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Can Internet Development Inhibit Carbon Emission Efficiency of Industrial Sector? Anew Perspective from Multiple Environmental Regulations

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To achieve industrial low-carbon transformation, the industrial sector is progressively adopting "smart manufacturing" and "digital transformation" strategies. This study examines whether these strategies enhance carbon emission efficiency of industrial sector (CEEI) and explores how the effects of Internet development on CEEI change under various environmental regulations. Using provincial data from China between 2011 and 2020, we investigate the influence of Internet development on CEEI under different types and intensities of environmental regulations. Our findings suggest that Internet development promotes CEEI but is influenced by various environmental regulations, including command-controlled environmental regulation (CER), market-incentive environmental regulation (MER), and voluntary public participation environmental regulation (VER). The impact of Internet development varies depending on the regulatory context, and regional differences also influence this relationship. Therefore, we recommend the implementation of diverse environmental policies that leverage Internet development to maximize CEEI improvements based on regional characteristics.

Keywords: *Command-Controlled Environmental Regulation; Market-Incentive Environmental Regulation; Voluntary Public Participation Environmental Regulation; Internet Development; Carbon Emission Efficiency of Industrial Sector; Threshold Panel Model.*

Introduction

The industrial sector is undeniably a cornerstone of China's economy, accounting for a significant portion of both energy consumption and CO_2 emissions (Bounman *et al.,* 2015; Hertwich & Wood, 2018; Guo & Yuan, 2020; Liu & Xiao, 2021). In 2020 alone, industrial added value constituted a substantial 30.8 % of GDP and contributed 33.6 % to GDP growth. Concurrently, industrial CO_2 emissions accounted for a staggering 62.0 % of China's total CO_2 emissions (Wu *et al.,* 2022). This data underscores the prevailing growth model within the sector, characterized by high input, high pollution, and low output-a model that not only consumes vast amounts of energy but also generates significant carbon emissions, ultimately impeding GDP growth. The recent introduction of the "dual carbon" goal highlights the urgent need to address carbon emissions as a central focus. However, China faces the formidable challenge of balancing economic development with environmental sustainability (Liu *et al.,* 2020). Consequently, there is a pressing imperative to align economic growth with objectives related to energy conservation and emission reduction (Li & Ge, 2022). In this context, the concept of Carbon Emission Efficiency of Industrial Sector (CEEI) emerges as a crucial solution. CEEI serves as a metric to evaluate the level of carbon emissions produced relative to a given desired output (Wang *et al.,* 2022). Nevertheless, addressing how to optimize the industrial production process, enhance green technology in industrial production, manage environmental performance, and bolster CEEI has become a pressing issue within the sphere of environmental regulation.

The continuous advancement and evolution of network information technologies-such as fifth-generation networks, blockchain, and artificial intelligence-hold immense potential to significantly advance industrial intelligence and environmental sustainability (Vu *et al.,* 2023; Fang *et al.,* 2021). Recognizing this potential, China has been actively investing in internet infrastructure and fostering the growth of the digital economy. By the close of 2022, China's internet penetration rate had reached an impressive 75.6 %. This widespread access to the internet opens new avenues for improving industrial carbon efficiency. Previous research has demonstrated that internet development can enhance energy efficiency by facilitating the matching of labor and capital resources, driving technological innovation, and prompting upgrades in industrial structure (May *et al.*, 2017; Khuntia *et al.,* 2018; Li & Du, 2021).

However, contrary views posit that Internet technologies may trigger an energy rebound effect, resulting in a substantial increase in product and energy demand (Ahmed *et al.,* 2023; Belkhir, 2020). Indeed, evidence suggests that Internet technologies have contributed to a surge in energy consumption during industrial production (Avom *et al.,* 2020). Moreover, Salahuddin et al. (2016) observed that Internet usage in OECD countries correlates with increased CO_2 emissions. Consequently, the relationship between Internet development and carbon emissions remains a subject of debate (Park *et al.,* 2018; Zhang, 2023). Furthermore, limited research has delved into the impact of Internet development on CEEI. CEEI, as a comprehensive metric, evaluates both economic development and emission reduction within the industrial sector, providing a valuable reference point for guiding low-carbon transformations (Wang *et al.,* 2022). Therefore, it is imperative to thoroughly examine the relationship between the Internet and CEEI concerning environmental concerns.

Against the backdrop of diverse and unpredictable environmental regulatory policies, their influence on the relationship between Internet development and CEEI is pivotal. Research suggests that regions with well-established Internet infrastructure and high penetration rates often witness increased public involvement in environmental regulation (Liu & Fan 2021; Wu *et al.,* 2022). Public participation can effectively reduce information disparities between regulators and companies, compelling businesses to lower emissions. Additionally, the "compliance cost hypothesis" posits that stringent environmental regulations lead to higher pollution control costs for enterprises (Zhang *et al.,* 2022), potentially diverting investments in industrial information technology. Consequently, environmental regulations significantly impact the effect of Internet development on CEEI. However, past research has overlooked exploring the nonlinear relationship between the Internet and carbon emission efficiency. Furthermore, there is a lack of categorization of environmental regulations to determine whether regulations of varying natures and intensities yield different outcomes in the interplay between Internet development and CEEI. These questions remain unanswered.

Taking these considerations into account, we pose the following questions: What role does Internet development play in CEEI, and how does environmental regulation influence this relationship? Do different types and intensities of environmental regulations exert varying impacts on this relationship? In what intensity range do the three types of environmental regulation yield the most significant effects on CEEI in the context of Internet development? How can the government construct an optimal mix of multiple environmental regulatory tools? We hope that addressing these issues will offer valuable insights for governments aiming to establish enduring and effective environmental regulation systems.

The contributions of this paper are primarily threefold. Firstly, our study fills a crucial gap in the literature by providing a comprehensive investigation into the relationship between Internet development and CEEI within the industrial sector. Unlike previous studies that primarily focus on the direct effects of Internet technologies on energy consumption and CO_2 emissions, our research specifically examines how Internet advancements influence CEEI. By doing so, we offer a nuanced understanding of how digitalization intersects with environmental sustainability, shedding light on potential pathways for achieving low-carbon industrial transformations.

Secondly, our study delves into the multifaceted impact of command-controlled environmental regulation (CER), market-incentive environmental regulation (MER), and voluntary public participation environmental regulation (VER) on the relationship between Internet development and CEEI. While existing literature has acknowledged the role of regulatory frameworks in shaping environmental outcomes, our research goes beyond simplistic categorizations to analyze the nuanced effects of various regulatory mechanisms. By examining how different types and intensities of regulations interact with Internet development to influence CEEI, we offer a more comprehensive understanding of the regulatory dynamics driving sustainable industrial development. Through this detailed analysis, we contribute to advancing knowledge on the complex interplay between regulatory approaches, technological advancements, and environmental performance within the industrial sector.

Lastly, our study conducts a detailed regional analysis to unveil how Internet development impacts CEEI across diverse regions and under different environmental regulations. By examining regional disparities, we identify nuanced patterns that shed light on the relationship between Internet development, environmental regulations, and CEEI performance. The findings underscore the importance of tailoring regulatory strategies to each region's specific needs. By doing so, policymakers can better address local challenges and leverage opportunities to enhance CEEI performance while minimizing adverse environmental impacts. Overall, our regional analysis offers valuable insights for designing region-specific policies that promote sustainable industrial growth and contribute to broader environmental goals.

The structure of this paper is as follows: "Literature Review and Hypotheses" delves into relevant literature and formulates research hypotheses. "Models and Variables" outlines empirical models and variables. "Empirical Results and Analysis" details the measurement of CEEI and scrutinizes the empirical findings. "Conclusion and Policy Implications" provides a summary of the results, offers policy implications, and outlines directions for future research.

Literature Review and Hypotheses

Carbon Emission Efficiency of Industrial Sector

The study of Carbon Emission Efficiency (CEE) has gained increasing attention, with numerous scholars dedicated to developing CEE measurement methods (Zhou *et al.,* 2010; Xie *et al.,* 2021). Currently, these measurement methods primarily fall into two categories: single-factor carbon emission efficiency (Chen & Golley, 2014; Xie *et al.,* 2021) and total-factor carbon emission efficiency (Zhou *et al.,* 2010; Li & Cheng, 2022). The former approach often employs carbon intensity (Wang *et al.,* 2022; Gan *et al.,* 2022; Sun *et al.,* 2022) and carbon productivity (Du & Li, 2019) as indicators for carbon emission efficiency. While this method is straightforward, it has the drawback of focusing solely on outputs while disregarding inputs (Cheng *et al.,* 2023).

In contrast, the latter method, total-factor carbon emission efficiency, considers a comprehensive range of inputs and outputs generated in the carbon emission production processes. This approach has gained widespread acceptance for efficiency estimation. Data Envelopment Analysis (DEA) has been the primary model in the field of total-factor carbon emission efficiency estimation, with Charnes et al. (1978) introducing the initial DEA method, known as CCR-DEA (named after the initials of the three academics). To date, CCR-DEA and its various improved models have been widely used to compute total-factor carbon emission efficiency (Ignatius *et al.,* 2016; Meng, 2016). Based on DEA, research into carbon emission efficiency has seen significant expansion. For instance, Feng et al. (2022) decomposed CEE into three components using a three-hierarchy meta-frontier DEA model, while Zhou et al. (2019) applied super-SBM DEA to assess CEE in the construction industry, and Liu et al. (2022) used a three-stage DEA to calculate CEE in China.

However, these DEA methods employed in previous research often relied on self-assessment by each decision-making unit (DMU), leading to an overestimation of DMU weights and generating multiple valid DMUs that couldn't be further ranked (Yang & Wei, 2019; Dong et al., 2020). To address this issue, Liang et al. (2008) introduced the Game cross-efficiency DEA model (GCE-DEA) by incorporating a pair-to-pair game mechanism among DMUs. They argued that in practice, DMUs do not make decisions in isolation but rather make decisions by considering the practices of other DMUs. This implies competition among DMUs, making the results of DMUs' pairwise games, obtained through an iterative process, more reflective of the real-world dynamics. This method has found applications in measuring energy efficiency in the construction industry, green growth assessment, and related fields (Wang *et al.,* 2021).

Internet Development and Carbon Emission Efficiency of Industrial Sector

The integration of Internet technology with industrial production is expected to yield several significant benefits, including increased economic output and reduced carbon emissions (Pan *et al.,* 2023). Internet technology has the potential to empower regulatory systems by enhancing the monitoring of pollution emissions, compelling enterprises to adopt environmentally friendly production practices and process improvements, ultimately leading to a reduction in CO_2 emissions (Yang *et al.,* 2021). Research conducted by Silva (2023) in the United States indicated that the Internet has the capacity to lower energy intensity, thus improving overall economic efficiency. Increased Internet penetration has the potential to decrease energy consumption in industrial and construction sectors, consequently reducing CO_2 emissions (Khuntia *et al.,* 2018).

Furthermore, the combination of Internet technologies with manufacturing processes, leading to the optimization of production systems, has the potential to reduce CO_2 emissions, as argued by Pan (2011). Ishida (2015) used panel data for Japan from 1980 to 2010 to demonstrate that investments in information and communications technology could reduce energy consumption. Amin (2019) found that ICT could alleviate energy scarcity and environmental pollution to varying degrees.

The application of the Internet can also enable enterprises to gain competitive advantages through improved product performance, enhanced network environments, and increased enterprise value (Dimian *et al.,* 2022). This, in turn, leads to more efficient allocation of input resources, as the Internet contributes to improved energy efficiency through innovation and optimal resource allocation (Li *et al.,* 2021). Additionally, the Internet's role in information transmission and data sharing can streamline transaction processes, reducing energy consumption and CO_2 emissions. Moreover, it promotes efficient coordination and communication pathways that encourage enterprises to optimize their human resource structures (Miglani *et al.,* 2020).

Moreover, the use of the Internet can stimulate economies of scale, which, when combined with industrial production, can transform the traditional extensive growth model into a more sustainable development approach. In the long run, this transition can reduce dependence on natural resources and minimize pollutant emissions. Additionally, industrial Internet platforms can facilitate energy conservation and reduced consumption throughout the entire industrial chain (Zhu *et al.,* 2021). In summary, based on the above points, this study proposes the following hypothesis:

Hypothesis 1: *There is a positive relationship between the internet development and CEEI.*

Internet Development, Heterogeneous Environmental Regulations, and Carbon Emission Efficiency

Environmental regulations serve as essential tools to mitigate environmental degradation. In China's pursuit of the "dual carbon" goal, there has been a concerted effort to promote industrial energy conservation and emission reduction. A series of environmental regulations, including the "three simultaneous" policy and the "environmental protection tax," have been introduced to combat pollution from various sources (Cheng & Kong, 2022; Liu *et al.,* 2022). In light of these efforts, we introduce heterogeneous environmental regulations and explore the impact of Internet development on CEEI under different regulatory frameworks.

Command-controlled environmental regulation (CER) encompasses laws, regulations, and administrative orders formulated by legislative bodies or government agencies. Under CER, enterprises are obligated to comply with environmental protection standards and regulations, or adopt government-prescribed technologies, with potential severe penalties for non-compliance (Feng & Wang, 2019). CER is currently the most widely adopted regulatory tool in various countries. For enterprises, CER introduces mandatory requirements that may increase the costs associated with pollution control, potentially impacting their profitability and stifling incentives for technological innovation (Li *et al.,* 2022).

However, owing to the technical attributes of the Internet, industrial enterprises can enhance their capacity for resource integration, operational efficiency, production, and pollution control through Internet technologies (Pan *et al.,* 2023). Nevertheless, when CER intensity is high, enterprises may prioritize adhering to the "compliance cost hypothesis," allocating more financial resources to pollution abatement. Consequently, investments in industrial Internet-related technologies may be crowded out, limiting the application of such technologies and, consequently, impacting emission reduction performance (Yin *et al.,* 2023). In line with "Porter's hypothesis," moderate CER intensity could encourage enterprises to invest capital in the industrial Internet sector, ultimately enhancing CEEI (Cui *et al.,* 2023).

Furthermore, the communicative nature of the Internet, coupled with strict regulatory oversight, allows for the rapid dissemination of government environmental information. This aligns with Reputation theory, where information disclosure and effective communication can mitigate moral hazards for enterprises involved in environmental governance. Enterprises, keen to protect their reputation, are more inclined to adopt environmentally responsible practices, which, in turn, positively influence carbon emission efficiency (Chand *et al.,* 2022; Liu *et al.,* 2023). In summary, based on the above points, we propose the following hypothesis:

Hypothesis 2: *The relationship between Internet development and CEEI is influenced by the different degrees of CER.*

Market-incentive environmental regulation (MER) constitutes an economic incentive-based approach to regulating business operations. It leverages market mechanisms through economic incentives to influence the environmental decisions made by enterprises (Li *et al.,* 2023). Well-structured MER can guide enterprises toward transitioning from end-of-pipe pollution control to cleaner production practices, which can lead to more cost-effective emission reduction for society in the long run (Cheng *et al.,* 2022).

The development of the Internet indirectly promotes improved energy efficiency by reducing the mismatch between labor and capital resources (Wu *et al.,* 2021). Additionally, given the market-driven nature of MER, it can effectively address resource mismatches. Consequently, this enhances the regulatory role of Internet development on carbon efficiency (Wang *et al.,* 2021).

Moreover, enterprises, driven by profit motives, are inclined to favor technologies with commercial value, potentially leading to insufficient investment in environmentally friendly technologies (Yang *et al.,* 2020). However, because MER incorporates reward and penalty mechanisms, the cost of emissions reduction is significantly reduced for enterprises. This creates a strong incentive for enterprises to adopt environmentally biased technological advancements (Song *et al.,* 2022). In sum, based on the points mentioned, we propose the following hypothesis:

Hypothesis 3: *The relationship between Internet development and CEEI is influenced by different degrees of MER.*

Voluntary public participation environmental regulation (VER) is emerging as a significant component of environmental governance, with increasing attention from researchers (Le *et al.,* 2019; Yew & Zhu, 2019; Wang *et al.,* 2022). VER represents an approach to environmental governance in which the public, who possess a comprehensive understanding of environmental issues, can provide effective suggestions, and actively engage in the regulatory process (Hasan *et al.,* 2018). The 19th CPC National Congress laid the foundation for an environmental governance system where the government plays a leading role, enterprises function as the primary actors, and social organizations and the public are encouraged to participate (Zhang, 2021; Zhang *et al.,* 2021). This shift signifies that public participation in environmental governance is no longer a theoretical concept, and research increasingly focuses on exploring effective channels and methods to enhance the effectiveness of VER (Chang *et al.,* 2022).

The Internet plays a pivotal role in improving information flow efficiency and reducing information asymmetry (Wu *et al.,* 2022). It makes it easier for the public to access information related to environmental pollution, raises awareness about environmental protection, and encourages consumers to opt for environmentally friendly products. This, in turn, motivates industrial enterprises to choose environmentally friendly production technologies in alignment with consumer preferences and invest in R&D for technological innovation (Huang *et al.,* 2021). Additionally, the Internet serves as a new platform for the public to engage in environmental management. Through online platforms, the public can report on-site environmental pollution information and instances of environmental violations to environmental protection authorities. Furthermore, they can actively oversee the performance of environmental governance based on feedback from these authorities (Zhang *et al.,* 2019; Safarzadeh *et al.,* 2020). In light of the points discussed above, we propose the following hypothesis:

Hypothesis 4: *The relationship between Internet development and CEEI is influenced by different degrees of VER.*

For summarizing, we illustrate the influence mechanism with a diagram, as shown in Figure1.

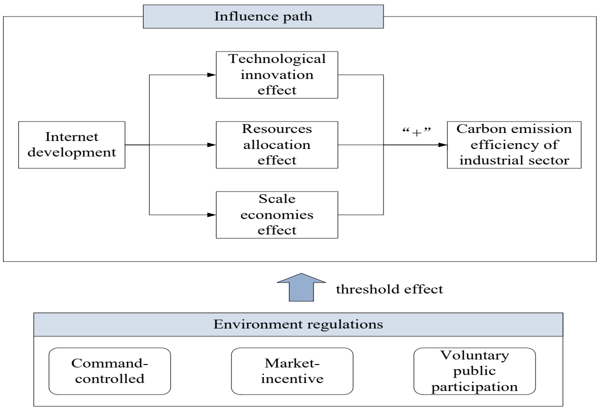

Figure 1. Influence Mechanism between Internet Development, Environmental Regulations and CEEI

Models and Variables

Measurement of CEEI

Measurement Methods

The GCE-DEA model represents an enhancement of the Cross-Efficiency Data Envelopment Analysis (CE-DEA) model, as introduced by Liang et al. in 2008. In CE-DEA, the efficiency of n DMUs is calculated n times, employing optimal weights derived from n linear programming iterations to obtain an average result. This approach addresses the issue with traditional DEA that relies solely on self-evaluation for weight determination. However, the results are non-unique and not well-suited for comparisons (Xie *et al.,* 2018). The GCE-DEA model, on the other hand, utilizes the initial values provided by the original CE-DEA average for iterative operations, ultimately guiding each DMU towards the optimal value. The specific details of the GCE-DEA model can be found in Equation (1).

$$\max \sum_{r=1}^{s} u_{rj}^{d} y_{rj}$$

$$\text{s.t.} \quad \sum_{i=1}^{m} v_{ij}^{d} x_{il} - \sum_{r=1}^{s} u_{rj}^{d} y_{rl} \geq 0, \; l=1,2,\ldots,n \quad (1)$$

$$\max \sum_{i=1}^{m} v_{ij}^{d} x_{ij} = 1$$

$$e^{d} \sum_{i=1}^{m} v_{ij}^{d} x_{id} - \sum_{r=1}^{s} u_{rj}^{d} y_{rd} \leq 0$$

$$v_{ij}^{d} \geq 0, i = 1,2,\ldots,m$$

$$u_{rj}^{d} \geq 0, r = 1,2,\ldots,s$$

Where x and y are input and output vector, v_{ij}^{d} and u_{rj}^{d} are the weight of ith input and rth output. e^{d} is a parameter and its initial value is DMU_d's original average cross-efficiency. The d-cross-efficiency value of the GCE-DEA of DMU_j relative to DMU_d can be calculated according to Eq. (2).

$$e_{dj} = \frac{\sum_{r=1}^{s} U_{rj}^{d} y_{rj}}{\sum_{i=1}^{m} v_{ij}^{d} x_{ij}}, d = 1,2,\ldots,n \quad (2)$$

Then, averaging all e_{dj} (d = 1, …, n), we could obtain the average game cross-efficiency value $\bar{e}_j$ of DMU_j (j=1, …, n) using Eq. (3).

$$\bar{e}_j = \frac{1}{n} \sum_{d=1}^{n} \sum_{d=1}^{n} U_{rj}^{d*} (e_d) y_{rj} \quad (3)$$

Furthermore, CO_2 is the undesired output during industrial processes, thus, the GCE-DEA model should maximize CO_2 emissions reductions while maximizing the desired output in the industrial sector. Drawing on Xie (2012) and Wang (2021), we transform the undesirable output by conversion function $f(U) = -U$ and adopt in the GCE-DEA model. Refering to Eq. (4) for details.

$$\max \sum_{r=1}^{s} u_{rj}^{d} y_{rj} - \sum_{k=1}^{q} w_{kj}^{d} b_{kj}$$

$$\text{s.t.} \quad \sum_{i=1}^{m} v_{ij}^{d} x_{il} - \left(\sum_{r=1}^{s} u_{rj}^{d} y_{rl} - \sum_{k=1}^{q} w_{kj}^{d} b_{kj} \right) \geq 0, \; l=1,2,\ldots,n \quad (4)$$

$$\max \sum_{i=1}^{m} v_{ij}^{d} x_{ij} = 1$$

$$e^{d} \sum_{i=1}^{m} v_{ij}^{d} x_{id} - \left(\sum_{r=1}^{s} u_{rj}^{d} y_{rd} - \sum_{k=1}^{q} w_{kj}^{d} b_{kd} \right) \leq 0$$

$$v_{ij}^{d} \geq 0, i = 1,2,\ldots,m$$

$$u_{rj}^{d} \geq 0, r = 1,2,\ldots,s$$

$$w_{kj}^{d} \geq 0, k = 1,2,\ldots,q$$

Therein, b_{kj} is the kth undesirable output in DMU_j, w_{kj}^{d} is the weight. The other explanations are the same as those for Eq. (1). In this case, the game cross-efficiency is defined as follows:

$$e_{dj} = \frac{\sum_{r=1}^{s} u_{rj}^{d} y_{rj} - \sum_{k=1}^{q} w_{kj}^{d} b_{kj}}{\sum_{i=1}^{m} v_{ij}^{d} x_{ij}}, d = 1,2,\ldots,n \quad (5)$$

The DMUj's average game-cross efficiency can be measured through Eq. (6):

$$\bar{e}_j = \frac{1}{n} \sum_{d=1}^{n} \left(\sum_{r=1}^{s} u_{rj}^{d*} (e_d) y_{rj} - \sum_{k=1}^{q} w_{kj}^{d*} (e_d)\, b_{kj} \right) (6)$$

Selection of Indicators

Input Indicators

(1) Energy Input: In this study, we quantify energy input by converting eight primary energy sources into the equivalent of 10,000 tons of standard coal. These energy sources include coal, coke, crude oil, gasoline, diesel, kerosene, fuel oil, and natural gas.

(2) Capital Input: To gauge capital investment, this study utilizes the "total amount of industrial assets." To mitigate the impact of inflation, the total amount of industrial assets is adjusted to constant prices using the GDP index reduction method, with the base year set at 2000 (indexed to 100).

(3) Labor Input: In this study, labor input within the industrial sector is determined by using the average number of industrial workers.

Output Indicators:

(1) Economic Output: This study measures desirable output by utilizing the business income of principal industries. To account for changes in the price level, the income is deflated using the 2005 GDP price indices.

(2) CO_2 Emission: As an indicator of undesired output, this study employs CO_2 emissions. Emissions are calculated in accordance with the formula recommended by the Intergovernmental Panel on Climate Change (IPCC).

$$CO_2 = \sum_i fc_i \times cv_i \times cc_i \times cor_i \times 44/12$$

Therein, i indicates the type of carbonaceous fossil fuel, fc_i represents consumption of fossil fuel i, cv_i, cc_i and cor_i are the low calorific value, the carbon content and the rate of carbon oxidation of fuel i, respectively. These values by type of fuel can be found in research of Cheng (Cheng *et al.*, 2023).

Econometric Model Design

Benchmark Regression Model

To elucidate the impact of Internet development on CEEI, this study establishes a benchmark regression model and employs a two-way fixed-effect model for regression analysis. The following equation is used:

$$CEEI_{i,t} = \beta_0 + \beta_1 ID_{i,t} + \gamma_i X_{i,t} + \varepsilon_{i,t} \quad (7)$$

where i and t denote region and year, respectively. CEEI is the carbon emission of industrial sector. $ID_{i,t}$ represents the level of internet development, β_0 is the constant terms. β_1 and γ_i are the corresponding coefficients of the variables. $X_{i,t}$ represent control variables.

Threshold Regression Model

Panel threshold models, as introduced by Hansen (1999) and further developed by Su et al. (2022), are effective tools for addressing nonlinearities within economic systems. Building on the earlier analysis, it is evident that environmental regulations play a pivotal role in shaping the relationship between Internet development and CEEI. Considering this, we employ Hansen's panel threshold model to delve into the nonlinear relationship between the level of Internet development and CEEI, influenced by CER, MER, and VER. In the following section, we use CER, MER, and VER as threshold variables to construct the threshold effect model, detailed in Equations (8) to (10).

$$CEEI_{i,t} = \alpha_0 + \alpha_1 GI_{i,t} + \alpha_2 URB_{i,t} + \alpha_3 IS_{i,t} + \alpha_4 R\&D_{i,t} + \alpha_5 PGDP_{i,t} + \alpha_6 ID_{i,t} + \alpha_7 ID_{i,t} I(CER_{i,t} < \gamma_1) + \alpha_8 ID_{i,t} I(\gamma_1 \le CER_{i,t} \le \gamma_2) + \ldots + \alpha_{m+7} ID_{i,t} I(CER_{i,t} > \gamma_m) + v_t + \varepsilon_{i,t} \quad (8)$$

$$CEEI_{i,t} = \delta_0 + \delta_1 GI_{i,t} + \delta_2 URB_{i,t} + \delta_3 IS_{i,t} + \delta_4 R\&D_{i,t} + \delta_5 PGDP_{i,t} + \delta_6 ID_{i,t} + \delta_7 ID_{i,t} I(MER_{i,t} < q_1) + \delta_8 ID_{i,t} I(q_1 \le MER_{i,t} \le q_2) + \ldots + \delta_{n+7} ID_{i,t} I(MER_{i,t} > q_n) + v_t + \varepsilon_{i,t} \quad (9)$$

$$CEEI_{i,t} = \tau_0 + \tau_1 GI + \tau_2 URB_{i,t} + \tau_3 IS_{i,t} + \tau_4 R\&D_{i,t} + \tau_5 PGDP_{i,t} + \tau_6 ID_{i,t} + \tau_7 ID_{i,t} I(VER_{i,t} < p_1) + \tau_8 ID_{i,t} I(p_1 \le VER_{i,t} \le p_2) + \ldots + \tau_{z+7} ID_{i,t} I(VER_{i,t} > p_z) + v_t + \varepsilon_{i,t} \quad (10)$$

In the above model, the variables' meanings are consistent with that in equation (7), $CER_{i,t}$, $MER_{i,t}$ and $VER_{i,t}$ are threshold variables, α_0, δ_0 andτ_0 are constant terms. $\alpha_0, \alpha_1 \ldots \alpha_{m+8}$, $\delta_0, \delta_1 \ldots \delta_{n+8}$, τ_0, $\tau_1 \ldots \tau_{z+8}$ are the variables' corresponding coefficients. m, n and z represent the number of thresholds of CER, MER and VER respectively. $\gamma_1, \gamma_2 \ldots \gamma_m, q_1, q_2$ *and* q_n *and* p_1, p_2 *and* p_z are the threshold sizes of CER, MER, and VER. $I(+)$ is an indicative function.

Variables and Data Sources

Dependent Variable: CEEI

The CEEI serves as the primary variable in this study and can be computed with reference to the methodology outlined in Section 3.1.

Independent Variable: Internet Development

In this study, the primary independent variable under investigation is the Internet development index. To construct this index, we draw upon relevant measurement indicators from prior research and consider data availability, as indicated in studies like Li & Du (2021). The Internet development index is conceptualized across four key dimensions associated with Internet application and output. These dimensions encompass the Internet penetration rate, quantified by the number of Internet users per 100 people, the proportion of Internet-related employees in the computer services and software industry to the total unit employees, the Internet-related output measured by total telecommunications business per capita, and the number of mobile Internet users represented by the count of mobile phones per 100 people. To synthesize these dimensions into a comprehensive index, they are standardized, and the entropy evaluation method is employed. This composite index effectively encapsulates the level of Internet development for the purpose of our analysis.

Threshold Variables: CER, MER and VER

CER: CER involves the government's imposition of mandatory constraints on entities that impact the environment, primarily through the enactment of environmental laws and regulations. The number of environmental administrative penalty cases decided by the government each year is employed as a proxy to gauge the regulatory intensity of CER, following the approach outlined in Li (2023).

MER: MER leverages market-based mechanisms to encourage environmentally responsible behavior by enterprises, prompting them to incorporate pollution control measures in their production processes. This approach notably encompasses the implementation of tradable emissions and pollution charges, as indicated by Xi et al. (2022). For this study, pollutant charges are utilized as an indicator to measure MER.

VER: VER primarily takes the form of environmental proposals submitted by the public in the context of environmental governance, reflecting the public's heightened concern for environmental issues. In alignment with Wang's (2022) methodology, environmental proposals are utilized to represent VER in this study.

Control Variables

Drawing from prior research and real-world scenarios, we consider several control variables that could influence carbon efficiency. These variables encompass economic growth (PGDP), industrial structure (IS), research and development (R&D), and openness level (OPEN). To measure these controls, we employ GDP per capita, the ratio of added value of the tertiary industry to regional GDP (Guo et al., 2020), the number of domestic patent applications granted (Zhang et al., 2021), and the proportion of total import and export trade to regional GDP (Li et al., 2023).

Descriptive Statistics of Data Sources and Variables

For the sake of data availability, our analysis focuses on 30 Chinese provinces, with the exclusion of Tibet, Taiwan, Hong Kong, and Macau. We employ panel data spanning the period from 2011 to 2020. The data sources primarily comprise the China Statistical Yearbook, China Environmental Statistical Yearbook, China Environmental Yearbook, and provincial statistical yearbooks. Nominal data are anchored to the year 2000 and are adjusted for inflation using the general production index and consumer price index. In cases where data is partially missing, trend fitting techniques are applied for estimation. Furthermore, to address heteroskedasticity concerns, we employ data transformations, primarily using ratios or natural logarithms. Table 1 offers an overview of the data characteristics for each variable.

Table 1

Descriptive Statistics of all Variables

Variable	Obs.	Mean	Std. dev.	Min	Max
CEEI	300	0.7587	0.1423	0.3916	1.0000
ID	300	0.2183	0.1779	0.0331	1.0000
CER	300	4.5613	2.3418	0.6931	9.9330
MER	300	6.3869	5.3442	0.2849	35.8888
VER	300	5.5100	5.0269	0.3100	58.4500
PGDP	300	5.3841	2.7041	1.6024	16.4158
IS	300	0.4097	0.0807	0.1597	0.6196
R&D	300	1.4329	0.9274	0.0490	4.2763
OPEN	300	0.2743	0.2898	0.0080	1.4640

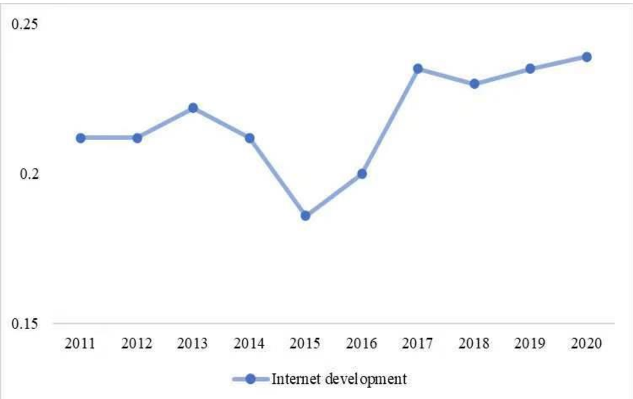

Figure 2. The Trends of Internet Development

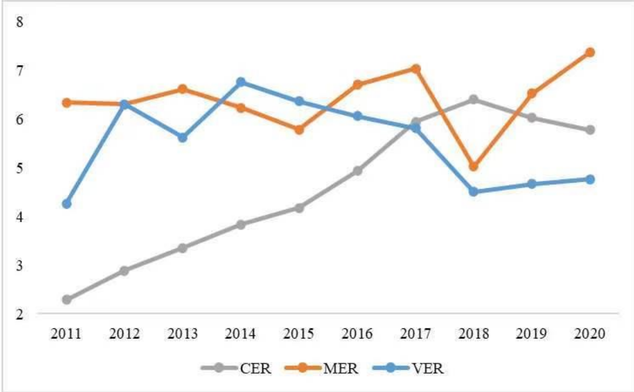

Figure 3. The Trends of CER, MER and VER

Empirical Results and Analysis

Spatiotemporal Change of CEEI

Utilizing the GCE-DEA approach, we calculate the Carbon Emission Efficiency of 30 Chinese provinces and municipalities for the period spanning 2011 to 2020. Figure 2 illustrates the CEEI across regions and the entire nation during this study period. These regions are classified into three economic zones—eastern, central, and western regions—based on National Bureau of Statistics standards and their developmental and productivity conditions (Guo *et al.,* 2020).

Over the study period, there was a modest improvement in CEEI, with a distinct spatial pattern characterized by "higher levels in the east and lower levels in the west." Notably, the CEEI in the eastern region consistently outperformed the national average, driven by its more advanced economy and strong commitment to sustainable industrial development and innovation. In contrast, the western region exhibited the lowest CEEI, primarily due to its dependence on resource-rich provinces, which primarily engage in extensive development practices at the expense of environmental considerations.

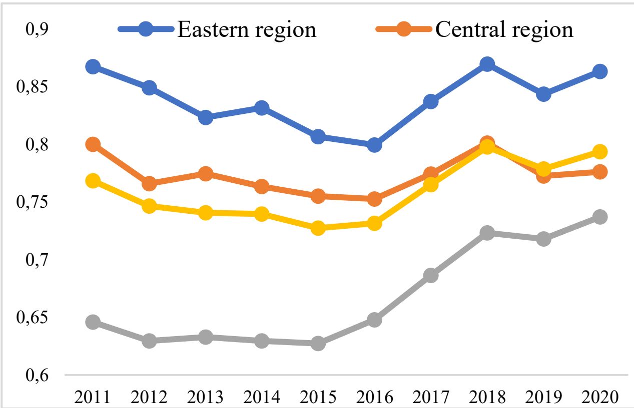

Figure 4. The Evaluation Trend of CEEI in National and 4 Regions, 2011-2020

In terms of the temporal perspective, the period from 2011 to 2016 witnessed a decline in CEEI in both the eastern and central regions, while CEEI in the western regions remained relatively low. This trend can be attributed to China's industrial transformation during this period, with the economic growth model shifting from a "high-growth, high-energy consumption, and high-pollution mode" to a more sustainable "low-growth, low-energy consumption, and low-emission mode" of industrial production (Zhang et al., 2022). Subsequently, from 2016 to 2018, regional CEEI exhibited an upward trajectory, primarily driven by the implementation of policies aimed at "cutting excess capacity, reducing excess inventory, deleveraging, lowering costs, and strengthening areas of weakness."

However, from 2018 to 2020, CEEI fluctuated, signifying that there is still room for improvement in China's CEEI. Provinces should continue to prioritize sustainable industrial development and aim to enhance environmental benefits while carefully considering economic advantages. This underscores the ongoing need for a balanced and harmonious approach to industrial growth.

Benchmark Regression Results

The results of the two-way fixed-effect model are presented in Table 2. To ensure the robustness of the findings, control variables are incrementally introduced into the original model. Model (1) serves as the base model without control variables, with subsequent columns (2) to (5) incorporating control variables one by one.

Across all models (1)-(5), the coefficients associated with Internet development (ID) consistently exhibit a positive and highly significant relationship at the 1% level. Taking Model (5) as an example, when accounting for control variables, Internet development displays a significant positive correlation with CEEI. In other words, an enhancement in Internet development significantly promotes CEEI, with this effect being highly significant at the 1% level. This could be attributed to the Internet's role in bolstering the innovation capacity of industrial enterprises, reducing the costs associated with the flow of production factors, and driving the transformation of traditional industries towards low-carbon practices, thereby contributing to the enhancement of CEEI. Consequently, Internet development stands as a catalyst for the improvement of CEEI, thereby corroborating hypothesis 1.

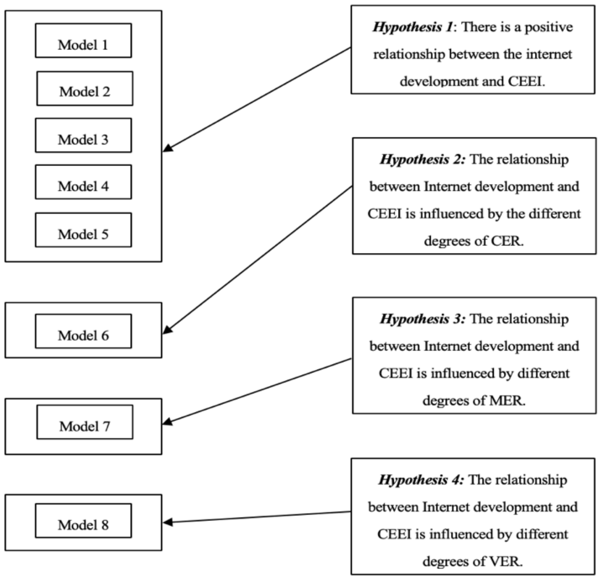

Figure 5. The Theoretical Framework of Model Specification

Table 2

Results of Baseline Regression

	Model 1	Model 2	Model 3	Model 4	Model 5
ID	0.3298*** (3.01)	0.3343*** (3.30)	0.3613*** (3.51)	0.4152*** (4.03)	0.3771*** (3.59)
R&D		0.0587** (2.40)	0.0519** (2.24)	0.0400* (1.73)	0.0387* (1.68)
IS			0.9671*** (2.66)	0.8373*** (4.93)	0.7892*** (4.60)
PGDP				0.0175*** (2.95)	0.0249*** (3.40)
OPEN					0.0975* (1.71)
Constant term	0.6868*** (28.48)	0.5959*** (13.30)	0.2093*** (2.66)	0.1735** (2.21)	0.1369* (1.68)
individual FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	300	300	300	300	300
R-squared	0.8631	0.8661	0.8816	0.8855	0.8868

[Note: *t*-Statistics in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.*]*

Threshold Effect Test and Robustness Estimation

In this section, we utilize CER, MER, and VER as threshold variables to assess their influence on the relationship between Internet development and CEEI. The results reveal that the effect of Internet development on CEEI exhibits different threshold patterns based on these regulatory variables, as presented in Table 2 and Table 3.

The findings in Table 3 indicate that CER undergoes a single-threshold test, with a calculated threshold value of 7.2269 at the 10 % significance level. In contrast, MER passes a double-threshold test at the 5% significance level, revealing two distinct thresholds at 11.3466 and 14.1788. Moreover, VER passes a single-threshold test with a threshold value of 5.8100 at the 1 % significance level. These threshold tests highlight the non-linear nature of the relationship between Internet development and CEEI, with different regulatory mechanisms dictating specific threshold values and significance levels. This underscores the complex interplay between Internet development and CEEI, which is further influenced by distinct environmental regulations.

This study delves deeper into the threshold effects of various environmental regulations, and the findings are presented in Table 4. Throughout the sample period, the relationship between Internet development and CEEI undergoes changes in response to different thresholds. Model 6 in Table 4 illustrates the threshold regression results for CER. The outcomes reveal that when CER falls below 7.2269, the regression coefficient stands at 0.4020, signifying significance at the 1 % level. However, when CER exceeds this threshold, the coefficient decreases to 0.2711, while maintaining significance at the 1 % level. This suggests that as CER intensity increases, the positive impact of Internet development on CEEI weakens. This phenomenon may be attributed to the mandatory nature of CER, which, under high environmental regulatory pressure, leads enterprises to channel their investments into environmental compliance at the expense of technological advancements. Consequently, the Internet's facilitative role in traditional industries diminishes. These results affirm Hypothesis 2 and offer valuable insights for government authorities to fine-tune CER intensity.

Model 7 in Table 4 explores the threshold regression results for MER. Notably, there exists a non-linear relationship between Internet development and CEEI in relation to the strength of MER. Specifically, when MER falls below the threshold, denoting low-strength MER, the regression coefficient registers at -0.0430, significant at the 10 % level. As MER moves between the two thresholds, indicating moderate-strength MER, the coefficient surges to 0.8719, bearing significance at the 1 % level. However, if MER surpasses the second threshold, characterizing high-strength MER, the regression coefficient decreases.

Table 3

Test of Threshold

Threshold variables	Threshold effects	F-statistics	P-values	Critical values 1%	5%	10%	Threshold values	95% confidence interval
CER	Single threshold	15.78*	0.0967	32.6524	23.3317	19.0391	7.2269	(6.7708,7.3052)
	Double threshold	Failed. There is no double and triple threshold effect of Internet development.						
	Triple threshold							
MER	Single threshold	15.59**	0.0310	18.8819	13.7454	11.5855	11.3466	(10.8669,11.4505)
	Double threshold	14.19**	0.0320	18.2820	12.8362	10.2911	14.1788	(13.8451,14.4588)
	Triple threshold	Failed. There is no triple threshold effect of Internet development.						
VER	Single threshold	40.41***	0.0010	25.0514	18.8172	16.0331	5.8100	(5.7900,5.9150)
	Double threshold	Failed. There is no double and triple threshold effect of Internet development.						
	Triple threshold							

[Note: *t*-Statistics in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.*]*

These outcomes signify that Internet development impedes CEEI under lax MER. This phenomenon arises because the growth of the Internet augments market demand, reducing the life cycle cost of products through factors integration and labor demand substitution effects. This, in turn, bolsters the expected output of the industrial economy. In the pursuit of profit, industrial enterprises tend to allocate resources to factor-biased technologies, emphasizing commercial value over eco-friendly technologies. Consequently, there is limited improvement in the industrial environment's undesirable output. Hence, in a low-strength MER context, Internet development suppresses CEEI. However, when MER crosses the threshold, its innovation influence comes into play, motivating enterprises to harness the Internet for environmentally responsible technologies that curb carbon emissions, subsequently elevating CEEI. It is important to note that when MER intensity becomes excessively high, this promotion effect weakens. These findings validate Hypothesis 3 and offer guidance for optimizing market-based environmental regulation policies.

Moving forward, Model 8 in Table 4 examines the threshold regression results for VER. These results reveal a distinctive relationship between Internet development level and CEEI concerning the intensity of VER. With increasing VER intensity, the dynamics between Internet development and CEEI assume an "inverted U" shape. When VER falls below the threshold value, the regression coefficient stands at 0.4709. In this scenario, Internet development bolsters CEEI. However, when VER surpasses the threshold, the coefficient drops to -0.1328, signifying significance at the 10 % level. At this juncture, a higher level of Internet development inhibits CEEI. These findings substantiate Hypothesis 4.

The extensive and open nature of the Internet provides a fertile ground for the public to engage with environmental issues. Moderate public participation serves to bridge the information gap between government environmental regulations and corporate pollution behavior, increasing the cost of pollution for businesses. Consequently, enterprises lean toward cleaner production, thereby enhancing CEEI (Zhang *et al.,* 2021). Moreover, Mohanty (2021) established that perceived government environmental measures motivate pro-environmental behavior among the public, spurring green consumption that compels companies to manufacture cleaner products, thereby uplifting CEEI. However, as the Internet rapidly advances, excessive public participation may foster the emergence of "opinion leaders" whose environmental behaviors are unpredictable (Iman *et al.,* 2019). Furthermore, in the Internet era, an exceedingly high level of VER generates public opinion pressure on companies, with intense scrutiny of corporate conduct applying pressure on their operations and transformations (Pan *et al.,* 2023). Hence, the formulation of effective environmental regulation policies necessitates the careful consideration of reasonable VER intensity and channel development.

Robustness Tests

To ensure the reliability of our findings, we conducted robustness tests by following Li (2023) to adjust the research sample. This adjustment involved excluding municipalities with unique political and economic status, high levels of marketization, leading Internet development, and relatively high degrees of industrial intelligence. Consequently, our refined sample included 26 provinces. In Table 5, we present the regression results for the threshold effects while excluding municipalities.

Remarkably, under the threshold effects of the three environmental regulations, the influence coefficients and significance levels of the explanatory variables closely mirror those in our earlier research. This similarity reaffirms the robustness of our analysis. In essence, the results in Table 5 align with those in Table 4, consolidating the credibility and reliability of our study's outcomes.

Table 4

Panel Threshold Regression Under Full Sample

Model 6 (CER)		Model 7 (MER)		Model 8 (VER)	
CER<7.2269	0.4020*** (4.20)	MER<11.3466**	-0.0430* (-1.51)	VER<5.8100**	0.4709*** (5.11)
CER≥7.2269	0.2717*** (2.63)	11.3466**<MER<14.1788*	0.8719*** (6.60)	VER≥5.8100**	-0.1328* (-1.73)
		MER≥14.1788*	0.3723** (2.29)		
R&D	0.0142 (0.74)	R&D	0.0300* (1.66)	R&D	0.0324* (1.84)
IS	0.8336*** (6.71)	IS	0.5986*** (4.54)	IS	0.6929*** (5.80)
PGDP	0.0389*** (6.20)	PGDP	0.0251*** (4.76)	PGDP	0.0239*** (4.65)
OPEN	0.1087** (2.05)	OPEN	0.1091** (2.10)	OPEN	0.0983* (1.93)
Constant term	0.0766 (1.04)	Constant term	0.2264*** (2.95)	Constant term	0.1948*** (2.75)
N	300	N	300	N	300
R-sq	0.3247	R-sq	0.3546	R-sq	0.3769

[*Note*: *t*-Statistics in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.]

Table 5

Robustness Tests of Panel Threshold Regression Under Sample Without Municipalities

Model 7 (CER)		Model 8 (MER)		Model 9 (VER)	
CER<4.5850**	0.5652*** (5.36)	MER<11.4505*	-0.0973*** (-3.76)	VER<5.8100***	0.5553*** (5.47)
CER≥4.5850**	0.3245*** (3.00)	11.4505*<MER<14.1788**	0.9439*** (6.61)	VER≥5.8100***	-0.0823 (-1.65)
		MER≥14.1788**	0.3560** (2.11)		
R&D	0.0150 (0.73)	R&D	0.0253 (1.25)	R&D	0.0303 (1.55)
IS	0.7482*** (5.73)	IS	0.6187*** (4.34)	IS	0.6710*** (5.24)
PGDP	0.0399*** (5.74)	PGDP	0.0275*** (4.14)	PGDP	0.0235*** (3.65)
OPEN	0.0691 (0.86)	OPEN	0.0753 (0.94)	OPEN	0.0849 (1.09)
Constant term	0.123 (1.64)	Constant term	0.2257*** (2.77)	Constant term	0.2194*** (2.94)
N	260	N	260	N	260
R-sq	0.3614	R-sq	0.3668	R-sq	0.3986

[*Note*: *t*-Statistics in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.]

Regional Heterogeneity Analysis

Given the variations in economic development, digital infrastructure, public environmental consciousness, and pollution profiles across different regions, it is imperative to explore regional heterogeneity in the relationship between Internet development, environmental regulations, and CEEI. To this end, we conducted heterogeneity tests for the Eastern, Central, and Western regions, respectively.

Columns 1-6 in Table 6 elucidate the impact of Internet development on CEEI in the Eastern region under different environmental regulations. Notably, the relationship between the Internet and CEEI in this region closely mirrors the trends observed in the overall sample, particularly in response to changes in the intensities of CER and VER. This consistency is aligned with the findings presented in models 6 and 8 in Table 4.

Moreover, it is important to highlight that the threshold value for MER in the Eastern region is determined to be 10.3343, a statistically significant result at the 1% level. This region appears to exhibit the most pronounced response to MER. When MER surpasses this threshold, the Internet becomes a significant driver of CEEI, with a regression coefficient of 0.4004, significant at the 5 % level. Conversely, in the absence of such regulatory intensity, the impact on CEEI is not statistically significant. This observation could be attributed to the Eastern region's strong economic foundation, rapid development, robust innovation ecosystem, and high level of openness. Under the purview of market-based environmental regulations, enterprises in this region are more inclined to utilize the Internet to drive advancements in clean technology within industrial production, optimize resource allocation, and consequently bolster CEEI in the long run.

Columns 7-12 in Table 6 present the findings for the Central region. In the context of CER and VER, the relationship between the Internet and CEEI mirrors the overall sample's trends, aligning with the results in Models 6 and 8 in Table 4. However, there is a noteworthy divergence in the impact of MER in the Central region, contrary to the broader sample. Under low-intensity MER, the development of the Internet promotes CEEI. When the MER threshold is breached, the Internet inhibits CEEI, although this inhibitory effect is not statistically significant. This counterintuitive result may be attributed to the Central region's relatively weaker economic foundation and slower pace of development, leading to substantial economic burdens from pollutant discharge fees, especially under the high-intensity MER. Thus, in the Central region, a moderate amalgamation of CER, MER, and VER appears to be more conducive to enhancing the Internet's impact on CEEI.

Columns 13-18 in Table 6 shed light on the Western region's outcomes. It is evident that the threshold effect is observed in CER and MER, and the nature of this effect differs from the overall sample. For CER, the threshold is established at 1.3863, a significant result at the 1 % level. Notably, this value is significantly lower than the threshold observed in the Eastern and Central regions, suggesting that the Western region is notably responsive to command-based environmental regulations. Specifically, when CER is below the threshold, the Internet's role in promoting industrial carbon emission efficiency is more pronounced, supported by a coefficient of 0.9711, significant at the 1 % level. When CER intensity surpasses the threshold, the promotion effect weakens but remains significant, with a coefficient of 0.4765. This implies that the Internet is highly effective in enhancing CEEI when CER is below the threshold.

Furthermore, the relationship between MER and Internet development and its impact on CEEI in the Western region are also distinct. The MER threshold is identified as 8.7890, a significant result at the 1 % level. When MER falls below this threshold, the Internet's promotion effect on CEEI is muted. Conversely, when MER exceeds the threshold, the promotion effect intensifies, resulting in a coefficient of 0.7344. This indicates that a moderate level of MER is most suitable for the Western region, emphasizing the importance of formulating well-balanced CER and MER policies to optimize the Internet's role in advancing CEEI and fostering low-carbon development.

Discussion and Conclusion

Theoretical Implications

This study employs panel data from 30 Chinese provinces spanning the years 2011 to 2020 to explore the intricate, nonlinear threshold effects of Internet development on CEEI under various environmental regulations. The following key findings emerge from this research: Firstly, the study quantifies CEEI across China's provinces using the Game Cross Efficiency DEA approach and confirms the positive impact of Internet development on CEEI, thereby confirming Hypothesis 1. Over the study period, the national average CEEI exhibited a pattern of decline followed by an increase, with a distribution trend of "high in the east and low in the west." Specifically, from 2011 to 2016, CEEI decreased in the eastern and central regions while remaining relatively stable in the western region. This trend was primarily attributed to the growth patterns of the eastern and central regions, which came at an environmental cost. Subsequently, from 2016 to 2018, there was a significant increase in CEEI across all regions. However, from 2018 to 2020, fluctuations occurred, highlighting the urgent need to enhance China's industrial transformation for sustainable development.

Furthermore, the study delves into the nuanced impact of CER, MER, and VER on the interplay between Internet development and CEEI. The results underscore the nonlinearity of the Internet's impact on CEEI under these regulations, which aligns with previous research. Remarkably, CER and VER exhibit single-threshold effects, while MER demonstrates a double-threshold effect. Specifically, when CER falls below the threshold, Internet development has a more pronounced positive effect on CEEI. Similarly, when MER operates between the two thresholds, the Internet's influence on CEEI peaks. However, below the VER threshold, the Internet promotes CEEI. Conversely, exceeding the second MER threshold or the single VER threshold hinders CEEI. These findings not only complement prior research but also confirm Hypotheses 2, 3, and 4, providing a fresh perspective on exploring the complex relationship between Internet development and CEEI.

Lastly, regional analysis reveals significant heterogeneity in the impact of Internet development on CEEI across regions and under various environmental regulations. In the eastern region, the patterns closely mirror the national trends, with MER exhibiting the most substantial influence. In the central region, the impact of CER and VER aligns with the national findings. However, MER yields contrasting results under higher intensity, reflecting the region's weaker economic footing. In the western region, CER and MER demonstrate significant threshold effects, with CER notably sensitive to the region's compliance. This regional distinction underscores the necessity of balanced CER and MER policies for optimizing the Internet's role in promoting CEEI and facilitating low-carbon development.

Policy Implications

The policy implications of this work are as follows:

(1) It is imperative for the government to consider the threshold effects of Internet. development on CEEI and account for the multifaceted landscape of environmental regulations. Internet development's impact on CEEI is dynamic, shaped by varying environmental regulations. As a result, tailored environmental policies are needed to maximize the contribution of Internet development to enhancing CEEI. First, the government should be attuned to the interplay between "compliance cost" and "innovation compensation" effects stemming from CER. A balanced, moderate-intensity management system is crucial, with differentiated CER policies crafted based on regional economic development, industrial structure, and innovation dynamics.

Second, special attention should be paid to MER, emphasizing its role in propelling industrial transformation and innovation. This entails designing policies that foster the alignment of market mechanisms with industrial upgrading. Lastly, considering VER as an informal environmental regulatory tool, it is essential to regulate the intensity and forms of participation. While broadening channels for public engagement in environmental matters, it is equally vital to establish a structured network feedback mechanism. This will ensure that public participation in the digital environment adheres to established norms and enables VER to be an effective force in environmental regulation.

(2) Regional disparities necessitate tailored approaches to environmental regulations, influencing the impact of Internet development on CEEI. To harness the full potential of Internet development in enhancing CEEI, the government must adopt flexible governance strategies that align with each region's unique development characteristics. In the Eastern region, policymakers should prioritize the role of market mechanisms, especially by enhancing the pollutant discharge charging system. By doing so, they can unlock the compensatory potential of MER in fostering regional innovation and driving industrial enterprises towards green transformations, thus elevating regional economic performance.

In the Central region, a balanced approach is recommended. It is vital to prevent the excessive regulatory intensity from stifling CEEI due to the Internet's inhibitory effects. Furthermore, the region should adopt a rational CER and fully optimize its potential for impact. In the Western region, a prudent approach is advisable. Initiating measures to control CER within a reasonable range should be the starting point. Subsequently, the strength of MER should be fine-tuned dynamically, while continually assessing its impact on CEEI. These adjustments should be made in response to the evolving regional circumstances to maximize the desired outcomes.

Limitations and Future Research

As any studies, this paper has its limitations that open valuable avenues for future research. First, the research is conducted at the provincial scale with a relatively limited sample size. Future investigations could extend the analysis to a city-scale level and provide comparative findings to enhance the depth of understanding. Second, the study does not explore the potential spillover effects of the Internet. Subsequent research should delve into the spillover effects and thoroughly examine how Internet development influences CEEI on a broader scale. Addressing these limitations will contribute to a more comprehensive and nuanced understanding of the subject matter.

Acknowledgment

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Table 6

Threshold Regression Results Based on Regional Heterogeneity

The eastern region					
CER		MER		VER	
PGDP	0.0421*** (5.00)	PGDP	0.02167*** (2.91)	PGDP	0.0394*** (5.09)
IS	2.0956*** (7.42)	IS	1.1769*** (3.40)	IS	2.2099*** (7.80)
R&D	0.0812*** (2.77)	R&D	0.0563* (1.85)	R&D	0.0709** (2.45)
OPEN	0.0798 (1.08)	OPEN	0.0668 (0.91)	OPEN	0.0532 (0.74)
CER< 7.7866*	0.1548* (1.75)	MER< 10.3343*	-0.1557 (-0.76)	VER< 1.0600*	0.2075* (1.84)
CER≥ 7.7866*	0.0124* (1.96)	MER≥ 10.3343*	0.4004** (2.02)	VER≥ 1.0600*	-0.0130 (-0.07)
Constant term	-0.5519*** (-2.87)	Constant term	0.0797 (0.36)	Constant term	-0.4886*** (-2.66)
N	300	N	300	N	300
R-sq	0.4172	R-sq	0.4154	R-sq	0.4369

The eastern region					
CER		MER		VER	
The central region					
CER		MER		VER	
PGDP	0.0603*** (5.01)	PGDP	0.0547*** (4.59)	PGDP	0.0672*** (6.14)
IS	0.4640*** (3.13)	IS	0.6281 (4.00)	IS	0.4817*** (3.65)
R&D	-0.0732** (-2.44)	R&D	-0.0717** (-2.34)	R&D	-0.0947*** (-3.47)
OPEN	0.1642 (0.75)	OPEN	-0.0542 (0.24)	OPEN	0.2169 (1.09)
CER< 4.3945*	0.1288* (1.79)	MER< 11.6622*	0.3514* (1.95)	VER< 6.100**	0.8187*** (3.54)
CER≥ 4.3945*	-0.1322 (-0.52)	MER≥ 11.6622*	0.1216 (0.56)	VER≥ 6.100**	-0.3738 (-1.65)
Constant term	0.3884*** (4.87)	Constant term	0.7474*** (4.55)	Constant term	0.3342*** (4.61)
N	300	N	300	N	300
R-sq	0.3810	R-sq	0.3037	R-sq	0.4975
The western region					
CER		MER		VER	
PGDP	0.0416*** (4.40)	PGDP	0.0339*** (3.32)	PGDP	0.0372*** (3.72)
IS	0.3892* (1.67)	IS	0.4394* (1.72)	IS	0.5740** (2.28)
R&D	0.0020 (0.05)	R&D	0.0314 (0.76)	R&D	0.0334* (0.83)
OPEN	0.0986 (0.68)	OPEN	0.0847* (0.54)	OPEN	0.03411 (0.22)
CER< 1.3863***	0.9711*** (6.76)	MER< 8.7890*	0.4892*** (3.94)	The threshold for VER does not exist	
CER≥ 1.3863***	0.4765*** (4.32)	MER≥ 8.7890*	0.7344*** (4.24)		
Constant term	0.2455** (2.23)	Constant term	0.2318* (1.92)	Constant term	0.1629 (1.36)
N	300	N	300	N	300
R-sq	0.6318	R-sq	0.5581	R-sq	0.5830

*[Note: t-Statistics in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.]*

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