sustainability

Article

Impact of Digital Economy on the Upgrading of Energy Consumption Structure: Evidence from Mainland China

Yating Zeng , Xinyue Xu, Yuyao Zhao and Bin Li *

School of Economics and Management, Beijing University of Chemical Technology, Beijing 100029, China
* Correspondence: libin@mail.buct.edu.cn

Abstract: The digital economy is fundamentally altering human productivity and lifestyles, gradually becoming a new engine that drives energy technology transformation and optimizes the energy consumption structure. This paper examines the impact of the digital economy on upgrading the energy consumption structure using panel data from 30 Chinese provinces from 2013 to 2019. The empirical findings indicate that the digital economy's development can help to improve energy consumption structure, and this impact can have a threshold effect. Heterogeneity analysis reveals that upgrading the energy consumption structure affected by the digital economy is more significant in lower digital divide regions, the eastern and central regions, and provinces with high economic development levels. Moreover, the findings of a mechanism analysis demonstrate that the digital economy primarily influences green technology innovation, and government environmental regulation affects the major upgrades of the energy consumption structure.

Keywords: digital economy; energy consumption structure; threshold effect; green technology innovation; environmental regulation

Citation: Zeng, Y.; Xu, X.; Zhao, Y.; Li, B. Impact of Digital Economy on the Upgrading of Energy Consumption Structure: Evidence from Mainland China. *Sustainability* **2023**, *15*, 5968. https://doi.org/10.3390/su15075968

Academic Editor: Wen-Hsien Tsai

Received: 24 February 2023
Revised: 18 March 2023
Accepted: 20 March 2023
Published: 30 March 2023

1. Introduction

Energy is the fundamental guarantor of economic growth and human well-being. Global energy-related CO_2 emissions hit a new high in 2021. A coal-based energy consumption structure would significantly increase carbon emissions and reduce sustainable economic growth [1]. With fossil energy supply becoming increasingly tight, ecological and environmental problems have attracted widespread global attention. Optimizing the energy consumption structure is a major issue that needs to be considered.

At present, the digital economy is growing rapidly, and it is expanding in scale. The digital economy is a new social quality efficiency and global economic growth engine, and it also provides new possibilities for the structure of energy use. The deep integration of digital technology and traditional industries supports the intelligent transformation of traditional industries, and the deep integration with the energy industry supports energy efficiency improvement and technological innovation. Additionally, research revealed that the digital economy had shown a strong impetus for the optimization of the industrial chain [2–4], green consumption [5–7], green production [8], and green government affairs [9]. Therefore, in theory, the digital economy is essential for enhancing energy consumption structure and fostering the development of a green economy.

Scholars have focused extensively on the link between energy challenges and economic development. Many factors affect the optimization and upgrading of the energy consumption structure, including the state of the environment, social conditions, rate of economic development, industrial organization, and governmental regulations. As a precursor to both the technology and industrial revolutions, the digital economy has also become an effective way to improve energy consumption [10,11]. First of all, energy efficiency can be greatly increased through the digital economy. The adoption of digital technology, for instance, can change consumer behavior to lower household electricity consumption [12], can help to automate production to reduce energy consumption [13,14], and can promote the upgrading of buildings [15], hotels [16], transportation [17], and other sectors of society. Second, the digital economy has the obvious potential to promote the use of renewable energy and the high-quality development of the energy industry. The digitalization of energy has increased the level of energy innovation [18], the transition to green energy [19,20], and the efficient allocation of energy [21], and has spurred a reduction in fuel intensity [22,23]. Third, the convergence of digitalization and everyday life has given rise to new consumption patterns and changed energy consumption patterns [24]. For example, online shopping, online education, and digital healthcare are typical digital consumption patterns. They change the traditional way of energy consumption and reduce energy consumption through dematerialized information transmission modes. Summarizing the existing research from the perspective of energy consumption, most of them discuss the influencing factors of energy consumption efficiency and energy consumption, but the existing research has not given a systematic answer to the question of whether the digital economy is conducive to the upgrading of the energy consumption structure.

The following are some of this paper's potential contributions to the literature: (1) a thorough examination of the internal theoretical logic of a digital economy as it affects the energy consumption structure, confirming that it has a threshold effect on upgrading the energy consumption structure and that it also has network effects that promote the upgrading of the energy consumption structure, and (2) an exploration of the role of green technology innovation and environmental regulation in the intermediary mechanism, as it offers a new mechanism explanation for comprehending how the growth of the digital economy influences energy consumption.

This is the rest of the paper: the second section is the mechanism analysis and puts forward the research hypothesis; the third section explains the research model and sample data; the fourth section gives the empirical results and the robustness test regression results; the fifth section is the heterogeneity test; the sixth section is the mechanism test; and the last section is the conclusion and implications.

2. Theoretical Analysis and Research Hypothesis

2.1. The Effects of Digital Economy on Energy Consumption Structure

Modernizing the energy consumption structure aims to improve traditional energy efficiency while increasing the use of new energy. One aspect of the digital economy is to promote and accelerate technological innovation, which can both improve energy efficiency and support the production and use of new energy sources. On the other hand, by strengthening the government's environmental rules and guidance, the digital economy can optimize the energy consumption structure.

First, the digital economy promotes technological progress in the energy field, promotes the creation and use of new energy, improves traditional energy efficiency, and optimizes the energy consumption structure. In terms of energy efficiency improvement, first of all, the digital economy optimizes the accuracy of business management decisions and market forecasting. Through the intelligent transformation of the energy production process, enterprises can collect, detect, transmit, and analyze energy data flow in real time. Moreover, manufacturing methods and technologies have been innovated, and energy efficiency has been improved through the use of intelligent devices [25,26]. In addition, the role of information, communication technologies, and services in economic development have been emphasized in the digital economy. Real-time information can be better used in the digital economy to advocate for flexible production models; these can prevent unnecessary energy waste and can significantly improve energy efficiency [27,28]. In terms of research, development, and the utilization of new energy on one hand, digital technology helps to accelerate the research, development, and utilization of new energy. The digital economy, with big data and cloud computing as typical features, squeezes traditional high-pollution and high-energy-consuming enterprises. These can efficiently integrate talents, capital, technology, knowledge, and other innovative elements quickly and effectively, supporting the innovation of green technology. On this basis, the acceleration of R&D and the utilization of green energy [20,29] are byproducts. On the other hand, digital technology will help develop and improve energy consumption patterns, accelerate the increase in demand for new energy consumption in various industries, and usher in a green era of energy. In addition, the digital economy can also use digital media to spread the concept of green life to consumers, guide the public to protect the environment, save resources, improve the public's awareness of green innovation, and force the green transformation of energy from the consumption side.

Also, as the digital economy grows, the government will be better able to monitor and manage energy use, which will improve the way that it is consumed. To start, because the digital economy is rapidly expanding, governments now have access to a wide range of digital surveillance tools. By constructing digital platforms, advanced digital applications enable governments to collect and analyze routine information from massive amounts of data, as well as to establish energy consumption feedback mechanisms. Governments have improved their refinement and their responsiveness in energy consumption control, and this has led to cleaner energy consumption and the decarbonization of regional development [30,31]. In addition, the digital economy offers the potential to improve the efficiency of energy information exchange and to enable the real-time sharing of energy supply and demand data between governments and market participants. The problem of information asymmetry between government departments, between governments and businesses, and among the public has been addressed. This allows government decision making to become more scientific and refined. Expanding the reach and scope of the application of environmental supervision regulations is facilitated by expanding corporate publicity and public environmental oversight channels through digital media. Additionally, the digital economy has the joint role of integrating the market and stimulating market vitality. Big data and other technologies can assist governments in identifying future energy development paths and market needs, allowing them to make sound environmental decisions. Finally, the cross-spatial, cross-field, and cross-time characteristics of the digital economy foster the smooth flow of production factors. Examples include using digital government to improve regional government cooperation, coordinating policy formulation to guide the greening of social production, and expanding the space for the promotion and utilization of new energy sources [32].

Accordingly, the following hypothesis is proposed.

Hypothesis 1 (H1). *The digital economy has a positive impact on the upgrading of the energy consumption structure.*

2.2. Digital Economy's Threshold Effect on Energy Consumption Structure

Unique laws, such as Moore's Law and Metcalfe's Law, regulate the advancement of digital technology, which forms the basis of the digital economy [33,34]. The network effects are theoretically present in the digital economy's compensation system, as well. This is in stark contrast to traditional economic inputs, which are governed by the law of diminishing marginal benefits. As more people participate, the digital economy will expand in size and value, which will, in turn, lure more individuals to join. This demonstrates that as the digital economy grows in size, its marginal impact on the energy consumption structure will grow as well.

Specifically, in the early days of the digital economy, digital networks were small, as were the number of consumers and producers who participated in the digital economy. Therefore, the marginal impact of the digital economy on the energy consumption structure at this time will be minimal. Then, with the acceleration in the scale of the digital economy, the optimal allocation of resource elements such as knowledge, technology, capital, and talents will further reduce the cost of technology circulation. Metcalfe's law states that the value of a network is proportional to the square of the number of connected users. This means that the more users a network has, the more valuable it is [35]. As the digital economy grows and expands, more people will be drawn into the digital world, and the marginal role of the digital economy will grow rapidly [36]. In addition, once the digital economy develops to a certain extent, network users will break through a certain threshold and will trigger a positive feedback mechanism to achieve explosive growth in network value. At that time, the marginal effect of the digital economy on upgrading the energy consumption structure will be significantly improved.

Accordingly, the following hypothesis is proposed.

Hypothesis 2 (H2). *The digital economy has a threshold effect on the upgrading of the energy consumption structure.*

3. Model Construction and Data Description

3.1. Metrology Model Setting

The digital economy opens up new possibilities for the optimization and upgrading of the energy consumption structure. To determine whether this impact exists significantly, model (1) is constructed:

$$ECS_{it} = \alpha_0 + \alpha_1 DIG_{it} + \alpha_j \Sigma X_{jit} + v_t + \eta_t + \varepsilon_{it}, \quad (1)$$

where t stands for the year, i for the province, ECS_{it} stands for the energy consumption structure, DIG_{it} marks the degree to which each province's digital economy has developed, X_{jit} is a series of control variables, v_t is the time fixed effect, η_t is the provincial fixed effect, and ε_{it} is the random perturbation term. When the regression coefficient, α_1, is significantly negative, it indicates that the digital economy helps to optimize energy consumption structure, and H1 is verified.

Further testing is needed to determine whether the digital economy has a nonlinear effect on the energy consumption structure and whether there are threshold conditions. That is, tests are needed to determine whether a certain level of the digital economy will considerably alter the marginal influence on the structure of energy use. This paper draws on the practices of Hansen [37] and Tran et al. [38] to set the panel threshold model. Assuming only one threshold point, a single threshold model (2) is used.

$$\begin{gathered} ECS_{it} = \varphi_0 + \varphi_1 DIG_{it} \times I(DIG_{it} \le \omega) + \varphi_2 DIG_{it} \times I(DIG_{it} > \omega) + \varphi_j \Sigma X_{jit} + \\ v_t + \eta_t + \varepsilon_{it} \end{gathered} \quad (2)$$

In this formula, DIG is a threshold dependent variable and is also the core explanatory variable, ω is the threshold value, $I(.)$ represents an indicative function, if the conditions in parentheses match the actual situation, the value is 1; if they do not, the value of the indicated function is 0. φ_0 is the constant term, φ_1 and φ_2 are the parameters to be estimated, φ_1 is the influence coefficient of the digital economy on consumption structure upgrading at $DIG \le \omega$, φ_2 is the influence coefficient of the digital economy on the consumption structure upgrading at $DIG > \omega$.

If there are two thresholds, extend the model (2) to a double threshold model (3).

$$\begin{gathered} ECS_{it} = \rho_0 + \rho_1 DIG_{it} \times I(DIG_{it} \le \omega_1) + \rho_2 DIG_{it} \times I(\omega_1 < DIG_{it} < \omega_2) \\ + \rho_3 DIG_{it} * I(DIG_{it} \ge \omega_2) + \rho_j \Sigma X_{jit} + v_t + \eta_t + \varepsilon_{it} \end{gathered} \quad (3)$$

Among them, ω_1 and ω_2 are two thresholds, and $\omega_1 < \omega_2$, these two thresholds divide the total sample into 3 intervals; ρ_1, ρ_2 and ρ_3 are the regression coefficients of DIG of three core explanatory variables in different intervals, and if there are three or more thresholds, this method can be used to establish a multi-threshold model.

3.2. Variable Selection

The energy consumption structure (ECS) is the dependent variable, affected by the characteristics of China's energy resource endowment of "more coal, less oil and lack of gas". Coal still dominates the energy consumption structure [39]. The fundamental purpose of optimizing energy consumption structure is to decrease the proportion of fossil energy, such as coal, in total energy consumption. Based on this, this paper refers to Wu et al. [40], Sun and Ren [41], and Xue et al. [42] to sort out and use the ratio of total coal consumption to total energy consumption as a proxy variable. The data are collected from the China Energy Statistical Yearbook.

The Digital Economy Index (DIG) is the independent variable. At present, there is still great controversy in the academic community about how to comprehensively measure the digital economy in various provinces. Considering that the digital economy is not only reflected in digital infrastructure construction but also in the digital transactions, this paper refers to the views of Wang and Xu [43] and Li et al. [44] to incorporate the indicators of the three major aspects of information development, Internet development, and digital transaction development into the measurement index system. The data are collected from the China Statistical Yearbook, the China Science and Technology Statistical Yearbook, and Provincial Statistical Yearbooks. As shown in Table 1, in the specific calculation, the relevant data are standardized, and the weights of each index in the assessment system are determined using the entropy approach. Then, the multi-objective linear weighted function method is used to weight the index. Finally, the digital economy index of each province is obtained, expressed as DIG.

Table 1. Digital Economy Index (DIG).

Primary Indicators	Secondary Indicators	Measurement Indicators
Informatization development Indicators	The level of investment in informatization construction	Ratio of the length of the optical cable to the area (6.19%)
		Ratio of the number of mobile phone base stations to the area (6.93%)
		Ratio of employees in information transmission, software and information technology services to total employment (3.77%)
	The output level of informatization construction	Total telecom services (10.24%)
		Software business revenue (15.96%)
Internet development indicators	The level of Internet fixed broadband terminal construction	Internet access port density (7.33%)
	The level of Internet mobile terminal construction	Ratio of the number of mobile phones to the total population (1.95%)
	The output of Internet fixed broadband terminal construction	Ratio of fixed broadband subscribers to the total population (4.56%)
	The output of Internet mobile terminal construction	Ratio of mobile Internet users to the total population (2.17%)
Digital transaction development indicators	The level of Digital transaction construction	Ratio of the number of company's website to the number of enterprises (0.73%)
		Ratio of the number of computers used by the enterprise to the number of enterprises (3.27%)
		Ratio of enterprises with e-commerce transaction activities in the total number of enterprises (5.8%)
	The output level of digital transaction	E-commerce sales (13.04%)
		Online retail sales (18.06%)

The selection of control variables in the model refers to previous studies [29,42,45], and the data is collected from the China Statistical Yearbook and Provincial Statistical Yearbooks.

Control variables include the level of economic development ($lnGDP$), industrial structure (IS), foreign direct investment (FDI), human capital (HC), urbanization rate (UR), and infrastructure (BI). In addition, set the annual dummy variable ($Year$) and the province dummy variable ($Province$) to control the impacts of the year and individual effects. Table 2 displays the specific variable names and measurement methods.

Table 2. Main variable measurement methods.

Variable	Description
Dependent variable	
ECS	Energy consumption structure. Usage of coal as a percentage of total energy consumption.
Independent variable	
DIG	Digital economy index. The indicators are weighted using a multi-objective linear weighting function method, and then each region's digital economy index is obtained.
Control variable	
lnGDP	Level of economic development. The gross regional product logarithm.
IS	Industrial structure. The proportion of the tertiary industry's added value to the secondary industry's contributed value.
FDI	Foreign direct investment. The ratio of the amount of foreign capital actually deployed in each region to regional GDP is used.
HC	Human capital. The number of students in tertiary education in each region as a proportion of the district population.
UR	Rate of urbanization. The ratio of urban to regional population is employed.
BI	Infrastructure. The local road miles logarithm.
Year	The year effect.
Province	The province effect.

3.3. Data Sources

This paper analyzes panel data from 30 provinces in China from 2013 to 2019 to ensure data accessibility and consistency throughout time. The exclusion of Tibet, Hong Kong, Macao, and Taiwan owes to missing data in some years. The primary sources of the data are the China Statistical Yearbook, the China Energy Statistical Yearbook, the China Science and Technology Statistical Yearbook, and Provincial Statistical Yearbooks. The data on digital financial inclusion are obtained from the Digital Finance Research Center of Peking University.

Table 3 shows the descriptive statistics. To make the estimation more intuitive, this paper uses ArcGIS software to show the energy consumption structure of 30 provinces in China in the form of maps in 2013 and 2019 (shown in Figure 1). It can be clearly seen that compared with 2013, the proportion of coal consumption in total energy consumption in 2019 has decreased significantly, and there are obvious differences between different provinces, which laid a good foundation for the regression test below.

Table 3. Descriptive statistics.

Variable	N	Max	Min	Mean	Median	Std. Dev.
ECS	210	0.666	0.012	0.379	0.397	0.144
DIG	210	0.701	0.073	0.206	0.184	0.112
lnGDP	210	11.59	7.446	9.834	9.918	0.868
IS	210	5.234	0.665	1.365	1.192	0.729
FDI	210	1.22	0.001	0.201	0.181	0.178
HC	210	0.039	0.009	0.02	0.019	0.005
UR	210	0.942	0.365	0.588	0.571	0.119
BI	210	33.71	1.26	15.299	15.875	8.008

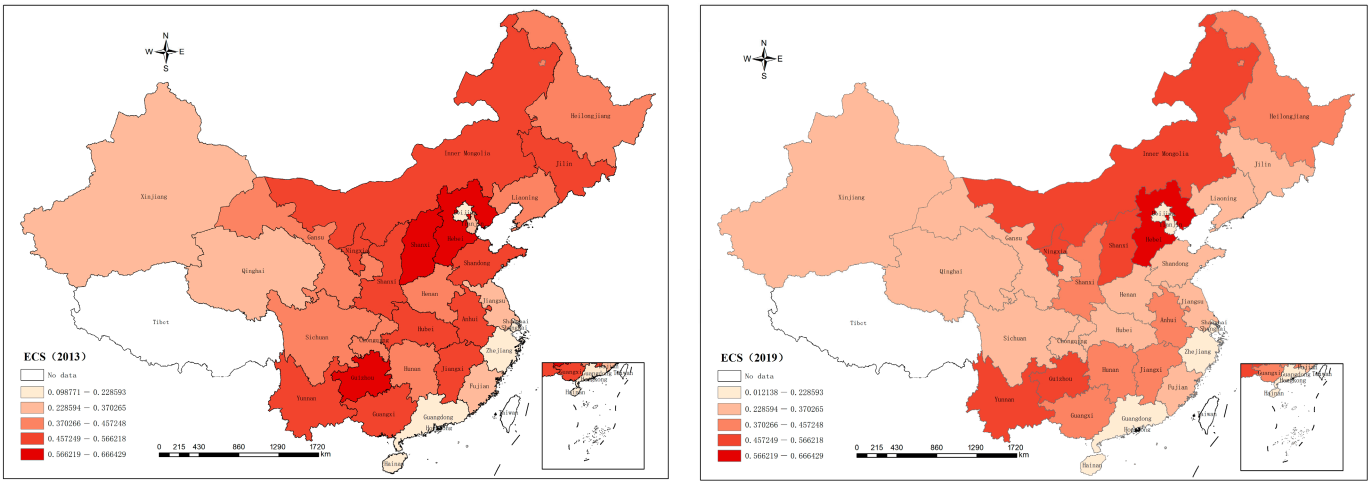

Figure 1. Energy consumption structure in China in 2013 (**Left**) and 2019 (**Right**).

4. Empirical Results

4.1. Baseline Regression and Endogenous Problem Treatment

Table 4 displays the statistical baseline findings of the effect of the digital economy (DIG) on the energy consumption structure (ECS). The fixed-effects model is chosen in this study based on the findings of the Hausman test, where the *p*-value is 0.0000. Hence, the outcomes of the two-way fixed-effect model are used in the discussion that follows. Column (1) of Table 4 demonstrates the impact of the DIG on the ECS. The DIG regression coefficient is −0.3638 and is significant at the 1% level. For every percentage increase in the digital economy, the proportion of coal consumption in total energy consumption will decrease by 0.3638 percent. This shows that the digital economy will help the upgrading of energy consumption structure. Hypothesis H1 is confirmed.

Considering that provinces with a more reasonable energy consumption structure may attach more importance to the development of the digital economy, the reverse causal relationship between the DIG and ECS brings endogenous problems. In this paper, the lagging one-stage independent variable and the instrumental variable were used for endogenous testing. First, this paper uses lagging one-stage independent variables to further test hypothesis 1. Column (2) of Table 4 shows that the impact coefficient of the DIG on the ECS in the lagging period is −0.4826. It is still significantly negative at the 1% level. For every unit increase in the digital economy, the proportion of coal consumption will decrease by 0.4826 percent. H1 is still robust.

Table 4. Baseline regression and endogenous test results.

Variable	Bidirectional Fixed Effect (1) ECS	Lag One-Stage Independent Variable (2) ECS	2SLS (3) ECS
DIG	−0.3638 *** (−4.0085)		
L.DIG		−0.4826 *** (−4.0975)	
RDLS			−2.1181 *** (−4.4135)
lnGDP	0.0783 * (1.7102)	0.0898 (1.6537)	0.1441 *** (3.2231)
IS	−0.0013 (−0.0611)	0.0094 (0.3813)	−0.0051 (−0.2089)
FDI	0.0236 (1.2237)	0.0163 (0.7509)	−0.1679 *** (−3.3109)

Table 4. *Cont.*

Variable	Bidirectional Fixed Effect (1) ECS	Lag One-Stage Independent Variable (2) ECS	2SLS (3) ECS
HC	−7.3082 ***	−8.0679 **	−8.1520 *
	(−2.7034)	(−2.6049)	(−1.9332)
UR	−0.1989	−0.3151	0.2682 *
	(−0.8997)	(−1.1890)	(1.7158)
BI	−0.0127 ***	−0.0115 ***	−0.0046
	(−3.8125)	(−3.0667)	(−1.5948)
_cons	0.1318	0.0823	−0.5997 *
	(0.2836)	(0.1491)	(−1.7942)
Year	Control	Control	Control
Province	Control	Control	
N	210	180	210
R2	0.688	0.684	0.494

Note: The value of T in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Second, this paper uses instrumental variables to solve endogenous problems so as to ensure more stable and reliable estimation results. Referring to Duflo [46] and Ivus et al. [47], the product of topographic undulations and dummy variables by year (RDLS) was selected as the instrumental variable for this study. The two-stage least squares (2SLS) method is used for regression. The logic of selecting instrumental variables is as follows: on the one hand, the terrain undulations reflect the complexity of the terrain, and the complexity of the terrain will directly affect the installation and commissioning of the digital infrastructure. Therefore, the more undulating the terrain, the greater the cost and challenge of building digital infrastructure and the less developed the digital economy. On the other hand, topographic undulations as a natural factor are not directly related to other factors. The details of the instrumental variables' regression findings are presented in Column (3) of Table 4. After taking into account the endogeneity issue, the effect of the DIG on the ECS is notably negative. This suggests that Hypothesis H1 still holds. For every unit increase in the digital economy, the proportion of coal consumption will decrease by 2.1181 percent. Under-identification is not a problem, as evidenced by the under-identification test's LM statistic value of 13.083, which corresponds to a p-value of 0.0000, which is less than 0.05. There is no weak instrumental variable in the equation, according to the Cragg-Donald Wald F value of 13.022 in the weak identification test, which is higher than the empirical value of 10 for the relevant instrumental variable suggested by Staiger et al. [48].

4.2. Robustness Test

Based on the robustness of the endogenous testing, this paper also adopts the method of substituting the independent variable and the dependent variable to test the robustness.

(1) Change the DIG's measurement. This paper builds on the methods of Gao et al. [49] to create a comprehensive digital economy development level index (DIG1) from the dual dimensions of Internet development [50] and digital inclusive finance [51]. To establish a comprehensive digital economy development index as an explanatory variable for robustness testing, this study uses principal component analysis to normalize, downscale, and finally standardize the data of the five indicators of Internet development and digital inclusive finance. For the development of digital finance, the China Digital Financial Inclusion Index is used, which is jointly compiled by the Digital Finance Research Center of Peking University and Ant Financial Services Group. Other data are collected from the Provincial Statistical Yearbooks.

Column (1) of Table 5 shows a coefficient of −0.0535 for DIG1 and a significant 1% level. The share of coal consumption will decrease by 0.0535 percent for every unit increase in the digital economy, indicating that hypothesis 1 remains robust.

Table 5. Replace the key variable robustness test results.

Variable	(1) ECS	(2) EL
DIG1	−0.0535 ***	1.5044 ***
	(−2.8095)	(5.2817)
lnGDP	0.0830 *	−0.5276 ***
	(1.7107)	(−3.6721)
IS	0.0141	−0.0090
	(0.6232)	(−0.1366)
FDI	0.0149	−0.0354
	(0.7620)	(−0.5852)
HC	−4.8146 *	13.4861
	(−1.7969)	(1.5897)
UR	0.0276	−0.1282
	(0.1294)	(−0.1848)
BI	−0.0121 ***	0.0301 ***
	(−3.5607)	(2.8876)
_cons	−0.1338	9.8474 ***
	(−0.2709)	(6.7526)
Year	Control	Control
Province	Control	Control
N	210	210
R2	0.674	0.720

Note: The value of T in parentheses. *** $p < 0.01$, * $p < 0.1$.

(2) Change the ECS's measurement. This study tests the robustness of the ECS using the low-carbon level index (EL) of each province's energy consumption pattern as a proxy variable. The data are collected from the China Energy Statistical Yearbook.

The exact calculation procedure is as follows:

$$EL = arccos(\cos(\theta_1))^3 + arccos(\cos(\theta_2))^2 + \mathrm{arccos}(\cos(\theta_3))$$
$$\cos\theta_1 = \sqrt{\frac{\alpha}{\alpha^2+\beta^2+\gamma^2}} \qquad \cos\theta_2 = \sqrt{\frac{\beta}{\alpha^2+\beta^2+\gamma^2}} \qquad \cos\theta_3 = \sqrt{\frac{\gamma}{\alpha^2+\beta^2+\gamma^2}}$$

Among them, α, β and γ are the ratios of coal, oil, and other energy consumption to the total energy consumption in each province. The higher the indicator of the low-carbon index, the more reasonable the energy consumption structure. Column (2) of Table 5 shows the regression coefficient of DIG is 1.5044 and significant at the level of 1%. For every percentage increase in the digital economy, the energy decarbonization index will increase by 1.5044 percent. It is assumed that H1 remains robust.

4.3. Threshold Effect Regression

Before the threshold effect analysis, the threshold model needs to be tested for significance to determine both the threshold number and whether there is a significant threshold effect. This paper uses "self-sampling" to repeat the estimate 300 times. Table 6 shows the p value obtained after the threshold effect test of the impact of the digital economy on energy consumption structure under three assumptions: with a single threshold, a double threshold, and three thresholds. Based on Table 6, there is a significant single threshold, and there is not a significant double or triple threshold. When the single threshold point is that the digital economy is equal to 0.173, there is a significant difference between the marginal effects of the digital economy on the structure of the energy consumption before and after the single threshold value of 0.173. Figure 2 is the threshold estimation test chart; the part where the curve falls below the reference line indicates that the single threshold value is significant. The threshold model will be constructed based on the single threshold later.

Table 6. Threshold effect existence test.

Model	*F*-Value	*p*-Value	Threshold Estimates	Different Significance Cut-Offs		
				1%	5%	10%
Single threshold	23.69	0.020 **	0.173	27.044	16.838	14.425
Double threshold	5.19	0.677	0.245	23.565	16.051	13.452
Triple threshold	4.00	0.747	0.423	18.762	12.763	10.617

Note: ** $p < 0.05$.

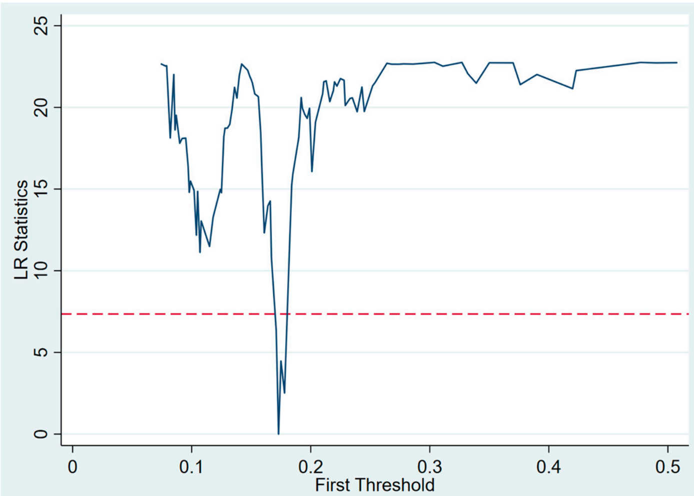

Figure 2. Threshold variable estimation.

When the digital economy level is less than 0.173, seeing in Table 7, the DIG regression coefficient is −0.167, which is significant at the 5% level. The marginal impact coefficient of DIG on ECS rises to −0.341 and the significance level to 1% when the digital economy level exceeds the threshold. It can be seen that the digital economy plays a role in upgrading energy consumption structure when it is at a low level, and when the digital economy reaches a high level, its promotion effect is multiplied, and the significance of the impact is also significantly improved.

Table 7. Single sill panel regression results.

Variable	Coefficient	SD	T	P	95% CI
DIG (*DIG* $\leq$ 0.173)	−0.167 **	0.080	−2.090	0.038	(−0.326, −0.009)
DIG (*DIG* $>$ 0.173)	−0.341 ***	0.074	−4.580	0.000	(−0.487, −0.194)
lnGDP	0.060 *	0.035	1.700	0.090	(−0.010, 0.130)
IS	0.003	0.017	0.150	0.882	(−0.031, 0.036)
FDI	0.004	0.019	0.200	0.840	(−0.033, 0.041)
HC	−5.355 **	2.399	−2.230	0.027	(−10.091, −0.619)
UR	−0.153	0.169	−0.900	0.368	(−0.486, 0.181)
BI	−0.009 ***	0.003	−2.730	0.007	(−0.015, −0.002)
Cons	0.176	0.292	0.600	0.549	(−0.401, 0.753)
N			210		

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The rationale is that "Metcalfe's law" is essentially how the digital economy develops. Due to the limitations of the institutional environment, the infrastructure level, human capital, and other constraints in the early stages, the network effect brought by it cannot be effectively exerted. The digital economy is less integrated with the energy consumption structure. However, as the digital economy develops further, the marginal costs of innovation and research and development continue to decline, and the energy industry sector gradually produces economies of scale. It can take full advantage of the benefits of digitalization, introduce advanced energy production technologies, and better improve the structure of energy consumption. Thus, the threshold effect of the level of digital economic growth is confirmed, the hypothesis H2 is validated.

5. Heterogeneity Analysis

To make the regional heterogeneity division more intuitive, this paper uses ArcGIS software to show the digital economy in 30 provinces in China in the form of maps in 2013 and 2019 (shown in Figure 3). Figure 3 demonstrates that there are very noticeable regional differences in the process of the development of the digital economy. For instance, the level of the digital economy has been relatively high in China's eastern coastal region, and it has also recently experienced rapid growth in the central and western regions. Additionally, taking into account that different regions of China have varying levels of economic development models and digital infrastructure construction. The heterogeneity of the digital divide, regional heterogeneity, and economic development level heterogeneity is used in this study to assess how the digital economy has affected energy consumption structure.

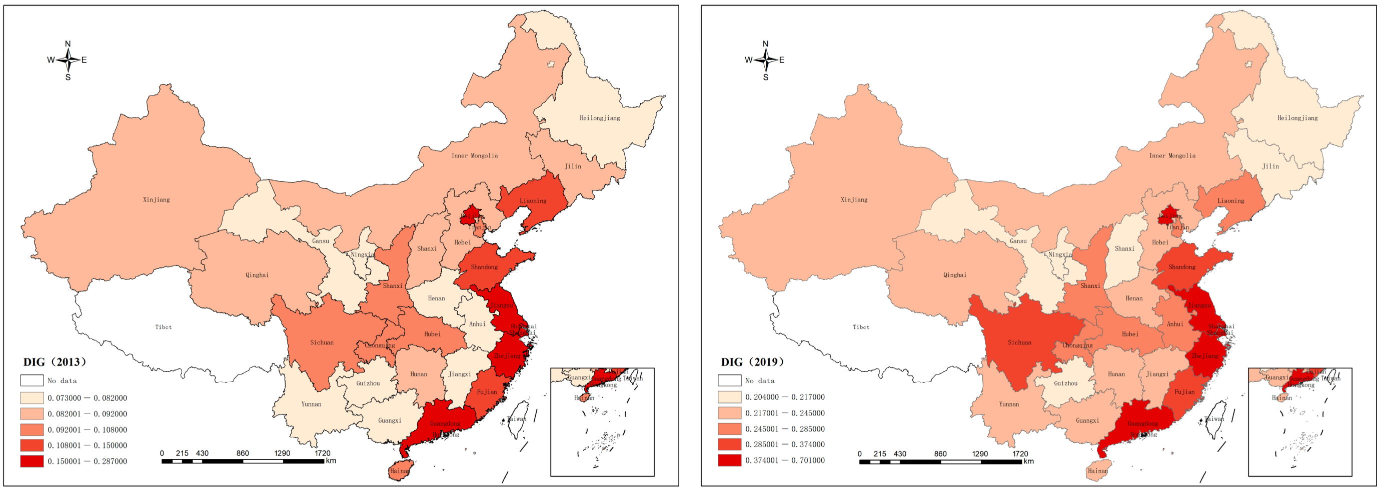

Figure 3. Digital economy development in China in 2013 (**Left**) and 2019 (**Right**).

5.1. Heterogeneity of Digital Divide Levels

The digital economy is based on digital technologies. Due to the large differences in the application of information and network technology in different regions, the digital divide will inevitably be reflected in the digital economy. It will also have varying effects on the upgrading of the energy consumption structure. Drawing on the methodology of the China Digital Divide Report 2013 of the National Network Center to construct a comprehensive relative gap index (DD) of the digital divide among provinces in China from 2013 to 2019, reflecting the gap between different provinces in the ownership and use of major information technology products (Comprehensive relative gap index = 0.25 * Internet penetration relative gap index + 0.25 * home computer ownership relative gap index + 0.25 * home TV ownership relative gap index + 0.125 * fixed telephone penetration rate relative gap index + 0.125 * mobile phone penetration relative gap index. Among them, the Internet penetration relative gap index = (national average Internet penetration rate—regional Internet penetration rate)/national average Internet penetration rate, and so on for other relative gap indicators. All raw data are measured from the official website of the National Bureau of Statistics). Provinces with a comprehensive relative gap index greater than zero are classified as areas with a lower digital divide, and provinces with less than zero are classified as areas with a high digital divide.

Furthermore, China has seen the leading development of economically backward provinces in the development of the digital economy, such as China's Guizhou Province, which continues to consolidate its digital infrastructure and strive to seize new opportunities in the implementation of the digital economy strategy. In the White Paper on the Development of China's Digital Economy (2022), Guizhou's digital economy grew at a rate of 20.6% in 2021, 4.4 percent higher than the national average, and the province ranked first in the country for seven consecutive years. As a result, this paper considers whether the digital economy can hasten the improvement of energy consumption structure from the standpoint of the digital divide between regions.

Columns (1) and (2) of Table 8 show the influence of the DIG on the ECS is significantly negative at the level of 1% in provinces with a low digital divide, but not in provinces with high levels of the digital divide. The results show that the role of the digital economy in upgrading the energy consumption structure is selective, and the precondition is that the regional digital technology level is high.

Table 8. Three heterogeneous regression results.

Variable	**High DD (1) ECS**	**Low DD (2) ECS**	**Eastern (3) ECS**	**Central (4) ECS**	**Western (5) ECS**	**Low GDP (6) ECS**	**High GDP (7) ECS**
DIG	−0.1389	−0.8313 ***	−0.3652 ***	−1.6204 ***	−0.4280	−0.2638	−0.2571 **
	(−1.2599)	(−3.8425)	(−3.9032)	(−3.0077)	(−1.0440)	(−0.6145)	(−2.2854)
lnGDP	0.1640	0.1395 ***	0.3347 ***	0.2508 ***	−0.1411	0.0692	0.1959 *
	(1.4390)	(2.6383)	(3.8406)	(3.3346)	(−1.1004)	(1.2334)	(1.9032)
IS	−0.0746 **	0.0702 **	−0.0267	0.1446 ***	−0.0558	0.0479	−0.0345
	(−2.3020)	(2.3849)	(−0.9344)	(3.5577)	(−0.9735)	(1.6000)	(−1.0421)
FDI	0.0015	−0.0297	−0.0253	0.0653	−0.2133	0.0422*	0.0081
	(0.0524)	(−0.4989)	(−1.1314)	(0.9582)	(−1.4058)	(1.9276)	(0.1072)
HC	7.7720	−9.7131 ***	−8.5066	−10.0041 **	−4.8391	−15.5866 ***	−5.7537
	(0.9524)	(−3.4296)	(−1.2711)	(−2.3709)	(−0.9229)	(−3.6340)	(−1.1411)
UR	−0.8093 **	−0.9155 **	−0.3927	1.5902 **	−1.7305 **	−1.7474 ***	−0.0193
	(−2.1598)	(−2.3477)	(−1.2496)	(2.3407)	(−2.6028)	(−3.5437)	(−0.0599)
BI	−0.0060	−0.0130 ***	0.0060	−0.0083 *	−0.0145 *	−0.0069	−0.0171 ***
	(−0.7636)	(−3.3409)	(0.5927)	(−1.8088)	(−1.7502)	(−1.0375)	(−4.0063)
_cons	(−0.6348)	(−0.0074)	−2.5634 ***	−2.4250 ***	2.9660 ***	1.0667 *	−1.1266
	−0.1389	−0.8313 ***	(−2.6732)	(−3.7183)	(2.8135)	(1.8405)	(−1.0405)
Year	Control	Control	Control	Control	Control	Control	Control
Province	Control	Control	Control	Control	Control	Control	Control
N	60	150	77	56	77	105	105
R2	0.811	0.713	0.797	0.898	0.735	0.690	0.750

Note: The value of T in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2. Regional Heterogeneity

Given China's vast territory and the potential differences in the geospatial, economic development model and information openness of the eastern, central, and western regions, referring to the research of relevant scholars [52,53], this paper divides the sample into eastern, central, and western regions by province, and uses the benchmark regression model (1) for regression.

Columns (3), (4), and (5) of Table 8 show the influence of the DIG on the ECS is significantly negative at the level of 1% in the eastern and central regions but not in the western regions. The reason for this could be that the eastern and central provinces have an advantage in terms of economic development, information openness, geographical space, and the digital economy has a greater impact on the eastern and central provinces. The western region, on the other hand, has long relied on traditional resources, and the digital economy has had little impact on upgrading its energy consumption structure. Furthermore, the central provinces have always been an important industrial and energy base in China, and the digital economy has promoted the upgrading of high-energy-consuming industries in the central provinces, making significant contributions to upgrading the energy consumption structure.

5.3. Heterogeneity of Economic Development Levels

The structure of energy consumption is closely related to the level of economic development. Changes in social production and lifestyle and the change of energy consumption concepts under the economic background directly affect the restructuring and modernization of the energy consumption pattern. According to the median gross domestic product (GDP), this paper is divided into the group with a low economic development level and the group with a high economic development level.

Columns (6) and (7) of Table 8 display that the DIG regression coefficient of the low economic development level group is negative but not significant, whereas the DIG regression coefficient of the high economic development level group is negative and significant at the 5% level. This demonstrates that the impact of the digital economy on the upgrading of the energy consumption structure is more pronounced in provinces with high levels of economic development.

The shift to a stage of high-quality economic development may be a significant factor since it alters the structure of the demand for energy use. The industrial model of "high energy consumption, high pollution, and high emissions" cannot be the foundation for good-quality economic growth, and the expansionary growth of "high resource consumption, high environmental pollution, and cheap labor costs" must be abandoned.

6. Mechanism Verification

To further open the black box of the impact mechanism of the digital economy on the upgrading of energy consumption structure, this paper employs an intermediary model to verify. Specifically, the practice of Baron and Kenny [54] and Shahbaz et al. [45] is borrowed, and the hierarchical regression method is used for verification. In terms of mechanism testing, this paper combines the actual availability of variables and data and still follows the analysis logic of main regression from "digital economy-green technology innovation-energy consumption structure" and "digital economy-government environmental regulation-energy consumption structure".

6.1. Mediating Mechanism of Green Technology Innovation

The regression model of this study uses green technology innovation as a mediating variable. Referring to Chen et al. [55], Feng et al. [56], and Su et al. [57], the number of green invention patents (PGP) per capita obtained in a given year was used as a proxy variable for green technology innovation. The China Research Data Service Platform's Green Patent Database serves as the source of the green patent information (GPRD). Models (3) and (4) are based on Model (1), with PGP standing for Green Technology Innovation. The remaining variables are identical to those found in the benchmark regression model (1).

$$PGP_{it} = \theta_0 + \theta_1 DIG_{it} + \theta_j \Sigma X_{jit} + v_t + \eta_t + \varepsilon_{it} \quad (4)$$

$$CES_{it} = \pi_0 + \pi_1 DIG_{it} + \pi_2 PGP_{it} + \pi_j \Sigma X_{jit} + v_t + \eta_t + \varepsilon_{it} \quad (5)$$

When θ_1 is significantly positive, π_2 is significantly negative, and $\pi_1 < \alpha_1$, PGP is the mediating variable between the development of the DIG and the ECS.

Column (2) of Table 9 displays that the DIG regression coefficient is 0.7690, which is 1% significant. This suggests that the digital economy can encourage businesses to innovate in the field of green technology. The regression coefficient of PGP is −0.0905 in the regression findings in column (3), which is 1% significant. DIG's regression coefficient is −0.2942, which is 1% significant. Therefore, green technology innovation has played an intermediary role in the impact of the digital economy on energy consumption structure.

Table 9. Regression results of the mediating role of green technology innovation.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	ECS	**PGP**	**ECS**	**ECS**	**PGP**	**ECS**
DIG	−0.3638 ***	0.7690 ***	−0.2942 ***			
	(−4.0085)	(2.6303)	(−3.3105)			
L.DIG				−0.4826 ***	0.8087 **	−0.4115 ***
				(−4.0975)	(2.3000)	(−3.5404)
PGP			−0.0905 ***			−0.0879 ***
			(−3.9290)			(−3.1834)
lnGDP	0.0783 *	0.5379 ***	0.1270 ***	0.0898	0.4944 ***	0.1333 **
	(1.7102)	(3.6467)	(2.7827)	(1.6537)	(3.0492)	(2.4525)
IS	−0.0013	0.5164 ***	0.0455 *	0.0094	0.4631 ***	0.0502 *
	(−0.0611)	(7.6263)	(1.9420)	(0.3813)	(6.2634)	(1.8452)
FDI	0.0236	0.0836	0.0312 *	0.0163	0.0442	0.0201
	(1.2237)	(1.3456)	(1.6755)	(0.7509)	(0.6842)	(0.9591)
HC	−7.3082 ***	−14.3551	−8.6080 ***	−8.0679 **	−12.1233	−9.1337 ***
	(−2.7034)	(−1.6484)	(−3.2923)	(−2.6049)	(−1.3112)	(−3.0263)
UR	−0.1989	−2.3690 ***	−0.4134 *	−0.3151	−2.4818 ***	−0.5333 **
	(−0.8997)	(−3.3263)	(−1.8876)	(−1.1890)	(−3.1369)	(−2.0074)
BI	−0.0127 ***	−0.0180 *	−0.0143 ***	−0.0115 ***	−0.0140	−0.0127 ***
	(−3.8125)	(−1.6818)	(−4.4477)	(−3.0667)	(−1.2496)	(−3.4855)
_cons	0.1318	−3.8517 **	−0.2170	0.0823	−3.4229 **	−0.2186
	(0.2836)	(−2.5730)	(−0.4773)	(0.1491)	(−2.0767)	(−0.4026)
Year	Control	Control	Control	Control	Control	Control
Province	Control	Control	Control	Control	Control	Control
N	210	210	210	180	180	180
R2	0.688	0.683	0.715	0.684	0.662	0.706

Note: The value of T in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The lag period of DIG is incorporated into the mediation model at the same time. Table 9 columns (4), (5), and (6) show the test results, and the mediation results are reliable.

6.2. Mediating Mechanism of Government Environmental Regulation

In this paper, environmental regulation is included as a mediating variable in the regression model. Referring to Morgenstern et al. [58], environmental regulation is measured by the proportion of investment in industrial pollution control in each province to the secondary industry. Models (6) and (7) were further established on the basis of model (1), where $NERI_{it}$ represents the level of environmental regulation.

$$NERI_{it} = \beta_0 + \beta_1 DIG_{it} + \beta_j \Sigma X_{jit} + v_t + \eta_t + \varepsilon_{it} \quad (6)$$

$$CES_{it} = \delta_0 + \delta_1 DIG_{it} + \delta_2 NERI_{it} + \delta_j \Sigma X_{jit} + v_t + \eta_t + \varepsilon_{it} \quad (7)$$

When β_1 is significantly positive, δ_2 is significantly negative, and $\delta_1 < \alpha_1$, environmental regulation is the intermediary variable between the development of the DIG and the ECS.

Column (2) of Table 10 shows the DIG's regression coefficient is 0.0171 and is significant at the 5% level, indicating that the digital economy can strengthen the government's environmental regulation. Column (3) shows that the regression coefficient of environmental regulation is −3.8951 and is significant at the 1% level. The regression coefficient of the DIG is −0.2970 and is significant at the 1% level. Therefore, government environmental regulation has played intermediary role in the impact of the digital economy on the energy consumption structure.

Table 10. Results of regression of the mediating effect of environmental regulation.

Variable	(1) ECS	(2) NERI	(3) ECS	(4) ECS	(5) NERI	(6) ECS
DIG	−0.3638 ***	0.0171 **	−0.2970 ***			
	(−4.0085)	(2.6023)	(−3.3346)			
L.DIG				−0.4826 ***	0.0191 **	−0.4106 ***
				(−4.0975)	(2.0847)	(−3.5773)
NERI			−3.8951 ***			−3.7649 ***
			(−3.7988)			(−3.5906)
lnGDP	0.0783 *	0.0012	0.0831 *	0.0898	0.0030	0.1010 *
	(1.7102)	(0.3724)	(1.8864)	(1.6537)	(0.7004)	(1.9341)
IS	−0.0013	0.0048 ***	0.0173	0.0094	0.0063 ***	0.0332
	(−0.0611)	(3.1301)	(0.8325)	(0.3813)	(3.2701)	(1.3458)
FDI	0.0236	0.0006	0.0259	0.0163	0.0010	0.0200
	(1.2237)	(0.4281)	(1.3971)	(0.7509)	(0.5922)	(0.9624)
HC	−7.3082 ***	0.1190	−6.8446 ***	−8.0679 **	0.0565	−7.8550 ***
	(−2.7034)	(0.6065)	(−2.6288)	(−2.6049)	(0.2344)	(−2.6427)
UR	−0.1989	0.0057	−0.1769	−0.3151	0.0207	−0.2371
	(−0.8997)	(0.3524)	(−0.8313)	(−1.1890)	(1.0033)	(−0.9291)
BI	−0.0127 ***	0.0003	−0.0117 ***	−0.0115 ***	0.0003	−0.0102 ***
	(−3.8125)	(1.0800)	(−3.6327)	(−3.0667)	(1.1569)	(−2.8288)
_cons	0.1318	−0.0243	0.0373	0.0823	−0.0513	−0.1109
	(0.2836)	(−0.7195)	(0.0832)	(0.1491)	(−1.1930)	(−0.2082)
Year	Control	Control	Control	Control	Control	Control
Province	Control	Control	Control	Control	Control	Control
N	210	210	210	180	180	180
R2	0.688	0.367	0.713	0.684	0.362	0.711

Note: The value of T in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The lag period of the DIG is incorporated into the mediation model at the same time. Table 10 columns (4), (5), and (6) show the test results, and the mediation results are reliable.

7. Conclusions and Implications

This paper puts forward research conclusions based on the research content and policy implications based on the research conclusions. The exploration of how the digital economy has influenced the energy consumption structure has led to the following conclusions: First, the digital economy directly reduces the proportion of coal in total energy consumption, which has a positive impact on upgrading the energy consumption structure. Second, the digital economy has a threshold effect on upgrading the energy consumption structure. The higher the level of the digital economy, the more obvious the upgrade effect on the energy consumption structure. Third, the impact of the digital economy on the upgrading of the energy consumption structure is heterogeneous in different regions. Specifically, this role is more pronounced in provinces with low levels of digital divide, the eastern and central provinces, and high levels of economic development. Fourth, environmental regulation and green technology innovation play an intermediary role in the impact of the digital economy on the energy consumption structure. Specifically, the digital economy affects environmental regulation and green technology innovation, which in turn affects the energy consumption structure.

Based on the research results, the following recommendations are made. First, accelerate the development of the digital economy and the construction of digital infrastructure, increase the application of digital technology in the energy field, and provide new momentum for the upgrading of energy consumption structure, especially in provinces with a higher level of the digital divide, the western provinces, and provinces with a lower level of economic development. Based on the results of heterogeneity analysis, it is necessary to accelerate the construction of digital technology infrastructure and promote the application of digital technology in various fields, such as production, life, transportation and energy consumption, in these regions. Additionally, the formulation of digital economy development policies should be tilted towards these regions, and the development of the digital economy in these regions can be promoted by formulating preferential taxation and active fiscal policies.

Second, take advantage of the development of the digital economy to improve the government's environmental regulation capabilities. Studies show that environmental supervision plays an intermediary role in the digital economy and energy consumption structure upgrading, so it is necessary to use digital technology to establish a more scientific and systematic environmental regulation system to optimize the energy consumption structure and improve environmental governance capabilities.

Third, use digital technology to strengthen scientific and green technology and promote the development of green technology innovation. The research shows that green technology innovation plays an intermediary role in the digital economy and the energy consumption structure. Therefore, with the help of the rapid development of the digital economy and digital technology, we should accelerate the research, development, and innovation of green technologies to continuously improve energy efficiency and promote the upgrading of energy consumption structure.

The research in this paper also has certain shortcomings, which provide certain enlightenment for future research. First, the perspective of the energy consumption structure research can be multi-dimensional. This paper is only from the perspective of primary energy consumption, combined with the energy resource endowment characteristics of China's "more coal, less oil and gas shortage", focusing on the change of the proportion of unsustainable coal energy in total energy consumption. In the future, the impact of the digital economy on the energy consumption structure can be further explored from the perspectives of energy consumers, industry energy utilization, and new energy development. Second, the impact of the digital economy on different industries and digital industries in the process of development is different, and further detailed research can be carried out in the future in combination with the energy consumption structure.

Author Contributions: Conceptualization and Design, Y.Z. (Yating Zeng), X.X., Y.Z. (Yuyao Zhao) and B.L.; methodology, software, X.X. and, Y.Z. (Yuyao Zhao); validation and formal analysis, X.X. and Y.Z. (Yating Zeng); investigation, X.X. and Y.Z. (Yuyao Zhao); resources, X.X., Y.Z. (Yating Zeng) and Y.Z. (Yuyao Zhao); data curation, X.X.; writing—review and editing, Y.Z. (Yating Zeng), X.X., Y.Z. (Yuyao Zhao) and B.L.; visualization, Y.Z. (Yating Zeng); supervision, Y.Z. (Yating Zeng) and B.L.; project administration, B.L.; funding acquisition, Y.Z. (Yating Zeng) and B.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Humanities and Social Science Foundation of Ministry of Education of China (Grant No. 20YJC790005) and (Grant No. 21YJA790028).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Wang, Z.; Jia, X. Analysis of energy consumption structure on CO_2 emission and economic sustainable growth. *Energy Rep.* **2022**, *8*, 1667–1679. [CrossRef]
2. Ndubuisi, G.; Otioma, C.; Tetteh, G.K. Digital infrastructure and employment in services: Evidence from Sub-Saharan African countries. *Telecommun. Policy* **2021**, *45*, 102153. [CrossRef]
3. Zuo, P.; Jiang, Q.; Chen, J. Internet development, urbanization and the upgrading of China's industrial structure. *J. Quant. Technol. Econ.* **2020**, *7*, 71–91.
4. Wu, H.; Hao, Y.; Ren, S.; Yang, X.; Xie, G. Does internet development improve green total factor energy efficiency? Evidence from China. *Energy Policy* **2021**, *153*, 112247. [CrossRef]
5. Yang, J.; Li, X.; Huang, S. Impacts on environmental quality and required environmental regulation adjustments: A perspective of directed technical change driven by big data. *J. Clean. Prod.* **2020**, *275*, 124126. [CrossRef]

6. Tian, J.; Liu, Y. Research on total factor productivity measurement and influencing factors of digital economy enterprises. *Procedia Comput. Sci.* **2021**, *187*, 390–395. [CrossRef]
7. Ren, S.; Li, L.; Han, Y.; Hao, Y.; Wu, H. The emerging driving force of inclusive green growth: Does digital economy agglomeration work? *Bus Strateg. Environ.* **2022**, *31*, 1656–1678. [CrossRef]
8. Moyer, J.D.; Hughes, B.B. ICTs: Do they contribute to increased carbon emissions? *Technol. Forecast. Soc. Chang.* **2012**, *79*, 919–931. [CrossRef]
9. Deng, H.; Bai, G.; Shen, Z.; Xia, L. Digital economy and its spatial effect on green productivity gains in manufacturing: Evidence from China. *J. Clean. Prod.* **2022**, *378*, 134539. [CrossRef]
10. Wu, H.; Xue, Y.; Hao, Y.; Ren, S. How does internet development affect energy-saving and emission reduction? Evidence from China. *Energy Econ.* **2021**, *103*, 105577. [CrossRef]
11. Wang, J.; Jiang, Q.; Dong, X.; Dong, K. Decoupling and decomposition analysis of investments and CO_2 emissions in information and communication technology sector. *Appl. Energy* **2021**, *302*, 117618. [CrossRef]
12. Bastida, L.; Cohen, J.J.; Kollmann, A.; Moya, A.; Reichl, J. Exploring the role of ICT on household behavioural energy efficiency to mitigate global warming. *Renew. Sustain. Energy Rev.* **2019**, *103*, 455–462. [CrossRef]
13. Longo, S.B.; York, R. How does information communication technology affect energy use? *Hum. Ecol. Rev.* **2015**, *22*, 55–72. [CrossRef]
14. May, G.; Stahl, B.; Taisch, M.; Kiritsis, D. Energy management in manufacturing: From literature review to a conceptual framework. *J. Clean. Prod.* **2017**, *167*, 1464–1489. [CrossRef]
15. Koseleva, N.; Ropaite, G. Big data in building energy efficiency: Understanding of big data and main challenges. *Procedia Eng.* **2017**, *172*, 544–549. [CrossRef]
16. Kahn, M.E.; Liu, P. Utilizing "Big Data" to improve the hotel sector's energy efficiency: Lessons from recent economics research. *Cornell Hosp. Q.* **2016**, *57*, 202–210. [CrossRef]
17. Fetene, G.M.; Kaplan, S.; Mabit, S.L.; Jensen, A.F.; Prato, C.G. Harnessing big data for estimating the energy consumption and driving range of electric vehicles. *Transp. Res. Part D Transp. Environ.* **2017**, *54*, 1–11. [CrossRef]
18. Loock, M. Unlocking the value of digitalization for the European energy transition: A typology of innovative business models. *Energy Res. Soc. Sci.* **2020**, *69*, 101740. [CrossRef]
19. Nijhuis, M.; Gibescu, M.; Cobben, J.F.G. Assessment of the impacts of the renewable energy and ICT driven energy transition on distribution networks. *Renew. Sustain. Energy Rev.* **2015**, *52*, 1003–1014. [CrossRef]
20. Shahbaz, M.; Wang, J.; Dong, K.; Zhao, J. The impact of digital economy on energy transition across the globe: The mediating role of government governance. *Renew. Sustain. Energy Rev.* **2022**, *166*, 112620. [CrossRef]
21. Liu, P.; Lu, C. Strategic analysis and development plan design on digital transformation in the energy industry: A global perspective. *Int. J. Energy Res.* **2021**, *45*, 19657–19670. [CrossRef]
22. Noussan, M.; Tagliapietra, S. The effect of digitalization in the energy consumption of passenger transport: An analysis of future scenarios for Europe. *J. Clean. Prod.* **2020**, *258*, 120926. [CrossRef]
23. Hao, Y.; Li, Y.; Guo, Y.; Chai, J.; Yang, C.; Wu, H. Digitalization and electricity consumption: Does internet development contribute to the reduction in electricity intensity in China? *Energy Policy* **2022**, *164*, 112912. [CrossRef]
24. Blom, V.; Lönn, A.; Ekblom, B.; Kallings, L.V.; Väisänen, D.; Hemmingsson, E.; Ekblom-Bak, E. Lifestyle habits and mental health in light of the two COVID-19 pandemic waves in Sweden, 2020. *Int. J. Environ. Res. Public Health* **2021**, *18*, 3313. [CrossRef] [PubMed]
25. Chen, X.; Despeisse, M.; Johansson, B. Environmental sustainability of digitalization in manufacturing: A review. *Sustainability* **2020**, *12*, 10298. [CrossRef]
26. Zhang, S.; Ma, X.; Cui, Q. Assessing the impact of the digital economy on green total factor energy efficiency in the post-COVID-19 era. *Front. Energy Res.* **2021**, *9*, 798922. [CrossRef]
27. Gruber, H. Proposals for a digital industrial policy for Europe. *Telecommun. Policy* **2019**, *43*, 116–127. [CrossRef]
28. Usman, A.; Ozturk, I.; Hassan, A.; Zafar, S.M.; Ullah, S. The effect of ICT on energy consumption and economic growth in South Asian economies: An empirical analysis. *Telemat. Inform.* **2021**, *58*, 101537. [CrossRef]
29. Wang, J.; Wang, B.; Dong, K.; Dong, X. How does the digital economy improve high-quality energy development? The case of China. *Technol. Forecast. Soc. Chang.* **2022**, *184*, 121960. [CrossRef]
30. Zekić-Sušac, M.; Mitrović, S.; Has, A. Machine learning based system for managing energy efficiency of public sector as an approach towards smart cities. *Int. J. Inf. Manag. Sci.* **2021**, *58*, 102074. [CrossRef]
31. Plageras, A.P.; Psannis, K.E.; Stergiou, C.; Wang, H.; Gupta, B.B. Efficient IoT-based sensor BIG Data collection–processing and analysis in smart buildings. *Future Gener. Comput. Syst.* **2018**, *82*, 349–357. [CrossRef]
32. Erdmann, L.; Hilty, L.M. Scenario analysis: Exploring the macroeconomic impacts of information and communication technologies on greenhouse gas emissions. *J. Ind. Ecol.* **2010**, *14*, 826–843. [CrossRef]
33. Schaller, R.R. Moore's law: Past, present and future. *IEEE Spectr.* **1997**, *34*, 52–59. [CrossRef]
34. Zhang, X.Z.; Liu, J.J.; Xu, Z.W. Tencent and Facebook data validate Metcalfe's law. *JCST* **2015**, *30*, 246–251. [CrossRef]
35. Peterson, T. Metcalfe's Law as a Model for Bitcoin's Value. *CAIA* **2018**, *2*, 9–18. [CrossRef]
36. L'Hoest, R. The European dimension of the digital economy. *Int. Econ.* **2001**, *36*, 44–50. [CrossRef]
37. Hansen, B.E. Threshold effects in non-dynamic panels: Estimation, testing, and inference. *J. Econ.* **1999**, *93*, 345–368. [CrossRef]

38. Tran, B.L.; Chen, C.C.; Tseng, W.C. Causality between energy consumption and economic growth in the presence of GDP threshold effect: Evidence from OECD countries. *Energy* **2022**, *251*, 123902. [CrossRef]
39. Xuan, D.; Ma, X.; Shang, Y. Can China's policy of carbon emission trading promote carbon emission reduction? *J. Clean. Prod.* **2020**, *270*, 122383. [CrossRef]
40. Wu, H.; Hao, Y.; Weng, J.H. How does energy consumption affect China's urbanization? New evidence from dynamic threshold panel models. *Energy Policy* **2019**, *127*, 24–38. [CrossRef]
41. Sun, W.; Ren, C. The impact of energy consumption structure on China's carbon emissions: Taking the Shannon–Wiener index as a new indicator. *Energy Rep.* **2021**, *7*, 2605–2614. [CrossRef]
42. Xue, Y.; Tang, C.; Wu, H.; Liu, J.; Hao, Y. The emerging driving force of energy consumption in China: Does digital economy development matter? *Energy Policy* **2022**, *165*, 112997. [CrossRef]
43. Wang, J.; Xu, T. Environmental impact of Information Communication Technology: A review of econometric assessment methods, influential mechanism, and influential direction. *Environ. Impact Assess. Rev.* **2021**, *89*, 106590. [CrossRef]
44. Li, Y.; Yang, X.; Ran, Q.; Wu, H.; Irfan, M.; Ahmad, M. Energy structure, digital economy, and carbon emissions: Evidence from China. *Environ. Sci. Pollut. Res.* **2021**, *28*, 64606–64629. [CrossRef] [PubMed]
45. Shahbaz, M.; Song, M.; Ahmad, S.; Vo, X.V. Does economic growth stimulate energy consumption? The role of human capital and R & D expenditures in China. *Energy Econ.* **2022**, *105*, 105662.
46. Duflo, E.; Pande, R. Dams. *Q. J. Econ.* **2007**, *122*, 601–646. [CrossRef]
47. Ivus, O.; Boland, M. The employment and wage impact of broadband deployment in Canada. *Can. J. Econ.* **2015**, *48*, 1803–1830. [CrossRef]
48. Staiger, D.O.; Stock, J.H. Instrumental variables regression with weak instruments. *Econometrica* **1997**, *65*, 557–586. [CrossRef]
49. Gao, D.; Li, G.; Yu, J. Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. *Energy* **2022**, *247*, 123395. [CrossRef]
50. Huang, Q.H.; Yu, Y.Z.; Zhang, S.L. Internet development and manufacturing productivity improvement: Internal mechanism and China's experience. *China Ind. Econ.* **2019**, *8*, 5–23.
51. Guo, F.; Wang, J.; Wang, F.; Kong, T.; Zhang, X.; Cheng, Z. Measuring the development of digital inclusive finance in China: Index compilation and spatial characteristics. *Econometrics* **2020**, *19*, 1401–1418.
52. Lin, B.; Xu, M. Regional differences on CO_2 emission efficiency in metallurgical industry of China. *Energy Policy* **2018**, *120*, 302–311. [CrossRef]
53. Zhou, P.; Zhang, H.; Zhang, L.P. The drivers of energy intensity changes in Chinese cities: A production-theoretical decomposition analysis. *Appl. Energy* **2022**, *307*, 118230. [CrossRef]
54. Baron, R.M.; Kenny, D.A. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. Personal. Soc. Psychol.* **1986**, *51*, 1173. [CrossRef] [PubMed]
55. Chen, H.; Yi, J.; Chen, A.; Peng, D.; Yang, J. Green technology innovation and CO_2 emission in China: Evidence from a spatial-temporal analysis and a nonlinear spatial durbin model. *Energy Policy* **2013**, *172*, 113338. [CrossRef]
56. Feng, S.; Zhang, R.; Li, G. Environmental decentralization, digital finance and green technology innovation. *Struct. Chang. Econ. Dyn.* **2022**, *61*, 70–83. [CrossRef]
57. Su, X.; Pan, C.; Zhou, S.; Zhong, X. Threshold effect of green credit on firms' green technology innovation: Is environmental information disclosure important? *J. Clean. Prod.* **2022**, *380*, 134945. [CrossRef]
58. Morgenstern, R.D.; Pizer, W.A.; Shih, J.S. Jobs versus the environment: An industry-level perspective. *J. Environ. Econ. Manag.* **2002**, *43*, 412–436. [CrossRef]