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Spatial Effects of Energy System Digitization on Carbon Emissions: Evidence from China

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Abstract: This study empirically examines the spatial effects and spatial mechanisms of energy system digitization on carbon emissions by using the projection pursuit method and spatial Durbin model with panel data of 30 provinces in China from 2013 to 2021 as samples. The results show that (1) the digitization of the energy system reduces the carbon emission intensity of the surrounding areas by 2.069%, which has a significant spatial emission reduction effect. (2) Technological innovation and industrial structure optimization are important spatial impact mechanisms. (3) The spatial emission reduction effect of energy system digitization is significant in the eastern region, but not in the central and western regions, indicating that the spatial emission reduction effect of energy system digitization is spatially heterogeneous.

Keywords: carbon emissions; energy system digitization; industrial structure; smart energy; technological innovation

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1. Introduction

In the context of global climate change and the rapid growth of the digital economy, energy system digitization has emerged as one of the more crucial auxiliary tools for reducing carbon emissions and promoting energy transformation. Deep integration between the energy sector and digital technology has accelerated the growth of energy system digitization [1]. Energy system digitization performs an instrumental role in promoting productivity and improving quality of life [2]. Additionally, it provides optimized solutions for saving energy and reducing emissions, which is a crucial approach to decreasing carbon emissions [3]. Energy system digitization promotes profound changes in the mode of energy production and consumption and becomes an important instrument and vehicle for the achievement of carbon emission reduction goals, as well as a major catalyst for energy transformation [4]. Energy system digitization entails enhancing the entire efficacy of the energy system via the multidimensional integration and profound interconnection of energy, carbon, information, and value flows [5]. Energy system digitization improves energy efficiency by coordinating the precise matching of energy supply and demand to reduce carbon emissions [6]. Energy system digitization optimizes the energy structure by integrating multiple energy sources to minimize carbon emissions [7,8]. It is essential that energy system digitization may lead to interregional energy network technology sharing and enhance the degree of regional spatial interconnectivity, achieving a breakthrough in geographical distance constraints [9]. With information transfer and production element flows, energy system digitization can have a spatial influence on production and living in surrounding areas. Hence, energy system digitization may also affect the carbon emissions of surrounding areas.

This question follows: Since energy system digitization can reduce carbon emissions, does the reduction effect have spatial effects? If so, what are the specific influencing mechanisms? The answers to these questions will contribute not just to the accomplishment of regional carbon reduction goals but also to the strategic adjustment of regional energy system digitization construction.

Previous studies have failed to provide a unified framework for investigating the spatial effects of energy system digitization on carbon emissions. Meanwhile, due to the absence of a unified standard for measuring energy system digitization, there currently is a limitation of quantitative research on the spatial emission reduction in energy system digitization. In view of this, this study introduces energy system digitization technology and carbon emission factors into the endogenous growth model and analyzes the logical relationship and mechanism between energy system digitization and spatial carbon emission from the theoretical dimension by applying the dynamic optimization method. The projected tracer method serves to comprehensively evaluate the extent of energy system digitization, and the spatial measurement model is applied to verify the spatial effects of energy system digitization on carbon emissions.

In light of this, the potential marginal contributions of this paper encompass the following aspects: Firstly, this study's purpose is to enhance the theoretical awareness of the inherent connection between energy system digitization and carbon emission reduction. Secondly, adopting the projection pursuit method to comprehensively evaluate the level of energy system digitization will serve as an essential supplement to the existing literature. Finally, the spatial Durbin model is used to empirically examine the spatial effect of energy system digitization on carbon emissions and the effect's mechanism to compensate for the evident deficiencies of previous empirical investigations.

The remainder of this study is as follows: Section 2 reviews the relevant literature. Section 3 presents the theoretical analysis and research hypotheses. Section 4 presents the study methodology and data. Section 5 reports the empirical results of the impact of the energy system digitization on space carbon emissions. Section 6 discusses the findings of the study. Section 7 summarizes the study and makes several policy recommendations.

2. Literature Review

2.1. Energy System Digitization

Energy system digitization has lately emerged as a prominent subject in academic research, attracting substantial attention and sparking extensive discussion. The current field of study primarily emphasizes the discussion of energy system digitization in terms of concepts, technology applications, and actual practices.

The first focuses on the discussion of the concept of energy system digitization. The concept and content of "energy system digitization" lack a unified and precise definition, since the quick advancement of digital technology has caused varying interpretations of this term. In 2017, the International Energy Agency (IEA) published *Digitalization & Energy*, the first specific description of the digitization of energy, highlighting the consequences of digital technologies on the energy demand sector. In October 2022, the European Union introduced the "Digitalization of Energy: EU Action Plan," which focuses on the digitization of the energy field and its impact on the entirety of the energy value chain. Energy system digitization has been characterized by certain experts in terms of the impacts resulting from the application of digital technologies. Ren et al. declare that energy system digitization relies on energy big data and utilizes digital technology and control technology to facilitate the systematic movement of energy and accomplish efficient management and accurate alignment within energy supply and demand [5]. According to Baidya et al., the provision of energy may effectively meet the energy requirements of different areas, demographics, and scales, therefore producing a contemporary energy system that is characterized by high efficiency, cleanliness, and cost effectiveness [10]. This, in turn, enhances the stability, efficiency, accessibility, and sustainability of the energy system.

The second focuses on the utilization of digital technology within the energy field. The energy sector has witnessed the widespread utilization of digital technologies, including artificial intelligence, big data, cloud computing, and blockchain [11]. Hossein et al. investigate the implementation of IoT in the energy supply chain, specifically in smart cities and smart grids [12]. They indicate that the energy sector can become a decentralized and smart structure with the help of IoT technologies to change the originally centralized and hierarchical supply chain. Singh et al. perform a comprehensive review of the significance and practical implementation of digital technology in many aspects of electricity generation, distribution, transmission, grid management, and trading procedures [13]. Krawczyk et al. highlight the potential of utilizing big data technologies in energy data mining to generate novel data insights that can aid in decision making or facilitate the automated and intelligent functioning of corporations [14]. Ahmad and Zhang examine the incorporation of blockchain technology into energy systems to provide technical support for distributive and autonomous control operations as well as market transactions [1].

The third focuses on the specific practice of energy system digitization. For example, Kim et al. point out in their study that digital technologies have a dominant function in future sustainable smart city energy systems [15]; Wang and Zhan point out that energy digital technologies can provide smart solutions such as better energy planning and management for smart cities and industrial parks [16]. Wu et al. point out the impact of energy system digitization in the form of decentralized transactions enabled by the IoT as an infrastructure of energy consumption in the building and transportation sectors [17].

2.2. Energy System Digitization and Carbon Emissions

The increasing significance of energy system digitization for sustainable development is evident due to the rapid progress and widespread utilization of digital technologies in the energy sector. Consequently, there is a growing focus on researching the correlation with energy system digitization and carbon emissions. The current collection of research has predominantly concentrated on two key facets:

One facet is the theoretical examination of the correlation between energy system digitization and the generation of carbon emissions. For example, Zhu et al. investigate the potential influence of digital technology in the energy industry, specifically focusing on uncertainty forecasting, demand-side management, and multi-energy convergence. Additionally, the study explores the influence of smart energy on social sustainability [18]. Mahmud et al. demonstrate that the comprehensive integration of clean energy and information technology and the establishment of intelligent multi-energy systems with high intelligence, information transparency, and open interconnection are crucial to improving global energy efficiency and lowering emissions [19]. Zhang and Wu analyze the main shortcomings and weaknesses of energy transformation under the carbon emission reduction target from a theoretical perspective, systematically analyze the contribution of smart energy to the carbon emission reduction target, and finally point out that smart energy plays a supporting role for China’s energy transformation and carbon emission reduction target in energy supply, safe operation, and clean spending [20].

The second facet involves quantifying the influence of energy system digitization on carbon emissions. Raimi and Carrico study the association between smart grids and greenhouse gases and quantified the results, showing that smart grids have the potential to mitigate greenhouse gas emissions by around 0.9–2.2 gigatons annually, equivalent to approximately 2–5% of the world emissions [21]. This underscores the significance of smart energy systems as a crucial avenue for carbon emission reduction.

In summary, research related to energy system digitization is proceeding at a rapid pace, but due to problem identification and data limitations, the following shortcomings exist in terms of current research progress: First, direct research around energy system digitization and carbon emissions is not common and lacks rigorous theoretical clarification. Second, limited to case studies of energy system digitization, empirical studies that prove the effectiveness and transmission mechanism of its carbon emission reduction are clearly in short supply. Finally, existing research ignores its effect on the spatial dimension.

3. Theoretical Analysis and Research Hypothesis

In order to delineate the mechanism of action between energy system digitization and carbon emissions, an endogenous growth model incorporating energy digital technology and carbon emission levels is constructed, drawing on the research ideas of Haldar [22].

3.1. Basic Setting

First, the final product component: By introducing carbon emissions into the endogenous growth model, the output includes the carbon emission intensity (E) in addition to technological progress (A), labor (L), and capital (K) decisions [23], and the production function is shown specifically in Equation (1). The carbon emission intensity E ($E \in [0, 1]$) measures the degree of carbon emission from enterprise production [24]. When $E < 1$, it indicates that enterprises invest in some production factors for emission reduction and the actual output is lower than the potential output; when $E = 1$, it indicates that enterprises do not consider investing in production factors for carbon emission control and the actual output is equal to the potential output. The production function follows the Cobb–Douglas form, expressed as

$$y = f(A, L, K, E) = A^{\alpha}(\mu L)^{\alpha}K^{1-\alpha}E(0 < \mu < 1; 0 < \alpha < 1; A > 0) \tag{1}$$

In Equation (1), α represents the proportion of labor in the final production sector to the total labor force, and μ represents the effective labor elasticity coefficient.

Second, the energy data services sector. The enhancement of the energy digital level η depends on the workforce size $(1 - \mu)\, L$ and production capacity of the energy information services sector ω [25]. The dynamic equation on the upgrading of energy digital technology is expressed as

$$\dot{\eta} = \omega(1 - \mu)L\eta \quad (\omega > 0) \tag{2}$$

The utilization of digital technologies in the energy industry has led to the development of an energy network infrastructure, resulting in the enhanced dissemination capabilities of energy-related information and reduced costs associated with information exchange. Consequently, this has had a noticeable impact on the technological advancements within the output sector, gradually becoming more apparent. First, it is reflected in the influence of digital technology on the approach of energy transactions and production, as well as the effectiveness of factor production and the synergistic efficacy of the industrial chain [5]. Second, it is reflected in the diffusion of digital technology on energy information and energy information services, inducing technological transformation and the technological renewal of traditional industries [26]. Therefore, the technological transformation rate ε ($\varepsilon > 0$) is added to represent the technological progress of the final product component, which is set as in Equation (3).

$$A = \varepsilon\eta(\varepsilon > 0, \eta > 0) \tag{3}$$

In addition, we notice that the growth of digital technology breaks through the rigid constraints of geographic space–time distance, accelerates regional information sharing, knowledge accumulation, and technology diffusion, and contributes to the increasing economic spatial linkage, which requires consideration of the externality impact of energy information networks. This paper uses φ to portray the spillover effect of neighboring subjects' ICT network technology on the output sector, and the higher the level of energy information network technology η^* of neighboring subjects, the stronger the spillover effect $\varphi\,(\eta^*)$ of energy information services, $\frac{\partial\varphi(\eta^*)}{\partial\eta^*} > 0$, and the production function is adjusted to Equation (4):

$$Y = F(A, L, K, E) = \varphi A^{\alpha}\Big(\mu L)^{\alpha}K^{1-\alpha}E(\varphi > 0) \tag{4}$$

The increase in capital stock is equal to the surplus of total output Y minus total consumption C. The dynamic equation for capital accumulation is

$$\dot{K} = Y - C \tag{5}$$

Again, it is the level of carbon emissions (Z). The actual carbon emission level (Z) is jointly influenced by the environmental self-purification capacity θ and carbon emission YE^{γ}. The carbon emission level is defined as the difference between the actual carbon emission level and the desired optimal carbon emission level, where the dynamic equation is

$$\dot{Z} = -YE^{\gamma} - \theta Z(\gamma, \theta > 0) \tag{6}$$

where γ is the carbon emission regulation intensity, the larger γ is, the less the actual carbon emission of enterprises. The occurrence of extreme cases of destructive environmental damage is disregarded, so $\dot{Z} > 0$.

Finally, the objective function is constructed. The social welfare level is defined as a representative consumer's utility function U (C, Z) in relation to material consumption C and carbon emission level Z. The instantaneous utility function at time t has fixed intertemporal elasticity of substitution and additive differentiability and can be written as

$$U(C, Z) = \frac{C^{1-\sigma} - 1}{1-\sigma} - \frac{(-Z)^{1+\nu} - 1}{1+\nu}(0 < \sigma < 1, 0 < \nu < 1) \tag{7}$$

The social welfare objective of maximizing the total discounted value of instantaneous consumer utility can be expressed as

$$\Omega = \max \int_0^{\infty} U(C, Z)e^{-\rho t}dt \tag{8}$$

The relative risk aversion coefficient, denoted as σ, is equivalent to the reciprocal of the intertemporal elasticity of substitution; ν is the degree of consumer preference for the quality of carbon emission levels; and ρ is the time discount rate.

3.2. Model Solution

Social planners are faced with the task of optimizing intertemporal utility for consumers while simultaneously adhering to the dual constraints of promoting economic growth and managing carbon emissions. To address this challenge, a dynamic optimum control problem is formulated in the following manner:

$$\max \int_0^{\infty} U(C\ , Z)e^{-\rho t}dt \tag{9}$$

$$\begin{gathered}
\text{s.t. } \dot{K} = Y - C \\
\dot{\eta} = \omega(1-\mu)L\eta \\
\dot{Z} = -YE^{\gamma} - \theta Z \\
Y = \varphi A^{\alpha}(\mu L)^{\alpha}K^{1-\alpha}Z \\
A = \varepsilon\eta
\end{gathered}$$

Construct the Hamiltonian function as

$$H = U(C, Z) + \lambda_1(Y - C) + \lambda_2(\omega(1-\mu)L\eta) + \lambda_3(-YE^{\gamma} - \theta Z) \tag{10}$$

where λ is the Lagrange multiplier, C, E and μ are the control variables, and K, η, and Z are the state variables. Based on the maximum principle, the first-order conditions are obtained as follows:

$$\frac{\partial H}{\partial C} = 0 \Longrightarrow \lambda_1 = C^{-\sigma} \tag{11}$$

$$\frac{\partial H}{\partial E} = 0 \Longrightarrow \lambda_1 = \lambda_3(\gamma+1)E^{\gamma} \tag{12}$$

$$\frac{\partial H}{\partial \mu} = 0 \Longrightarrow \lambda_2 \omega L \eta = \frac{\alpha Y \gamma}{\mu(\gamma+1)} \tag{13}$$

The Euler equations are

$$\frac{\partial H}{\partial K} = \rho\lambda_1 - \dot{\lambda_1} \Longrightarrow \dot{\lambda_1} = \rho\lambda_1 - \frac{(1-\alpha)\gamma Y}{(\gamma+1)K}\lambda_1 \tag{14}$$

$$\frac{\partial H}{\partial \eta} = \rho\lambda_2 - \dot{\lambda_2} \Longrightarrow \dot{\lambda_2} = \rho\lambda_2 - \omega L \lambda_2 \tag{15}$$

$$\frac{\partial H}{\partial Z} = \rho\lambda_3 - \dot{\lambda_3} \Longrightarrow \dot{\lambda_3} = \rho\lambda_3 - (-Z)^{v} - \theta\lambda_3 \tag{16}$$

Taking the logarithm and deriving from Equation (9) the first-order-condition Equations (11)–(13) and Euler's Equations (14)–(16) gives

$$g_c = \frac{1}{\sigma}\left[(1-\alpha)\frac{\gamma}{\gamma+1}\frac{Y}{K} - \rho\right] = \frac{1}{\sigma}\left[(1-\alpha)\frac{\gamma}{\gamma+1}\varphi(\varepsilon\eta)^{\alpha}(\mu L)^{\alpha}K^{-\alpha}E - \rho\right] \tag{17}$$

$$g_Z = \frac{1-\sigma}{1+\omega}g_c = \frac{1-\sigma}{\sigma(1+\omega)}\left[(1-\alpha)\frac{\gamma}{\gamma+1}\varphi(\varepsilon\eta)^{\alpha}(\mu L)^{\alpha}K^{-\alpha}E - \rho\right] \tag{18}$$

Considering the optimal sustainable growth path, energy system digitization will be upgraded faster than physical capital accumulation to overcome the pressure on polluting output from diminishing returns to capital; thus, $g_c > 0$. To avoid the ecosystem experiencing irreversibility, the intertemporal elasticity of the substitution of rational consumers satisfies the preference constraint of $1/\sigma < 1$; thus, $g_z < 0$. It is clear that on the steady-state growth path, energy system digitization is a critical factor in sustaining economic growth and lowering carbon emissions. Combining Equation (18), solving the first-order differential equation yields

$$Z = Z_0 \exp\left\{\frac{(1-\sigma)t}{\sigma(1+\omega)}\left[(1-\alpha)\frac{\gamma}{\gamma+1}\varphi(\varepsilon\eta)^{\alpha}(\mu L)^{\alpha}K^{-\alpha}E - \rho\right]\right\} \tag{19}$$

Using Equation (19) to find the partial derivative of Z with respect to η, we obtain $\partial Z/\partial\eta > 0$, which implies that energy digital technology has a favorable impact on reducing carbon emissions. Using Equation (19) to find the partial derivative of Z with respect to φ, we obtain $\partial Z/\partial\varphi > 0$, indicating that the utilization of energy digital technology exhibits a geographical spillover phenomenon that contributes to the reduction in carbon emission intensity. In the context of regional connectedness facilitated by energy networks, the process of energy system digitization has the potential to impact not only the carbon emissions inside a specific region but additionally extends its influence to the neighboring regions. In view of this, the following assumptions are proposed in this study: Hypothesis 1. The development of energy system digitization contributes to the reduction in surrounding regions' carbon emissions, displaying a spatial emission reduction effect.

Combining Equations (2) and (3), the spatial emission reduction mechanisms for analyzing energy system digitization will be specifically divided into technological innovation and industrial structure optimization mechanisms.

In the mechanism of technological innovation, green technological innovation can be rapidly diffused to surrounding areas through the information network of energy system digitization. According to existing research, the accessibility of external information is recognized as a key factor affecting green technology innovation [27]. Temporal and spatial constraints limited the process of exchanging and obtaining information prior to the broad use of digital technology. Limited by traditional information collection tools and communication means, obtaining information on green technology innovation requires high search costs, tracking costs, and negotiation costs [28]. Energy system digitization depends on digital technology being widely used and incorporated into the energy sector. This makes energy information transmission timely, accurate, and sufficient, and it also helps reduce information inequality. Digitizing energy can potentially address the limitations of time and physical space, reducing expenses associated with searching for and tracking information related to green energy technology innovation. Moreover, this digitization can facilitate the spread of green technology innovation to neighboring regions, therefore yielding various benefits. On this basis, we propose Hypothesis 2, that energy system digitization can influence spatial carbon emission via the spread of green technology innovations.

In the mechanism of industrial structure optimization, energy system digitization affects the carbon emissions of the surrounding region by optimizing the industrial structure. The construction of energy system digitization will absorb a large amount of investment into the industry and guide the industry to transformation and advancement in the direction of clean, green, and low-carbon energy [29]. Simultaneously, it will also facilitate the advancement and enhancement of industries in the adjacent regions via the influence of economies of scale and competitive forces, hence mitigating carbon emissions in the bordering areas [30]. On this basis, Hypothesis 3 proposes that energy system digitization can optimize the industrial structure and thereby influence carbon emissions in the surrounding region.

4. Methodology and Data

4.1. Research Methods

Regions in China have extensive and interconnected economic connections, resulting in strong spatial correlations in various aspects of economic activities, such as regional digital economic development and carbon emissions. If such spatial correlations are ignored, biases may arise in coefficient estimation, and spatial econometric models need to be established. For that reason, it is necessary to examine and control for the spatial association when examining the influence of energy system digitization on carbon emission intensity. Therefore, we build the spatial Durbin model as follows:

$$\begin{aligned} lncei_{it} = a_0\sum_{j=1}^{n} W_{ij} lncei_{it} + b_0 lnesd_{it} + c_0 ln(X_{it}) + d_0 \sum_{j=1}^{n} W_{ij} lnesd_{it} \\ + e_0 \sum_{j=1}^{n} W_{ij} ln(X_{it}) + \mu_i + \nu_t + \varepsilon_{it} \end{aligned} \tag{20}$$

cei_{it} denotes the regional carbon emission intensity; $lnesd_{it}$ denotes the energy system digitization level of the explained variables; X_{it} denotes the control variable; a_0 is the spatial autocorrelation coefficient of the explanatory variable; b_0 denotes the regression coefficient of the explanatory variable; c_0 denotes the spatially lagged regression coefficient of the explanatory variable; μ_i,ν_t,ε_{it} denote the regional fixed effects, time fixed effects, and residual terms. W is the spatial weight matrix, using the geographical distance between regions as the weights.

4.2. Data and Variable Description

4.2.1. Explained Variables

The core explanatory variable selected for this study is carbon emission intensity (*cei*). This is precisely indicated by the amount of carbon emissions produced per unit of GDP. The carbon emissions data are obtained with reference to the IPCC carbon emission factor accounted method, while the GDP data are obtained from the China Statistical Yearbook [31].

4.2.2. Explanatory Variable

The degree of energy system digitization (*esd*) is the explanatory variable in this paper. Academics argue that the digital transformation of industries is often a complex process. The utilization of digital technology within the industrial sector is contingent upon several aspects, including the prevailing technological advancements and the current state of industry growth.

For researchers to fully analyze the consequences of digital technology on the energy industry, it is vital to carefully investigate the specific characteristics related to the incorporation of digital technology in this sector. Currently, there is no authoritative understanding of how to determine the degree of energy system digitization.

Nevertheless, the most representative approach to assess the digitalization level of different industries is through the use of indicator methods to build a multidimensional indicator system for quantitative assessment. Many scholars refer to the assessment system of the OECD to gauge the extent of informatization, and this research also refers to relevant studies to create a multidimensional index system for gauging the extent of regional energy system digitization. This paper considers digital infrastructure and digital applications as the primary indicators for measuring the first levels of energy system digitization, taking into account that digitalization is mainly expressed in these terms. In Table 1, we select specific measurement indicators. This paper uses Liu et al.'s projection pursuit method to perform a full evaluation because the data are high-dimensional, nonlinear, and not normal [32]. This method not only keeps as many of the original data's characteristics as possible but also gets around the problem of traditional evaluation methods being too subjective. Using the projection pursuit method to measure the extent of energy system digitization includes three main steps [33]:

Table 1. Energy system digitization level evaluation index system.

First-Level Indicators	Second-Level Indicators	Indicator Description
Energy system digitization foundation	Information infrastructure	Length of fiber-optic cable lines
	Mobile network infrastructure	Cell phone penetration rate
	Internet penetration rate	Number of computers per hundred people
	Digitalization level at the energy consumption end	Number of websites per hundred enterprises
	Electricity infrastructure	Length of 35 kV and above transmission line circuits
	Electricity digitalization investment	Investment in power grid construction
Energy system digitization applications	Industrial power availability	Industrial electricity prices
	Residential electricity availability	Residential electricity price
	Electricity reliability	Reliability rate of electricity supply
	Electricity responsiveness	Power outage time
	Electricity flexibility	Number of charging piles

Firstly, the data of the energy system digital indicator system are normalized. Assume that the indicator values are $\{x\ (i, j) \mid i = 1, 2, \ldots, n; j = 1, 2, \ldots, m\}$, where n and m are the number of samples and the number of indicators, respectively; the sequence of indicator eigenvalues $X\ (i, j)$ is obtained after normalization.

Secondly, construct the projection indicator function Q (q). Initially, the p-dimensional data $\{X\ (i, j) \mid j = 1, 2, \ldots, m\}$ in a one-dimensional projection with $q = \{q\ (1), q\ (2), \ldots, q\ (m)\}$

are given the one-dimensional projection value p (i) in the projection direction. Then, the projection indicator function Q (q) is constructed according to the principle that the projection value p (i) is dispersed as much as possible.

$$p(i) = \sum_{j=1}^{m} q(j) \times X(i,j)\ (i = 1, 2, \cdots, n) \tag{21}$$

$$S_p = \sqrt{\frac{\sum_{i=1}^{n} (p(i) - X(p))^2}{n-1}} \tag{22}$$

$$D_p = \sum_{i=1}^{n}\sum_{j=1}^{m} [(R - r(i,j))u(R - r(i,j))] \tag{23}$$

$$Q(q) = S_p \times D_p \tag{24}$$

where S_p is the standard deviation of the sequence p (i), D_p is the local density of the sequence p (i), and Q (q) is the projection indicator function.

Finally, the ideal projection direction is determined. The projection function Q (q) is a function of the projection direction q. The different q will exhibit different data structure characters. To ensure the maximum exposure of the data characteristics of the energy system digitization multidimensional indicators, this study searches for the most optimal projection direction q* by solving the projection function maximization method.

$$\begin{gathered} maxQ(q) = \max\{S_p \times D_p\} \\ s.t. \sum_{j=1}^{m} q^2(j) = 1 \end{gathered} \tag{25}$$

When using traditional methods to optimize the projection objective function, the objective function is generally required to be continuous, derivable, and computationally intensive, which is difficult to handle. To overcome this shortcoming, this paper invokes the real number encoding accelerated genetic algorithm (RAGA), which simulates the mechanisms of biological meritocracy and chromosomal information exchange within the whole population, to solve the problem and simplify the operation by using computer technology. The projection value of every sample is determined by putting the optimal projection direction (q*) obtained in the previous step into Equation (21).

4.2.3. Control Variable

Referring to the decomposition of carbon emission influencing factors in the IPAT model [34], we control the following variables that may impact carbon emissions: (1) population (*pop*), expressed using the total regional population [35]; (2) gross domestic product of the region (GDP), using the regional gross product [36]; (3) energy intensity (*ei*), expressed using energy consumption per unit of GDP [37]; (4) energy structure (*es*), expressed using carbon emissions per unit of energy consumption [38].

This study utilizes panel data, including 30 provinces in China from 2013 to 2021, as the sample for analysis. Due to limitations of the data availability, Tibet, Hong Kong, Macau, and Taiwan were excluded from the dataset. Relevant measures such as the digitization of energy systems, regional carbon emissions, and other control variables are selected from the China Statistical Yearbook (2013–2021), the China Electricity Statistical Yearbook (2013–2021), and the yearbooks of each province and city. Descriptive statistics of the variables involved in this paper are summarized in Table 2. The software used for data processing and empirical analysis in this study is Stata 17.0.

Table 2. Descriptive statistics of variables related to energy system digitization and carbon intensity.

Variables	Mean	Std. Dev.	Min	Max	Obs
cei	0.0182315	0.0143008	0.0022916	0.0808533	270
esd	1.245928	0.4588142	0.398113	2.38057	270
GDP	26,749.78	23,917.77	904.635	124,369	270
pop	3930.97	3029.346	163.2	11,192	270
iso	0.3957767	0.076695	0.159671	0.55762	270
git	4372.626	6244.653	22	45,359	270
es	357.2353	517.1539	1.24646	4576.07	270
ei	0.9022378	0.7090153	0.0542	3.20352	270

5. Empirical Results

5.1. Spatial Autoregressive Test

Prior to commencing the spatial econometric assessment, it must be imperative to ascertain the presence of a spatial correlation among the variables [39]. This investigation employs the global Moran's I index to determine the presence of a spatial correlation between the carbon emission intensity of Chinese provinces and cities. The corresponding calculation outcomes are shown below in Table 3**.**

Table 3. Moran's I index of China's emission intensity.

Year	Moran's I
2013	0.013 *
2014	0.028 **
2015	0.033 **
2016	0.033 **
2017	0.027 **
2018	0.023 *
2019	0.024 *
2020	0.011 *
2021	0.010 *

* $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

The outcomes in Table 3 reveal that the Moran's I index of the carbon emission intensity of Chinese provinces and cities from 2013 to 2021 has a minimum value of 0.010, and the Moran's I indexes are all positive and passed the significance test at the 10% level. This indicates that the distribution of the carbon emission intensity in Chinese provinces is characterized by spatial agglomeration, and it is necessary to add spatial geographic factors to analyze the impact of energy system digitization on regional carbon emission levels.

5.2. Baseline Results

Both the Wald test and the LR test indicated statistical significance at the 1% level, demonstrating the presence of both a spatial error term and a spatial lag term in the model. The initial hypothesis of using an SLM model and SEM model are rejected. The spatial Durbin model is considered suitable. The estimation results of the spatial Durbin model are shown in Table 4.

The baseline regression outcomes listed in column (1) of Table 4 show that the coefficient of the effect of energy system digitization on the carbon emission intensity is −0.822, which is significantly negative. The coefficient of the spatial spillover effect of energy system digitization is −2.069, which is also significantly negative. This indicates that energy system digitization can reduce both the local and neighboring carbon emission intensity.

Furthermore, this work adopts the partial differential approach for the purpose of effect decomposition and the results of the decomposition are displayed in Table 5. Energy system digitization has two distinct effects on carbon emissions: direct and indirect. The direct impact refers to the way energy system digitization affects the local carbon emissions. Simultaneously, the indirect effect pertains to the influence of energy system digitization on carbon emissions in the nearby regions. The decomposition analysis reveals that both the direct and indirect impacts coefficients are −0.780 and −0.396, respectively, and both are statistically significant. This demonstrates that energy system digitization has a suppressive effect on the carbon emission intensity of both local and surrounding areas.

Table 4. Spatial econometric model regression results.

Variable	Baseline Return	Technology Innovation		Industry Structure	
	(1)	(2)	(3)	(4)	(5)
esd	−0.822 ***	1.733 ***		−0.073 ***	
	(−10.624)	(27.021)		(−7.355)	
*esd * lngit*			−0.081 ***		
			(−11.940)		
*esd * iso*					−1.548 ***
					(−4.782)
*W * esd*	−2.069 ***	1.708 ***		−0.332 ***	
	(−3.696)	(3.006)		(−4.219)	
*W * esd * lngit*			−0.226 ***		
			(−4.392)		
*W * esd * iso*					−13.482 ***
					(−4.508)
Control variable			yes		
Year FE			yes		
Wald SLM	16.44 ***				
Wald SEM	16.51 ***				
N	270	270	270	270	270

* $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5. Decomposition effect results.

Variable	Baseline Return	Technology Innovation		Industry Structure	
	(1)	(2)	(3)	(4)	(5)
LR_Direct					
esd	−0.780 ***	1.718 ***		−0.062 ***	
	(−9.621)	(27.105)		(−6.353)	
*esd * lngit*			−0.076 ***		
			(−10.466)		
*esd * iso*					−0.989 ***
					(−3.739)
LR_Indirect					
esd	−0.396 *	0.810 ***		−0.069 ***	
	(−1.828)	(2.655)		(−2.649)	
*esd * lngit*			−0.041 **		
			(−2.230)		
*esd * iso*					−4.668 ***
					(−4.023)
LR_Total					
esd	−1.176 ***	2.528 ***		−0.131 ***	
	(−5.752)	(8.066)		(−4.805)	
*esd * lngit*			−0.117 ***		
			(−6.880)		
*esd * iso*					−5.657 ***
					(−4.534)
N	270	270	270	270	270

* $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Research Hypothesis 1 verifies that the development of energy system digitization contributes to the reduction in surrounding regions' carbon emissions, displaying a spatial emission reduction effect.

5.3. Mechanism Results

This study examines the mediated effects model suggested by Zhang, Ge, and Liu to test the above mechanisms of energy system digitization to reduce spatial carbon emissions [40].

Set the specific models as follows:

$$\begin{gathered} Channel_{it} = a_{01}\sum_{j=1}^{n} W_{ij}Channel_{it} + b_{01}lnesd_{it} + c_{01}ln(X_{it}) + \\ d_{01}\sum_{j=1}^{n} W_{ij}lnesd_{it} + e_{01}\sum_{j=1}^{n} W_{ij}ln(X_{it}) + \mu_i + \nu_t + \varepsilon_{it} \end{gathered} \tag{26}$$

$$\begin{gathered} lncei_{it} = a_{02}\sum_{j=1}^{n} W_{ij}lncei_{it} + b_{02}lnesd_{it} + c_{02}ln(X_{it}) + f_1 Channel_{it} \times lnesd_{it} + \\ d_{02}\sum_{j=1}^{n} W_{ij}lnesd_{it} + e_{02}\sum_{j=1}^{n} W_{ij}ln(X_{it}) + f_2\sum_{j=1}^{n} W_{ij}Channel_{it} \times lnesd_{it} + \mu_i + \nu_t + \varepsilon_{it} \end{gathered} \tag{27}$$

where *Channel* denotes channels such as technological innovation and industrial structure optimization.

In the spatial mechanism test, technological innovation (*it*) is chosen as the scalar of the number of green patents [41]. Industrial structure optimization (*iso*) is denoted by the percentage of gross product from the secondary sector to the tertiary sector [42].

The test outcomes of the mechanism variables in Equation (26) are listed in columns (2) and (4) of Table 4. In column (2), the results of the technology innovation mechanism test, the coefficient of energy system digitization (*esd*) is 1.733, and the coefficient of spatial spillover (*W* * *esd*) is 1.708, both of which are statistically significantly positive, illustrating that energy system digitization has an essential function in promoting technological innovation in local and surrounding areas. In column (4) of the industrial structure mechanism test results, the coefficient of energy system digitization (*esd*) is −0.062, and the coefficient of spatial spillover (*W* * *esd*) is −0.069, both of which are statistically significant and negative, illustrate that energy system digitization has the ability to optimize the industrial structure of both local and surrounding areas.

The test outcomes of the mechanism variables resting on Equation (27) are displayed in columns (3) and (5) of Table 4. Both the regression coefficients of technological innovation (*it*) and industrial structure (*iso*) are significant, and the coefficient of energy system digitization (*esd*) becomes smaller and less significant compared to the baseline regression, indicating the existence of a transmission mechanism. Research Hypothesis 2, that energy system digitization can influence spatial carbon emission via the spread of green technology innovations, is verified. Research Hypothesis 3, that energy system digitization can optimize the industrial structure and thereby influence carbon emissions in the surrounding region is verified.

5.4. Robustness Results

Considering the possible endogeneity between energy system digitization and regional carbon emission levels [43,44], which could introduce bias in the estimation outcomes, the quasi-natural experiment of "smart energy" is used to further test the results. Smart energy is a typical practice in energy system digitization [45]. In 2016, the Chinese government put out the "Guiding Opinions on Promoting the Development of "Internet+" Smart Energy" policy. Subsequently, in 2017, they announced the initial selection of 55 demonstration projects for "Internet+" smart energy. These projects meet the criteria for quasi-natural experimentation.

The conventional difference-in-difference (DID) model needs to strictly satisfy the assumption that the individual treatment effect is stable [46], but according to the theoretical analysis, it is found that the energy system digitization will have an impact on the surrounding areas, which does not satisfy the SUTVA assumption. This study aims to enhance the existing model by including spatial analysis and introducing a spatial lag component to the conventional difference-in-difference model. Consequently, a spatial difference-in-differences model (S-DID) is formulated.

$$lncei_{it} = a_{03}\sum_{j=1}^{n} W_{ij} lncei_{it} + b_{03} dudt + c_{03} ln(X_{it}) + d_{03}\sum_{j=1}^{n} W_{ij} dudt + e_{03}\sum_{j=1}^{n} W_{ij} ln(X_{it}) + \mu_i + \nu_t + \varepsilon_{it} \quad (28)$$

where *du* denotes the pilot region dummy variable, *dt* denotes the time dummy variable, and other settings are as above.

The baseline regression outcomes of the S-DID are displayed in column (1) of Table 6. The policy interaction coefficient of the smart energy pilot (*dudt*) is −0.608 and the spatial spillover effect (*W* * *dudt*) coefficient is −2.822, which are statistically significant and negative, verifying that research Hypothesis 1 is true.

Table 6. Regression results of spatial difference-in-difference model for smart energy pilot regions.

Variable	Baseline	Technology Innovation		Industry Structure	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
dudt	−0.608 ***	1.113 ***		−0.048 ***	
	(−4.880)	(7.856)		(−4.600)	
*dudt * lngit*			−0.075 ***		
			(−5.484)		
*dudt * iso*					−1.355 ***
					(−3.816)
*W * dudt*	−2.822 ***	3.215 ***		0.017 *	
	(−3.091)	(3.255)		(0.232)	
*W * dudt * lngit*			−0.295 ***		
			(−2.863)		
*W * dudt * iso*					−10.333 ***
					(−3.603)
Control variable			yes		
Year FE			yes		
N	270	270	270	270	270

* $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

The findings of the S-DID spatial effect mechanism test are displayed in Table 6, columns (2)–(5). The results of the technological innovation mechanism test reveals that the spatial interaction coefficient between technological innovation and the policy dummy variable is negative for significance. This implies that smart energy may influence spatial carbon emissions by using the mechanism of technological innovation.

The results of the industrial structure optimization mechanism test reveals that the spatial interaction coefficient between industrial structure optimization and the policy dummy variable is also negative for significance. This indicates that smart energy has the ability to influence spatial carbon emissions by means of optimizing industrial structure.

Hence, the exogenous shock test of smart energy policies further validates that the aforementioned conclusions are robust.

5.5. Research on Regional Space

Since economic activities and carbon emissions are not all the same in different areas and the progress of digitalizing energy infrastructure is not all the same, it is likely that the effect of digitizing energy on the carbon emission intensity will be different in each area. This study aims to further examine this regional heterogeneity.

The sample is split into three regions: eastern, central, and western. The regional division is detailed in Appendix A, Table A1. The results of the subgroup regressions are shown in Table 7.

Table 7. Baseline regression results for different regions.

Variable	Eastern	Central	Western
esd	−1.067 ***	0.277	0.425
	(−17.756)	(1.197)	(1.005)
W * *esd*	−1.618 ***	−0.268	−2.505 *
	(−5.732)	(−0.344)	(−1.731)
Control variable		Yes	
Year FE		Yes	
N	99	72	99

* $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

In column (1) of Table 7, the test results for the eastern region show that the coefficient of the direct effect of energy system digitization on the carbon intensity in the eastern region is −1.067, and the coefficient of the spatial spillover effect in the eastern region is −1.618, and it is statistically significantly negative. This indicates that energy system digitization has both a direct carbon emission reduction effect and a spatial emission reduction effect in the eastern region. In column (2) of Table 7, the test results for the central region indicate that the core explanatory variables (*esd*, *W* * *esd*) do not pass the significance test, and it is not possible to verify that the digitization of the energy system has a significant impact on the carbon emission intensity in the central region. In column (3) of Table 7, the test results for the western region indicate that the spatial spillover effect coefficient (*W* * *esd*) of energy system digitization on carbon emission reduction in the western region is −2.505, and it is significantly negative. This demonstrates that energy system digitization has a spatial carbon emission reduction effect in the western region.

To explore the reasons for the differences in the emission reduction effects of energy system digitization in different regions, the spatial mechanism of energy system digitization in the subregions is further examined. The specific outcomes are presented in Table 8.

Columns (1), (2), (5), (6), (9), and (10) of Table 8 show the results of the test of technology innovation mechanism in different regions. The test of the impact of the digitization of the energy system in the eastern region on technological innovation in the core explanatory variables *esd* coefficient is 1.596; *W* * *esd* is 1.904, and is significantly positive; *W* * *esd* * *lngit* is −0.139, and is significantly negative. The test of the impact of the digitization of the energy system in the western region on technological innovation in the core explanatory variables *esd* coefficient is 1.589; *W* * *esd* is 2.897, and is significantly positive; *W* * *esd* * *lngit* is −0.0.592, and is significantly negative. The central region's technology innovation mechanism test results in the core explanatory variables do not pass the test of significance. This indicates that the eastern and western regions' green technology spillover to neighboring regions creates significant carbon emission reduction effects, while the central region's technological innovation mechanism is not significant. We analyze the reasons for this result: First, the eastern economically developed region has the foundation and advantages of technological innovation. Second, the western region is wealthy in clean energy resources, and the impact of relevant policies, policy support, and market choices in recent years have all been favorable to the growth of green technology innovation in the western region. Third, the central region lacks the corresponding conditions, and the technological innovation effect of energy system digitization is not significant, affecting its emission reduction effect.

Columns (3), (4), (7), (8), (11), and (12) of Table 8 show the results of the test of industrial structure optimization in different regions.

Table 8. Regression results for different regional spatial mechanisms.

Variable	Eastern				Central				Western			
	Technology Innovation		Industry Structure		Technology Innovation		Industry Structure		Technology Innovation		Industry Structure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
esd	1.596 ***		−0.064 ***		0.178		0.005		1.589 ***		−0.119 ***	
	(15.344)		(−3.940)		(1.154)		(0.159)		(3.187)		(−4.291)	
*esd * lngit*		−0.094 ***				0.029				−0.017		
		(−18.061)				(1.038)				(−0.395)		
*esd * iso*				−1.843 ***				1.102 **				2.366 **
				(−6.447)				(2.379)				(2.216)
*W * esd*	1.904 ***		0.018		−1.304 **		0.011		2.897 *		−0.442 ***	
	(4.396)		(0.223)		(−2.064)		(0.098)		(1.653)		(−4.710)	
*W * esd * lngit*		−0.139 ***				−0.019				−0.592 ***		
		(−4.761)				(−0.218)				(−4.401)		
*W * esd * iso*				−2.465				−0.163				0.458
				(−1.167)				(−0.090)				(0.119)
Control variable	Yes											
Year FE	Yes											
N	99	99	99	99	72	72	72	72	99	99	99	99

* $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

The test of the impact of the digitization of the energy system in the eastern region on industrial structure optimization on the core explanatory variables *esd* coefficient is −0.064, *W* * *esd* is 0.018, and *W* * *esd* * *lngit* is −0.139. However, the optimization effect of energy system digitization on the industrial structure in the central and western regions is not significant. Indeed, there is even a negative spillover of the emission reduction effect. This means that minimizing the amount of secondary industry will actually increase carbon emissions in neighboring regions. The change in industrial structure arising from energy system digitization leads to a shift in carbon emissions and negative spatial spillover effects. The main reason for this change is the strong demand for economic growth in the central and western areas.

6. Discussion

Within the framework of the expeditious advancement of the digital economy, the process of energy system digitization has emerged as a significant approach to mitigate carbon emissions and expedite the shift towards sustainable energy sources. Whether energy system digitization can break through geographic and spatial constraints to produce spatial carbon emission reduction is emerging as a crucial concern in the current state of energy system digitization and energy green transformation. This study investigates, from the theoretical perspective, the logical relationship and mechanism of effect between energy system digitization and spatial carbon emissions.

Firstly, it is clear from the analysis of this study that the energy system digitization has a direct effect on the carbon emission intensity of the region and an indirect effect on the carbon emission intensity of the surrounding areas. This indicates that the digitization of energy system has a significant spatial emission reduction effect.

Secondly, as seen from the study of further spatial impact mechanisms, energy system digitization can produce significant carbon emission reduction effects through the spillover of technology innovation to the surrounding regions. Meanwhile, it can also guide industrial transformation and upgrading through the optimization of industrial structure and influence the carbon emission intensity of the surrounding regions.

Finally, considering the impact of differences between regions, further regional heterogeneity analysis is conducted. East China's energy system digitization implementation has both significant direct carbon emission decrease effects and spatial emission decrease spillover effects. Central and Western China's energy system digitization implementation does not have a significant effect on carbon emissions, mainly due to local demand for economic development, innovative sources, and other conditions.

7. Conclusions and Policy Implications

This study employs the projection pursuit method to generate a comprehensive evaluation index system for assessing the progress of energy system digitization in Chinese provinces from 2013 to 2021. The spatial econometric models are utilized to empirically test the spatial effect of energy system digitization on carbon emission reduction and spatial mechanisms. The main conclusions are as follows: (1) The energy system digitization significantly reduces the carbon emission intensity of the surrounding regions by 2.069%. (2) The spatial mechanism analysis results indicate that technological innovation and industrial structure optimization are the main transmission mechanisms. (3) The heterogeneity analysis reveals that the spatial emission reduction effect of energy system digitization is more significant in the eastern region, while it is not significant in the central and western regions.

The analysis concludes with the following proposed policy recommendations:

First, strengthen the radiation-driven role of energy system digitization. Energy system digitization can achieve spatial spillovers of carbon emission reduction through technological innovation and industrial structure optimization. Thereby, we can give full play to the leading demonstrative role of regions with higher levels of energy system digitization, establish technology alliances, industry alliances, and other cooperation and exchange platforms, and provide organizational support for regional alliances in order to strengthen the radiation-driven role of energy system digitization.

Second, encourage regional spatial linkage to carry out unified and coordinated construction and planning of energy system digitization. Energy system digitization, as a method for reducing digital carbon emissions, relies heavily on spatial linkage and its planning and development within the overall coordinated planning and development of the region. This approach is essential for maximizing the potential of energy system digitization in reducing carbon emissions.

Third, we should increase policies related to energy system digitization. The construction of energy system digitization is characterized by a large scale, a long cycle, and high costs. To accelerate the energy digital transformation, it is necessary to further guide the incentives and increase the relevant policies.

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Appendix A

Table A1. Regional division of Chinese provinces and cities.

Region	Province
Eastern	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central	Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan, Jilin, Heilongjiang
Western	Neimenggu, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

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