported intermediates, that is, trade policies have the potential to better contribute to sustainable development goals.

KEYWORDS

imported intermediates, technology spillover, R&D, pollution of enterprises, green development

1 Introduction

In recent decades, both academia and policymakers have focused on investigating the drivers of environmental deterioration. The combustion of fossil energy sources is primarily responsible for the explosion of emissions and consequent climate change. Voluminous research studies have unfolded several key determinants including financial development, innovation, globalization, and trade openness (Ahmad et al., 2020; Can et al., 2021; Ahmad et al., 2022). One of the main conclusions drawn from these results is that firms are in the center of the stage. Also, along with the deepening of globalization, a lot of attention has been paid to the environmental effect of trade. Given the positive impact from trade-induced technique effect, bilateral trade liberalization would not necessarily harm the environment of developing countries. Here, the technique effect is proxied by the emission intensity. International trade affects the emission intensity by altering the technologies used by firms, yet the extent of trade's contribution is inconclusive (Cherniwchan and Taylor, 2022).

Clearly, innovation and technological progress are among the two fundamental driving forces in alleviating the environmental pressure in response to the imperative fight against pollution. Green technology can be derived not only from indigenous research and development but also from the introduction and integration of foreign advanced clean technologies. In the era of global value chain and widespread production networks, developed countries often locate certain parts of the production chain as well as lead international technological innovation. On the one hand, for firms in developed economies, offshoring is cost-effective via taking the advantage of low cost in developing economies. On the other hand, for firms in developing countries, trade in intermediate goods serves as one means of global technology transfer and diffusion. The positive side of such exchange of materials among firms can be summarized as follows: the knowledge spillover from high-tech imported intermediate products may bring benefits for firms that are not yet at the production technology frontier. Enterprises can rapidly improve their own technical level and production efficiency by learning from trade. At the same time, diversified intermediate products that are mutually complementary with domestic products can be conducive to the optimal allocation of resources and promote the improvement of productivity. In this aspect, importing intermediate inputs might be beneficial for environmental protection. In He and Huang, (2022), they have illustrated that importing intermediates can effectively reduce pollution intensity. However, more empirical evidence should be provided to test this statement, given that the evidence from developing countries is still scant.

As one of the largest developing countries, China has made remarkable achievements in industrialization at the expense of serious pollution problems since the reforms and opening-up. During the 13th Five-Year Plan period, Chinese governments at all levels have taken actions to encourage technological transformation and upgrading in the industries. In particular, firms are encouraged to strengthen international communication and cooperation in green technology on many occasions. Furthermore, since the 1990s, China has been committed to reducing tariffs and non-tariff trade barriers and actively promoting trade in imports, especially since China accessed the WTO in 2001, the scale of Chinese intermediate input imports has continued to expand. Precisely, the volume reached 1.61 trillion US dollars in 2018, which is over nine-fold rise since 2000. Will the technology spillover from imported intermediates become an effective channel to assuage the environmental pressure of Chinese manufacturing enterprises? If so, what is the potential mechanism?

To formally tackle these issues, we begin with an estimation on the magnitude of technology spillover of imported intermediates, employing a unique Chinese manufacturing firms' dataset from 2000 to 2013. Next, we focus on the impact and pathways of technology spillover on pollution intensity at the firm level. By doing so, this study advances current research in three aspects detailed in the following paragraphs.

First, our study contributes to the long-lasting debates concerning trade and environment, especially at the micro-level. Our unique dataset, containing rich information on firms' importing and pollution emissions, allows us to open the "black box" of an import bundle to analyze the effect of imported intermediate inputs on firm's pollution control and thus also green development. Previous studies usually employ indirect indicators to explore the environmental effects of importing at a macro-level due to data constraints. For example, Gutiérrez and Teshima, (2018) used regional air pollution concentration to investigate the Mexican firms' environmental performance. Clearly, regional pollution, stemmed from various pollutants and their interactions, may not be a good proxy to reflect the emission of each firm. In this sense, our unique firm-level dataset provides arguably more comprehensive and accurate information about the emission of different pollutants. Therefore, it serves as a good data foundation for further identification of causal effects between importing and pollution.

Second, the empirical results hardly support the so-called pollution haven hypothesis. Using the micro-data of a developing country, we find that knowledge spillover plays an important role in enhancing the environmental performance. The effect diverges after differentiating the development degree of import sources. Although the relationship between import sources, firm's characteristics, and resulting increased productivity or innovation has been extensively discussed, import sources and their connection with firm's environmental performance have not been thoroughly investigated. Hence, by separating import sources into developing and developed countries, we delineate that importing from the developed sources tends to have a larger marginal effect on the reduction of pollution intensity. Moreover, compared with non-heavily polluting firms, we find that these heavily polluting firms engaging in the transaction of imported intermediate products can reduce their pollution intensity on account of the positive impact of the embedded technology. The two facts imply that firms in developing countries can benefit from the international trade in intermediate goods. The technology spillover from developed countries may contribute to alleviate the environmental pressure of pollution-choked firms.

Third, we also attempt to single out the role of the industrial chain. Shapiro (2020) stated that upstream industries rely more on dirty inputs like energy, while downstream industries spend more on relatively clean factor inputs like labor and intermediate inputs. At the firm level, we confirm Shapiro's findings, especially we find that downstream firms use more intermediate inputs and have lower pollution intensity. Meanwhile, relative to upstream firms, technology spillover from imported intermediate inputs in downstream firms exhibits a stronger impact on pollution intensity.

The rest of this study is structured as follows: we review related literatures and expound our contributions in section 2. In section 3, we describe our estimation strategy and data. Section 4 introduces the empirical analysis and discusses the findings with the underlying mechanism represented in Section 5. Concluding remarks are provided in Section 6.

2 Literature review

Recent literature has documented the critical role of trade in the firm's environmental performance, although the mechanism varies from scale effect, structural reform, technological progress due to learning effects, and arising competition in the domestic market (Cherniwchan, 2017; LaPlue, 2019). However, existing theories on firm's participation in international trade and pollution behavior mostly emphasize on exporting rather than importing (Batrakova and Davies, 2012; Kreickemeier and Richter, 2014; Forslid et al., 2018; Li et al., 2020; Pei et al., 2021). Relatedly, there is a growing literature exploring the relationship between importing behavior (Sun et al., 2018), input tariff reduction (Cui et al., 2020), and pollution. These articles usually take WTO accession or reduction of trade barriers as external shocks to importing. Clearly, such shocks tend to cause larger scales and more variety of imports, followed by fiercer competition and more technology diffusion. However, the environmental effects of such types of shocks are quite complicated and ambiguous at best. Few studies directly tackle the problem of firms' import behavior of intermediate inputs based on their pollution emission intensity. In a closely related work, He and Huang, (2022) found that importing intermediate goods will lead to an increase in firms' production scale, thereby increasing their total emission. Meanwhile, the importing behavior also increases abatement investment to reduce the emission intensity. Yet, their work does not mention the possible technological effects.

To advance this line of research, this study looks directly at the effect of imported intermediates on pollution using firm-level data. However, some researchers concentrating on the possibility that the intermediate imports can stimulate productivity and innovative activities provide indirect evidence to speculate the relation between intermediate imports and environment, as the enhancement of productivity and innovation are beneficial for alleviating the environmental pressure (Bloom et al., 2010; Shapiro and Walker, 2018).

Several studies find that imports of intermediate products or decline in input tariffs are conducive to productivity gains. Productivity can increase through three channels via imported intermediate inputs: learning, improved input quality, and increase in input variety. Amiti and Konings, (2007) found that a 10 percent fall in input tariffs in Indonesia leads to a 12 percent gain in the productivity of importing firms, much higher than the productivity gain from reducing output tariffs. Kasahara and Rodrigue, (2008) used plant-level Chilean manufacturing data to confirm the conclusion that imported intermediate goods can improve productivity. Topalova and Khandelwal, (2011) found a qualitatively similar conclusion based on Indian data. Bas and Strauss-Kahn, (2015) stated that using more varieties of imported input results in higher TFP and export scope. Halpern et al. (2015) constructed a model of importers in Hungarian and found that importing from all varieties would increase a firm's productivity by 22 percent due to imperfect substitution between foreign and domestic inputs. Elliott et al. (2016) found that importers importing high skill- and technology-intensive products and more varieties of inputs display stronger learning effects.

In terms of innovation, Bøler et al. (2015) showed that firms tend to increase imports with less expensive R&D. The action contributes to reducing production costs and ultimately boosting innovation. Liu and Qiu, (2016) investigated the effects of intermediate input tariff reduction on innovation of Chinese firms and also testified two opposite impacts. In particular, intermediate input tariff reduction can promote innovation by reducing innovation costs and restrain innovative activities due to the cheaper foreign technologies. Using a dataset of Chinese manufacturing firms, Chen et al. (2017) concentrated on the mechanism by which importing stimulated innovative activities and testified the effect of knowledge spillovers on R&D cost reduction.

The aforementioned studies suggest that a plausible channel through which imported intermediates affect firm performance is the technology spillover. Hence, measuring the technology content embodied in intermediate imports is of significance. To do so, several empirical research studies pioneered by Grossman and Helpman, (1991) and followed by Coe et al. (1997), Lichtenberg and Pottelsberghe de la Potterie, (1998), and Coe et al. (2009) measure the knowledge diffusion by R&D stocks and document the extent to which domestic and foreign knowledge affects productivity at the aggregate level. A common feature of these studies is that they construct measures of foreign R&D by using shares of total bilateral imports on GDP as weights for the foreign R&D stocks from source countries. In contrast, Madsen (2007) used patent counts to evaluate the knowledge content. Meanwhile, different from these previous studies, there are studies focusing on the industry level rather than aggregate data. The idea that intermediate inputs embody R&D knowledge and that their use is correlated with higher productivity at the industry level was examined by Scherer (1982), Griliches and Lichtenberg, (1984), Goto and Suzuki, (1989), and Keller (2004). Nishioka and Ripoll, (2012) proposed the concept of R&D content of intermediate input to represent the R&D stock embodied in intermediate goods used in production and used international input–output tables to capture transaction information of intermediate inputs at the industry level.

Building on the aforementioned studies, our article advances discussions concerning the environmental welfare of trade liberalization from the perspective of importing. In particular, we explicitly address how the technology spillover from imported intermediates contributes to pollution control. Moreover, we offer micro-evidence from a large developing country.

3 Empirical strategy and data

3.1 Estimation specification

To analyze panel data, a fixed effects model is a useful technique. This method can remove the effect of those omitted time-invariant factors that may bias the estimated results. Thus, we can assess the net effect of the predictors on the outcome variable. In this article, we used a fixed effects model to estimate the effects of technology spillover of intermediate input imports on the pollution intensity of Chinese manufacturing firms. Our baseline estimating equation is:

$$lnSO_{2it} = \alpha + \beta lnspillover_{it} + \gamma X_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where i is index firms and t is years. The variable $lnSO_{2it}$ denotes the emission intensity of SO_2 of a specific firm. $lnspillover_{it}$ is the technology spillover of imported intermediate inputs. λ_t denotes the year fixed effect, λ_i is the firm fixed effect, and ε_{it} is the error term. X_{it} denotes a set of control variables. Our coefficient of interest is β, the estimated relationship between the technology spillover of imported intermediates and pollution intensity.

3.2 Key variables

Our key independent variable is the technology spillover of intermediate input imports. According to the LP model constructed by Lichtenberg and Pottelsberghe de la Potterie, (1998), the specific process is as follows: foreign R&D capital stock CA_{ht} of country h in year t is obtained based on the perpetual inventory method of Berlemann and Wesselhöft, (2014):

$$CA_{ht} = (1 - \delta)CA_{h(t-1)} + rd_{ht}. \tag{2}$$

In formula 2, rd_{ht} is the R&D expenditure of country h in t period. The depreciation rate of R&D capital stock δ is assumed to be five percent. We set the time of initial R&D capital stock at year 2000. Then, we can get the total technology spillover of intermediate input imports for a given firm:

$$spillover_{it} = \sum_h \frac{input_{iht}}{GDP_{ht}} \times CA_{ht}. \tag{3}$$

In formula 3, $spillover_{it}$ is the firm's technology spillover of intermediate input imports in year t, GDP_{ht} is the gross domestic product of country h in year t, and $input_{iht}$ is the value of firm i importing intermediate inputs from country h in year t. The data of R&D expenditure and GDP of each country deflated to constant price in 2000 with purchasing power parity drawn from the UNESCO database.

Our dependent variable is the emission intensity of SO_2 by a firm in a given year. As encountering various observations of zero emission, we use the following transformed measure as our dependent variable $lnSO_{2it} = ln(SO_{2it}/realoutput_{it} + 1)$, where $realoutput_{it}$ is adjusted with the producers' price index (PPI) by industries and SO_{2it} represents the emission volume of sulfur dioxide of each firm. Also, we substitute the single pollution indicator with wastewater and dust to conduct the robust check. To indicate the complex environmental performance, we set a comprehensive pollution index using eight different pollutants and taking a simple average after standardization.

Following common practice and previous literatures, several financial indicators are included as control variables since they may affect the environmental performance. We control for the firm age as new firms tend to adjust with the latest pollution abatement technology better than the older ones (Cui et al., 2020). After subtracting from the open year from the current year, adding one and taking the logarithm, we can obtain the variable *lnage*. Then, we control the variable *size*, measured by the logarithm of total assets, to mitigate the potential scale effects on pollution. Moreover, a high level of enterprise debt can lead to stricter cost management and restrict the environmental expenditures (Xiao and Wang, 2020). Similarly, the firm's financing constraint can eventually impose pressure on environmental management (Zhang et al., 2019). Therefore, we add the two factors into our model to control for their potential influences.

Next, we divide total liability by total assets to obtain the variable *levity* and use the logarithm of interest expenditures to evaluate the financing ability *finance*. Many studies underpin that exporters have better environmental performance than non-exporters (Batrakova and Davies, 2012; Richter and Schiersch, 2017; and Pei et al., 2021). Thus, we add the firm exporting status *export* into the model specification. In terms of the external competition faced by each firm, we calculate the Herfindahl–Hirschman Index (HHI) based on the firm's main

TABLE 1 Summary statistics.

Variable	Obs.	Mean	St.dev	Min	Median	Max
lnSO_2	59,018	0.1965	0.3493	0.0000	0.0417	1.9036
lnspillover	83,865	5.5516	3.4091	0.0000	5.9442	17.0104
lnage	83,842	2.4056	0.6603	0.6931	2.3979	4.1271
size	83,861	12.2371	1.5368	8.8933	12.1891	16.1914
levity	76,018	0.5430	0.2434	0.0423	0.5501	1.2271
finance	74,736	6.1482	3.5685	0.0000	7.2160	11.9507
export	83,865	0.8121	0.3906	0.0000	1.0000	1.0000
HHI	83,865	0.0420	0.0590	0.0026	0.0215	0.3663

Source: Authors' calculations.

business income to evaluate the market competition. Generally, the smaller the value of *HHI*, the fiercer the competition. In order to alleviate the impact of extreme values on the efficiency and accuracy of the estimation result, we winsorize all the continuous variables at the level of 1 and 99%. Table 1 presents the summary statistics of the main variables used in this article.

3.3 Data

Our unique dataset is formed by manually combining firm-level operating data on Chinese manufacturing firms with firm-level customs data on trade transactions and pollution emission for the years 2000–2013. We introduce each dataset in order. Our first data source is the annual survey of manufacturing enterprises from China's National Bureau of Statistics. The database provides rich information on Chinese firms, containing official name, industry, location, ownership, employment, age, and financial performances such as assets, liability, output, and intermediate inputs. Our second data source is the Chinese green development database from China's National Bureau of Statistics. It collects information on production, emissions of various pollutants, and energy consumption of heavily polluting firms that account for over 85 percent of total emission of major pollutants in China. It is currently regarded as one of the most comprehensive and reliable micro-enterprise environmental data in China.

Our third data source, the disaggregated product-level trade transaction data and China's customs trade database are obtained from China's General Administration of Customs. It records a variety of information for each trading firm's product list, including identifiers, trading price, transaction quantities, the relevant customs regime (ordinary trade, processing trade, and other forms of trade), eight-digit HS product code, import sources, and export destinations. Since the tax code of the customs data is HS eight-digit, we need to transfer into HS six-digit. In order to identify the information of intermediate products imported by enterprises, we uniformly convert the tax codes contained in the database into BEC classification codes defined by the United Nations. When the BEC codes are 111, 121, 21, 22, 31, 322, 42, and 53, these eight categories of products are defined as intermediate products. Referring to the method of Brandt et al. (2017), we merge the three datasets using the firm code and official name of each firm and then double-check the matched outcomes using location information. Our analysis is based on this unique dataset, an unbalanced panel of 25,702 import enterprises and a total of 83,865 observations, with detailed information on firm characteristics, pollution emission, and international trade transaction during the period of 2000–2013.

To conduct mechanism analysis, this article utilizes the Chinese Patent Application Database to acquire the proxy variable of innovation at the enterprise level. R&D expenditure can reflect innovation input, but R&D of each firm is available only for the years 2001–2003 and 2005–2007. Moreover, due to the various subsidy schemes in China, the distortion of R&D data is much severer than patent data (Liu and Qiu, 2016). Thus, we do not employ R&D intensity to evaluate indigenous innovation. Rather, the patent database contains over 20 million patent data accepted and published by China's State Intellectual Property Office (SIPO) between 1985 and 2015, including relevant indicators such as the applicant's name, patent types, number of patents, and application time. This article merges the aforementioned databases by the firm name and company address year by year, consolidates different patent information of the same company, and finally obtains the detailed data of invention patents and other different patent types at the firm level from 2000 to 2013.

4 Empirical analysis and findings

4.1 Main results

Table 2 presents the regression results based on formula 1, with the control variables introduced step by step. The central estimation outcomes reveal that the technology spillover of intermediate input imports can dramatically reduce the firm's SO_2 emission intensity. In column 1, with only firm fixed effect and year fixed effect being controlled for, we find a statistically significant and negative estimate for *lnspillover*. The negative sign indicates that firms importing intermediate inputs can acquire benefits of pollution reduction as the existing technology spillover. In columns 2–7, we include several time-varying control variables that may influence the environmental performance, such as age, firm size, financial ability, export status, and competition pressure. Apparently, the negative effect of technology spillover from imported intermediate inputs on pollution is robust to these additional controls. As for the effects of the control variables, we find that a firm with a shorter history, a larger size, and much stronger financial ability

TABLE 2 Baseline regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$lnSO_2$	$lnSO_2$	$lnSO_2$	$lnSO_2$	$lnSO_2$	$lnSO_2$	$lnSO_2$
lnspillover	-0.0038***	-0.0037***	-0.0025***	-0.0027***	-0.0028***	-0.0027***	-0.0027***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)
lnage		0.0111**	0.0120**	0.0128***	0.0128***	0.0130***	0.0131***
		(0.0048)	(0.0048)	(0.0049)	(0.0049)	(0.0049)	(0.0049)
size			-0.0341***	-0.0388***	-0.0364***	-0.0360***	-0.0361***
			(0.0044)	(0.0044)	(0.0045)	(0.0045)	(0.0045)
levity				0.0140	0.0170	0.0171	0.0168
				(0.0105)	(0.0105)	(0.0105)	(0.0105)
finance					-0.0013**	-0.0013**	-0.0013**
					(0.0006)	(0.0006)	(0.0006)
export						-0.0106**	-0.0108**
						(0.0050)	(0.0050)
HHI							0.1328**
							(0.0532)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	51,726	51,714	51,713	46,815	46,143	46,143	46,143
R-squared	0.7083	0.7086	0.7098	0.7353	0.7362	0.7362	0.7363

Note: all standard errors in parentheses are clustered at the firm level. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively.

has a better performance in curbing the emission. Exporters also performed better than non-exporters, which is consistent with the previous findings. The positive coefficient between *HHI* and $lnSO_2$ indicates that market competition can force firms paying more attention to pollution control. However, the effect of firm's levity is not statistically significant.

4.2 Endogeneity checks

If firms from cleaner sectors import more intermediate products, we have to disentangle the actual reason of the less pollution being more importing or cleaner sectors. Therefore, we conducted a two-sample *t*-test between clean sectors and heavily polluting sectors. It is found that the mean of *lnspillover* is significantly smaller than that of heavily polluting sectors.[1] Evidently, clean sectors do not seem to import more intermediate and have larger spillovers than heavily polluting sectors.

Then, to address the potential endogeneity issue arising from omitted variable concern, our strategy is the instrumental variable approach. This requires an instrument that is correlated with importing intermediates but uncorrelated with any characteristics of firms that may affect their environmental performance. We adopt the distance from the located city of each firm to the coastline (Nunn and Wantchekon, 2011) and the distance to the nearest port (Wang and Chanda, 2018; Souza-Rodrigues, 2019). The distances capture a firm's exposure to the external demand for imported intermediates, since maritime is the main transport mode of global trade covering over 90% of traded goods. Also, the transportation costs are contingent on the distances. Enterprises should pursue higher value under the limit of transportation costs. It is more beneficial for those remote enterprises to import high-tech intermediate products. Otherwise, they can obtain the low-tech and locally available intermediates nearby. Hence, the distances are positively correlated with the technology spillover of imported intermediates. Additionally, the distances hinge on the firms' location. They do not directly correlate with the pollution intensity.

Since geographic conditions cannot materially change during the sampling period, we multiply them with the annual average price of Brent crude oil in USD and the annual RMB/USD exchange rate to construct time-varying instrumental variables. Specifically, we extract the coastline from the administrative map of China and calculate the distance from the located city of each firm to the coastline. The data of ports are

1 The mean of *lnspillover* of cleaner sectors is 5.4797, and the mean of *lnspillover* of heavily polluting sectors is 5.6275 (t = -6.2371, P(T < *t*) = 0.0000).

TABLE 3 Addressing the endogeneity issue.

Part 1: first stage of IV regression

	(1)	(2)	(3)	(4)
	lnspillover	***lnspillover***	***lnspillover***	***lnspillover***
IV coastline	0.0020***	0.0016***		
	(0.0002)	(0.0002)		
IV port			0.0021***	0.0016***
			(0.0002)	(0.0002)
Firm controls	N	Y	N	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	50,218	44,762	50,218	44,762

Part 2: second stage of IV regression

	(5)	(6)	(7)	(8)
	lnSO₂	***lnSO₂***	***lnSO₂***	***lnSO₂***
lnspillover	-0.0839***	-0.0842***	-0.0723***	-0.0690***
	(0.0156)	(0.0200)	(0.0145)	(0.0180)
Firm controls	N	Y	N	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Anderson LM statistic	97.942	58.162	102.216	64.417
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cragg–Donald Wald F statistic	74.2872 (16.38)	43.2674 (16.38)	77.5352 (16.38)	46.4376 (16.38)
Observations	50,218	44,762	50,218	44,762

Note: firm-level controls include lnage, size, levity, finance, export, and HHI. All standard errors in parentheses are clustered at the firm level. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively. In columns 5–6, we use IV coastline as instrument variables. In columns 7–8, we use IV port.

from China's Ministry of Transport. The data of annual exchange rates are from China's National Bureau of Statistics. The Brent crude oil price is from the website of Intercontinental Exchange (ICE).

To guarantee the robustness of estimation, we run the first-stage regressions both with and without control variables. The results of the first-stage regression are reported in columns 1–4 of Table 3. The first-stage F-value exceeding 10 suggests no concerns about weak instrumental variables. In the second stage, we use the predicted technology spillover as independent variables and relate them to the SO_2 emission intensity. The results are reported in columns 5–8 of Table 3. We find that the exogenous increase in technology spillover from imported intermediate inputs has an inhibitory effect on the firm's pollution intensity. When we use the distance from each firm to the coastline and the distance closest to the port to construct the instrument variables, the coefficient of predicted technology spillover is significant at the 1% significance level whether we control for additional variables or not.

4.3 Robustness checks

In this subsection, we further check the robustness of our results to address other related concerns. Most of the results are presented in Table 4.

4.3.1 Alternative dependent variables

In the article, we adopt the logarithm of SO_2 emission intensity as the dependent variable in the baseline regression. However, firms emit various types of pollutants indicating that SO_2 may not be inclusive to reflect the overall environmental performance. In this regard, this article uses two alternative strategies to examine the outcome variables: 1) use of other main pollutants to reevaluate the firm pollution. Specifically, we mainly consider the discharge intensity of industrial sewage and dust as alternatives. 2) Constructing a comprehensive pollution index. After normalization, we assign the equal weights to five gaseous pollutants and three water pollutants and summarize to obtain the composite index pol_{it}. After the re-regression with different outcome variables, the estimation results are shown in

TABLE 4 Robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnwater	*lndust*	*pol*	*$lnSO_2$*	*$lnSO_2$*	*$lnSO_2$*	*$lnSO_2$*
lnspillover	-0.0058***	-0.0018***	-0.1432***	-0.0028***	-0.0022***	-0.0020***	-0.0027***
	(0.0011)	(0.0006)	(0.0325)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Firm controls	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	61,581	46,174	66,398	42,350	44,946	44,827	45,622
R-squared	0.8071	0.6236	0.6045	0.7406	0.7388	0.7505	0.7378

Note: firm-level controls include lnage, size, levity, finance, export, and HHI. All standard errors in parentheses are clustered at the firm level. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively. We also conducted estimation without firm controls. The significances remain the same with the outcomes in Table 4. Thus, we do not present the results without control variables here. In columns 1–3, we use alternative dependent variables. In column 4, we remove the impact of financial crisis. In column 5, we add the industry fixed effect and the interactive fixed effect of year and CIC four-digit industrial code. In column 6, we add the city fixed effect and interactive fixed effect of year and city. In column 7, we remove the relative city samples affected by the regional environmental regulations. These 16 cities include: Zhoukou city, Weinan city, Xiangfen city, Wuhu city, Bengbu city, Baiyin city, Lanzhou city, Puyang city, Handan city, Tangshan city, Lvliang city, Liupanshui city, Laiwu city, Chaohu city, Bayanchuoer city, and Hejin city.

columns 1–3 of Table 4. It is clear that, whether we use single pollution indicators or a comprehensive pollution index, the inhibitory effect of technology spillover from intermediate input imports on environmental pollution remains robust.

4.3.2 Addressing the impact of global financial crisis

The financial crisis in 2008 had imposed the far-reaching impact on the global economic trends and the ways how firms engage in international trade. The contraction of external demand brought about by the financial crisis affects the scale and composition of intermediate goods imported by enterprises. Therefore, the financial crisis may contaminate the specification and the estimation results. To address such concern, this article removes the samples of the financial crisis and conducts the regression again. The regression results are shown in column 4 of Table 4. The estimated coefficient remains significantly negative at the 1% level, proving yet another robustness (i.e., excluding the impact of the financial crisis).

4.3.3 Addressing the impact of related environmental policies

In response to heavy corporate pollution, the Chinese government has launched a wide range of administrative and market-regulated environmental policies. The environmental regulation policies during the sampling period are usually implemented across specific industries and regions. For instance, *Cleaner Production Industry Standards* and *Disposal of Outdated Production Capacity* are carried on several specific industries. To address these issues, we add the fixed effect of the four-digit CIC industrial code and the interaction term of four-digit industry code and year to control for the potential policy shock in related industries. The regression results shown in column 5 of Table 4 indicate that the technology spillover from the import of intermediate goods still has a significant mitigating effect on environmental pollution, after excluding the external shock of industrial environmental policies.

Moreover, in order to factor out the impact of the city-level restrictive environmental policies, this article controls the city fixed effect and the city-time interactive fixed effect. Since the regional environmental regulatory policies, such as *Permission Restriction on Regions and River Basins*, are applied in certain specific cities, this article reviews the baseline regression after excluding the relevant city samples. The corresponding results reported in columns 6–7 of Table 4, compared with the baseline estimation, have no significant changes. After excluding the impact of associated regional environmental regulatory policies over the same period, the technology spillover from importing intermediate inputs remains a stable effect on the suppression of corporate pollution.

4.4 Heterogenous effects

We explore the possible heterogeneous effects of technology spillover on pollution as firms performed differently in many dimensions. Results are reported in Table 5.

4.4.1 Import sources

Since imported inputs may differ in terms of their embodied technology level, inputs with a higher tech content will provide a greater contribution to productivity and thus may contribute more to pollution control. Due to the considerable technological gap between developing and developed countries, the sources of intermediate input imports may have a different impact on pollution. Thus, we test whether inputs imported from developed countries are particularly helpful in improving firm environmental performance by introducing separate import

TABLE 5 Heterogenous effects.

	Sourcing region		Ownership		
	(1)	(2)	(3)	(4)	(5)
	Developed economy	Developing economy	Foreign firm	SOE	Private firm
lnspillover	-0.0012*	-0.0011	-0.0029**	-0.0020	-0.0008
	(0.0007)	(0.0011)	(0.0011)	(0.0019)	(0.0015)
Observations	46,143	25,420	25,265	6,179	6,297
R-squared	0.7361	0.7146	0.7146	0.7979	0.7172
Firm controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

	Pollution intensity		Geographical location	
	(6)	(7)	(8)	(9)
	Heavily-polluting firm	Non-heavily polluting firm	Firms in East China	Other firms
lnspillover	-0.0056***	0.0001	-0.0029***	-0.0016
	(0.0016)	(0.0003)	(0.0008)	(0.0022)
Firm controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	13,265	29,480	39,103	7,040
R-squared	0.7741	0.7055	0.7265	0.7542

Notes: firm-level controls include lnage, size, levity, finance, export, and HHI. All standard errors in parentheses are clustered at the firm level. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively. We also conducted estimation without firm controls. The significances remain the same with the outcomes in Table 5.

measures in our baseline specification, which enables us to observe the differential benefits of inputs sourced from developed countries compared with the intermediate inputs importing from developing counterparts. As a result, in columns 1–2 of Table 5, we indicate that the technology spillover from the developed countries can drastically reduce pollution at the firm level, whereas this is not evident in developing countries.

4.4.2 Firm ownership

In terms of ownership structure, we can divide them into three main types: state-owned enterprises (SOEs), foreign enterprises, and private enterprises. This article examines the effect of technological spillover on environmental pollution from intermediate input imports from firms with different characteristics. The results of columns 3–5 in Table 5 specify that the technology spillover of imported intermediates can promote pollution control of foreign enterprises, whereas this is not obvious for state-owned enterprises and private enterprises. Foreign enterprises can often obtain advanced technical guidance, management experience, and knowhow and tacit information from the parent company, acquiring more technology spillover of imported intermediate inputs. However, in terms of technology absorption and innovation, and research and development, the private enterprises are difficult to compare with the foreign companies. State-owned enterprises are less responsive to the environmental regulations and subsequent cost fluctuations. Compared with the foreign firms, they rely less on imported intermediate inputs to boost innovation and technology improvement. Therefore, the effect on SOEs is not evident.

4.4.3 Pollution intensity

The pollution haven hypothesis speculates that developing countries often become pollution havens for developed countries to transfer local pollution due to the weaker environmental regulations. We divided the sample into heavily polluting (pollution intensity larger than the average in the same four-digit CIC industry) and non-heavily polluting firms and conducted grouped regression. Columns 6–7 in Table 5 states that the heavily polluting firms can restrain emissions by the technology spillover of imported

TABLE 6 On mechanisms.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnpatent	$lnSO_2$	$lnSO_2$	*imvariety*	*lnpatent*	$lnSO_2$	$lnSO_2$
lnspillover	0.0080***		-0.0030***	0.0248***		-0.0030***	-0.0050***
	(0.0013)		(0.0008)	(0.0011)		(0.0008)	(0.0014)
lnpatent		-0.0050*	-0.0153**				
		(0.0030)	(0.0066)				
lnspillover × *lnpatent*			0.0016*				
			(0.0009)				
imvariety					0.0302**	-0.0309*	
					(0.0129)	(0.0166)	
lnspillover × *imvariety*						0.0032***	
						(0.0012)	
VA/Y							-0.1056***
							(0.0249)
lnspillover × *VA/Y*							0.0070*
							(0.0036)
Firm controls	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	65,768	45,622	45,622	66,398	66,398	46,143	25,169
R-squared	0.5989	0.7377	0.7379	0.8842	0.6001	0.7363	0.7757

Notes: firm-level controls include lnage, size, levity, finance, export, and HHI. All standard errors in parentheses are clustered at the firm level. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively. We also conducted estimation without firm controls. The significances remain the same with the outcomes in Table 6.

intermediate products, while those non-heavily polluting firms cannot gain the same benefit. The outcomes are at best inconsistent with the conclusion of the pollution haven hypothesis (PHH). China has not become a "dust bin" to accommodate pollution exported from developed countries. In the previous discussion, we have verified that technology spillover from developed countries dominates the reduction of Chinese firms' pollution intensity. Then, we find that the technology spillover from imported intermediate inputs is conducive to alleviate the environmental burden of pollution-choked firms. Such evidence implies that trade in intermediate goods may not be considered a means to transfer pollution for developed countries. Rather, the embedded R&D content brings environmental benefits to enterprises in developing countries.

4.4.4 Geographical location

The different levels of economic development and environmental regulation in different regions of China lead to diverged environmental performance of companies as they have a specific geographical location. In general, compared with other regions in China, the eastern region has more advanced awareness of green development concept and better experience in green governance. Columns 8–9 in Table 5 present the existing differences in technology spillover from importing intermediate inputs if we consider the geographical location of firms. It appears that only enterprises located in eastern areas can benefit from the intermediate input imports.

5 Mechanism

Why does technology spillover from intermediate input imports can reduce the firm-level pollution emissions? To understand the empirical results, we conducted further analysis to examine several possible channels including innovation, import variety, and industrial spillover. Moreover, we explore that whether firms' behavior of pollution control can be affected by the intermediate input imports.

5.1 Innovation

In this article , we use the logarithm of the number of annual patents of each firm as the proxy variable to measure the innovation performance of the firm. There are different types of patents in the database, such as invention, utility model, and design. We here use the approved invention patents. To examine whether technology spillover from intermediate input imports can influence pollution by the way of innovation, we add the interaction term of innovations *lnpatent* and technology spillover *lnspillover* in the baseline regression model. Column 1 in Table 6 states that technology spillover can strengthen the firm's innovation. Column 2 in Table 6 indicates that innovation is also beneficial to the pollution control. The positive coefficient of interaction term in column 3 of Table 6 shows that the increasing innovation will weaken the environmental effect of technology spillover from the intermediate input imports. When the capability of independent innovation is insufficient, the cost-reducing importing technology can play a complementary role. When the innovation increases, the marginal environmental effect of the relative economic importing strategy will decrease. The corporate innovation becomes more effective in substituting imported intermediate inputs, namely, firms with a higher level of innovation depend less on the technology spillover to restrain individual pollution.

5.2 Import diversity

Column 4 in Table 6 shows that importing intermediate products can increase the import variety, which can encourage innovation as shown in column 5 of Table 6. The positive interaction term of import variety and technology spillover in column 6 of Table 6 clarifies that the increasing variety will curb the impact on pollution imposed by technology spillover from intermediate imports. The more the varieties of imported intermediate products, the more the technologies available for enterprises to choose. The sufficient substitution between imports relatively decreases acquisition cost and positively pulls up firms' innovation. The technological spillover of imported intermediate products indirectly affects the innovation of enterprises through a variety of intermediate products to ultimately reduce the pollution intensity of enterprises, namely, the diversity of intermediate products is also an important channel for embedded technology to affect the environmental pollution.

5.3 Industrial chains' spillover

In general, the firm embedded in the relatively downstream in the value chain can acquire more technology spillover as more intermediate inputs can be utilized. Following Antràs and Chor, (2018), we apply the value-added rate[2] *VA/Y*, i.e., the value added divided by the principal business income, to measure the downstream degree by the distance from the primary factor input. The smaller the value of *VA/Y*, the more intermediate inputs relative to the use of primary factor input and the more downstream (i.e., closer to final users) the firm is embedded in the industrial chain. Then, we introduce the interaction term of downstream degree and technology spillover in the benchmark regression and observe the coefficient sign to examine whether technology spillover from imported intermediate input can affect corporate pollution by the diffusion of industrial chain.

In column 6 of Table 6, the positive coefficient indicates that downstream firms have lower pollution intensity, echoing the findings in Shapiro (2020). In column 7 of Table 6, the significantly positive coefficient of the interaction term means that technology spillover of imported intermediate inputs for downstream firms can impose a stronger inhibitory effect on pollution intensity. Downstream firms are possible to acquire more knowledge, information, and advanced technology embodied in the intermediate inputs. The spillover encourages domestic enterprises to improve production efficiency and innovative capabilities, thereby promoting pollution control and reducing the firm's emission.

5.4 Pollution prevention and treatment

This article first examines whether the technology spillover of imported intermediate products cuts back on the emission reduction expenditure of enterprises. Due to the lacking of pollutant discharge fees from specific enterprises in consecutive years, this article quantifies the in-kind abatement investment. Since the purchase of emission reduction equipment is a sort of direct and effective method of end-of-pipe processing, we use the logarithm of the following three indicators: the ratio of the amount of desulfurization equipment to the actual total output, the ratio of the quantity of waste gaseous treatment equipment to the actual total output, and the ratio between the number of wastewater treatment equipment and the actual total output. The results in columns 1–3 of Table 7 confirm that the technology spillover of imported intermediate products can save costs of end-of-pipe treatment at the firm level. This article uses the sulfur dioxide removal rate as an indicator to measure the regulatory intensity of environmental policies for enterprises. The results in column 4 of Table 7 imply that the technology spillover from imported intermediate products do not result in a relaxation of environmental regulations. In other words, the government does not intend to eliminate environmental control to reduce the firm's external costs to stabilize the domestic production affected by the competition from imported intermediate inputs.

The utilization of efficient and relatively clean energy can directly reduce sulfur dioxide emissions from fossil fuels and impose an immediate impact on pollution at the source. The efficiency of energy utilization can reflect the technical level of pollution control, energy conservation, and corporate emission reduction. Therefore, this article examines whether the

2 Following Antràs et al. (2017), a simple measure to capture such GVC positioning is the ratios *VA/Y*, with large values of this measure being associated with higher upstreamness (i.e., further away from final users) or lower downstreamness (i.e., closer to primary inputs).

TABLE 7 Mechanism: pollution prevention and treatment.

	(1)	(2)	(3)	(4)	(5)
	Desulfurization equipment	Processing equipment of waste gas	Processing equipment of wastewater	SO_2 removal rate	Energy efficiency
lnspillover	-0.0167***	-0.0224***	-0.0258***	0.0010	0.0108*
	(0.0060)	(0.0032)	(0.0020)	(0.0012)	(0.0064)
Firm controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	4,931	20,545	47,368	17,512	30,369
R-squared	0.8957	0.8446	0.9052	0.5713	0.7183

Notes: firm-level controls include lnage, size, levity, finance, export, and HHI. All standard errors in parentheses are clustered at the firm level. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively. We also conducted estimation without firm controls. The significances remain the same with the outcomes in Table 7.

technological spillover of imported intermediate products can finally enhance governance, promote technology upgrades, and reduce pollution at the point of origin. Energy efficiency can be expressed by dividing the total value of a firm's industrial production by energy consumption, that is, the value of industrial production per unit of energy consumption. Due to the lack of complete data on the energy consumption structure of enterprises in China's green development database, this article instead selects the consumption of crude coal and fuel oil, which generate more sulfur dioxide during combustion than clean energy, converts them into standard coal, and summarizes to represent the corporate energy consumption. The results in column 5 of Table 7 suggest that the technology spillover of imported intermediate products can improve the corporate energy efficiency by source monitoring and technology upgrades to curb the expansion of pollutant emission.

6 Concluding remarks

There is substantial empirical evidence on the impact of imported intermediate inputs on firm's productivity and innovations. We know less about the relationship between the technology spillover from the intermediate imports and pollution emission at the firm level. This article is among the first attempts to fill in the gap. Based on the merged panel data of multiple micro-enterprise datasets, we aim to examine the impact of imported intermediate inputs on the environmental performance of enterprises through technological spillover effects and interpret the mechanism behind the impact. Employing a unique combined rich dataset of Chinese manufacturing firms and using geographical conditions, exchange rate, and global oil price to construct instruments for potential endogenous variables, we document a negative causal relationship between technology spillover of intermediate input imports and firms' pollution intensities. The estimation results remain hold after a battery of robustness checks. The estimation results are consistent with many studies on the environmental effects of imports. Indubitably, import-induced technique effect suppresses pollution emissions. The special contribution of this article is to explain how the technology spillover of imports plays a role.

Our analysis of the underlying mechanism finds that: 1) in terms of lower pollution, firms with less innovation depend more on the technology spillover and benefit more from importing intermediate inputs. 2) As more foreign high-tech intermediate inputs in the domestic market, the increasing imports diversity in the domestic market can promote innovation, thereby indirectly affecting pollution reduction. 3) Technology spillover can continuously transmit along the industrial chain, so that downstream firms benefit more from the complex and diversified intermediate inputs to improve their environmental performance. Moreover, in terms of firms' pollution prevention and treatment, the technology spillover of imported intermediate inputs can save expenditures in end-of-pipe processing. Alternatively, it encourages firms to adopt source governance to control pollutant generation by improving energy efficiency and promoting energy transition and technological upgrading.

Our study emphasizes the importing side for green development. Empirical findings show that the expansion of imported intermediate goods can bring various benefits, at least for the firm-level innovation and pollution reduction. In this aspect, those policies promoting trade openness can encourage imported technology and thus reduce environmental burden. Nonetheless, the government has to strike for a balance between trade gains and sustainable development. Indeed, many countries tend to impose lower tariffs on relatively dirty industries than clean industries. Imposing high tariffs on downstream goods rather than upstream goods forces consumers to demand more relatively dirty factors and leads to more pollution (Shapiro, 2020). Moreover, boosting imports can lead to an explosion of output and thus also emissions. For example, regional trade agreements, following WTO rules, are committed to employing zero or close to zero tariffs among members. Tian et al. (2022) showed that complete tariff elimination among the Regional Comprehensive Economic Partnership (RCEP) members would increase the yearly global CO_2 emissions from fuel combustion by about 3.1 percent, doubling the annual average growth rate of global CO_2 emissions in the last decade. In this sense, inclusive policies such as expanding green product lists and promoting trade facilitation are urgently needed for balancing trade gains and environmental protection.

Furthermore, the scope of our article is limited to manufacturing firms. Wang and Lu, (2020) argued that servicification is positively correlated with innovation, and the effect differs in different economies with distinct characteristics such as income and structural transition phases. An in-depth study on the role of servicification can be conducted. Additionally, the environmental impact on importing is manifold. We only focus on the technology spillover. The competition effect on firms' environmental performance deserves a more detailed explanation. Wu et al. (2022) examined the impact of import competition on the pollution intensity of heterogeneous manufacturing enterprises. We leave these interesting topics for future research.

Data availability statement

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

Author contributions

YH and JP designed the study, conducted the analysis, and wrote the 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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Carbon market volatility analysis based on structural breaks: Evidence from EU-ETS and China

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In recent years, carbon market transactions have become more active. The number of countries participating in carbon market regulation is increasing, and the carbon market's overall turnover continues to grow. It is important to study the features of carbon allowance price volatility for the stable development of the carbon market. This paper constructs a modified ICSS-GARCH model to analyze the volatility of carbon price returns and the dynamic characteristics of price fluctuations in the emissions trading system of the European Union (EU-ETS) and the Chinese carbon pilot markets in Hubei. The results show that fluctuations in carbon price returns have a leverage effect and that the impact of negative news on the market is stronger than that of positive news. The international climate and energy conferences, abnormal changes in traditional energy prices, and global public health emergencies all affect volatility and cause shocks to the carbon trading market. The modified ICSS-GARCH model with structural breaks can reduce the pseudovolatility of the return series to a certain extent and can improve the accuracy of the model. This research can give policymakers some implications about how to develop the carbon market and help market participants control the risks of fluctuations in carbon allowances. Regulators should enhance carbon price monitoring and focus on short-term shocks in the carbon market to reduce trading risks. The Chinese carbon market should strengthen the system design and develop carbon financial derivatives.

KEYWORDS

carbon market volatility, EU-ETS, ICSS algorithm, GARCH model, Chinese carbon market

1 Introduction

Countries around the world are taking steps to reduce emissions of greenhouse gases such as carbon dioxide because of climate change and other environmental and ecological problems (Can et al., 2022). To reduce carbon emissions, many countries have signed the United Nations Framework Convention on Climate Change (UNFCCC), the Kyoto Protocol and the Paris Agreement, etc. The Kyoto Protocol outlines the obligations of developed economies to reduce emissions and proposes three flexible mechanisms to reduce emissions, of which carbon trading is one (Can et al., 2021b). According to the International Carbon Action Partnership's (ICAP) Emissions Trading Worldwide Status Report 2021, there are currently 25 emissions trading system (ETS) in operation around the world, with another 22 scheduled to go operational in the near future. Carbon emissions trading will cover 17% of global emissions. The existing trading systems include EU emissions trading system (EU-ETS) and US trading system (RGGI), etc.

The EU-ETS was established in 2005 and is currently the world's largest and most active carbon emissions trading system. EU-ETS carbon allowances trading reaches 8,1 billion tons of carbon dioxide (CO_2) in 2020, representing approximately 90 percent of the total global carbon trading volume, with a trading volume of €20 billion. It has been implemented in four phases and is currently in its fourth phase. In the first three phases of EU-ETS development, the range of countries, industries and enterprises covered by trading gradually expanded, and the proportion of auctions in the allowance allocation process gradually increased (instead of free allocation). The major difference between the three phases is the change from grandparenting[1] to benchmarking[2] in the allocation of allowances, indicating the continuous maturation of the EU-ETS management system. In the EU-ETS, the turnover of EUAs is higher than that of other trading varieties, such as certified emission reductions (CERs). EU allowance (EUA) futures allow carbon credits to be traded on commodity futures exchanges, such as soybeans, oil, and other commodities. The EU-ETS has become the world's largest carbon futures market, with over 90% of the total volume traded in the EU carbon market (Lamphiere et al., 2021). The carbon futures market has made the market more open and has become a model for other countries and regions.

According to the International Energy Agency (IEA), China's carbon emissions exceed 11.9 billion tons in 2021, covering about one-third of the world's carbon emissions. The Chinese government announced at the Paris Climate Conference that CO_2 emissions will peak around 2030 and then decline by 60–65 percent compared to 2005. China is exploring the use of market mechanisms to reduce greenhouse gas emissions in response to the pressures of CO_2 emission reduction and sustainable development. As an important developing country and CO_2 emitter, China expects that the carbon market will help achieve its emissions reduction objectives and reduce the global greenhouse effect at the lowest economic cost among the available emission reduction policies (Liu et al., 2015; Gozgor and Can, 2017). Since 2013, China has initiated eight regional carbon market pilots in Shenzhen, Shanghai, Beijing, Guangdong, Tianjin, Hubei, Chongqing, and Fujian (Ren and Lo, 2017). The pilot markets have been operational for only a short period, and there are still some unstable factors in the carbon market (Zhao et al., 2016). The carbon market in China covered about 3,000 emitting enterprises in the steel, electricity, and cement industries, establishing a large-scale market initially. China's carbon emissions trading market has grown to become the world's second largest, and it now plays an important role in the international energy trading market. Under these circumstances, it is more important and urgent to study how carbon prices change in both the EU-ETS market and the Chinese carbon market.

Both the EU carbon market and the Chinese carbon pilot cover significant emission sectors such as industry and power. However, because of the different development processes, there are many differences between the two markets. The major variation is in the allocation of carbon allowances. The auction is employed in the EU-ETS, with the European Commission determining the overall number of carbon allowances and allocating them to each member. The auction method ensures the scarcity of carbon allowances. The Chinese carbon market adopts the free allocation approach and is susceptible to surplus. Both the EU-ETS and Chinese markets have excess carbon allowances, leading to a carbon price failure. The Chinese market is particularly affected. Chinese carbon credits can only be traded on the spot market. The diversity of carbon financial instruments and trading activity is restricted compared to the EU-ETS.

In recent years, the effectiveness of carbon markets, the volatility and risk assessment of carbon prices, and the spillover effects between carbon markets and traditional energy markets have been hot topics (Benz and Truck, 2009; Chevallier, 2009; Zhang and Sun, 2016; Chang et al., 2017; Zhao et al., 2020; Can et al., 2021a). In prior studies, time series of financial asset markets, such as the stock market or crude oil market, and structural breaks have been widely studied as the iterative cumulative sum of squares (ICSS) algorithm for detecting breaks is now well established (Malik and Hassan, 2004; Malik et al., 2005; Wen et al., 2018). However, less research has been conducted on structural breaks in carbon markets. Price volatility in the carbon market is influenced by external factors such as political change, climate change, and allowance allocation. External factors cause carbon price instability and risk spillover. Moreover, exploring the reasons and mechanisms of structural breaks is important for carbon market policymakers to effectively adjust market policies. In this paper, we adopt the modified ICSS algorithm to investigate the structural breaks in carbon market returns and add structural breaks as a dummy variable in the model to estimate the volatility characteristics of the EU-ETS and the Chinese carbon market.

The current research on carbon market volatility is mainly focused on the EU-ETS. In the existing literature, the volatility of

1 Grandparenting allows covered enterprises to get emission permits based on their previous emissions within a base year or base period.

2 Benchmarking rewards efficient installations and can more easily assimilate new entrants.

carbon prices, the factors influencing carbon prices, the effectiveness of carbon markets, and the measurement of risk in carbon markets have been examined. Benz and Truck (2009) and Daskalakis et al. (2009) analyzed the European carbon market and found that emission allowance returns exhibit skewness, excess kurtosis, and volatility clustering. Byun and Cho (2013) used the GARCH model to estimate the price volatility of carbon futures prices. Dutta (2018) used the GARCH-jump model to investigate the volatility of the EU-ETS prices and provide recommendations to investors and policymakers. Guo et al. (2018) used the GARCH model to analyze the impact of the EU-ETS emission announcements in phases I and II on trading behavior and prices. The findings confirm the maturity of the EU-ETS in phase II. Fan et al. (2017) analyzed the impact of 50 policy announcements from the EU ETS on carbon prices. The aggregate impacts of the 50 events studied were small, and only sections of the policies impacted carbon prices. Wang et al. (2019) demonstrated that all externalities of the carbon market, whether energy prices or policy announcements, are reflected in trading behavior and they impact the demand and supply of carbon permits through trading, which influences carbon pricing (Wang et al., 2019). Zhang et al. (2018) adopted the EGARCH model to examine the price of carbon pilot markets in China and discovered a long memory in the sequence of carbon price returns. Zhao et al. (2016) demonstrated that the market efficiency of ETS pilots in China is not satisfactory, although ETS system designs have achieved some promising preliminary results.

In this paper, we compare the price of EUA futures, the most actively traded variant in the EU-ETS, with the spot price of the Chinese carbon pilot market and analyze the price fluctuations in the carbon market. This paper makes the following contributions to the existing literature: Firstly, to the best of our knowledge, prior studies have concentrated on the value-at-risk of the carbon market while disregarding the impact of structural breaks on risk assessments, thus making carbon market risk underestimated (Zhang et al., 2018). Our research is a useful supplement. Secondly, we noticed that policy announcements and important events can cause structural changes in carbon price returns, which can have an impact on the carbon market or create market risks. We detect the structural change points by using the modified ICSS algorithm. We then use the structural change points as dummy variables to study how event shocks affect the volatility of the carbon market. This is a novel approach in the study of carbon market volatility to incorporate structural breaks estimated by the modified ICSS algorithm into carbon market volatility research. Furthermore, we explore the asymmetry of the carbon price. This is an extension of the study of the characteristics of carbon market prices. The findings confirm that carbon price returns are also asymmetrical and that the impact of positive and negative news on the carbon price varies, which is similar to those of other financial assets. These important results and conclusions will be used to make important suggestions about how the carbon finance market will grow in the future and how governments and market participants will manage such a market and invest in it.

The remainder of this paper is structured as follows. Section 2 is a literature review. Section 3 introduces the methodologies used in this paper. Section 4 reports the empirical results. Section 5 provides further discussion on EU-ETS futures in phase II and provides policy recommendations. Section 6 provides the conclusions of the paper.

2 Related literature

2.1 Carbon price volatility

In previous papers, time series of financial asset markets, such as the stock market or crude oil market, with structural breaks have been widely studied with the iterative cumulative sum of squares (ICSS) algorithm for detecting breaks now well established (Malik and Hassan, 2004; Malik et al., 2005; Wen et al., 2018). However, less research has been done on structural breaks in carbon markets.

The carbon market is an emerging financial market. Existing literature on carbon markets is mainly focused on carbon prices, including carbon market volatility, factors influencing carbon prices, carbon market effectiveness, and carbon market risk measurement.

For example, Benz and Truck (2009) and Daskalakis et al. (2009) analyzed the European carbon market and found that emission allowance returns exhibit skewness, excess kurtosis, and volatility clustering. Byun and Cho (2013) estimated the volatility of carbon futures prices using IV, k-NN, and GARCH-type models. The results indicate that the GJR-GARCH model offers the most information on the volatility of carbon futures. Paolella and Taschini (2008) found asymmetries in the spot carbon price, which are essential for risk management in the carbon market. Dutta (2018) tested for extreme values in EUA and investigated the volatility of EU-ETS prices using the GARCH-jump model. The results demonstrate that the GARCH-jump model can capture discrete jumps in asset returns. Outliers and time-varying jumps play a crucial role in the risk management of the carbon market. Wang et al. (2019) demonstrated that all externalities of the carbon market, whether energy prices or policy announcements, are reflected in trading behavior and impact the demand and supply of carbon permits *via* trading, which influences carbon pricing. Gorenflo (2013) investigates the price efficiency of EUA futures and spot. The results show that futures markets are better at finding prices than spot markets, with carbon futures playing a bigger role.

Numerous studies have examined the performance of the carbon market in China. For example, Zhang et al. (2018) adopted the EGARCH model to examine the price of carbon pilot markets in China and discovered a long memory in the

TABLE 1 Characteristics of the different phases of EU-ETS.

	Phase I (2005–2007)	Phase II (2008–2012)	Phase III (2013–2020)	Phase IV (2021–2030)
Emission allowances ($MtCO_2e$)	2096	2049	2084	1,610
Greenhouse gas	CO_2	CO_2 and N_2O	CO_2, N_2O and PFCs	CO_2, N_2O, and PFCs
Decline rate	—	—	1.74%	2.20%
Allowance allocation	Free allocation	10% of general allowances were auctioned off	57% of general allowances were auctioned off	57% of general allowances were auctioned off
Industry	Power sector	Power sector, Aviation sector	Expanded industrial sector	Consistent with Phase III

sequence of carbon price returns. Lyu et al. (2020) investigates the dynamic characteristics of volatility using the MCMC-SV model and Chinese carbon price returns in Hubei, Shenzhen, and Shanghai from 2015 to 2018. The results demonstrate that the Chinese carbon prices indicate an aggregation of volatility, although the long-term volatility is not highly cyclical. Zhao et al. (2016) demonstrated that the market efficiency of ETS pilots in China is not satisfactory, with huge price differences and insufficient liquidity across ETS pilots, although ETS system designs have achieved some promising preliminary results. This result was caused by the inappropriate allocation of allowances and the low motivation of businesses to trade. Liu et al. (2020) examined the operational efficiency of China's seven carbon markets, using a variance ratio test. The findings suggest that the markets in Hubei and Guangdong are weakly efficient, while the remainder of the markets are less efficient.

Prior research indicates that the modified ICSS model has been widely utilized in measuring the volatility of financial assets and is capable of analyzing the volatility of carbon market prices (Malik and Hassan, 2004; Wen et al., 2018). In addition, a comparative study of EU-ETS and Chinese carbon pilot markets could help the carbon market develop better.

2.2 EU-ETS and China carbon pilots

The EU Emissions Trading System (EU-ETS), established in 2005, is a carbon trading mechanism based on EU regulations and national legislation. The EU-ETS is the world's most developed carbon trading system and dominates the international carbon financial market. Currently, the EU-ETS is in its fourth phase, following three phases of development and gradual improvement. During previous phases of development, the carbon market's coverage of covered sectors and gases gradually expanded, and the proportion of auctions in the allowance allocation process gradually increased. Table 1 shows the difference between the different phases of EU-ETS.

In the EU-ETS, the turnover of EUAs is higher than that of other trading varieties, such as certified emission reductions (CERs). In this paper, EUA futures phase III prices are used to analyze the behavior of price volatility in the carbon market, while phase II prices are used for the comparative analysis. Figure 1 shows the price trend of EUA futures from 2005 to 2021.

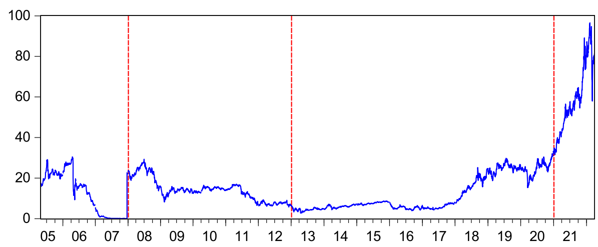

FIGURE 1
Price trends in EUA futures. The vertical lines mark the beginning of the different phases: phase I (2005–2007), phase II (2008–2012), phase III (2013–2020), and phase IV (2020–present).

The carbon market was immature during the first phase of the EU-ETS due to a lack of experience with relevant allocations. In the first phase, numerous factors affected the futures price, and there were significant price fluctuations. Because of the inability to store Phase I and Phase II allowances across phases, the EUA price fell to an all-time low of €0.01 at the end of 2007, undermining the effectiveness of the EU-ETS market. In the second and third phases, the European Commission revised the trading mechanism and the way allowances are allocated. Since 2008, EUA futures prices have shown regular changes, influenced by global economic trends and energy prices. The EU-ETS matured after the initial two stages of exploration and development. Thus, this paper analyzes the volatility characteristics of futures prices in the third stage.

As the main supplier of demand for clean development mechanism (CDM) projects, China participates in worldwide emission reduction missions. In 2013, China established eight regional ETS pilots. The pilots have different prices, turnover, and volumes. Figure 2 shows the price trend for the major pilots. The price trend of each carbon pilot in China is different, and the eight carbon market pilots have their own transaction rules and systems. Furthermore, most studies use trading data from the carbon pilots

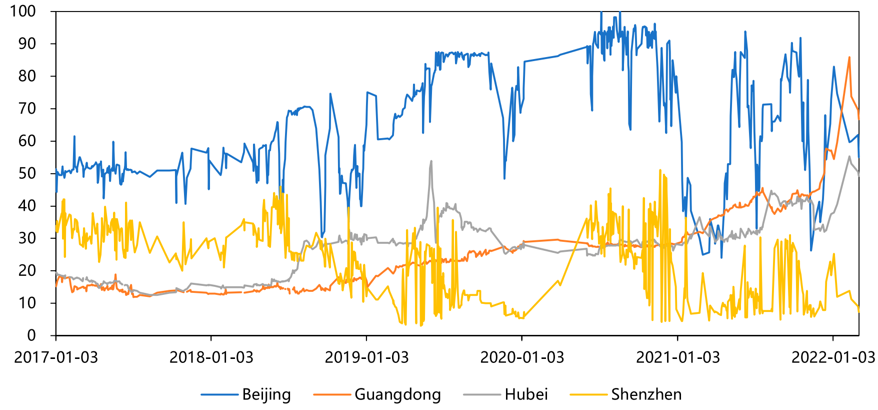

FIGURE 2
Price trends of major carbon pilots in China, including the Beijing, Guangdong, Hubei, and Shenzhen pilots.

in Shenzhen, Guangdong, and Hubei because these three pilots have higher market shares and liquidity than other carbon pilots (Fan and Todorova, 2017; Chang et al., 2018; Zhao et al., 2020). The Hubei spot price is used in this study because it is the largest market in terms of turnover and is relatively active and mature.

3 Methodology

3.1 Modified ICSS algorithm

The iterative cumulative sums of squares (ICSS) algorithm was proposed by Inclan and Tiao (1994). This method is used to distinguish structural break points of volatility based on the cumulative sum (CUSUM) test statistic. At the start of the process, the method assumes that the variance of the time series is the same for a certain period of time. The variance changes at the time of the unexpected event and then remains constant. There is a sudden structural change during an event. The procedure is as follows.

Assume that the sample has T observations and that the residual sequence of the sample $a_t \sim i.i.d.N(0, \sigma_t^2)$, with N_T structural variance points, can be divided into N_T +1 intervals. The sequence of structural mutation points is written as $\{k_1, k_2, \ldots\ldots k_{N_T},\}$, $1 < k_1 < k_2 < \ldots < k_{N_T} < T$. Each interval's variance is denoted by σ_j^2, where $j = 0, 1, 2, \ldots, N_T$, i.e.,

$$\begin{array}{ll} \sigma_0^2 = a_0^2 & 1 < t < k_1 \\ \sigma_1^2 = a_1^2 & k_1 < t < k_2 \\ \sigma_{N_T}^2 = a_{N_T}^2 & k_{N_T} < a < T_1 \end{array} \tag{1}$$

$C_k = \sum_{i=1}^{k} \epsilon_t^2, k = 1, 2, \ldots\ldots, T$ represents the cumulative sum of squares of the return series up to moment k. Then, $C_T = \sum_{t=1}^{T} \epsilon_t^2$. Define IT as the statistic.

$$IT = \sup_k \left| \sqrt{T/2} D_k \right| \tag{2}$$

where $D_k = \frac{C_k}{C_t} - \frac{k}{T}$ and $D_0 = D_T = 0$ Assuming that _t is a normally distributed random variable that is distributed independently and identically at zero mean, the asymptotic distribution of the test statistic is

$$IT \Rightarrow sup_k |W_r^*| \tag{3}$$

D_k follows a Brownian bridge process that fluctuates up and down around the zero axis if the sample is homoscedastic over the estimation period. If there is a structural change in the interval, D_k will deviate from zero and have a certain probability of crossing the boundary. A structural break point is considered to exist in the interval when $\sqrt{T/2} D_k$ exceeds the upper and lower bounds of 1.358 at a 95% confidence interval.

The ICSS algorithm assumes that $\{\epsilon_t\} \sim i.i.d.N(0, \sigma^2)$ and that the variance in the subintervals is constant. The idea that returns from financial assets are normally distributed underpins many traditional financial theories, but the reality is that many (even most) assets do not conform to this assumption. Instead, empirical distributions exhibit higher peaks and fatter tails. Sanso and Malik thus proposed a modified ICSS algorithm. The modified test statistic is shown below (Sansó et al., 2004; Malik et al., 2005).

$$\kappa_2 = sup \left| \frac{G_K}{\sqrt{T}} \right| \tag{4}$$

Previous research has shown that event shocks can cause structural break points in time series (Malik, 2003). Dummy variables incorporated into the model can reduce the pseudovolatility of the return series and improve model accuracy. The modified ICSS algorithm is used to detect structural break points in the following study. We use the news to determine which major events they correspond to and add them to the model as dummy variables.

3.2 GARCH model

Engle (1982) proposed the autoregressive conditional heteroskedasticity (ARCH) model for studying the volatility of asset prices. Bollerslev (1986) proposed the generalized ARCH (GARCH) model. The GARCH model adds the lagged values of the conditional variance across periods to the ARCH model to describe the long memory of financial assets. The GARCH (p, q) model is given by the following equation:

$$\begin{aligned} a_t &= \sigma_t \epsilon_t \\ \sigma_t^2 &= \alpha_0 + \sum\nolimits_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum\nolimits_{j=1}^{q} \beta_j \sigma_{t-j}^2 \end{aligned} \tag{5}$$

where $\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0$ and $0 < \sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_i < 1$. These constraints on the coefficients ensure the nonnegativity of the variance. The GARCH (1, 1) model is by far the most commonly used model because it avoids a large number of delays that were previously associated with it, and thus it is our preferred model within the GARCH family of models.

3.3 Exponential GARCH model

Many studies have found a leverage effect in financial assets. The leverage effect is caused by the fact that negative returns have a greater impact on future volatility than positive returns (Christie, 1982). The exponential GARCH (EGARCH) model was proposed by Nelson (1991). On the left side of the model equation, the conditional variance is logarithmized. This model overcomes the critical limitation of GARCH models, which is parameter nonnegativity. The conditional variance equation of the EGARCH (1, 1) model is given by the following equation.

$$\ln(\sigma_t^2) = \alpha \ln(\sigma_{t-1}^2) + \beta \left| \frac{\mu_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\mu_{t-1}}{\sigma_{t-1}} + \omega \tag{6}$$

The $\frac{\mu_{t-1}}{\sigma_{t-1}}$ term replaces the μ_{t-1} term in the EGARCH model. It improves the model's ability to describe the effect magnitude and persistence. The model describes the asymmetry of volatility through the additional parameter. The leverage effect is achieved by the second and third terms on the right side of the equation.

If the coefficient of the asymmetric term $\gamma = 0$, there is no leverage effect. If the coefficient of the asymmetric term $\gamma < 0$, it means there is a leverage effect. This ensures that positive return shocks induce less volatility than negative return shocks (Engle and Ng, 1993). It is clear that negative shocks will have a larger effect on future volatility than positive shocks of the same size.

The normal distribution, which forms the basis of portfolio theory, may not necessarily apply to financial asset price patterns. Therefore, we assume that the residuals follow a generalized error distribution (GED) in the following analysis. The distribution is given by the following equation.

$$f(x|v) = \frac{v}{\lambda \times 2^{1+\frac{1}{v}} \times \Gamma\left(\frac{1}{v}\right)} e^{-\frac{1}{2} \times \left|\frac{x}{\lambda}\right|^{v}}, x \in (-\infty, \infty)\,(0 < v \leq \infty) \tag{7}$$

$$\lambda = \left[2^{-\frac{2}{v}} \times \frac{\Gamma\left(\frac{1}{v}\right)}{\Gamma\left(\frac{3}{v}\right)} \right]^{\frac{1}{2}} \tag{8}$$

where v is the degrees of freedom.

3.4 Modified ICSS-GARCH model

In this paper, we adopt the AR (1)-GARCH (1, 1) model to fit the EUA futures returns and MA (1)-GARCH (1, 1) to fit the Hubei spot returns. The ICSS-GARCH models used to describe the EUA futures returns and Hubei spot returns are shown in Eqs 9, 10, respectively.

$$\begin{aligned} r_t &= \phi_1 r_{t-1} + a_t \\ a_t &= \sigma_t \varepsilon_t \\ \sigma_t^2 &= \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \sum\nolimits_{k=1}^{n} d_k D_k \end{aligned} \tag{9}$$

$$\begin{aligned} r_t &= \theta_1 a_{t-1} + a_t \\ a_t &= \sigma_t \varepsilon_t \\ \sigma_t^2 &= \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \sum\nolimits_{k=1}^{n} d_k D_k \end{aligned} \tag{10}$$

4 Empirical analysis

4.1 Data

In this paper, we collect a dataset of EUA futures prices and Hubei carbon spot prices. In this part, we use data on EUA futures from phase III. The sample period for EUA futures is from 1 January 2013, to 31 December 2020. The sample period for spot prices on the Hubei carbon market is from 1 July 2019, to 30 July 2021, encompassing two emissions trading compliance periods. The Chinese carbon market is still in the development stage. To better capture price fluctuations, we chose data from recent years. The logarithm of the prices is used to calculate all yield series data.

$$R_t = \ln Y_t - \ln Y_{t-1} \tag{11}$$

where Y_t represents the carbon price on day t, Y_{t-1} represents the carbon price on day t-1, and R_t represents the carbon returns.

Figure 3 shows the trend of returns. It can be noted that the sample is stationary, but simultaneously shows volatility clustering. Furthermore, all of the return series in the figure are subject to extreme volatility.

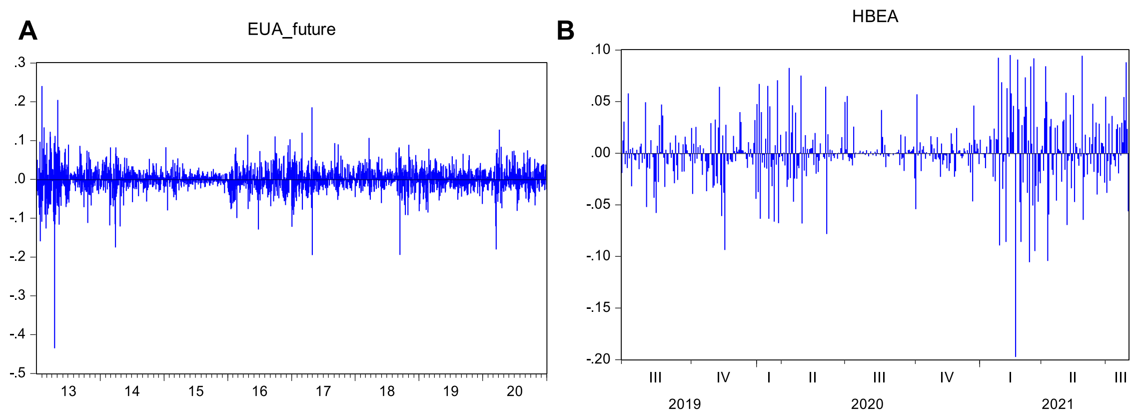

FIGURE 3
Carbon price yield trends. **(A)** EUA futures return trend; **(B)** Hubei spot price return trend. The sample period is from 1 January 2013, to 31 December 2020, for EUA futures and from 1 July 2019, to 30 July 2021, for Hubei spot returns.

TABLE 2 Data descriptive statistics. This table presents the descriptive statistics results of carbon price returns considered for the whole sample period. JB denotes the Jarque-Bera test statistic for the null of normality.

Variables	R_{EUA3}	R_{HBEA}
Mean	0.0008	0.0001
Median	0.0000	−0.0003
Maximum	0.2405	0.0952
Minimum	−0.4347	−0.1972
Std. Dev	0.0342	0.0306
Skewness	0.5423	−0.4601
Kurtosis	20.2870	8.1436
Jarque-Bera	26,073.8000	538.0974
Prob	0.0000	0.0000

4.2 Descriptive analysis

Table 2 shows the basic characteristics of EUA futures and Hubei spot returns. The minimum values of the two returns are −0.4347 and −0.1972. The maximum values of the EUA futures returns and Hubei spot returns are 0.2405 and 0.0952, respectively. Meanwhile, the mean value of the EUA futures returns is 0.0008 and the mean value of Hubei spot returns is 0.0001. The standard deviations of EUA futures returns and Hubei spot returns are 0.0342 and 0.0306, respectively. The kurtosis of all the return series exceeds three, and the skewness of these returns is not equal to zero. The skewness of the EUA futures return is greater than zero, indicating a right-skewed distribution. The skewness of the Hubei spot return is less than zero, indicating a left-skewed distribution. The two series have the same characteristics as other financial time series, with higher peaks and fatter tails.

The JB statistic shows that none of the return series follow a normal distribution. Figure 4 indicates that the quantile-quantile plot test results confirm this as well. Therefore, using the generalized error distribution (GED) to characterize the data in the modeling approach in this paper can more accurately explain the statistical features of the carbon return series.

4.3 Carbon price volatility characteristics

In this part, we examine the volatility characteristics of the series because the GARCH family model requires the series to be stable and to have conditional heteroskedasticity. Thus, before we establish the GARCH models, it is essential to test whether the two series are stationary and heteroskedastic.

4.3.1 Unit-root test

We examine whether the series is stationary by using the Augmented Dickey Fuller (ADF) test. Table 3 shows the results from the ADF test. The results for the EUA futures and Hubei spot return series all reject the null hypothesis, since the t-statistic values are equal to 0.0000, indicating that the two series are both stationary.

4.3.2 ARCH-LM test

We examine whether the series is heteroskedastic by using the ARCH-LM test. We regress the return series on the constant term to obtain the residual series and take the lags of order 1, order 5, and order 10 for the test. Table 4 shows the results of the ARCH effect test for the return series. Both the F-statistic and LM-statistic are significantly larger than the critical values, and the residuals of the return series have conditional heteroskedasticity. This means that the GARCH family of models can be used.

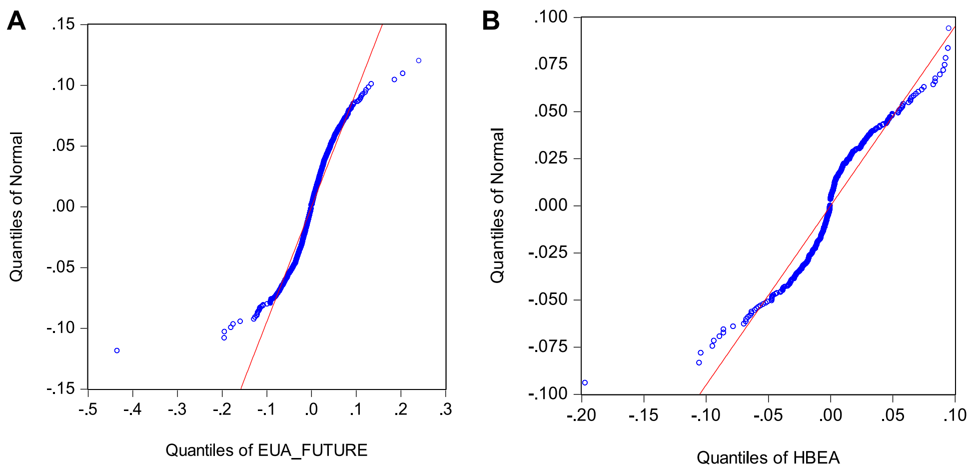

FIGURE 4
Quantile-quantile plots for returns. **(A)** EUA futures; **(B)** Hubei spot. The sample period is from January 1, 2013, to December 31, 2020, for EUA futures and from July 1, 2019, to July 30, 2021, for Hubei spot returns.

TABLE 3 ADF test of EUA futures and Hubei spot returns. The null hypothesis of the ADF test is the presence of a unit root, that is, the series is nonstationary.

	R_{EUA3}	R_{HBEA}
t-Statistic	−35.2274	−19.3779
Prob.*	0.0000	0.0000
Test critical values		
1%Level	−2.5661	−2.5699
5%Level	−1.9410	−1.9415
10%Level	−1.6166	−1.6162

4.4 Empirical results

In this part, we perform a modeling analysis of carbon price returns. First, we use the EGARCH model to evaluate the impact of positive and negative news on returns. Then, we use the modified ICSS algorithm to locate structural breaks in the returns and find the times when structural changes occur; then, we introduce them into the GARCH model as dummy variables to investigate the impact of event shocks on return volatility. In this paper, some of the structural breaks are generated at the time corresponding to the associated announcement in the news and are added to the model as dummy variables to investigate the impact of event shocks on return volatility. In further discussions, we compare data from phases II and III of EUA futures to see if there is continuity in the causes driving structural fractures.

4.4.1 Leverage effect analysis based on the EGARCH model

It is known that the volatility of financial assets tends to be asymmetric, which means that good news and bad news have different impacts on financial assets (Nelson, 1991). Therefore, this paper establishes an EGARCH model to study the leverage effect of the volatility of carbon return series. Table 5 shows the estimation results for the EUA futures. The fluctuations of EUA futures and Hubei spot returns are asymmetric, i.e., rises and falls in carbon price returns have different effects on future volatility.

TABLE 4 ARCH-LM test results. The null hypothesis is that a series of residuals exhibits no conditional heteroscedasticity. The *p*-value represents the significance of the corresponding test.

	Number of lags	F-statistic	Prob	Obs*R-squared	Prob
R_{EUA3}	1	27.9778	0.0000	27.6299	0.0000
	5	13.4695	0.0000	65.3989	0.0000
	10	7.1150	0.0000	69.1253	0.0000
R_{HBEA}	1	9.5616	0.0021	9.4109	0.0022
	5	9.9415	0.0000	45.4617	0.0000
	10	7.4020	0.0001	21.3779	0.0001

TABLE 5 Estimation results of the EGARCH (1, 1) model for EUA futures returns from 1 January 2013, to 31 December 2020.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Mean Equation				
AR (1)	−0.0740	0.0209	−3.5432	0.0004
Variance Equation				
α	−0.3501	0.0537	−6.5191	0.0000
β	0.2363	0.0260	9.0825	0.0000
γ	−0.0340	0.0166	−2.0462	0.0407
ω	0.9754	0.0063	155.8713	0.0000

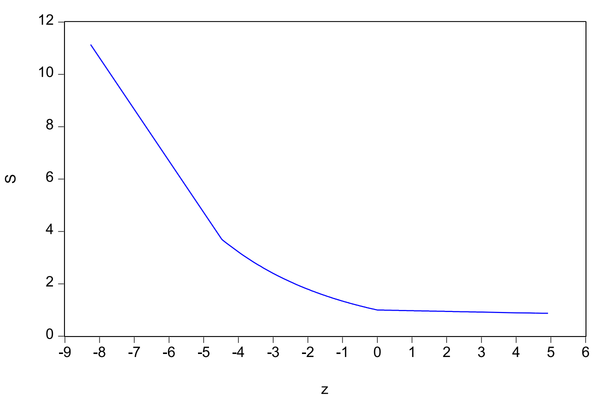

FIGURE 5
News impact curve of the EGARCH (1, 1) model of EUA futures returns.

In addition, the coefficient of the asymmetric term γ is −0.0340, indicating that there is a leverage effect on the impact of carbon return volatility and that the impact of negative news on carbon market volatility is greater than that of positive news. Positive news generates a shock of a factor of 0.2023 $(\beta + \gamma)$ to the volatility of EUA futures, and negative news generates a shock of a factor of 0.2703 $(\beta - \gamma)$. The news impact curve for EUA futures returns is shown in Figure 5, which confirms the asymmetry of the impact.

Table 6 shows the estimation results for the Hubei spot returns. Although the coefficient γ of the asymmetric term of the Hubei spot returns is less than 0, the asymmetric term is not statistically significant, which means that there is no significant leverage effect. The reason is that China's carbon trading market is still at an early stage of development, and the main trading entities are enterprises whose emissions are controlled. In addition, China only has a spot trading market, which is less active than the EU market. After years of development and innovation, the EU-ETS has become more mature, with a broader investor structure and larger trade volume. Thus, compared to its traditional financial market, China's carbon market still needs to be developed.

TABLE 6 Estimation results of the EGARCH (1, 1) model for Hubei spot returns from 1 July 2019, to 30 July 2021.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Mean Equation				
AR (1)	−0.2565	0.0433	−5.9280	0.0000
Variance Equation				
α	-0.9801	0.1045	−9.3756	0.0000
β	0.3803	0.0499	7.6175	0.0000
γ	0.0504	0.0349	1.4450	0.1485
ω	0.9015	0.0115	78.3068	0.0000

TABLE 7 Structural breaks of EUA futures and Hubei spot returns.

	R_{EUA3}	R_{HBEA}
1	2013.05.14	2019.12.27
2	2014.02.24	2020.06.04
3	2014.05.21	2021.01.26
4	2015.06.02	2021.04.13
5	2015.12.10	
6	2016.11.10	
7	2017.04.28	
8	2020.03.11	

4.4.2 Volatility analysis based on the modified ICSS-GARCH model

4.4.2.1 Structural break tests based on the modified ICSS algorithm

Using the modified ICSS algorithms presented in Section 2, we begin by detecting the structural breaks. We set the significance level for the algorithms at 0.05. Table 7 shows the results of structural break tests for the carbon market using the modified ICSS algorithm. There are nine structural change points in the EUA futures returns and four structural change points in the Hubei spot returns in the sample period. In this paper, some of the structural breaks are generated at the time corresponding to their announcement in the news and are added to the model as dummy variables. We find that the international climate and energy conferences, abnormal changes in prices of traditional energy such as oil, and global public health emergencies all affect the volatility of the carbon market and cause certain shocks to the carbon trading market.

Table 8 shows the events that occurred on the dates corresponding to the structural breaks; the results indicate that the major event shocks caused the variance to change structurally. Next, we add the structural breaks as dummy

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TABLE 8 Events corresponding to structural breaks.

	Date	Event
R_{EUA3}	2013.05.14	Shale oil production in the United States has expanded dramatically. The International Energy Agency (IEA) predicts that the United States will produce one-third of additional world crude oil supply during the next 5 years
	2014.02.24	The United Nations held a special event to highlight the importance of the needs of small island developing states in addressing climate change
	2015.06.02	Paris, France hosts the 26th World Gas Conference
	2015.12.10	The adoption of a new agreement on global climate change at the Paris Climate Change Conference will have an impact on the EU-ETS and EUA prices will fall in the future
	2016.11.10	The 22nd Conference of the Parties to the United Nations Framework Convention on Climate Change (UNFCCC), held in Morocco, focused on the key role of cities in the implementation of the Paris Agreement
	2017.04.28	The U.S. signs an executive order to expand offshore oil and gas drilling
	2020.03.11	The World Health Organization (WHO) declares the novel coronavirus (COVID-19) outbreak a global pandemic. Oil prices continue to be affected by global uncertainties
	2020.04.22	COVID-19 pandemic stalls global economic recovery. The combination of falling demand, rising supply caused such a pronounced crude petroleum price plunge
R_{HBEA}	2019.12.27	The UN Climate Change Conference COP 25 took place under the Presidency of the Government of Chile
	2020.06.04	Price changes due to approaching performance period
	2021.01.26	China stated it will further strengthen domestic efforts to adapt to climate change and comprehensively improve climate risk resilience at the Climate Adaptation Summit

TABLE 9 Parameter estimates of the AR (1)—GARCH (1, 1) model for EUA futures returns in phase III, without structural breaks from 1 January 2013, to 31 December 2020.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Mean Equation				
AR (1)	−0.0703	0.0213	−3.3053	0.0009
Variance Equation				
α	0.1190	0.0161	7.3805	0.0000
β	0.8743	0.0155	56.501	0.0000

TABLE 10 Parameter estimates of the MA (1)—GARCH (1, 1) model for Hubei spot returns without structural breaks from 1 July 2019, to 30 July 2021.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Mean Equation				
MA (1)	−0.2862	0.0397	−7.2178	0.0000
Variance Equation				
α	0.2436	0.0367	6.6409	0.0000
β	0.7403	0.0250	29.6049	0.0000

variables to the GARCH model to compare how important events affect the volatility of carbon prices.

4.4.2.2 Analysis of the GARCH model based on structural breaks

Using the modified ICSS algorithm, we have found structural breaks. Then we introduce them into the GARCH model for comparative analysis. We compare two models: one without structural change points and the other with structural change points, which are given individually in both cases.

4.4.2.2.1 GARCH model without structural breaks. First, we use the GARCH model without structural breaks. Tables 9, 10 show the estimation results of the GARCH model. For EUA futures and Hubei spot returns, all parameters are significant. The coefficients of α and β in the model are positive, and their sum is close to 1, indicating that the volatility of the carbon market has persistence and long memory.

TABLE 11 Parameter estimates of the AR (1)—GARCH (1, 1) model for EUA futures returns in phase III, with structural breaks from 1 January 2013, to 31 December 2020.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Mean Equation				
AR (1)	−0.0679	0.0216	−3.1376	0.0017
Variance Equation				
α	0.1175	0.0165	7.1255	0.0000
β	0.8695	0.0156	55.8617	0.0000
Dummy	0.0006	0.0002	3.3950	0.0007

4.4.2.2.2 GARCH model with structural breaks. We adopt the modified ICSS-GARCH model to further analyze the volatility characteristics of the carbon market. Tables 11, 12 illustrate the results of the estimation. We find that the characteristics of volatility are attenuated when we consider structural breaks. We observe a decrease in the sum of α and

TABLE 12 Parameter estimates for the MA (1)—GARCH (1, 1) model for Hubei spot returns with structural breaks from 1 July 2019, to 30 July 2021.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Mean Equation				
MA (1)	−0.2796	0.0409	−6.8393	0.0000
Variance Equation				
α	0.1745	0.0273	6.3987	0.0000
β	0.7985	0.0212	37.734	0.0000
dummy	0.0013	0.0005	2.5024	0.0123

β for both EUA futures and Hubei spot returns. The sum of α and β for EUA futures returns decreases from 0.9933 to 0.9870, and the sum of α and β for Hubei spot returns decreases from 0.9838 to 0.9730. This indicates that the strong persistence and long memory characteristics of volatility become weaker after we add the structural breaks as a dummy variable to the model. The modified ICSS-GARCH model reduces the pseudovolatility of the return series and enhances the model's accuracy (Malik et al., 2005).

Table 13 depicts the results of the ARCH-LM test for the residuals after we model the return series. The p-value of the residual series is greater than 0.05 for lag orders of 1, 5 and 10, and therefore the null hypothesis is accepted. This shows that after modeling, the conditional heteroskedasticity in the series is removed, which means that the model fits well.

5 Further discussion

5.1 Analysis of EU-ETS phase II

We replace our dataset with the EU-ETS phase II trading data for further discussion of the volatility of EUA futures' returns. Due to data availability, the scope for the prices of EUA futures' returns is from 2 January 2008, to 31 December 2012. Table 14 illustrates the basic characteristics of EUA futures returns in phase II. The descriptive statistics show that the mean value of the return in phase II is -0.0010, which is lower than the value of 0.0008 in phase III, indicating that the return of EUA futures is gradually increasing. The standard deviation of phase II is 0.0271, which is not significantly different from phase III, and the price fluctuation is more stable. In addition, the returns of both phases have the characteristics of higher peaks and fatter tails and do not follow a normal distribution.

We also conducted ADF and ARCH-LM tests on the data of EUA futures in phase II, and the results show that the returns remain stationary and the residuals of the return series are conditionally heteroskedastic. Next, we analyze the volatility of EUA futures returns in phase II using the same methods as in Section 3.

The estimation results for the EGARCH (1, 1) model are shown in Table 15. The fluctuations in phase II of the EUA futures are asymmetric. The coefficient of the asymmetric term γ is −0.0674, indicating that there is a leverage effect on the impact of carbon return volatility and that the impact of negative news on carbon market volatility is greater than that of positive news. Positive news generates a shock of a factor of 0.1475 $(\beta + \gamma)$ to volatility, and negative news generates a shock of a factor of 0.2823 $(\beta - \gamma)$.

We examine the structural break points uncovered by using the modified ICSS algorithms. There are four structural breaks in the EUA futures returns in phase II: they occurred on 21 October 2008; 16 June 2009; 28 May 2010; and 22 June 2011. We also add these structural breaks to the model as dummy variables. Table 16 illustrates the estimation results of the GARCH (1, 1) model without the structural breaks. Table 17 shows the results of the ICSS-GARCH (1, 1) model with structural breaks. The findings show that the characteristics of volatility are attenuated once we consider structural breaks. There is a decrease in the sum of α and β for both phases. The sum of α and β for EUA futures returns decreases from 0.9936 to 0.9847.

This is consistent with the findings for phase III, in which EU-ETS volatility does not change significantly between the two phases, confirming that phase II volatility characteristics persist into phase III. This also indicates that the strong persistence and long memory characteristics of volatility become weaker after we add the structural breaks as dummy variables to the model. The

TABLE 13 ARCH-LM test results for residual series. The null hypothesis is that a series of residuals exhibits no conditional heteroscedasticity. The p-value represents the significance of the corresponding test.

	Number of lags	F-statistic	Prob	Obs*R-squared	Prob
R_{EUA3}	1	0.0626	0.8025	0.0626	0.8024
	5	0.3687	0.8703	1.8471	0.8699
	10	0.5542	0.8519	5.5569	0.8510
R_{HBEA}	1	0.9329	0.3346	0.9350	0.3336
	5	0.5851	0.7114	2.9448	0.7085
	10	0.6466	0.7738	6.5295	0.7690

TABLE 14 Phase II data descriptive statistics. This table presents the descriptive statistics results of carbon price returns considered for the whole sample period. JB denotes the Jarque-Bera test statistic for the null of normality.

Variables	Mean	Std. Dev	Skewness	Kurtosis	Jarque-bera	Prob
R_{EUA2}	−0.0010	0.0271	0.0837	6.9123	819.7549	0.0000

TABLE 15 Estimation results of the EGARCH (1, 1) model of EUA futures returns in phase II from 2 January 2008, to 31 December 2012.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Variance Equation				
α	−0.3826	0.0744	−5.1423	0.0000
β	0.2149	0.0340	6.3273	0.0000
γ	−0.0674	0.0170	−3.9598	0.0001
ω	0.9709	0.0080	120.7018	0.0000

TABLE 16 Parameter estimates of the GARCH (1, 1) model for EUA futures returns in phase II without structural breaks from 2 January 2008, to 31 December 2012.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Variance Equation				
α	0.1008	0.0167	6.0045	0.0000
β	0.8928	0.0170	52.5048	0.0000

TABLE 17 Parameter estimates of the GARCH (1, 1) model for EUA futures returns in phase II with structural breaks from 2 January 2008, to 31 December 2012.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Variance Equation				
α	0.0947	0.0170	5.5775	0.0000
β	0.8970	0.0172	52.223	0.0000
dummy	0.0005	0.0002	2.2230	0.0262

modified ICSS-GARCH model reduces the pseudovolatility of the return series and enhances the model's accuracy. A proper assessment of short-term price and volatility is a critical issue in the carbon market since effectively measuring volatility risk is critical for carbon market managers in a complex market.

To summarize, our study shows the following findings: First, there is a leverage effect on the impact of carbon return volatility, and the impact of negative news on carbon market volatility is greater than that of positive news. This is consistent with previous research demonstrating that the returns on financial assets are leveraged and that positive and negative news have different impacts on return volatility (Paolella and Taschini, 2008; Dutta, 2018). Secondly, we find that the international climate and energy conferences, abnormal changes in prices of traditional energy such as oil, and global public health emergencies all affect the volatility of the carbon market and cause certain shocks to the carbon trading market. Wang et al. (2019) demonstrated that all externalities of the carbon market, whether energy prices or policy announcements, are reflected in trading behavior and impact the demand and supply of carbon permits *via* trading, which influences carbon pricing. We extend this conclusion. Finally, our results are consistent with previous results using the modified ICSS-GARCH model to study financial market data (Malik et al., 2005; Wen et al., 2020). The results show that the modified ICSS-GARCH model is also applicable to the study of carbon market volatility and that the model can reduce the pseudovolatility of the return series to a certain extent and improve the accuracy of the model.

5.2 Policy recommendations

The findings of this study are potentially significant for further research into carbon emission permits. They help policymakers and investors in the carbon market identify risks and develop strategies to minimize them.

Firstly, regulators should enhance carbon price monitoring and focus on short-term shocks in the carbon market to reduce trading risks. Studies have shown that when the carbon market is subject to exogenous shocks, prices are prone to dramatic fluctuations and the market does not compensate for potential risks. Market managers should recognize and identify abnormal price fluctuations and forecast the trend. In addition, market management should establish stability reserves in order to minimize extreme price changes in response to exogenous shocks, reduce trade risks, and improve market stability.

Second, the Chinese carbon market should improve the system design. The findings indicate that the EU-ETS price is less volatile and more stable than the carbon market in China. In the short term, the Chinese carbon market is inactive, participants are risk-averse, and products lack diversity. In the long term, the Chinese carbon market needs a comprehensive development plan and a well-structured market framework. It still needs to be improved in many ways, and the design of the system should be strengthened.

Finally, the Chinese market should boost the development of carbon finance instruments. Chinese carbon credits can only be traded on the spot market. To increase the liquidity of the carbon market, policymakers should encourage the development of derivative products such as carbon futures, which can diversify investment portfolios and attract more investors to participate in trading. Stability in the carbon market can be established through the use of derivatives for price discovery and risk aversion. Prior studies suggest that the EU-ETS reduces the volatility of spot prices after the introduction of futures products, and spreads the uncertainty of spot prices through a hedging mechanism (Chevallier et al., 2011). Furthermore, derivatives can be used for price discovery and risk aversion in order to stabilize the carbon market. It can also increase market activity and encourage both institutional and individual investors to trade actively in the carbon market.

6 Conclusion

Responding to climate change, realizing carbon emission reductions at the lowest cost by economic market means and reversing the increasing trend of greenhouse gas emissions are major challenges for the world.

In this paper, we investigate the volatility characteristics of the EU-ETS and the Chinese Hubei carbon market, by using the modified ICSS-GARCH model. The study shows the following findings. 1) There is a leverage effect on the impact of carbon return volatility, and the impact of negative news on carbon market volatility is greater than that of positive news. The leverage effect in the Hubei carbon market was not statistically significant during the sample period. We surmise that this result could be due to inactive market trading and trading entity limits. 2) We find that the international climate and energy conferences, abnormal changes in prices of traditional energy such as oil, and global public health emergencies all affect the volatility of the carbon market and cause certain shocks to the carbon trading market. 3) We adopt the modified ICSS algorithm to find the structural breaks and introduce them as dummy variables to investigate the impact of event shocks on the volatility of the carbon market. The results indicate that the ICSS-GARCH model can reduces the pseudovolatility of the return series to a certain extent and improve the accuracy of the model. In addition, our results hold after we replace the data from EUA futures phase III with those from phase II, indicating that our model is robust and that the factors affecting phase II persist into phase III.

Our findings could be important for carbon emission permit research. They help policymakers and investors identify risks and develop prevention measures. Regulators can minimize trade risks by enhancing monitoring of carbon prices. Policymakers should improve the way the system is set up and speed up the development of carbon finance instruments for the Chinese carbon market.

Data availability statement

The CSV data used to support the findings of this research are available from the corresponding author upon request.

Author contributions

HY: conceptualization, software, data curation, and writing original draft; HW: methodology, reviewing, and editing; CL: software, data curation, and writing original draft; ZL: methodology, reviewing, and editing; SW: conceptualization, supervision, and funding acquisition.

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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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