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Original Research

How Does the Digital Economy Improve Energy Eco-Efficiency? Evidence from Provincial Panel Data in China

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Abstract

As a new driver for promoting energy eco-efficiency, the digital economy has practical significance in ensuring energy security and constructing ecological civilization. This study examines the impact of the digital economy on China's inter-provincial energy eco-efficiency from 2013 to 2020 using slacks-based measures. Firstly, the development of the digital economy significantly improves inter-provincial energy eco-efficiency. This conclusion holds true even after conducting several robustness and endogeneity tests. Secondly, the transition in energy consumption serves as the pathway of influence, especially during its initial stage. Specifically, the digital economy enhances energy eco-efficiency by reducing reliance on fossil fuels and decreasing consumption intensity; however, the promotion effect of renewable energy consumption is not evident between the two. Thirdly, the quality of green technology innovation, rather than the quantity, plays a crucial role in acting as the influence path. Lastly, the analysis of heterogeneities indicates that non-resource-based provinces and central regions benefit from the digital economy's contribution to their overall energy eco-efficiency.

Keywords: digital economy, energy eco-efficiency, energy consumption transition, green technology innovation

Introduction

Energy is vital for human existence and progress, directly influencing a nation's economic stability and security [1]. Nonetheless, the declining energy efficiency and worsening environmental degradation have reached critical levels, posing significant threats to sustainable economic growth, the construction of social-ecological civilization, and residents' welfare. Against the backdrop of global sustainable development strategies, enhancing energy eco-efficiency is of paramount practical importance in fostering the coordinated growth of energy, economy, environment, and society. As the largest energy consumer and polluter, how to effectively improve energy eco-efficiency has consistently been an urgent issue in need of resolution in China. To address this, China has exerted considerable efforts, but the outcomes have not been satisfactory. However, the emergence of the digital economy presents new opportunities for enhancing energy eco-efficiency.

Presently, the entire world has moved into the era of the digital economy. The new production modes

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spurred by the digital economy can effectively drive the transformation of the economic sector towards green and low-carbon practices. To expedite and enhance energy conservation and emission reduction efforts, the Chinese government has issued relevant policy instructions. For instance, China's National Development and Reform Commission and the National Energy Administration collaboratively released the "Guidelines for Facilitating the Development of 'Internet +' Smart Energy" in 2016. This document aimed to bolster energy eco-efficiency and facilitate a transition towards green energy by establishing an energy Internet. In the current policy context, it's imperative to investigate whether the digital economy can effectively improve energy eco-efficiency. For this purpose, this paper attempts to answer several questions through empirical research: What influence does the digital economy have on energy eco-efficiency? What mechanisms underlie this impact? Moreover, does this effect vary based on regional disparities and resource endowments? The results of this study have significant implications for government initiatives aimed at harmonizing energy production and distribution, thereby promoting social and economic sustainability.

This essay offers several potential innovations and contributions. Firstly, current research on the influencing factors of energy eco-efficiency primarily focuses on three areas: economic development [2, 3], industrial aggregation [4, 5], and enterprise behavior [6]. However, the digital economy, as a new form in the field of economic development, has received limited discussion regarding its impact on energy eco-efficiency. Moreover, the majority of current research focuses on energy economic efficiency. Given the imperative of sustainable development, investigating the influence of the digital economy on energy eco-efficiency is highly practical. This study aims to fill this gap in the literature. Secondly, most research on energy eco-efficiency index systems primarily focuses on GDP as the sole output indicator. However, the World Business Commission on Sustainable Development stresses that eco-efficiency should take social welfare implications into account [7]. Therefore, different from prior studies, we incorporate social welfare factors in addition to real GDP levels. This comprehensive approach allows us to capture the complex interrelationships among energy, economy, environment, and society. Additionally, we employ the slacks-based measure to evaluate China's interprovincial energy eco-efficiency. Finally, there is a lack of research on the specific influential processes and mechanisms between the digital economy and energy eco-efficiency. This paper fills this gap by introducing mediating factors, such as green technology innovation and the transition in energy consumption, aiming to explore the underlying mechanisms.

The remaining sections of this paper are arranged as follows: A brief review of the literature is given in Section 2. The study's research hypothesis is presented in Section 3. The methods and data used are introduced in Section 4. The empirical results are presented and discussed in Section 5. Lastly, findings and associated policy implications are provided in Section 6.

Literature Review

Definition and Measurement of Energy Eco-Efficiency

Energy eco-efficiency, which originated from the notion of eco-efficiency, represents the proportion of economic activity benefits to environmental impacts [8]. The rapid industrialization and urbanization of the world have resulted in serious environmental pollution caused by the extensive use of fossil and mineral resources. Consequently, researchers have focused on integrating environmental factors into energy efficiency studies, which has given rise to the concept of energy ecological efficiency [9]. Currently, academia generally defines "energy eco-efficiency" as total factor energy efficiency, encompassing all environmental, economic, and energy-related aspects [10, 11]. However, some scholars argue that energy eco-efficiency cannot be fully represented even when environmental impact is considered [12]. Furthermore, the World Business Commission on Sustainable Development's definition of eco-efficiency highlights the clear links among factor inputs, environmental performance, and social welfare [7]. Since improving people's well-being is the ultimate goal of promoting sustainable economic, environmental, and social development, it's important for energy eco-efficiency to also consider its impact on social welfare. In this study, energy eco-efficiency is defined as optimizing economic benefits and social welfare while minimizing energy consumption and pollution emissions during production activities.

To assess energy eco-efficiency and its determinants efficiently, it is necessary to measure it accurately. Initially, the academic community focused on studying energy efficiency based solely on economic output. However, with the emergence of climate change, marine pollution, and other environmental issues, scholars realized that they frequently overlooked these environmental factors in their measurements of energy efficiency [13]. As a result, to account for undesirable outputs, such as environmental factors, researchers began incorporating total factor energy efficiency into their studies. For instance, Rashidi et al. [14] used data envelopment analysis to estimate energy savings in OECD countries, and then identified eco-efficient nations. Similarly, Yang and Li [3] examined sulfur dioxide emissions as an indicator of undesirable output in China's cities. They selected a general upward fluctuation in the overall energy eco-efficiency across 275 cities. Furthermore, Liu and Wu [10] evaluated China's energy efficiency of ecosystems utilizing the slacks-based measure undesirable model. They discovered that, contrary to expectations, the average efficiency was lower. Traditional approaches like data envelopment analysis and stochastic frontier analysis have limitations, such as ignoring slack variables or focusing on single outputs. Therefore, scholars increasingly prefer adopting slacks-based measures and energy-based models to overcome these drawbacks.

Potential Determinants of Energy Efficiency

Several studies have examined the potential determinants of energy efficiency from various perspectives, including industrial concentration, openness to the outside world, population agglomeration, industrial structure, and investment in science and technology [4, 10, 15, 16].

Recently, there has been increasing recognition of the digital economy's influence on energy efficiency. Various essays have found evidence supporting a positive correlation between the two. For instance, Song et al. [17] argue that the digital economy may enhance energy efficiency by encouraging resource reallocation and fostering information flows. Wang and Shao[18] emphasize entrepreneurship's positive role in both. Nonetheless, several studies indicate a possible inverse link between the two. According to Li et al. [19], inefficiency and increased energy consumption are consequences of the growing digital economy. Zhang et al. [20] argue that although the expanding digital economy does not directly improve efficiency, it indirectly contributes to increased carbon emissions.

Research Gaps

Research has verified the link between the digital economy and energy efficiency. However, further study is required. Currently, research primarily focuses on economic aspects, but given the global responsibility for energy security and reducing carbon emissions, it is more practical to study the digital economy's influence on energy eco-efficiency. Additionally, using GDP as a single output index for energy efficiency lacks comprehensiveness and fails to effectively capture the relationship among energy, economy, environment, and society. Furthermore, there haven't been many empirical studies on how the digital economy affects energy eco-efficiency. It is also necessary to conduct comprehensive analyses that consider regional differences and resource endowment heterogeneity.

Theoretical Analysis and Hypotheses

The emergence of the digital economy facilitates the integration of traditional economic sectors with advanced technologies such as blockchain, artificial intelligence, and big data. This integration can drive transformations in energy consumption patterns and spur innovation in green technologies. Consequently, these advancements can mitigate imbalances in energy supply and demand structures through environmentally friendly means, thereby enhancing energy eco-efficiency.

Many countries have traditionally depended on electricity, oil, and gas for their energy needs. However, this system exhibits strong interdependency, resulting in low energy efficiencies and challenges in restructuring energy consumption patterns [21]. The emergence of digital technologies can facilitate the transition from fossil fuels to cleaner energy consumption. Firstly, government departments can employ digital technology for real-time monitoring of environmental pollutants [22]. Enhanced monitoring effectiveness enables the formulation of targeted policies to reduce carbon emissions among consumers, encompassing tiered electricity pricing, energy use taxes, and subsidies for purchasing new energy vehicles. Secondly, the integration of emerging digital technologies into businesses enables real-time monitoring of production processes and precise material placement. This integration reduces redundancy and waste in research and development (R&D) activities and manufacturing processes, thus minimizing unnecessary energy losses [23, 24]. According to the Global Digital Transformation Benefits Report 2019, businesses that implemented digital technology platforms achieved significant energy savings of up to 85%, with an average decrease of 24%. Lastly, the digital economy fosters innovative energy consumption practices by encouraging the adoption of green products [25]. For instance, mobile payment software enables consumers to make online purchases and pay utility bills electronically, reducing unnecessary trips. The promotion of new energy vehicles also boosts demand for renewable energy and facilitates low-carbon transportation. Moreover, mobile renewable charging equipment, shared trolley buses, and initiatives such as "ant forests"[1] improve universal resource access while effectively reducing pollution emissions. Overall, as the energy consumption mode evolves gradually, the use of highly polluting fossil fuels will decrease, while clean energy will increasingly dominate consumption. This will reduce environmental pressure and improve energy eco-efficiency.

Addressing the imbalance between energy supply and demand requires more than just transforming energy consumption; it is essential to enhance the extraction, storage, and transmission capacity of clean energy and traditional fossil fuels. These goals heavily rely on the assistance of green technologies. The digital economy and technology can aid companies in overcoming challenges such as knowledge gaps, talent shortages, and financial constraints when pursuing green innovation activities. Firstly, the digital economy centered on digital technology can reduce information

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[1] Ant Forest, a public service project proposed by Alipay, which aims to motivate the public to engage in green consumption behavior, was awarded the United Nations' Champions of the Earth Award on September 19, 2019.

asymmetry by breaking down "information silos" and establishing interconnected information dissemination platforms [26]. This promotes resource exchange and knowledge sharing among innovation stakeholders, thereby stimulating green innovation in businesses. Secondly, the digital economy generates information effects that accelerate the efficient circulation of market information. This fosters fairer employment and promotion opportunities, attracting a concentration of talent [27]. Moreover, it stimulates the growth of strategic emerging industries, increasing the demand for highly skilled talents while displacing low-educated labor, thereby supporting the continual enhancement of the human capital structure [28]. Thirdly, the application of digital technology in finance has introduced novel business models, such as digital finance. This enhances the efficient flow of information, improving accuracy in matching supply and demand in financial markets. Consequently, it mitigates constraints on enterprise financing and provides adequate capital for transforming enterprises' green innovation efforts.

The digital economy increases the capacity to extract, store, and transport renewable and fossil energy by improving green technology innovation. For instance, enterprises can leverage advanced technologies like clean coal to lower extraction costs and establish a whole-process energy supply chain for low-energy production. Furthermore, the adoption of green packaging and energy-efficient transportation methods can mitigate environmental strain caused by excessive energy loss. Simultaneously, firms driven by digital technology have the opportunity to integrate intelligent algorithms, such as "machine learning", into their innovation strategies, fostering complementary innovations [29]. This integration enables companies to enhance their capacity in extracting and storing renewable sources, such as photovoltaic and wind energy.

In summary, the convergence of emerging digital technologies with the real economy drives energy consumption transformation and green technology innovation, characterized by significant technological advancements and minimal ecological impact [30]. These technologies alleviate energy structure imbalances and reduce environmental burdens [31], ultimately enhancing people's livelihoods and well-being. Thus, considering the technical attributes of the digital economy and the implicit requirements of energy eco-efficiency, we conclude that:

$H1_a$: Energy eco-efficiency is positively impacted by the growth of the digital economy.

$H1_b$: Digital economy improves energy eco-efficiency by facilitating energy consumption transition.

$H1_c$: Digital economy enhances energy eco-efficiency by promoting green technological innovation.

Method and Data

Econometric Model

Inquiring into the impact of the digital economy on energy eco-efficiency, this essay creates the subsequent linear regression equation:

$$Effi_{it} = \alpha_0 + \alpha_1 Diec_{it} + \alpha_c Control_{it} + \mu_i + \mu_t + \varepsilon_{it} \quad (1)$$

Where the province and year are indicated by the subscripts i and t, respectively. $Effi_{it}$ depicts the dependent variable of energy eco-efficiency. $Diec_{it}$ is an independent variable that indicates the level of the digital economy. In this research, the coefficient of primary interest is marked by α_1. If it is notably positive, it suggests that the digital economy successfully enhances energy eco-efficiency. $Control_{it}$ encompasses a collection of control variables at the interprovincial level of the host province. μ_i and μ_t denote the area and time fixed effects, respectively, while ε_{it} represents the random error term.

To better understand how the digital economy affects energy eco-efficiency, we will use Baron and Kenny's [32] approach to construct a mediating effect model based on Equation (1):

$$M_{it} = \beta_0 + \beta_1 Diec_{it} + \beta_c Control_{it} + \mu_i + \mu_t + \varepsilon_{it} \quad (2)$$

$$Effi_{it} = \gamma_0 + \gamma_1 Diec_{it} + \gamma_2 M_{it} + \gamma_c Control_{it} + \mu_i + \mu_t + \varepsilon_{it} \quad (3)$$

Among them, M_{it} represents the mediating variable that serves as a proxy for energy consumption transition and green technology innovation based on the examination of the mechanism in the preceding section. The test procedures are as follows: we assess the significance of coefficients β_1 in Eq. (2), and γ_1 and γ_2 in Eq. (3), respectively, to ascertain the presence of a mediating impact, depending on the notable positive coefficient α_1 in Eq. (1).

Variable Measures

Dependent Variable: Energy Eco-Efficiency (Effi)

In this study, we use MATLAB software to estimate the energy eco-efficiency of China's interprovincial provinces. The assessment employs the slacks-based measure model to account for undesirable output:

$$\rho = \min \frac{1 - \frac{1}{M} \sum_{m=1}^{M} \frac{s_m^x}{x_{i'm}^{t'}}}{1 + \frac{1}{P+Q} \left(\sum_{p=1}^{P} \frac{s_p^y}{y_{i'p}^{t'}} + \sum_{q=1}^{Q} \frac{s_q^z}{z_{i'q}^{t'}} \right)} \quad (4)$$

$$s.t.\sum_{t=1}^{T}\sum_{i=1}^{I}\lambda_i^t x_{im}^t + s_m^x = x_{i'm}^{t'}, m = 1,...,M \tag{5}$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I}\lambda_i^t y_{ip}^t - s_p^y = y_{i'p}^{t'}, p=1,...,P \tag{6}$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I}\lambda_i^t z_{iq}^t + s_q^z = z_{i'q}^{t'}, q=1,...,Q \tag{7}$$

$$\lambda_i^t \geq 0, s_m^x \geq 0, s_p^y \geq 0, s_q^z \geq 0, i=1,...,I \tag{8}$$

In the given context, ρ is the efficiency value. M, P, and Q denote the quantities of inputs, intended outputs, and unwanted outputs, respectively. The slack variables for inputs, intended outputs, and non-desired outputs are denoted by $s_m^{\ x}$, $s_p^{\ y}$, and $s_q^{\ z}$, respectively. $x^{t'}_{i'm}$ represents the actual input value in period *t'* for decision unit *i'*, $y^{t'}_{i'p}$ represents the actual desired output value in period *t'* for decision cell *i'*, $z^{t'}_{i'q}$ denotes the actual undesired output value in period *t'* for decision cell *i'*, and $\lambda_i^{\ t}$ denotes the weight of the decision unit. When $\rho = 1$, it indicates that the decision unit is efficient. Otherwise, if ρ is not equal to 1, it implies that the decision unit is becoming less efficient and there is room for improvement of inputs and outputs at this time.

It is widely accepted that the most reasonable approach for constructing the energy eco-efficiency index system is by interpreting its underlying connotations [4]. Traditionally, energy eco-efficiency has been perceived as reflecting the intricate interplay among energy, economy, and environment, leading to the construction of index systems focusing on resource input, economic output, and environmental unexpected output. However, recent research highlights limitations in solely using GDP as the economic output indicator [12]. Moreover, the definition of eco-efficiency by the World Business Commission on Sustainable Development underscores the importance of considering social welfare [7]. Based on these insights, we augment the selected indicator system by incorporating social welfare factors, ensuring its rationality and comprehensiveness, while also drawing from previous indicator selection frameworks. Our study selects the following indicators. We recognize the significant investment of labor and capital in energy-related activities and have, therefore, chosen three input indicators for our analysis. Firstly, the number of employed individuals, measured by the year-end count in the secondary industry. Secondly, fixed capital stock, evaluated using the perpetual inventory approach with 2013 as the base year for fixed asset investment [33]. Lastly, total energy consumption which encompasses primary sources such as petroleum, raw coal, natural gas, and electricity converted to standard coal and aggregated. Unlike prior studies, we incorporate social welfare factors alongside real GDP levels regarding expected output. Presently, indicators to measure social welfare primarily include the Human Development Index (HDI) released by the United Nations Development Program and average life expectancy. However, due to constraints in continuous data acquisition, our paper opts for factors affecting public well-being as outlined in the 14th Five-Year Plan for National Economic and Social Development. These encompass the social security level, years of education per capita, employment rate, and urban green space area per capita. Undesired outputs comprise five industrial emissions: smoke (dust), solid waste, wastewater, sulfur dioxide, and carbon dioxide.

Table 1 illustrates the designed system clearly, while Fig. 1 shows the calculation results in 2013 and 2020. As Fig. 1 illustrates, compared with 2013, China's energy eco-efficiency in 2020 has improved on the whole. Regionally speaking, the east exhibits the highest efficiency, followed by the center, and then the west region has the lowest efficiency levels. The calculation results of the energy eco-efficiency values of each province are detailed in Appendix A.

Independent Variable: Digital Economy (Diec)

In academia, the digital economy is widely regarded as a new economic paradigm that prioritizes digital information as a critical production factor, utilizing modern information networks as essential conduits. This enables intelligent and digital development through the fusion of digital technology with the real economy [18, 27, 34]. According to this definition, advancing the digital economy hinges on enhancing digital infrastructure construction while promoting the integrated application of digital technology within the real economy. The measurement framework outlined in the White Paper on China's Digital Economy Development 2023 aligns with these principles, focusing on both digital foundation and application aspects. Accordingly, the following indicators are selected to gauge the digital economy's progress in these dimensions, per the research framework delineated in the white paper. Accordingly, the following indicators are selected to gauge the digital economy, per the research framework delineated in the white paper. Regarding digital foundation, the white paper highlights critical sectors such as the Internet, electronic information manufacturing, information and communication, and software service industries. These sectors reflect the level of digital technology innovation and digital product production. Drawing from this insight, we refer to relevant research [35, 36] and adopt the following second-level index system: the quantity of Internet broadband access users per 100 people, total telecommunication service amount per capita, amount of cell phone subscribers per 100 people, and the percentage of workers in the computer services and software sector among urban unit employees. In terms of digital applications, it primarily entails the increased output and efficiency resulting from the utilization of digital technologies and products in non-digital industrial sectors. As the largest emerging economy globally, China's life service industry, manufacturing industry, transportation industry, and financial industry hold significant sway in the national economy. Therefore, drawing from existing research [37, 38], the following indicators are selected to gauge the level of digital life, intelligent manufacturing, intelligent logistics, and digital finance in China. Secondary indicators encompass e-commerce sales, the number of businesses participating in e-commerce trading, revenue from intelligent logistics measured by express delivery service revenue, and the Digital Financial Inclusion Index [39]. Table 1 displays the designed system. Referring to previous studies [35, 40], the principal component analysis method is employed to assess the digital economy level of each province in China.

Mediating Variables

The transition of energy consumption occurs in stages, gradually shifting from fossil fuels to clean energy. Clean energy consumption represents the final stage of this transition process. Renewable energy is widely accepted as a form of clean energy, and raising its proportion in overall energy consumption is seen as the correct direction for energy transition [41]. This paper aims to explore whether energy consumption transition is a possible impact pathway from fossil and renewable energy sources. For fossil fuels, we consider two factors: the structure of energy consumption (Struc) and the intensity of energy consumption (Eci). The structure refers to the percentage of raw coal consumed within overall fossil energy consumption, while intensity measures the proportion of all fossil energy consumption to GDP. As for renewable energy, concerning data accessibility, we use the number of transactions involving green power certificates (referred to as "green certificates") as a proxy variable for measuring renewable power consumption[2]. To avoid possible heteroskedasticity and facilitate the examination of explanatory variables' elasticity, we take logarithm values plus one divided by ten (lnGrec) for the trading volume of green certificates.

Based on the research conducted by Wang and Du [42], we measure the quality of green technological innovation in each province by selecting the number of authorized green invention patents and taking their logarithm (lnGrep). Additionally, we measure the quantity of green technological innovation in each province by selecting the amount of authorized green utility model and design patents and taking their logarithm (lnGrup).

Control Variables

According to the researches conducted by Tao et al. [35], Lin and Du [43], and Shi and Li [44], we have selected the following control variables for our analysis. The variable representing energy consumption is denoted as lnConsum, calculated as the logarithmic value of the sum of converted standard coal derived from primary sources, such as raw coal, oil, natural gas, and electricity. Urbanization level is symbolized by Urban and is defined as the percentage of urban population to the entire population in each province. Foreign direct investment level is denoted as FDI and expressed as the proportion of FDI to GDP. The industrial structure is denoted by Industry, which represents the portion of value added from secondary Industry to GDP. Lastly, the environmental regulation index (Eregu) was computed using an entropy method that considers emissions of industrial wastewater, industrial sulfur dioxide, and industrial smoke (dust) in each province.

Data Sources and Descriptive Statistics

This study utilizes data from 30 provinces in China (excluding Tibet) between 2013 and 2020[3]. The data on energy eco-efficiency is sourced from various publications, including the China Environmental Statistics Yearbook, China Urban Statistics Yearbook, and China Energy Statistics Yearbook. However, some information regarding industrial sulfur dioxide and industrial smoke (dust) emissions is missing. To address this gap, we manually collected and compiled data from cities within the missing provinces to supplement our analysis. Data about the digital economy, energy consumption structure, and energy consumption intensity are gathered through the manual collation of sources such as the China Statistical Yearbook, China Tertiary Industry Statistical Yearbook, and China Stock Market & Accounting Research Database. Green patent data was obtained from the China Research Data Service Platform, while green certificate transaction volume figures were sourced from the China Renewable Energy Information Management Center[4]. The remaining data were extracted from provincial statistical yearbooks and national economic and social development statistical bulletins. A bilateral 1% shrinkage treatment was applied to all continuous variables to mitigate any potential impact of outliers on our findings.

Table 2 displays the variables' descriptive statistics. It illustrates that the energy eco-efficiency variable ranges

[2] Green Certificates are the sole evidence of China's renewable energy electricity's environmental attributes. They also serve as the exclusive voucher for acknowledging both renewable energy power production and consumption. 1 Green Certificate represents 1,000 kilowatt-hours of renewable energy electricity.

[3] Tibet Province has serious data deficiencies and has been excluded. E-commerce sales indicators are included in the China Statistical Yearbook from 2013, and key data such as total energy consumption and coal consumption are seriously missing after 2020, so the sample interval of this paper is 2013-2020.

[4] The green certificate trading system was piloted in 2017, so the sample size of trading information was 120.

from 0.354 to 1, with an average of only 0.622. This suggests that energy eco-efficiency varies significantly across provinces, with a low mean value. Similarly, the digital economy index exhibits a low average value and a large standard deviation. Additionally, the energy consumption structure has a mean value of 0.599, indicating that coal consumption constitutes the largest proportion of fossil fuel usage in China, aligning with its "coal-rich, oil-poor, gas-poor" energy structure. The average energy consumption intensity reaches 0.725, while the mean value of green electricity consumption is only 0.167, implying that China has a high intensity

Table 1. Energy eco-efficiency and digital economy indicator system.

Variable	Primary index	Secondary indicators	Units
Energy eco-efficiency	Inputs	number of employed persons	ten thousand
		Fixed capital stock	billions
		Total energy consumption	tons of standard coal
	Desired outputs	Real GDP	billions
		Level of social security	%
		Years of schooling per capita	year/person
		Employment rate	%
		Urban green space per capita	m^2 /person
	Undesired outputs	Industrial fume (dust) emissions	tons
		Industrial solid waste emissions	tons
		Industrial wastewater discharge	tons
		Industrial sulfur dioxide emissions	tons
		Carbon dioxide emissions	million tons
Digital economy	Digital foundation	Number of Internet broadband access subscribers	per 100 people
		Total telecommunication service per capita	¥/person
		Number of cell phone subscribers	per 100 people
		Percentage of workers in the computer and software sector in the urban workforce	%
	Digital application	E-commerce sales	billions
		Number of businesses participating in e-commerce trading	thousands
		Smart Logistics Revenue	billions
		Digital Financial Inclusion Index	/

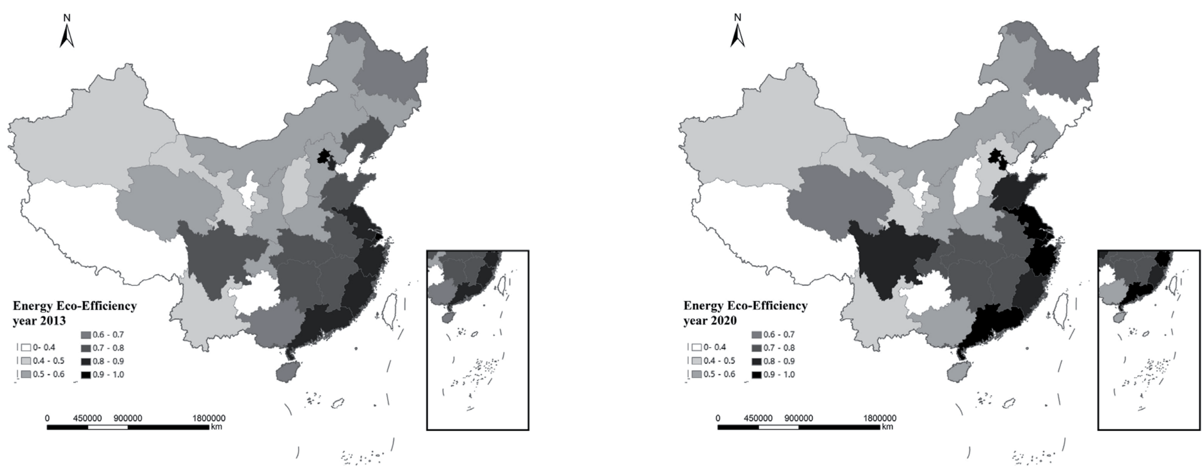

Fig. 1. China's energy eco-efficiency in 2013 and 2020.

Table 2. Descriptive statistics for variables.

Variable	N	Mean	SD	Min	P25	Median	P75	Max
Effi	240	0.622	0.174	0.354	0.486	0.583	0.710	1
Diec	240	0	1.729	-2.038	-1.253	-0.422	0.565	6.168
Struc	240	0.599	0.227	0.027	0.434	0.589	0.817	0.972
Eci	240	0.725	0.414	0.240	0.445	0.568	0.898	1.916
lnGrec	120	0.167	0.245	0	0	0	0.276	0.875
lnGrep	240	6.222	1.296	2.996	5.291	6.282	7.140	8.778
lnGrup	240	8.287	1.352	5.036	7.331	8.322	9.180	11.818
lnConsum	240	9.453	0.640	7.558	9.033	9.405	9.915	10.611
Urban	240	0.603	0.116	0.402	0.523	0.587	0.661	0.893
FDI	240	0.018	0.016	0	0.006	0.017	0.024	0.105
Indust	240	0.416	0.082	0.186	0.384	0.430	0.474	0.554
Eregu	240	0.535	0.550	0	0.125	0.342	0.750	2.179

of fossil energy consumption and poor renewable energy consumption. Furthermore, the mean values of green invention patents and utility model patents are 6.222 and 8.287, respectively, with a better level of green technological innovation.

Empirical Analysis

Baseline Regression Results

Table 3 displays the findings of the OLS regression examining how the digital economy affects energy eco-efficiency. Regardless of whether fixed effects are controlled, columns (1) and (2) demonstrate that the coefficients for the primary explanatory variable, digital economy, are strongly positive. This trend persists in columns (3) and (4), even after including control variables. For instance, in column (4), the estimated coefficient for the primary explanatory variable is 0.02, with a significance level of 1%. It suggests that as the digital economy integrates with traditional sectors, leveraging technologies like big data and artificial intelligence characterized by high technological content and low environmental costs enhances energy eco-efficiency. Therefore, hypothesis H_{1a} is confirmed.

Robustness and Endogeneity Tests

Excluding Special Samples

Due to the unique characteristics of economic development and urban planning, municipalities and regular provinces differ significantly in terms of digitization and energy efficiency. Therefore, we re-evaluated the samples by excluding the municipalities of Beijing, Tianjin, Shanghai, and Chongqing. Table 4's column (1) displays the test outcomes. It is evident that even after removing the municipality samples, the digital economy continues to enhance energy eco-efficiency significantly at a 1% significance level. This underscores the reliability of our previous findings.

Substitution of Independent Variables

The definition and statistical scope of the digital economy have yet to be standardized in the academic community. As a result, there are significant differences in measurement methods and results among scholars and institutions. To guarantee the credibility of our benchmark regression findings, we adopt Zhao Tao's construction principles for the digital economy indicator system and re-measure it according to the five measurement indicators he selected by applying principal component analysis. This reevaluation serves as the primary independent variable. In column (2) of Table 4, we observe that the coefficient for the digital economy is positive at a threshold for significance of 10%, suggesting that advancements in this field can contribute to improvements in energy eco-efficiency.

Substitution of Dependent Variables

Following the methodology of You et al. [4], we recalculated the energy eco-efficiency values according to their chosen input and output indicators system. After substituting the dependent variable, the regression results in Table 4's column (3) indicate that the coefficient for the digital economy is 0.016. This finding demonstrates a significant enhancement in inter-provincial energy eco-efficiency at a statistical significance level of 1%, thus validating the robustness of our benchmark regression analysis.

Table 3. Results of benchmark regression.

	(1)	(2)	(3)	(4)
Variables	Effi	Effi	Effi	Effi
Diec	0.073***	0.008***	0.047***	0.020***
	(0.00)	(0.00)	(0.00)	(0.01)
lnConsum			0.008	0.024
			(0.02)	(0.03)
Urban			0.673***	0.608***
			(0.09)	(0.19)
FDI			2.047***	-0.463**
			(0.48)	(0.21)
Indust			0.286***	-0.034
			(0.09)	(0.07)
Eregu			-0.021	-0.002
			(0.02)	(0.01)
_cons	0.622***	0.967***	-0.003	0.251
	(0.01)	(0.01)	(0.14)	(0.23)
Year	NO	YES	NO	YES
Province	NO	YES	NO	YES
N	240	240	240	240
r^2	0.526	0.988	0.724	0.989

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Figures in () are the Standard errors in parentheses of the coefficients. Same in the table below.

Instrumental Variables Approach

The instrumental variable approach is used for testing to mitigate the potential impact of omitted variables on the benchmark results. With reference to Huang et al. and Tao et al.'s research method [35, 45], this article selects the number of Internet users in the country in the previous year and fixed-line telephones per 10,000 people in each province in 1984 in China to construct an interaction term (IV) as an instrumental variable. It is employed to assess each province's degree of digital economy. The rationale behind this approach is twofold. On the one hand, Huang et al. [45] has shown that digital technologies, like the Internet, originated with the rise of landline telephones. Therefore, provinces with higher fixed telephone penetration may also develop the digital economy to a greater extent. That is to say, basic communication conditions play a substantial role in driving subsequent developments of digitalization. On the other hand, the number of landlines in the past also had a negligible impact on energy eco-efficiency. Therefore, the instrumental variable we select meets relevant criteria such as relevance and exclusivity.

Based on the findings in column (5) of Table 4, the coefficient for the digital economy is 0.039. This positive result is statistically significant at a level of 10%, even after controlling for the endogeneity of the independent variables. These results are consistent with previous findings. Furthermore, the weak instrumental variable test indicates that F = 51.881 (>16.38) and p-value = 0, rejecting the initial assumption and validating the choice of instrumental variables in this study.

Exogenous Policy Testing

The research mentioned above illustrates the potential enhancement of energy eco-efficiency by the digital economy. However, it is plausible that provinces with higher energy eco-efficiency are already more economically developed, facilitating a higher degree of digitalization. This leads to a potential causal link between the two variables. To address this endogeneity concern, we employ an exogenous policy event and the difference-in-difference model. Drawing from the methodology employed by Zhang et al. [46], the national e-government comprehensive reform pilot policy is chosen as the exogenous event impact. In 2017, the Cyberspace Administration of the CPC Central Committee and the National Development and Reform Commission issued a notice on carrying out the National E-Government Comprehensive Pilot Program.

This initiative selected eight provinces as national e-government comprehensive pilot program participants. The policy aims to enhance the "Internet + government services" level through network infrastructure construction, which is vital for digital economy development. Moreover, the capacity expansion characteristics of the pilot policy offer a suitable quasi-natural experimental environment for this study.

First, this paper constructs the following regression model for the parallel trend test:

$$Effi_{it} = \eta_0 + \sum_{t=-4}^{3} \eta_t P_t + \eta_c Control_{it} + \mu_i + \mu_t + \varepsilon_{it} \tag{9}$$

In formula (9), P represents the annual dummy variable before and after the policy implementation, with the year of policy implementation denoted as P_0. Other variables remain consistent with those mentioned above. The focus of this paper is on η_t. If the coefficients of η_{-4}, η_{-3}, η_{-2} and η_{-1} are not significant, it indicates the validity of the parallel trend assumption. The regression analysis results are presented in Table 4. The coefficients of η_{-4}, η_{-3}, $\eta_{-2,}$ and η_{-1} are not significant, confirming the validity of the parallel trend hypothesis and enabling the use of the DID model for testing. Additionally, the coefficients of η_0, η_1, $\eta_{2,}$ and η_3 are significantly positive, suggesting an impact of the policy on energy eco-efficiency.

Table 4. Parallel trend test.

Variable	Effi
P_{-4}	0.052
	(0.05)
P_{-3}	0.065
	(0.05)
P_{-2}	0.063
	(0.05)
P_{-1}	0.062
	(0.05)
P_0	0.081*
	(0.04)
P_1	0.088**
	(0.04)
P_2	0.099**
	(0.04)
P_3	0.101***
	(0.04)
_cons	-0.360**
	(0.15)
Controls	YES
Province	YES
Year	YES
N	240
r^2	0.679

Once the parallel trend hypothesis is established, this paper constructs the DID model as shown in equation (10). In this model, when the time is 2017 (the policy year) or later, the value of $Time_{it}$ is set to 1. If the province is a pilot province, the $Treat_{it}$ value is set to 1. The focus of the analysis is on the coefficient of θ_3. A significantly positive coefficient indicates that the policy pilot can impact energy eco-efficiency.

$$\begin{aligned} Effi_{it} = \theta_0 + \theta_1 Time_{it} + \theta_2 Treat_{it} + \theta_3 Time_{it} \times Treat_{it} \\ + \theta_c Control_{it} + \mu_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{10}$$

The results of the DID test are presented in column (6) of Table 5. The coefficient of Time × Treated is 0.056, which is significant at the 5% level. This signifies that the findings of this paper remain robust.

Mechanism Test

Mechanism Analysis of Energy Consumption Transition

Table 6 presents the mechanism test findings regarding energy consumption transition. In columns (1) and (3), where the structure and intensity of fossil energy consumption are employed as mediating variables, the coefficients for the digital economy are significant (-0.038 and -0.036, respectively). This indicates that the digital economy can drastically reduce the structure and intensity of fossil fuel consumption.

Columns (2) and (4) add the above mediating variables to the baseline regression model. Their coefficients remain significantly negative, and the coefficients of the digital economy decrease to 0.018 and 0.016, respectively. Furthermore, a Sobel test is conducted in this paper. The results indicate that the P-values are lower than 0.1 and 0.05, with the proportion of the mediating effect being 11.53% and 17.43%, respectively. The above suggests that by reducing the structure and intensity of fossil fuel usage, the digital economy facilitates the transformation of energy consumption, enhancing energy eco-efficiency.

In columns (5) and (6), renewable electricity consumption is employed as a mediating variable. The digital economy's coefficient in column (5) is 0.012 but insignificant, indicating no meaningful positive correlation between the utilization of renewable power sources and the digital economy. However, the coefficient of renewable power consumption in column (6) is 0.029 and statistically significant at the 1% level, demonstrating the benefit of applying clean energy to enhance energy eco-efficiency. The Sobel test also failed to reach the significance level, indicating that the

Table 5. Robustness and endogeneity tests.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Effi	Effi	Effi	Diec	Effi	Effi
Diec	0.025***	0.019*	0.016***		0.039*	
	(0.01)	(0.01)	(0.01)		(0.02)	
IV				0.000***		
				(0.00)		
Time×Treat						0.056**
						(0.03)
_cons	-0.151	0.485**	0.826***	7.964**	-0.008	0.420***
	(0.24)	(0.22)	(0.26)	(4.01)	(0.38)	(0.14)
Controls	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Province	YES	YES	YES	YES	YES	YES
N	208	240	240	240	240	240
r^2	0.987	0.988	0.988	0.975	0.988	0.687

Table 6. Regression results of mechanism test of energy consumption transition.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Struc	Effi	Eci	Effi	lnGrec	Effi
Diec	-0.038***	0.018***	-0.036**	0.016***	0.012	0.014**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.08)	(0.01)
Struc		-0.061*				
		(0.03)				
Eci				-0.095***		
				(0.03)		
lnGrec						0.029***
						(0.01)
_cons	-0.268	0.234	-3.565***	-0.090	6.449	-0.600
	(0.61)	(0.22)	(0.97)	(0.23)	(4.59)	(0.51)
Controls	YES	YES	YES	YES	Controls	YES
Year	YES	YES	YES	YES	Year	YES
Province	YES	YES	YES	YES	Province	YES
N	240	240	240	240	120	120
r^2	0.967	0.989	0.984	0.990	0.703	0.996
Sobel		0.002*		0.003**		0.000
Proportion		11.53%		17.43%		-

intermediary effect was invalid. The outcomes reported above mean that increasing renewable electricity consumption does not effectively impact energy eco-efficiency through digitization. One possible reason is that China's pilot program for the renewable energy electricity trading system began in 2017, with clean energy still being vigorously promoted rather than being a primary source of power generation yet due to China's stronger reliance on traditional resources such as coal, oil, and gas. On the contrary, digitization efforts and technological advancements have effectively adjusted China's long-standing fossil fuel-based electricity system. Synthesizing these findings from Table 5 leads us to conclude that during the early stages of transition towards sustainable practices, the digital economy has boosted energy eco-efficiency regarding fossil fuel consumption structure and intensity.

Mechanism Analysis of Green Technology Innovation

The findings of the mechanism test for green technology innovation are displayed in Table 7. In columns (1) and (3), the primary explanatory variables exhibit statistically positive coefficients of 0.117 and 0.083, respectively. This suggests that the digital economy significantly enhances the quality and quantity of green technological innovation. Column (2) includes the quality of green technological innovation in the benchmark regression model. At the 1% statistical significance level, the intermediate variable's coefficient is 0.048. Additionally, the coefficient of the digital economy decreases from 0.02 to 0.014, suggesting an established intermediary effect. The Sobel test indicated that the P-value is less than 0.01, with the proportion of the mediating effect being 28.38%. These findings demonstrate how the digital economy encourages energy eco-efficiency by improving the quality of green technology innovation. Moving on to column (4) investigates how the digital economy relates to both the quantity of green technological innovation and energy eco-efficiency. The outcomes reveal no significant coefficient for the quantity of green technological innovation, proving that increasing its quantity fails to boost the improvement of energy eco-efficiency. The Sobel test did not achieve significance, indicating that the intermediary effect was not established. The result may be attributed to the fact that, compared to the quality of green innovation, the quantity of green innovation tends to possess lower technical content, practicality, and creativity. Consequently, its contribution to energy eco-efficiency may be insignificant.

Heterogeneity Check

Heterogeneity in Types of Economic Development

Compared to provinces that do not rely on natural resources for economic development, resource-based provinces consume more energy due to their preference for heavy industries. Therefore, the influence of the digital economy on energy eco-efficiency might show differences depending on each province's resource endowment. So, whether it is a resource-based province becomes the main basis for dividing samples in the grouping test. The grouping test results regarding the digital economy can be found in columns (1) and (2) of Table 8.

Column (1) reports results for non-resource-based provinces, showing a significantly positive coefficient for the digital economy variable at the 1% level.

Table 7. Regression results of mechanism test of green technology innovation.

	(1)	(2)	(3)	(4)
Variables	lnGrep	Effi	lnGrup	Effi
Diec	0.117***	0.014**	0.083**	0.019***
	(0.02)	(0.01)	(0.04)	(0.01)
lnGrep		0.048***		
		(0.01)		
lnGrup				0.005
				(0.01)
_cons	2.843**	0.113	11.236***	0.194
	(1.43)	(0.22)	(2.49)	(0.24)
Controls	YES	YES	YES	YES
Year	YES	YES	YES	YES
Province	YES	YES	YES	YES
N	240	240	240	240
r^2	0.960	0.990	0.983	0.989
Sobel		0.006***		0.000
Proportion		28.38%		-

Table 8. Heterogeneity test.

	(1)	(2)	(3)	(4)	(5)
Variables	Non-resource-based provinces	Resource-based provinces	Eastern regions	Central regions	Western regions
Diec	0.019***	-0.010	0.009	0.043***	0.022
	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)
_cons	0.606	-0.504	-0.346	0.314	0.268
	(0.41)	(0.32)	(0.57)	(0.32)	(0.60)
Controls	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
Province	YES	YES	YES	YES	YES
N	184	56	73	79	88
r^2	0.990	0.976	0.988	0.987	0.961

This indicates that the digital economy significantly contributes to energy eco-efficiency improvement in these provinces. Additionally, column (2) shows the results for resource-based provinces. In this case, although the coefficients of main explanatory variables are positive, they are not statistically significant, which means the digital economy does not significantly affect energy eco-efficiency in resource-based provinces. There are several possible reasons for this finding. Firstly, digital economy development is relatively low in resource-based provinces, with limited integration of emerging technologies and industries. Consequently, its marginal utility is not effectively realized. Secondly, these regions face challenges such as over-reliance on traditional fossil fuels and homogenization of industrial structures. The strong dependence on resources hinders efforts to improve energy efficiency due to long-term high consumption levels. This extensive development pattern is often called the "resource curse" dilemma [47].

Regional Heterogeneity

According to the results above, it is evident that the digital economy positively impacts energy eco-efficiency. However, does this marginal effect vary depending on geographical location? This paper attempts to set geographic spatial differences as the main basis for dividing samples in the grouping test. Group regression analysis findings are presented in columns (3)-(5) of Table 8. Columns (3) and (5) display the results for the Eastern and Western regions. The coefficients of the digital economy are not statistically significant in these regions, indicating that it does not significantly contribute to improving energy eco-efficiency there. Column (4) presents the results demonstrating that the digital economy enhances energy eco-efficiency in the Central region at a significance level of 1%.

We try to provide specific explanations of the following aspects. First, although the level of digitalization is relatively high in Eastern China, most low-end industries with negative environmental influences, such as heavy pollution and high energy consumption, have been relocated to resource-rich Western and Central regions. This limits opportunities for improvement through digital economy initiatives. Additionally, provinces such as Beijing and Shanghai have already achieved maximum levels of energy eco-efficiency. Therefore, the effect of promotion on the digital economy cannot be effectively realized. Second, compared to the Eastern and Central regions, the level of the digital economy in Western is relatively backward. Consequently, long-term problems such as unbalanced resource allocation and lack of green innovation resources cannot be effectively solved, and improving energy ecological efficiency is insignificant. Third, the central regions have a superior geographical location and abundant energy resources. This is conducive to the digital economy to improve energy eco-efficiency.

Conclusions and Policy Implications

Conclusions

This study employs the slacks-based measure within the total factor production theory framework to calculate each province's energy eco-efficiency evaluation based on China's inter-provincial panel data from 2013 to 2020. This research looks at how the digital economy affects energy eco-efficiency and investigates the mechanism behind it using models of mediating effects. The findings reveal several vital insights. Firstly, there is a strong correlation between the energy eco-efficiency and the digital economy. Even after performing several robustness tests, this conclusion holds. Secondly, the transformation of energy consumption serves as an important pathway. Specifically, this influence primarily occurs during the initial stage of transformation, indicating that the digital economy enhances energy eco-efficiency by reducing both consumption structure and intensity of fossil fuels. Thirdly, green technology innovation emerges as another important pathway. The impact is particularly noticeable in the quality of green technology innovation. Lastly, heterogeneity testing demonstrates that non-resource-based provinces and those in central regions experience a significant positive effect between the digital economy and energy eco-efficiency. In contrast, resource-based provinces and those in eastern and western regions do not exhibit such an effect.

Policy Implications

Firstly, it is crucial to take several measures to enhance and optimize the digital economy. On the one hand, the government should actively promote the marketization of digital elements and enhance the research and development capacity of digital technologies. On the other hand, enhancing governance in the digital economy is essential. In particular, to fully utilize the benefits of the digital economy for energy efficiency, it is imperative to focus on advancing quantum communications, artificial intelligence, neurochips, and other cutting-edge technologies within the energy sector.

Secondly, several measures should be implemented to promote the transition towards more sustainable energy consumption. For one thing, the government needs to actively enhance and refine the renewable energy trading system, expand channels for trading renewable energy, and guide society to green consumption. Additionally, price policies, fiscal measures, and financial support can be used to restrain excessive consumption. It is also crucial to incentivize businesses to undergo digital transformation to enhance energy efficiency in their production processes and operations while minimizing unnecessary energy waste.

Thirdly, it is imperative to raise the level of green technological innovation in order to establish a solid foundation for energy eco-efficiency. This may be accomplished by reforming the allocation mechanism for scientific and technological funding, thereby stimulating the vitality of green innovation. Additionally, promoting deeper collaboration between industry, academia, and research institutions led by enterprises will improve the conversion rate of innovative achievements.

To fully leverage the advantages of the digital economy, it is crucial to implement customized and adaptable strategies. This involves transferring data and financial resources to western regions and resource-based provinces, considering their specific economic conditions and regional disparities. Additionally, adjustments should be made based on energy consumption patterns and green innovation capabilities, aiming to promote a new model of digital economy development that enhances energy efficiency.

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Conflict of Interest

The authors declare no conflict of interest.

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Appendix A. The value of energy eco-efficiency by province from 2013 to 2020.

	2013	2014	2015	2016	2017	2018	2019	2020
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	0.809	0.889	0.897	0.914	0.910	0.917	0.911	0.905
Hebei	0.509	0.501	0.487	0.498	0.488	0.475	0.472	0.469
Shanxi	0.441	0.449	0.455	0.452	0.436	0.425	0.430	0.435
Inner Mongolia	0.537	0.525	0.532	0.517	0.534	0.516	0.521	0.526
Liaoning	0.608	0.585	0.576	0.570	0.580	0.585	0.571	0.557
Jilin	0.499	0.486	0.465	0.461	0.459	0.476	0.461	0.446
Heilongjiang	0.576	0.564	0.596	0.577	0.585	0.570	0.579	0.588
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Jiangsu	0.829	0.837	0.830	0.835	0.835	0.827	0.846	0.865
Zhejiang	0.785	0.808	0.815	0.822	0.826	0.825	0.837	0.849
Anhui	0.617	0.638	0.635	0.631	0.627	0.647	0.652	0.657
Fujian	0.736	0.729	0.734	0.737	0.741	0.730	0.736	0.742
Jiangxi	0.675	0.696	0.690	0.692	0.681	0.672	0.670	0.668
Shandong	0.686	0.697	0.704	0.716	0.729	0.735	0.719	0.703
Henan	0.534	0.540	0.530	0.534	0.531	0.518	0.515	0.512
Hubei	0.616	0.652	0.617	0.620	0.621	0.624	0.635	0.646
Hunan	0.627	0.632	0.635	0.641	0.647	0.650	0.654	0.658
Guangdong	0.829	0.909	0.917	0.934	0.930	0.937	0.931	0.925
Guangxi	0.580	0.594	0.572	0.525	0.557	0.552	0.553	0.554
Hainan	0.578	0.574	0.569	0.572	0.555	0.569	0.562	0.555
Chongqing	0.535	0.540	0.544	0.552	0.556	0.640	0.647	0.654
Sichuan	0.608	0.613	0.625	0.617	0.692	0.699	0.694	0.689
Guizhou	0.354	0.354	0.380	0.422	0.427	0.424	0.435	0.446
Yunnan	0.411	0.404	0.412	0.391	0.387	0.448	0.455	0.462
Shanxi	0.512	0.475	0.487	0.486	0.493	0.476	0.504	0.532
Gansu	0.422	0.434	0.421	0.429	0.420	0.426	0.448	0.470
Qinghai	0.535	0.567	0.604	0.590	0.594	0.605	0.614	0.623
Ningxia	0.359	0.354	0.368	0.382	0.355	0.380	0.405	0.430
Xinjiang	0.457	0.450	0.452	0.434	0.432	0.430	0.443	0.456