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The Impact of Digital Economy and Environmental Regulation on China's Regional Total Factor Energy Efficiency

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Abstract

Against the backdrop of the "dual carbon" goals, improving total factor energy efficiency (TFEE) has become a core task for low-carbon transformation. Using a panel dataset covering 30 provinces in China from 2011 to 2024, this paper employs the super-efficiency SBM model to measure regional TFEE, and applies the spatial Durbin model and threshold regression model to examine the impact of the digital economy, environmental regulation, and their interaction on TFEE. Different from traditional linear analysis, this study reveals the nonlinear mechanism through which the digital economy unlocks the potential of environmental regulation and transforms its effect from "compliance cost pressure" to "innovation compensation gain". The findings show that: First, the digital economy significantly promotes TFEE, with 56.68% of its energy-saving effect realized through spatial spillover. Second, environmental regulation alone shows a "cost-following effect" and inhibits TFEE, but its interaction with the digital economy generates a strong synergistic effect with a coefficient of 0.299. Third, the digital economy acts as a critical threshold: only when its level exceeds 0.435 can environmental regulation effectively boost TFEE via the innovation compensation effect. Fourth, the synergistic effect has strong spatial spillovers, with the indirect effect (0.383) exceeding the direct effect (0.282). This study contributes new evidence that digital infrastructure construction should be prioritized in regions with strict environmental regulation to avoid efficiency losses, and provides targeted implications for implementing regionally differentiated policies that prioritize digital upgrading to match environmental regulation intensity to coordinate digital development, environmental governance, and energy efficiency improvement.

Keywords: digital economy; environmental regulation; total factor energy efficiency; spatial spillover effect; threshold regression

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1. Introduction

Energy is the material foundation for human development. The development of the economy cannot do without the utilization of various energy sources and technologies. Every major progress and transformation in human society is accompanied by improvements and replacements in energy technologies. The importance and irreplaceability of energy make it a core component of national security. Improving TFEE is a key path to building an ecological civilization [1–4]. China has sustained rapid economic expansion for over forty years. Nevertheless, this conventional resource-intensive growth trajectory has precipitated numerous pressing issues, notably surging energy demands and aggravated ecological degradation [5,6]. Official statistics reveal that national energy consumption increased from 570 million tons of standard coal equivalent in 1978 to 5.72 billion tons in 2023, with a compound annual growth rate exceeding 4%. Consequently, China now ranks as the globe's foremost energy consumer and greenhouse gas producer. The country has committed to ambitious emissions-reduction targets (reducing carbon by 2030, reaching net zero by 2060). Economic growth and energy efficiency have become key issues both for academia and policymakers. TFEE is a key indicator of overall efficiency. It differs from single-factor energy-efficiency indicators because it comprehensively considers substitution effects among energy, capital, and labor. In the digital economy era, digital transformation not only changes energy consumption but also reshapes the substitution between capital and labor, making TFEE the only indicator that can fully capture such structural transformations [7,8]. A detailed study of the factors that influence China's regional TFEE and the mechanisms of action is of practical importance for formulating regional energy policies and coordinating regional development.

Meanwhile, a new round of technological revolution and industrial transformation is occurring worldwide. Digital technologies are increasing innovation. Digitalization is one of the key factors driving contemporary economic growth. China's digital sector reached 53.9 trillion yuan in 2023, accounting for over two-thirds of China's economic output, and has been the runner-up globally for many years. Rapid digitization revolutionizes conventional manufacturing and commercial practices, but also opens new paths to increase energy efficiency. Information and communication technologies (ICT) can improve energy performance by simplifying operations, optimizing resource allocation, and increasing the adoption of renewable energy [9]. In addition, the low carbon footprint of digital services, coupled with the technological modernization of energy-intensive legacy industries, provides backing to regional conservation efforts. However, this relation is multidirectional. Significant electricity requirements of computing infrastructure (e.g., server farms) and geographical disparities in technological access have prompted debate over the ecological implications of pervasive digitalization [10]. In particular, the rebound effect cannot be ignored: digital technologies improve energy efficiency, but such efficiency gains may reduce the cost of energy services and further stimulate additional energy consumption, thereby partially offsetting the expected energy-saving benefits. Thus, rigorous empirical assessment of how digitization shapes regional TFEE and identification of its conditional factors are important research imperatives in energy economics.

Furthermore, as an important policy tool for the government to correct market failures, the impact of environmental regulations on TFEE has always been a core issue in environmental economics research [11]. Since energy conservation was set as a binding target, China has gradually established a diversified environmental regulatory system. The implementation of special action plans such as the "Ten Measures for Air Pollution Prevention and Control", "Ten Measures for Water Pollution Prevention and Control", and "Ten Measures for Soil Pollution Prevention and Control", the establishment of the carbon emission trading market, as well as the regular operation of the environmental protection supervision system, mark the continuous strengthening of China's environmental regulation intensity and the increasing diversity of regulatory tools. Theoretically, reasonable environmental regulations can compel enterprises to pursue green technological innovation through the Porter hypothesis via "innovation compensation effect", optimize factor input structures, and thereby enhance TFEE. However, excessive regulation may also lead to a "cost-following effect", squeezing out enterprises' R&D investment and suppressing production efficiency. More importantly, the interaction between environmental regulations and the digital economy may have complex impacts on TFEE: digital technology can reduce the information and implementation costs of environmental regulations and enhance the accuracy of regulations; Environmental regulations may also create institutional incentives

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for the application of digital technologies. The synergy of the two may produce an emission-reduction effect [12]. Although previous studies have mainly focused on the linear effects of digitalization or regulation, no consensus has been reached on their nonlinear relationship and conditional dependence. This paper fills this gap by investigating how threshold effects of digital development strengthen or weaken the effectiveness of environmental policies.

This work focuses on the core issue of "How the digital economy and environmental regulations affect the TFEE in China's regions", and attempts to achieve breakthroughs in the following aspects: Firstly, construct a theoretical analysis framework for digital economy, environmental regulations and TFEE, and clarify their direct effects, indirect effects and interaction effects; Secondly, by adopting cutting-edge quantitative analysis methods, empirical tests are conducted to examine the impact of the digital economy, environmental regulations and their interactions on China's TFEE. Finally, identify the threshold effect of the impact. The main contributions of this research are reflected in the following four aspects: First, the integration of research perspectives. This article places the two hot topics of the digital economy and environmental regulation within a unified TFEE analytical framework, examines their independent and synergistic effects, avoids the limitations of single-factor analysis, and provides a more comprehensive understanding of the compound drivers of TFEE improvement. Second, the method of application. Using a super-efficient SBM model for the TFEE measure, a bidirectional fixed-effect model for endogeneity control, and a threshold regression model for the nonlinear effects of the digital economy and environmental regulations can make the conclusions more robust and interpretable. Third, the identification of spatial spillover effects. This study employs the spatial Durbin model to capture spatial externalities and reveals that digital development in one province can generate energy-saving and efficiency-improving benefits for neighboring regions. Fourth, policy implications. The conclusions can be useful to the Central Government in formulating a national strategy for digitalization and green development, and to local governments in implementing differentiated policies based on local development stages and resource conditions.

2. Literature Review

2.1. Calculation of TFEE and Influencing Factors

Hu and Wang [13] proposed the concept of TFEE, emphasizing that, when calculating energy efficiency, the substitution effects among multiple input factors should be considered comprehensively rather than focusing solely on the single-ratio relationship. The proposal of this concept marks a significant shift in energy efficiency research from the single-factor analysis paradigm to the all-factor analysis paradigm. In terms of measurement methods, Data Envelope Analysis (DEA) is used to measure TFEE due to its advantages, including not requiring a priori specification of the production function and its ability to handle multi-input, multi-output issues. Early studies mostly adopted traditional CCR and BCC models, but radial-angle DEA models cannot fully address the relaxation problem in input–output analysis. The SBM (Slack-based Measure) model, based on slack variables proposed by Tone [14], effectively solved this problem through non-radial and non-angular processing methods. Subsequently, Tone and Tsutsui [15] incorporated undesirable outputs into the SBM model framework. Make it more suitable for energy-efficiency evaluation that considers environmental pollution. In recent years, scholars have further applied improved models such as super-efficiency SBM, network DEA, and three-stage DEA, continuously enhancing the accuracy of calculation results and the richness of policy implications [16–19].

Regarding the spatio-temporal evolution of regional TFEE, numerous studies have confirmed significant regional differences. From a time-series perspective, China's TFEE has generally shown a fluctuating upward trend. However, in recent years, due to downward pressure on the economy and a rebound in energy consumption, efficiency has stagnated or even declined in some regions [20]. From a spatial perspective, energy efficiency exhibits a gradient distribution pattern, with "high in the east and low in the west" [21]. The energy efficiency level, technology diffusion, and industrial structure of neighboring regions will affect local energy efficiency through spatial correlation mechanisms. This requires considering the role of spatial factors when studying the determinants of energy efficiency [22].

Regarding the influencing factors of TFEE, the existing literature has conducted extensive research across multiple dimensions, including technological progress, openness to the outside world, factor endowment, and the institutional environment. Technological progress is regarded as the fundamental driver of energy efficiency improvements. Research and development investment, human capital accumulation, and technology introduction have a significant positive promoting effect on energy efficiency [23]. In terms of industrial structure, the excessively high share of the secondary industry, especially heavy industry, is an important factor hindering improvements in energy efficiency. However, the service industry and industrial agglomeration can enhance energy utilization efficiency [24,25]. FDI affects energy efficiency through spillover effects and competition. However, the "Pollution Paradise Hypothesis" holds that foreign capital may relocate highly polluting industries to regions, thereby reducing energy efficiency [26–28]. In addition, factors such as financial development, urbanization, and energy price reform have been shown to significantly affect energy efficiency. However, most studies overlook the deep changes brought about by the digital economy, which reshapes factor allocation and input substitution relationships, making TFEE particularly critical in the digital era. Against this background, this study aims to investigate whether the digital economy can act as a catalyst for environmental regulations to improve TFEE, rather than merely examining their separate linear effects. We attempt to reveal the synergistic mechanism, threshold conditions, and spatial spillovers among digitalization, environmental regulation, and TFEE.

2.2. Research on the Relationship Between the Digital Economy and TFEE

There are mainly two viewpoints: the "empowerment theory" and the "energy consumption theory". Scholars who hold the "empowerment theory" believe that the digital economy improves TFEE through multiple channels. First, the optimization effect of digital technology can achieve precise control of the production process and intelligent energy management, reduce energy waste, and improve TFEE [29]. Second, the effect of industrial structure upgrading. The digital industry itself is low-energy-consuming and high-value-added. The adoption of digital technology in traditional industries drives them to reduce energy consumption [30]. Third, the effect of optimizing factor allocation. Digital platforms have reduced information asymmetry, improved resource allocation efficiency, and reduced energy waste caused by market frictions [31]. Fourth, the substitution effect of clean energy. Digital energy technologies, such as smart grids and distributed energy systems, have optimized the energy consumption structure [32]. In terms of empirical research, Wen and Zhang [33] found that the digital economy has significantly improved energy efficiency. Jiang et al. [34] demonstrated that the digital economy optimizes urban industrial layout through its structural attributes, thereby achieving energy "consumption reduction".

Scholars who hold the "energy consumption theory" focus on the energy consumption costs associated with the digital economy. First, digital infrastructure, such as data centers, 5G base stations, and blockchain networks, consumes a large amount of electricity; with the explosive growth of data volume, its energy consumption is rising rapidly [35]. Second, the rebound effect. While digital technology improves energy efficiency, it may also stimulate increased energy consumption by reducing the cost of energy services, partly offsetting the energy-saving effect, known as the "Jevons Paradox" in energy economics [36]. Third, the digital divide effect. The imbalance of the digital economy may lead to regional development disparities. Backward regions may be trapped on a high-energy-consumption development path during industrial transfer [37]. Fourth, hidden energy consumption. Energy consumption in manufacturing digital equipment and recycling is often overlooked, leading to overestimation of the effect of the digital economy [38]. Some empirical studies have found a nonlinear relationship between the digital economy and TFEE. In the early stage of digital economy development, energy consumption may increase due to infrastructure construction and industrial expansion. Only after crossing a certain threshold can the energy-saving effect be truly realized [39].

Furthermore, a few scholars focus on the regulatory mechanisms and heterogeneous effects of the digital economy on TFEE. They found that its energy-saving effects are influenced by factors such as regional innovation levels, human capital stock, marketization, and the completeness of infrastructure. Li et al. [40] found that the digital economy significantly improves TFEE and is robust. Regional heterogeneity is significant. After 2006, the digital economy's impact on TFEE has become more pronounced, and the degree of benefit varies among cities with different resource endowments. Cities based on natural resources have benefited the most. Some studies from an industrial perspective have found that the digital economy improves TFEE in the service sector more than in the industrial sector, and that there is a lag in its transformative effect on high-energy-consuming industries [41]. However, existing research rarely incorporates environmental policy factors into the analytical framework and fails to fully reveal the intrinsic mechanism.

Based on the above theoretical and empirical evidence, we propose Hypothesis H1:

H1. *The digital economy has a significant positive direct effect on regional TFEE, and the effect exhibits prominent spatial spillover characteristics.*

2.3. Research on the Relationship Between Environmental Regulations and TFEE

The Porter Hypothesis suggests that appropriate environmental regulations can stimulate green innovation and improve productivity through the innovation compensation effect [42], which holds that environmental regulations can offset regulatory costs and enhance competitiveness through the "innovation compensation effect". This hypothesis provides a theoretical basis for environmental regulations aimed at improving TFEE.

From the perspective of transmission mechanisms, the paths through which environmental regulations affect TFEE mainly include: first, technological innovation. Strict environmental regulations force enterprises to develop new energy-saving and consumption-reducing processes and products, thereby improving energy utilization efficiency [43]. Second, the factor substitution effect. Environmental regulations have increased the cost of polluting factors, prompting enterprises to replace fossil fuels with clean energy and high-energy-consuming factors with high-tech factors, and to optimize the input structure [44]. Third, the effect of resource allocation. Environmental regulations enhance overall energy efficiency by eliminating outdated production capacity, restricting the entry of highly polluting enterprises, and reallocating resources to high-efficiency, low-pollution enterprises and sectors. Fourth, the effect of management optimization. To meet environmental regulations, enterprises need to establish a more refined energy management system to identify energy-saving potential and reduce energy waste [45].

However, the "cost compliance theory" holds that environmental regulations will increase enterprises' compliance costs, divert productive investment and R&D funds, and negatively affect energy efficiency. Some studies found that there is a nonlinear relationship between environmental regulations and TFEE, with a "U-shaped" or "inverted U-shaped" curve, that is, only when its innovation compensation effect exceeds the cost of following [46]. Some studies have also examined its differential effects and found that incentive-based environmental regulation is more effective at stimulating enterprises' intrinsic motivation than command-and-control regulation, and that its effect on improving energy efficiency is more lasting [47].

At the regional level, the impact of environmental regulations on TFEE is shaped by the regional development stage, industrial structure, technological foundation, and institutional environment. Sun and An [48] found that the impact of environmental regulations on energy efficiency is heterogeneous, which is consistent with the overall conclusion in energy-scarce areas. Environmental regulations promote improvements in energy efficiency. In energy-abundant regions, the impact of environmental regulations on energy efficiency is U-shaped. In addition, the interaction between spatial strategy and environmental regulation is an important research perspective. The strategic choices made by local governments between "bottom-race competition" and "top-race competition" will affect the distribution pattern of energy efficiency among regions [49]. Although research is abundant, most studies focus on the direct effects, and the examination of their interactions with technological change factors (especially the digital economy) is clearly insufficient. Accordingly, we propose Hypothesis H2:

H2. *Environmental regulation has a nonlinear threshold effect on TFEE, and its impact depends on the development level of the digital economy.*

2.4. Research on the Interaction Effects Between the Digital Economy and Environmental Regulation

With the penetration of digital technology across various fields of the social economy, scholars have begun to study the interaction between the digital economy and environmental regulation, but related research remains in its infancy. First, the digital economy can empower environmental regulations and enhance their effectiveness. Digital technology has provided new tools and means for environmental monitoring, pollution source traceability, and environmental law enforcement, reducing regulatory information and enforcement costs and enhancing their accuracy and timeliness [50]. A big data platform enables the real-time collection and sharing of environmental information, helping address the information gap in environmental regulations. Artificial intelligence and satellite remote sensing technology have improved the ability to identify environmental violations. Blockchain technology improves the credibility and traceability of environmental data [51]. Digital environmental regulation tools (online monitoring, intelligent early warning, and electronic trading of pollutant discharge rights) have improved the convenience of compliance for enterprises and reduced transaction costs. These studies focus on the effect of digital technologies on the efficiency of environmental regulation implementation rather than their synergies in substantive environmental performance (TFEE).

Second, environmental regulations may also guide the green development direction of the digital economy. Strict environmental regulations have created broad application scenarios and market demands for digital technologies, giving rise to new business forms such as smart environmental protection and environmental big data services [52]. Environmental regulations, by setting energy consumption and emissions standards, compel the digital industry to enhance energy efficiency and reduce carbon footprints, thereby promoting the recycling of electronic waste [53]. In addition, environmental regulations may affect the diffusion path of digital technologies, promoting their prioritization for high-energy-consuming fields [54]. However, most of these studies lack systematic empirical verification.

Regarding synergistic effects, a few studies have begun to explore the combined impact of the digital economy and environmental regulations. Some scholars have proposed the concept of two-way integration between "digital greening" and "green digitalization", arguing that deep integration of digital technology and environmental regulations is the key path to achieving carbon peaking and carbon neutrality [55]. Some empirical studies found that the digital economy can enhance the incentive effect of environmental regulations on innovation, while environmental regulations provide institutional guarantees for digital technologies. The synergy of the two has a positive interaction effect on TFEE [56]. However, these studies primarily focus on productivity or carbon emissions. Research specifically targeting TFEE is relatively scarce, and analyses of interaction mechanisms, threshold conditions, and regional heterogeneity are not sufficiently in-depth. Thus, we propose Hypothesis H3:

H3. *The interaction between the digital economy and environmental regulations generates a significant positive synergistic effect on TFEE, and this synergistic effect has significant spatial spillover effects among regions.*

2.5. Research Gaps and the Positioning of This Paper

Although existing studies have achieved abundant results, three critical gaps remain:

First, most studies investigate the digital economy or environmental regulation separately and lack a unified integrated framework. Linear analysis dominates, while the nonlinear relationship, conditional dependence, and threshold mechanism remain unclear. Second, the spatial spillover effect of digitalization—especially the Metcalfe effect—is rarely embedded into energy efficiency analysis. Traditional models ignore regional interactions, leading to biased estimation. Third, few studies reveal how digital development serves as a precondition for environmental regulation to take effect. The threshold for environmental policy to shift from cost pressure to innovation compensation has not been identified. This study fills the above gaps through three core innovations: (1) Perspective Innovation: Integrating the digital economy and environmental regulation into a unified TFEE analytical framework, in particular, it overlooks the enabling role of digitalization in enhancing the effectiveness of environmental policies and their conditional dependence, and fails to reveal the complex driving mechanisms behind improvements in energy efficiency. This gap makes it difficult to explain why environmental policies of the same intensity yield significantly different results across different regions; (2) Methodological Innovation: Most existing studies have been conducted within traditional frameworks, generally overlooking spatial correlations and regional spillover effects, and failing to account for the cross-regional network spillovers of the digital economy. This is inconsistent with the spatial attributes of digital technology revealed by the "Metcalfe effect" and leads to biased estimation results. Using the Spatial Durbin Model (SDM) to capture the Metcalfe effect and spatial spillovers of digitalization; (3) Mechanism Innovation: Identifying the critical digital threshold that enables environmental regulation to achieve the innovation compensation effect and improve TFEE. Compared with traditional TFEE measurement studies such as Hu and Wang [13] and Tone [14], this study further incorporates digital empowerment, policy synergy, spatial interaction, and threshold effects, providing a more systematic and forward-looking explanation for China's regional energy efficiency evolution; (4) Existing research has failed to identify the threshold conditions under which the digital economy influences environmental regulation, cannot explain when environmental regulation shifts from a "cost effect" to an "innovation compensation effect," and struggles to provide actionable dynamic policy ranges.

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3. Research Design

3.1. Method for Calculating TFEE

3.1.1. Super-Efficiency SBM Model

To accurately measure TFEE under the dual-carbon background, this paper adopts the input–output super-efficiency SBM model with undesirable outputs. The input–output model aims to minimize energy, capital, and labor inputs under the premise of fixed desirable output (GDP) and constrained undesirable outputs (carbon emissions and pollution), which is consistent with the core connotation of TFEE. Compared with traditional DEA models (CCR, BCC), the super-efficiency SBM model offers distinct advantages: traditional DEA models, which rely on radial and angular settings, cannot adequately address the issue of slack variables in inputs and outputs, leading to potential biases in efficiency measurements; in contrast, the SBM model directly incorporates slack variables through non-radial and non-angular methods, resulting in more precise measurement outcomes.

Compared to Stochastic Frontier Analysis (SFA), the super-efficiency SBM does not require a predefined production function form, making it more suitable for interprovincial energy efficiency evaluations involving multiple inputs and outputs. Additionally, the super-efficiency SBM can further rank efficient units on the frontier, thereby fully reflecting the actual differences in energy efficiency among Chinese provinces.

Therefore, this paper selects the super-efficiency SBM as the measurement method. Suppose there are n decision Units (DMUs), and each DMU uses m inputs $x = (x_1, x_2, \ldots, x_m) \in R^m$ to produce S_1 desirable outputs $y^g = \left(y_1^g, y_2^g, \ldots, y_{s_1}^g\right) \in R^{s_1}$ and S_2 undesirable outputs $y^b = \left(y_1^b, y_2^b, \ldots, y_{s_2}^b\right) \in R^{s_2}$.

Define the following matrix:

$$X = [x_1, x_2, \ldots, x_n] \in R^{m\times n}, Y^g = \left[y_1^g, y_2^g, \ldots, y_n^g\right] \in R^{s_1\times n}, Y^b = \left[y_1^b, y_2^b, \ldots, y_n^b\right] \in R^{s_2\times n}, \text{ and } X > 0, Y^g > 0, Y^b > 0 \quad (1)$$

The production possibility set of the undesirable output SBM model is defined as follows:

$$P = \left\{\left(x, y^g, y^b\right) \middle| x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0\right\} \quad (2)$$

Among them, λ is the intensity vector. Based on this set of production possibilities, the objective function of the undesirable output SBM model is as follows:

$$\rho^* = \min_{\lambda, s^-, s^g, s^b} \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{io}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{ro}^g} + \sum_{t=1}^{s_2} \frac{s_t^b}{y_{to}^b}\right)} \quad (3)$$

The constraint condition is as follows:

$$\begin{array}{ll} x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^-, & i = 1, 2, \ldots, m \\ y_{ro}^g = \sum_{j=1}^{n} y_{rj}^g\lambda_j - s_r^g, & r = 1, 2, \ldots, s_1 \\ y_{to}^b = \sum_{j=1}^{n} y_{tj}^b\lambda_j + s_t^b, & t = 1, 2, \ldots, s_2 \\ \lambda_j \geq 0, s_i^- \geq 0, s_r^g \geq 0, s_t^b \geq 0, & \forall i, r, t, j \end{array} \quad (4)$$

Among them, s_i^-, s_r^g and s_t^b respectively represent the slack variables of input, desirable output, and undesirable output. The value range of the objective function ρ^* is [0, 1]. When $\rho^* = 1$, it indicates that the decision-making unit is at the forefront of efficiency, that is, complete efficiency. When the value is $\rho^* < 1$, it indicates an efficiency loss. However, this inherent limitation is that the efficiency values of the decision units (DMUs) on the efficiency frontier are all 1, making it impossible to further distinguish and rank these effective DMUs. This limitation is particularly pronounced in TFEE evaluation: when multiple provinces or regions are simultaneously at the forefront of efficiency, traditional models cannot identify their relative strengths and weaknesses, limiting the precision of policy-making. The super-efficiency SBM model (Super-SBM) proposed by Tone [57] effectively solved this problem. This model re-evaluates and fully ranks valid units by excluding the evaluated DMUs from the reference set, thereby ensuring that the efficiency values of the effective DMUs exceed 1. Because provinces have very different economic sizes, variable returns to scale (VRS) is used.

Suppose there are n DMUs, and each DMU uses input $x \in R^m$ to produce desirable output $y^g \in R^{s_1}$ and undesirable output $y^b \in R^{s_2}$. For the evaluated $\mathrm{DMU_k}$, the production possibility set of the super-efficiency SBM-Undesirable model is defined as follows:

$$P \setminus \left\{x_k, y_k^g, y_k^b\right\} = \left\{(x, y^g, y^b) \mid x \geq \sum_{j=1, j\neq k}^{n} \lambda_j x_j, y^g \leq \sum_{j=1, j\neq k}^{n} \lambda_j y_j^g, y^b \geq \sum_{j=1, j\neq k}^{n} \lambda_j y_j^b, \lambda \geq 0\right\} \quad (5)$$

The objective function of the super-efficiency SBM model is as follows:

$$\delta^* = \min_{\lambda, s^-, s^g, s^b} \frac{\frac{1}{m}\sum_{i=1}^{m} \frac{\overline{x}_{ik}}{x_{ik}}}{\frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1} \frac{\overline{y}_{rk}^g}{y_{rk}^g} + \sum_{t=1}^{s_2} \frac{\overline{y}_{tk}^b}{y_{tk}^b}\right)} \quad (6)$$

Among them, the following applies:

$$\overline{x}_{ik} = \sum_{j\neq k} \lambda_j x_{ij} \text{ is the target value for input adjustment}$$

$$\overline{y}_{rk}^g = \sum_{j\neq k} \lambda_j y_{rj}^g \text{ is the target value for expected output adjustment}$$

$$\overline{y}_{tk}^b = \sum_{j\neq k} \lambda_j y_{tj}^b \text{ is the adjusted Target Value for Non} - \text{Desired Output}$$

Constraints are as follows:

$$\begin{cases} \overline{x}_{ik} \geq x_{ik} + s_i^-, & i = 1, 2, \ldots, m \\ \overline{y}_{rk}^g \leq y_{rk}^g - s_r^g, & r = 1, 2, \ldots, s_1 \\ \overline{y}_{tk}^b \geq y_{tk}^b + s_t^b, & t = 1, 2, \ldots, s_2 \\ \overline{x} \geq x_k, \overline{y}^g \leq y_k^g, \overline{y}^b \geq y_k^b & \\ \lambda_j \geq 0, s_i^- \geq 0, s_r^g \geq 0, s_t^b \geq 0, & \forall j \neq k, i, r, t \end{cases} \quad (7)$$

δ^* represents the super-efficiency score.

If $\delta^* > 1$, $\mathrm{DMU_k}$ is a super-efficiency unit, and its efficiency value is higher than the reference frontier, with the "excess efficiency" from the frontier being the super-efficiency value.

If $\delta^* = 1$, DMU happens to be on the frontier after excluding itself.

If $1 > \delta^* > 0$, DMU is an inefficient unit; the input–output configuration needs to be improved.

3.1.2. Selection of Input–Output Indicators

Drawing on the studies by Hu and Wang [13] and Zhou et al. [16], the study constructs the following input–output index system (Table 1).

Table 1. Input–output indicators for measuring TFEE.

Indicator Category	Specific Indicator	Unit	Data Source
Input indicators	Energy Input	10,000 tons of standard coal	China Energy Statistical Yearbook
	Capital Input	100 million yuan (2011 constant prices)	Capital stock estimated using the perpetual inventory method
	Labor Input	10,000 people	China Labor Statistics Yearbook
Desirable Output	Economic Output	100 million yuan (2011 constant prices)	China Statistical Yearbook
Undesired output	Carbon Dioxide Emissions	10,000 tons	Estimated using IPCC reference methods, based on coal, oil, and natural gas consumption and corresponding emission factors.
	Sulfur Dioxide Emissions	10,000 tons	China Environmental Statistics Yearbook

(1) Input indicators

Energy input: Measured as the total energy consumption of each province (10,000 tons of standard coal), including terminal consumption of all energy types, such as raw coal, crude oil, natural gas, and electricity. The data is sourced from the "China Energy Statistical Yearbook" and "Statistical Communique of the People's Republic of China on National Economic and Social Development 2024".

Capital investment: The capital stock estimated by the perpetual inventory method (in billions of yuan, constant price in 2011). The calculation formula is $K_t = I_t + (1-\delta)K_{t-1}$, where I_t represents fixed asset investment, and δ is the depreciation rate, with the depreciation rate set at 9.6%, referring to Wei and Shen [20].

Labor input: Measured by the total number of employed people in each province at the end of the year (in ten thousand), sourced from the "China Labor Statistical Yearbook".

(2) Desirable Output

Economic output: Measured by each province's regional GDP (in billions of yuan at constant 2011 prices), sourced from the "China Statistical Yearbook" and adjusted to constant prices using the GDP deflator.

(3) Undesired output

Carbon dioxide emissions: NOx, PM2.5, and other pollutants are not included due to the unavailability of long-term and complete provincial-level statistical data, which is a common data constraint in provincial energy-environment research. Estimated using the reference method provided by the IPCC, calculated based on the consumption of coal, oil, and natural gas in each province and the corresponding emission coefficients, with the unit being ten thousand tons. Sulfur dioxide emissions: Measured as industrial sulfur dioxide emissions (in 10,000 tons), sourced from the "China Environmental Statistical Yearbook" and "Statistical Communique of the People's Republic of China on National Economic and Social Development 2024".

3.2. Measurement Model Setting

3.2.1. Baseline Regression Model

To examine the direct impact of the digital economy and environmental regulations on TFEE, the following bidirectional fixed-effect model is constructed:

$$TFEE_{it} = \alpha_0 + \alpha_1 DIG_{it} + \alpha_2 ER_{it} + \alpha_3 DIG_{it} \times ER_{it} + \sum_j \beta_j Controls_{jit} + \mu_i + \lambda_t + \varepsilon_{it} \tag{8}$$

Here, i represents the province, and t represents the year. $TFEE_{it}$ is the explained variable, representing the TFEE. DIG_{it} and ER_{it} are digital economic and environmental regulations. $DIG_{it} \times ER_{it}$ is the interaction term, used to test the synergy effect between the two. $Controls_{jit}$ is the control variable, μ_i represents fixed effect, and λ_t represents the annual fixed effect, controlling for the temporal trends of macroeconomic fluctuations, etc. ε_{it} is the random error term.

3.2.2. Spatial Econometric Model

Given potential spatial correlation in regional TFEE, the study introduces a spatial econometric model to capture spillover effects. Firstly, Moran's I index is used to test as follows:

$$I = \frac{n\sum_i \sum_j w_{ij}(TFEE_i - \overline{TFEE})(TFEE_j - \overline{TFEE})}{\sum_i \sum_j w_{ij}\sum_i (TFEE_i - \overline{TFEE})^2} \tag{9}$$

Among them, w_{ij} is an element of the spatial weight matrix; the spatial weight matrix adopted in this paper is the 0–1 adjacency matrix. This matrix can objectively reflect spatial spillover and is widely used in provincial-level research. Construct the Spatial Durbin Model (SDM) as the benchmark spatial econometric model:

$$\begin{aligned} TFEE_{it} = \rho W \cdot TFEE_{it} + \gamma_0 + \gamma_1 DIG_{it} + \gamma_2 ER_{it} + \gamma_3 DIG_{it} \times ER_{it} + W \\ \cdot(\theta_1 DIG_{it} + \theta_2 ER_{it} + \theta_3 DIG_{it} \times ER_{it}) + \sum_j \delta_j Controls_{jit} \\ + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{10}$$

Among them, ρ is the spatial autoregressive coefficient, and W is the spatial lag term reflecting spatial spillovers. To alleviate potential endogeneity caused by reverse causality between the digital economy and TFEE, lagged terms of core explanatory variables are introduced in the robustness test.

3.3. Threshold Regression Model

The relationship between the digital economy and environmental regulations on energy efficiency is not a simple linear one: at lower levels of digitalization, environmental regulations primarily manifest as a "compliance cost effect," increasing the burden on enterprises and suppressing efficiency; once digitalization surpasses a critical threshold, mechanisms such as smart monitoring, targeted pollution control, and the diffusion of green technologies become feasible, prompting environmental regulations to shift toward an "innovation compensation effect."

This structural shift implies the existence of a significant "institutional tipping point," which traditional linear models cannot capture. Therefore, this paper employs a threshold regression model to identify the nonlinear discontinuity in the impact of environmental regulations when the digital economy serves as a threshold variable, thereby revealing the theoretical conditions under which policy effects shift. To examine the nonlinear characteristics, the panel threshold regression model is adopted. Take the threshold model of the digital economy as an example.

$$\begin{aligned} TFEE_{it} = \phi_0 + \phi_1 ER_{it} \cdot I(DIG_{it} \le \gamma) + \phi_2 ER_{it} \cdot I(DIG_{it} > \gamma) + \\ \sum_j \varphi_j Controls_{jit} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{11}$$

Among them, γ is the threshold value, and $I(\cdot)$ indicates the function. The Bootstrap method was used for repeated sampling 300 times to determine the number of thresholds and the significance of the threshold values. Meanwhile, the environmental regulation threshold model and the dual threshold model are constructed to comprehensively examine the nonlinear relationship.

3.4. Variable Selection

(1) Explained variable

Total Factor Energy Efficiency is calculated using the super-efficiency SBM model introduced throughout this paper.

(2) Explanatory variable

Digital Economy Development level (DIG). The connotation of the digital economy is rich, and its dimensions are diverse. The study draws on the research of Zhao et al. [30], Bai and Zhang [58], and constructs a comprehensive evaluation index system from four dimensions: digital infrastructure, digital industry development, digital technology application, and digital innovation environment (Table 2). The entropy-weighted method is used to determine index weights to avoid subjective bias.

Table 2. Evaluation Index System.

Primary Indicator	Secondary Indicator	Indicator Description	Attribute
Digital Infrastructure	Internet penetration rate	Number of Internet Access Users per 100 People	+
	Mobile phone penetration rate	Number of Mobile Phone Users per 100 People	+
	Telecommunications service volume per capita	Telecommunications Service Volume per Permanent Resident	+
Digital Industry Development	Share of digital industry value-added	Added Value of Information Transmission, Software, and Information Technology Services as a Percentage of GDP	+
	Employment Share in Digital Industries	Information Transmission, Software, and Information Technology Services Employment/Total Employment	+
Digital Technology Applications	Enterprise E-commerce Transaction Share	Enterprise E-commerce Sales Revenue/Enterprise Operating Revenue	+
	Digital Inclusive Finance Index	Digital Inclusive Finance Index	+
	ICT Investment Intensity of Enterprises Above Designated Size	Fixed Asset Investment in Information Transmission, Computer Services, and Software Industry/Total Fixed Asset Investment	+
Digital Innovation Ecosystem	Digital Patents per Capita	Number of digital technology-related patent applications per resident population	+
	Digital Talent Reserve	Information Transmission, Computer Services, and Software Industry Employment/Total Employment	+

The calculation steps using the entropy weight method are as follows:

The first step is data standardization processing. For positive indicators, the range standardization method is adopted:

$$x_{ij}^{'} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} \tag{12}$$

For negative indicators, the following applies:

$$x'_{ij} = \frac{max(x_j) - x_{ij}}{max(x_j) - min(x_j)} \tag{13}$$

The second step is to calculate the specific gravity of the index:

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}} \tag{14}$$

Step 3: Calculate the information entropy (The method for handling zero values after standardization is to add a very small constant of 0.0001):

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij}\ln(p_{ij}) \tag{15}$$

Step 4: Calculate the difference coefficient and weight as follows:

$$d_j = 1 - e_j, w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{16}$$

Step 5: Calculate the comprehensive score as follows:

$$DIG_i = \sum_{j=1}^{m} w_j \cdot x'_{ij} \tag{17}$$

Intensity of Environmental Regulation (ER). The measurement methods for environmental regulatory intensity primarily include the single-index and comprehensive-index methods. Single-indicator methods are difficult to fully capture the intensity of regulation. The comprehensive index method is more comprehensive by constructing a multi-dimensional index system. The study constructs a comprehensive index across three dimensions: regulation breadth, regulation depth, and regulation enforcement strength (Table 3). Among them, the indicator "number of environmental emergencies" is a negative indicator, which mainly reflects unexpected risks rather than steady-state pollution intensity. To avoid distortion of the ER index, we conduct robustness checks by excluding this indicator, and find that the empirical results remain stable.

The entropy weight method is also adopted to calculate the weights of each index, and the comprehensive index (ER) of environmental regulation intensity is synthesized. The larger this index is, the stronger the environmental regulations in the region.

(3) Control Variables

Economic development level (PGDP): A large body of research shows that economic development has brought enterprises increasingly advanced equipment and technologies, as well as improved organizational management. Moreover, people prefer clean, efficient energy to replace traditional, high-pollution, low-efficiency sources such as coal, thereby improving TFEE. Per capita GDP is used to reflect a region's economic development level, and it is converted to a comparable price index with 2011 as the base period, denoted PGDP.

Industrial structure (IND): Industry is the sector with the highest energy consumption. Changes in the scale and structure can affect TFEE. The industrial structure is represented by the proportion of each region's industrial added value to its GDP. This indicator reflects the industry's contribution to the region's economic growth.

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Foreign Direct Investment (FDI): Measured as the proportion of actual utilized foreign direct investment to GDP, it aims to control the impact of international technology spillovers and the "pollution paradise" effect on TFEE.

Energy consumption structure (ENS): Coal has been the main source of industrial energy consumption. This not only leads to low energy utilization efficiency but also causes serious environmental pollution. Based on available data, the study uses the proportion of coal consumption in total energy consumption to measure.

Financial development level (FIN): Measured as the proportion of financial institutions' loan balances to GDP, it controls for the impact of financial resource allocation efficiency on TFEE.

Table 3. Evaluation Index System for Environmental Regulation Intensity.

Primary Indicator	Secondary Indicator	Indicator Description	Attribute
Regulatory Scope	Number of Environmental Regulations	The cumulative number of local environmental regulations enacted that year	+
	Number of Environmental Standards	Cumulative number of local environmental standards implemented that year	+
Regulatory Depth	Industrial Pollution Control Investment Intensity	Industrial Pollution Control Investment Completed/GDP	+
	Percentage of Enterprises Undergoing Cleaner Production Audits	Number of enterprises that have undergone clean production audits/Number of industrial enterprises above the designated size	+
Regulatory Enforcement	Number of Environmental Administrative Penalty Cases	The number of environmental administrative penalty cases that year	+
	Pollution Discharge Fee Collection Intensity	Wastewater discharge fee collection amount/GDP	+
	Number of Environmental Emergencies	Number of sudden environmental incidents in the year (negative indicator)	−

Note: In light of China's 2018 "fee-to-tax" reform, this study adopts pollution discharge fee revenue as the environmental regulation proxy prior to 2018, and switches to environmental protection tax revenue thereafter; both are normalized as a percentage of GDP. The environmental protection tax fully continues the original pollution discharge fee system in the collection scope, tax base, and pollutant categories, ensuring statistical consistency and comparability between the two series. Additionally, a policy dummy variable for the fee-to-tax transition is included to control for institutional shocks and guarantee robust estimates.

4. Results

4.1. Interaction Effects and Sign Reversal Analysis

Table 4 reports the benchmark regression results. Model (1) only controls the fixed effects of provinces and years, Model (2) incorporates all control variables, and Model (3) further introduces the interaction term. To rule out the possibility that the drastic sign reversal in ER from 0.068 * to −0.148 ** is due to multicollinearity, we have calculated the variance inflation factor (VIF) for all core variables. The results show that the maximum VIF value is 2.31, and the average VIF is 1.64, both far below the critical threshold of 10, indicating no severe multicollinearity among DIG, ER, and DIG × ER. The VIF value of the interaction term (DIG × ER) tends to be relatively high due to its construction method. To strengthen the diagnostic discussion, we clarify that both DIG and ER were standardized by mean-centering before constructing the interaction term, which effectively reduces multicollinearity. The observed VIF values remain within an acceptable range, indicating no serious multicollinearity bias in the regression results. Therefore, the sign reversal genuinely reflects the conditional dependence of environmental regulation rather than econometric bias. To address potential endogeneity concerns, especially the simultaneity between the digital economy and TFEE, this study adopts the lagged one-period digital economy index (L.DIG) as the core explanatory variable in robustness checks. The estimation results remain highly consistent, confirming that the positive effect of the digital economy on TFEE does not suffer from serious simultaneity bias.

Table 4. Benchmark Regression Results.

Variable	Model (1)	Model (2)	Model (3)
DIG	0.277 *** (3.23)	0.235 *** (2.98)	0.186 *** (4.01)
ER	0.093 ** (2.02)	0.068 * (1.68)	−0.148 ** (−1.99)
DIG × ER	—	—	0.299 *** (3.33)
PGDP	—	0.032 *** (2.87)	0.023 *** (4.52)
$PGDP^2$	—	−0.011 ** (−2.39)	−0.014 *** (−1.84)
IND	—	−0.085 *** (−4.57)	−0.007 *** (−5.11)
ENS	—	−0.124 *** (−3.90)	−0.135 *** (−4.33)
FIN	—	0.012 *	0.013 *
Province fixed effects	Control	Control	Control
Year Fixed Effect	Control	Control	Control
Constant term	0.335 *** (5.23)	0.521 *** (3.33)	0.662 *** (3.95)

Note: ***, **, and * respectively indicate significance at the 1%, 5%, and 10% levels; *t* values are reported in parentheses.

Table 4 demonstrates that the digital economy promotes Total Factor Energy Efficiency (TFEE). More importantly, the digital economy functions not only as an independent explanatory variable but also as a fundamental infrastructure enabler that enhances the effectiveness of environmental regulation. When environmental regulation is examined in isolation, it exhibits a significant cost-following effect that hampers TFEE. However, when considered alongside the digital economy, the interaction term yields a significantly positive synergistic effect, suggesting that digital development effectively converts regulatory pressure into incentives for innovation. This structural transformation indicates that digital infrastructure provides the technical foundation necessary for environmental policies to achieve innovation compensation effects. In Model (2), the coefficient is 0.235. This positive effect can be attributed to three core mechanisms: (1) Digital technologies facilitate intelligent production and real-time energy monitoring, which directly reduce energy waste and enhance factor allocation efficiency; (2) The digital economy accelerates the upgrading of industrial structures toward low-energy-consumption and high-value-added sectors; (3) Digital platforms mitigate information asymmetry and market friction, further optimizing the allocation of energy-related resources. This finding is consistent with most of the existing literature [33], which supports the "digital empowerment effect" on energy efficiency. After adding the interaction term, the coefficient of DIG decreased (0.186), but remained highly significant, indicating that the fundamental energy-saving effect persists; this decline is due to the fact that some of the energy-saving effects originally attributed to the digital economy are actually achieved through synergy with environmental regulations. Once this interaction channel is identified separately, the direct effect of the digital economy weakens accordingly. However, this does not mean that the role of the digital economy has decreased; rather, it reveals the indirect mechanism by which it imposes environmental regulations and amplifies policy effects. From an economic perspective, it confirms the "multiplier effect" of the digital economy as a technology. Its value is not only reflected in the direct improvement of productivity, but also in creating technical conditions and application scenarios for the implementation of other policy tools (such as environmental regulations), thereby releasing greater space for the improvement of social welfare.

Second, in Model (2), the coefficient of environmental regulation is 0.068. This indicates that when the regulatory role of the digital economy is not considered, environmental regulation generally has a weak positive promoting effect on TFEE. This may be due to the gradual improvement of China's environmental regulation system during the sample period and the initial manifestation of the "innovation compensation" effect in some regions. However, after introducing the interaction term in Model (3), the coefficient of ER becomes -0.148, while the coefficient of the interaction term DIG $\times$ ER is as high as 0.299. This "symbolic reversal" phenomenon reveals the high degree of conditional dependence of environmental regulation effects: In regions where digital economy development lags behind, environmental regulations mainly function by "following the cost effect"—enterprises are forced to increase investment in pollution control to meet emission standards, squeezing up funds for technological R&D and equipment renewal, thereby suppressing production efficiency in the short term. Meanwhile, administrative measures, such as production restrictions and shutdowns, have directly reduced the output scale, leading to a decline in capacity utilization and TFEE losses. However, when the digital economy crosses a certain threshold, the "innovation compensation effect" of environmental regulation is fully realized. Digital technology reduces the information and enforcement costs of environmental supervision, enabling precise and differentiated regulation and avoiding the efficiency losses caused by the "one-size-fits-all" approach. Intelligent monitoring and big data analysis help enterprises identify key links in energy conservation and emissions reduction, translating abstract regulatory pressure into specific technological pathways. Digital platforms have facilitated the diffusion and trading of green technologies, enabling enterprises to access clean production technologies at a lower cost. The coefficient of the interaction term (0.299) far exceeds the absolute value of the direct effect of the digital economy (0.186) and the direct effect of environmental regulation (0.148), indicating that the synergistic benefits generated by the digital empowerment of environmental regulation exhibit a nonlinear pattern: "1 + 1 > 2", which means digital-enabled environmental regulation produces stronger efficiency-improving effects than the two factors separately. This provides empirical evidence for the integrated "digital + green" development model. From a policy perspective, it implies that merely increasing the stringency of environmental regulations may lead to a "regulatory dilemma": the stricter the environmental standards, the more likely they are to suppress economic growth and TFEE. However, integrating digital technology can break this deadlock by reducing compliance costs and enhancing returns on innovation, achieving a "win-win" outcome for environmental protection and TFEE. This also explains why some developed regions can achieve continuous improvement in TFEE while maintaining strict environmental regulations, while less developed regions face the dilemma of "regulation as a burden"; the key difference lies in the thickness of the digital technology foundation. The digital economy significantly enhances TFEE, primarily through three mechanisms: intelligent factor allocation, industrial structure upgrading, and green technology spillovers. When environmental regulations act independently, their effect is significantly negative, consistent with the short-term effects of the Porter hypothesis; however, the interaction term is significantly positive, indicating that digitalization mitigates the cost pressures of environmental regulations by reducing information costs and improving regulatory precision. The findings of this study align with the mainstream literature and further identify threshold conditions, thereby addressing the shortcomings of existing research regarding unclear mechanisms.

Thirdly, the results for the control variables. The coefficient of the first-degree term of the PGDP is positive (0.032), but the second-degree term is negative (−0.011). This indicates that TFEE shows an "inverted U-shaped" trend with economic development. This finding confirms the applicability of the environmental Kuznets curve in the energy field. In the early stages of economic development, industrialization accelerated, high-energy-consuming industries expanded rapidly, and the growth rate of energy consumption exceeded the economic growth rate, leading to a decline in TFEE. When per capita income crosses a specific threshold, factors such as the transformation of the industrial structure towards the service industry, the increase in technology-intensive industries, and the strengthening of consumers' environmental protection preferences work together to drive TFEE into a continuous improvement channel. This nonlinear relationship implies that, for the central and western provinces still in the middle stage of industrialization, pursuing economic growth may come at the expense of TFEE, and that it is necessary to promote simultaneous upgrading of industrial structures. As for the developed eastern regions, they have reached a stage where TFEE improves automatically as economic growth increases. The policy focus should shift to deepening the application of digital technology and strengthening environmental regulations.

The coefficient of industrial structure (IND) is significantly negative, suggesting that a higher proportion of secondary industry correlates with a reduction in total factor energy efficiency (TFEE). In contrast to the service sector, traditional heavy industry is marked by high energy consumption and low digital penetration. The digital transformation of heavy industry primarily emphasizes equipment automation and production monitoring, which involves lengthy cycles and substantial costs. In comparison, the service industry can rapidly enhance efficiency through platformization and intelligent solutions. Consequently, the energy-saving effects of digitalization in the service sector are both stronger and more immediate than those observed in industry.

The coefficient for the coal consumption proportion (ENS) is −0.124, underscoring the significance of a clean energy structure. China's energy profile, characterized by "abundant coal, scarce oil, and limited gas," has resulted in the prolonged dominance of coal. This situation indicates that, to ensure energy security, it is essential to gradually reduce coal consumption while increasing the use of non-fossil energy sources as structural strategies to enhance TFEE. The role of digital technology is also critical; smart grids and distributed energy systems have improved the capacity to integrate renewable energy, while big data has optimized energy dispatching and demand response, thereby providing technical support for the transformation of the energy structure. The financial development coefficients are 0.012 and 0.013, indicating that financial deepening has a mild positive effect on TFEE, achieved through capital allocation optimization and industrial structure transformation. However, the "duality" feature is obvious: the distorted effects of credit expansion, stimulating high-energy-consuming investment and shadow banking that evade regulation, partially offset the positive effects. Moreover, the proportion of green finance remaining below 10% limits its marginal contribution, suggesting the need to deepen green finance reform and prevent a "shift from the real economy to the virtual economy" to unleash the potential for energy conservation.

4.2. Results of Spatial Metrological Analysis

4.2.1. Spatial Autocorrelation Test

First, conduct a spatial autocorrelation test on the TFEE. Table 5 reports the Moran's I index and its significance test results for each year from 2011 to 2024.

Table 5. Global Moran's I Index of TFEE.

Year	Moran's I	*p*-Value	Year	Moran's I	*p*-Value
2011	0.285	0.000	2018	0.322	0.000
2012	0.287	0.000	2019	0.339	0.000
2013	0.289	0.000	2020	0.348	0.000
2014	0.293	0.000	2021	0.359	0.000
2015	0.299	0.000	2022	0.377	0.000
2016	0.301	0.000	2023	0.395	0.000
2017	0.315	0.000	2024	0.424	0.000

Annual estimates of Moran's I consistently exceeded zero at the 99% confidence level, indicating an upward trajectory throughout the observation window. Such findings corroborate pronounced geographical clustering in China's regional TFEE—territories demonstrating superior conservation performance systematically border counterparts with analogous attributes, thereby generating distinct spatial concentration phenomena. These empirical regularities substantiate the methodological imperative to incorporate spatial dependence specifications in subsequent econometric analyses.

4.2.2. Estimation Results of the Spatial Econometric Model

Before performing spatial regression, we construct a 0–1 spatial contiguity matrix to capture geographic adjacency effects, which is the most widely used and robust specification in provincial-level research. The selection of the Spatial Durbin Model (SDM) is further justified by Wald and LR tests, both rejecting the degeneration to SAR or SEM.

The results in Table 6 clearly indicate that the Spatial Durbin Model (SDM) is used for the study. First, Moran's I index is highly significant, indicating strong spatial autocorrelation in regional TFEE. It is necessary to adopt spatial econometric models instead of traditional OLS. Secondly, both the Wald and LR tests strongly reject the null hypothesis that SDM degenerates into SAR or SEM, indicating that the spatial lag explanatory variables (W × DIG, W × ER, W × DIG × ER) are jointly significant. Ignoring these spatial interaction terms will lead to model setting bias and estimation inconsistency. From the goodness-of-fit perspective, the log-likelihood value of SDM is significantly higher than that of SAR and SEM, and the AIC is the smallest, further supporting SDM's superiority. This choice has significant economic implications: TFEE is influenced not only by the local digital economy and environmental regulations, but also by the spillover effects of policy choices and levels of digitalization in neighboring regions. Policy-making must take spatial correlations into account to avoid "beggarity" or "bottom-chasing competition". Therefore, the regression results are shown in Table 7.

The results show that, first, the spatial autoregressive coefficient $\rho = 0.133$ indicates a positive spatial spillover effect on TFEE. For every one-unit increase in TFEE in adjacent areas, this area's TFEE increases by an average of 0.133 units. The economic implication is that TFEE improvement in one region can drive efficiency growth in neighboring regions through demonstration effects, technology diffusion, and factor flow.

Second, the spatial lag term (W × DIG) coefficient for the digital economy is significantly positive (0.076 and 0.089), which reflects the network externality and Metcalfe effect of digital infrastructure: the value of digital systems increases with network scale, enabling cross-regional technology and knowledge spillovers at near-zero marginal cost.

Thirdly, the coefficient of the spatial lag term (W × DIG × ER) in the interaction term is 0.149 and significant at the 5% level. This is a key finding that differs from most of the existing literature, which rarely considers the spatial spillover of the synergistic effect. It implies that "digital + regulation" integrated policies have strong regional radiation capacity.

Table 6. Selection and Verification Results of Spatial Econometric Models.

Test Type	Statistic	Value	*p* Value	Conclusion
Wald Test (SDM vs. SAR)	$\chi^2(3)$	18.88	0.000	Refuse to let SDM degenerate into SAR
LR Test (SDM vs. SAR)	$\chi^2(3)$	19.28	0.000	Refuse to let SDM degenerate into SAR
Wald Test (SDM vs. SEM)	$\chi^2(3)$	16.35	0.001	Refusing SDM's Degeneration into SEM
LR Test (SDM vs. SEM)	$\chi^2(3)$	17.42	0.001	Refusing SDM's Degeneration into SEM
Comparison of Goodness of Fit				
Log-likelihood value (OLS)	—	−487.66	—	—
Log-likelihood value (SAR)	—	−452.53	—	—
Log-likelihood value (SEM)	—	−463.42	—	—
Log-likelihood value (SDM)	—	−441.02	—	Best Fit
AIC (SDM)	—	911.35	—	AIC Minimum
BIC (SDM)	—	978.17	—	—

Table 7. Estimation Results of Spatial Econometric Models.

Variable	Model (4) SDM	Model (5) SDM-Complete
Direct effect		
DIG	0.142 ***	0.133 ***
ER	−0.085 **	−0.112 ***
DIG × ER	—	0.253 ***
Spatial lag term		
W × DIG	0.076 ** (0.038)	0.089 ** (0.039)
W × ER	−0.066	−0.085
W × DIG × ER	—	0.149 **
ρ	0.201 *** (0.048)	0.133 ***
Control variables	Control	Control
Fixed effects	Control	Control
Log-L	466.35	481.77
AIC	−922.32	−939.52

Note: *** and ** respectively indicate significance at the 1% and 5% levels.

4.2.3. Spatial Effect Decomposition

To accurately identify the direct, indirect, and total effects of each variable, effect decomposition was conducted using Model (5), and the results are presented in Table 8.

Table 8. Decomposition Results of Spatial Effects.

Variable	Direct Effect	Indirect Effect	Total Effect
DIG	0.133 ***	0.174 **	0.307 ***
ER	−0.176 ***	−0.056	−0.232 **
DIG × ER	0.282 ***	0.383 ** (0.158)	0.665 ***

Note: *** and ** respectively indicate significance at the 1% and 5% levels.

The results of spatial effect decomposition reveal fundamental differences in the mechanisms of action between the digital economy and environmental regulation, offering critical insights into the spatial dynamics of technology diffusion and policy transmission. In the total effect of the digital economy (0.307), the direct effect (0.133) constitutes 43.32%, while the indirect effect (0.174) comprises 56.68%. This indicates that over half of the energy-saving impact of the digital economy is realized through spatial spillover channels. Consequently, maximizing these spillovers necessitates the establishment of a unified, standardized digital infrastructure at the national level to enhance inter-provincial network connectivity and data sharing. This inverted phenomenon of the "local-level" effect underscores the distinctive economic characteristics of digital technology: digital infrastructure demonstrates significant network externalities, with its value increasing exponentially as the user base expands, a phenomenon referred to as the "Metcalfe effect." The cross-regional connectivity facilitated by digital platforms has dismantled the geographical barriers to traditional factor flows, allowing energy-saving technologies, management practices, and best practices to disseminate to neighboring regions at nearly zero marginal cost. More importantly, regions leading in digital economy development exert competitive pressure and create demonstration effects on their surrounding areas by establishing "efficiency highlands," thereby compelling these areas to accelerate their digital transformation to avoid marginalization in regional competition. This spatial spillover effect suggests that the policy advantages of the digital economy generate significant "positive externalities." The initiatives undertaken by local governments to advance the digital economy not only benefit their own regions but also enhance TFEE improvements in adjacent areas through technology diffusion, thereby establishing a virtuous cycle of coordinated regional development.

While the total effect of environmental regulations is negative (−0.232), the indirect effect is not significant (−0.056), indicating that the adverse impacts of regulations are primarily localized. This finding supports the reverse logic of the "pollution paradise hypothesis" in environmental economics: stringent environmental regulations have increased compliance costs for local enterprises, potentially resulting in the relocation of highly polluting industries to neighboring regions with less stringent regulations. However, such industrial relocation has not significantly improved local TFEE (the direct effect is negative), nor has it yielded substantial spatial spillover effects on neighboring regions (the indirect effect is not significant). This phenomenon can be attributed to the strong administrative boundary characteristics of environmental regulations; the policy instruments employed by local governments, including environmental protection assessments, pollutant discharge permits, and environmental law enforcement, are often ineffective across administrative divisions, leading to a governance pattern where "each fights on its own." TFEE losses resulting from industrial transfer are frequently attributed to receiving areas rather than to transferring areas, leading to an underappreciation of spatial spillover effects. This situation indicates that an exclusive focus on enhancing local environmental regulations may result in a prisoner's dilemma characterized by "bottom-of-the-line competition in regulation." Therefore, it is essential to establish a cross-administrative-region environmental policy coordination system through mechanisms that facilitate central and regional collaboration.

The total effect of the interaction term is 0.665, with the indirect effect (0.383) surpassing the direct effect (0.282). This finding underscores the significant radiative capacity of the synergy between digital empowerment and environmental regulation across regions. It reveals a fundamental mechanism: digital technology transcends administrative boundaries, thereby enhancing the cross-regional dissemination of environmental policies. The synergistic effect establishes a "point-leading-surface" regional energy-saving pattern, representing a marginal innovation compared to previous non-spatial studies. This discovery constitutes the core innovation of this research, elucidating the nonlinear spatial amplification effect generated by the coupling of "technology and institution." When digital technology is integrated into the environmental regulation framework, the costs associated with policy implementation, previously confined within administrative boundaries, are substantially reduced. The real-time sharing of environmental information, precise traceability of pollution sources, and coordinated cross-regional enforcement of environmental laws become feasible, effectively overcoming the challenges posed by "regulatory segmentation". The green technology trading market on digital platforms facilitates the rapid dissemination of energy conservation innovations from leading regions to adjacent areas, establishing a progressive transmission mechanism characterized by "innovation demonstration–imitation learning–catching up and surpassing". The indirect effect of the interaction term (0.383) significantly surpasses that of the digital economy alone (0.174), suggesting that digital technology possesses inherent spatial spillover properties and functions as a "catalyst" to enhance the spatial reach of environmental regulations. This creates a regional energy-saving framework defined by "leading by point and radiating to surrounding areas." From a policy design perspective, the central government should prioritize enforcing stringent environmental regulations in regions with advanced digital infrastructure. By implementing a collaborative pilot program of "digital + regulation," the government can foster the development of regional green growth hubs. Subsequently, by leveraging the diffusion of digital technology, neighboring regions can emulate these initiatives, ultimately achieving a more substantial advancement in regional Total Factor Energy Efficiency (TFEE).

4.3. Threshold Effect Test

To examine the nonlinear effects of the two on TFEE, the panel threshold model is used for estimation. Table 8 reports the results of the threshold existence test, and Table 9 reports the specific threshold values and regression coefficients.

Table 9. Threshold Existence Test.

Model	Threshold Variable	Number of Thresholds	F-Statistic	*p*-Value	Threshold Value	95% Confidence Interval
Model A	DIG	Single Threshold	66.31 ***	0.000	0.234	[0.215, 0.298]
		Double Threshold	33.44 **	0.000	0.435	[0.389, 0.468]
		Triple Threshold	19.22	0.224	—	—
Model B	ER	Single Threshold	41.22 ***	0.000	0.327	[0.275, 0.356]
		Double Threshold	29.51 **	0.001	0.493	[0.445, 0.528]
		Triple Threshold	16.14	0.201	—	—

Note: *** and ** respectively indicate significance at the 1% and 5% levels.

The test results show that both the digital economy and environmental regulations have significant dual-threshold effects, but no triple thresholds. The threshold values are 0.234 and 0.435 (digital economy), 0.327 and 0.493 (environmental regulation), respectively. To maintain policy efficiency and flexibility, a real-time monitoring mechanism should be established to dynamically adjust regulatory intensity as regional digital economic levels improve.

In Table 10, first, the impact of environmental regulations on TFEE is adjusted for the threshold level of digital economic development. When DIG $\leq$ 0.234 (including Shanxi, Guizhou, Yunnan, Gansu, Qinghai, Ningxia, and Xinjiang), the ER coefficient is -0.177 and highly significant, indicating that in regions with weak digital infrastructure and insufficient digital technology adoption, environmental regulations produce a significant "compliance cost effect," suppressing TFEE improvements. When DIG > 0.435, the ER coefficient rises substantially to 0.238 and is highly significant. This indicates that in regions with advanced digital economies, environmental regulations significantly improve TFEEs through an "innovation compensation effect." This finding reveals that digital economic development is a crucial prerequisite for environmental regulations to achieve energy-saving effects. The economic rationale is that low digitalization leads to higher regulatory costs and weaker innovation capacity; hence, regulation exhibits cost-following effects. Above the threshold, digital supervision, precise governance, and green technology diffusion activate the innovation compensation effect. This theoretically explains why environmental regulation has heterogeneous effects across regions and complements the Porter Hypothesis with digital conditional evidence. When 0.234 < DIG $\leq$ 0.435, the ER coefficient turns positive (0.079) but is only marginally significant, indicating that as the digital economy develops, the negative effects of environmental regulations gradually diminish and shift toward positive outcomes.

Table 10. Threshold Regression Results.

Variable	Coefficient
Model A: Digital Economy Threshold	
ER × I (DIG $\leq$ 0.234)	−0.177 ***
ER × I (0.234 < DIG $\leq$ 0.435)	0.079 *
ER × I (DIG > 0.435)	0.238 ***
Control variables	Control
Fixed effects	Control
R^2	0.921
Model B: Environmental Regulatory Threshold	
DIG × I (ER $\leq$ 0.327)	0.091 *
DIG × I (0.327 < ER $\leq$ 0.493)	0.217 ***
DIG × I (ER > 0.493)	0.169 **
Control variables	Control
Fixed effects	Control
R^2	0.983

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

Second, the impact of the digital economy on TFEE is threshold-regulated by the intensity of environmental regulations. When ER $\leq$ 0.327 (low environmental regulation intensity), the DIG coefficient is 0.091 and marginally significant, indicating that in regions with lax environmental regulations, the spontaneous energy-saving effect of the digital economy is limited. When 0.327 < ER $\leq$ 0.493 (moderate environmental regulation intensity), the DIG coefficient significantly increases to 0.217 and is highly significant. This inverted U-shaped pattern indicates that overly weak regulation cannot stimulate green demand, while overly strict regulation raises compliance costs and restricts digital empowerment. This provides an operational policy interval that differs from existing threshold studies and lacks a clear economic interpretation. When environmental regulation intensity exceeds the second threshold (ER > 0.493), the coefficient of DIG decreases significantly from 0.217 to 0.169, indicating a clear crowding-out effect. Excessively stringent environmental regulation significantly raises corporate compliance costs, forcing firms to divert resources from production, innovation, and digital transformation to pollution control and regulatory compliance. This crowds out productive investment and restricts the application of digital technologies for intelligent monitoring, factor allocation, and energy optimization, thereby directly weakening digital empowerment and the efficiency-improving effects. However, the specific mechanism through which excessive regulatory burdens crowd out digital efficiency gains remains underexplored. It is necessary to clarify how overly strict regulation distorts resource allocation, inhibits technology diffusion, and offsets the synergistic benefits of digitalization. Only by revealing this crowding-out effect can we better demonstrate the existence of an optimal regulatory intensity and provide a solid theoretical basis for balancing environmental governance with digital-driven energy efficiency improvements. Thus, environmental regulation has an optimal intensity range; only moderate regulatory pressure can effectively unlock digital dividends without suppressing innovation vitality.

5. Discussion

Although the empirical results are econometrically robust, they need to be placed in a global research context to enhance external validity and theoretical contribution. This section compares our findings with international and domestic studies, interprets nonlinear thresholds and spatial spillovers, and clarifies consistencies and divergences with the existing literature.

Digital development has been widely proven to improve economic and environmental performance globally, but the transmission mechanisms differ across regions. In Eastern European economies, digital human capital and ICT skills training are critical drivers of enterprise operational efficiency, and enterprises that provide ICT skill-improving training significantly boost organizational performance [59]. This study focuses on macro-level digital infrastructure, digital industry development, and digital governance capacity as core driving forces of TFEE. By comparison, digital infrastructure provides hardware support for energy-saving governance, while digital skills represent software support for enterprise digital transformation [59]. The two are complementary. A critical theoretical advancement of this study is clarifying why digitalization serves as the missing condition that validates the Porter Hypothesis. In the traditional literature, the Porter Hypothesis was frequently questioned because environmental regulation often raised costs without enabling efficient innovation. In this study, we demonstrate that digital infrastructure removes the key constraint: digital monitoring, big data analysis, and cross-regional technology diffusion allow firms to rapidly optimize production processes, reduce compliance costs, and transform regulatory pressure into green innovation. Without digitalization, firms cannot respond quickly enough to activate innovation compensation; with digitalization, the Porter Hypothesis becomes empirically viable. This explains why earlier linear studies failed to support the hypothesis.

To verify the robustness and novelty of the results, this paper compares them with four recent representative studies. The benchmark regression coefficient for the digital economy (0.235) in this paper is highly consistent with the coefficient range (0.20–0.26) reported by Wen and Zhang [33], and both confirm that the digital economy significantly improves energy efficiency. Jiang et al. [34] concluded that the digital economy reduces energy consumption through structural upgrading and efficiency improvements, consistent with the mechanism proposed in this paper. Compared with existing studies, this paper further incorporates environmental regulation and interaction terms and finds that the synergistic effect is significantly positive, which is a marginal expansion of previous linear studies.

For nonlinear threshold characteristics, this paper identifies that the digital economy threshold is 0.435 and that environmental regulation shifts from a cost-following effect to an innovation compensation effect after exceeding the threshold. Most existing studies treat economic or technological development levels as threshold variables [46,48], whereas few treat the digital economy as a threshold variable. This paper further identifies the optimal interval for environmental regulation (0.327–0.493), a new empirical finding based on China's provincial data. Compared with similar studies in emerging economies, this threshold interval reflects the institutional and technological characteristics of China's development stage, and provides a quantitative basis for policy design.

In terms of the spatial spillover mechanism, this paper confirms that 56.68% of the energy-saving effect of the digital economy comes from spatial spillover channels, which supports the Metcalfe effect of digital network externalities. Specifically, it arises from provincial shared cloud-based energy monitoring platforms, unified data standards for green technologies, cross-regional digital technology trading markets, and replicable intelligent energy-saving solutions. Digital platforms enable provinces with advanced digital development to export green technologies and management experiences to neighboring regions at near-zero marginal cost, allowing firms in Province A to directly adopt green practices and efficiency-improving models from Province B. This conclusion is consistent with spatial econometric studies based on SDM in the energy field [22]. The difference is that existing studies mostly focus on the spatial spillover of a single factor, while this paper finds that the spatial spillover of the interaction term (indirect effect 0.383) is stronger than that of a single factor, proving that digital-enabled environmental regulation can break administrative boundaries and form cross-regional radiation effects. This extends the application of network externality theory to the fields of energy and the environment.

In general, this study is consistent with the existing literature in three aspects: first, the digital economy significantly improves energy efficiency [33,34]; second, environmental regulation has dual effects of cost and innovation [42,46]; third, regional TFEE has significant spatial spillover effects [22]. The marginal differences are reflected in three aspects: first, integrating digital economy and environmental regulation into a unified framework, and verifying the synergistic effect; second, taking digital economy as a threshold variable, revealing the transformation condition of environmental regulation effect; third, decomposing the spatial spillover of the interaction term, and expanding the Metcalfe effect to the "digital + green" synergy governance. These differences help to resolve the contradictions in the existing literature and provide more accurate theoretical support for the realization of the "dual-carbon" goal.

6. Conclusions and Implications

6.1. Conclusions

First, the digital economy can promote TFEE, and its spatial spillover effect is prominent; the average regional TFEE increases by 0.186 units. The spatial decomposition results show that 56.68% of the energy-saving effect of the digital economy is achieved through spatial spillover channels, reflecting the unique advantage of digital technology in breaking geographical boundaries and forming the "Metcalfe effect".

Second, environmental regulations affect shows a "conditional dependence" feature. The individual environmental regulation is manifested as "following the cost-effect" (coefficient −0.148), but when combined with the digital economy, it generates a significant positive synergy effect (interaction term coefficient 0.299), indicating that digital technology can transform regulatory pressure into innovation impetus and achieve the "innovation compensation" of the "Porter Hypothesis".

Thirdly, the digital economy is a key threshold for environmental regulations to achieve energy-saving effects. Threshold regression shows that only when the digital economy's development level exceeds the threshold of 0.435 do environmental regulations significantly promote TFEE through the "innovation compensation effect". There is also an "inverted U-shaped" threshold for the intensity of environmental regulations. A moderate intensity (0.327–0.493) is most conducive to the release of the energy-saving potential of the digital economy.

Fourth, policymakers should attach equal importance to local performance and spatial spillover contributions when evaluating provincial governments. Since the indirect effect (0.383) exceeds the direct effect (0.282), performance assessment should reward provinces that generate positive technology spillovers to neighbors, rather than merely focusing on local energy efficiency.

6.2. Policy Recommendations

Based on the above findings, this paper proposes targeted and operational policy suggestions.

First, priority should be given to increasing investment in digital infrastructure in provinces with relatively low levels of digital economy development. By tilting new infrastructure, such as computing power networks, monitoring platforms, and data sharing systems, toward less digitized provinces, China can narrow the regional digital divide, achieve energy conservation and carbon reduction at a lower cost, prevent further widening of the development gap between eastern and western regions, and lay a solid foundation for nationally unified digital-enabled green governance.

Second, we propose a digital ecological maturity index for carbon emission quota allocation. The index should be weighted by digital infrastructure, digital governance, and green innovation capacity. Instead of penalizing low-digital provinces, the index should provide additional quotas, subsidies, and policy support to help them catch up, thereby ensuring regional equity and preventing the widening of the east–west development gap.

Third, a regulatory sandbox for green fintech is recommended to combat greenwashing by adopting blockchain- and IoT-based real-time monitoring to improve the authenticity and transparency of green projects.

Fourth, in green financial governance, introduce a regulatory sandbox for green fintech to test new digital energy-efficiency solutions in a controlled environment before large-scale application, to prevent capital from distorting into the virtual economy and to support the real economy.

6.3. Limitations and Future Research Directions

This study enriches the integrated analytical framework of the digital economy and environmental regulation, but certain limitations deserve further exploration. First, the Jevons Paradox suggests that efficiency improvements may induce additional energy consumption, which requires future research to quantify the rebound effect.

Second, future studies may adopt more advanced data sources, such as web crawlers and real-time satellite imaging, to measure pollution and digital activities with higher precision, rather than relying solely on annual statistical data. These improvements will help capture dynamic changes more accurately and enhance the reliability of conclusions.

Third, this study uses provincial panel data; cross-sectional dependence (CSD) may exist among provinces due to factors such as common macroeconomic shocks, coordinated regional policies, interprovincial trade, and spatial spillover effects [60]. Future research may employ methods such as CD tests, CCEP, and MG to enhance robustness.

Fourth, there is a lack of international comparative studies. Focusing on the Chinese context, the universality of the research conclusion remains to be tested. In the future, it can be expanded to include developed economies such as the United States, the European Union, and Japan, as well as emerging economies like India and Brazil, to conduct cross-national comparative studies and distill universalizable theoretical laws.

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