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Influence of Digital Economy on Urban Energy Efficiency in China

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Abstract: The digital economy (DE) is characterized by invention, low energy consumption, cross-sector integration, and open sharing. It can effectively enhance social production methods, influence consumer behavior, and provide new pathways to enhance total factor energy efficiency (TFEE). This paper studies 280 Chinese cities, employing the entropy method and data envelopment analysis (DEA) model to evaluate and analyze urban DE and TFEE. It also constructs a system generalized method of moments model (SGMM model) and a threshold regression model (TR model) to examine the impact of the DE on TFEE in China. The main study findings include the following: (1) The regression results of the SGMM model indicate that the effect of DE on TFEE in Chinese cities shows a U-shaped trend. (2) The regression results of the TR model further confirm a U-shaped association connecting DE and TFEE, with the threshold estimated at 0.304. (3) The economic factors and industrial structure have a major impact on inhibiting the improvement of TFEE, whereas technological advancements and environmental regulations significantly facilitate its improvement.

Keywords: digital economy; total factor energy efficiency; impact mechanism; threshold regression model; a U-shaped impact

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1. Introduction

In the global fight against climate change and the pursuit of carbon neutrality, improving energy efficiency has become a key strategy for countries to lower carbon emissions, thereby helping to mitigate global warming. China holds the distinction of being the world's largest carbon emitter, accounting for approximately 34% of global emissions. Consequently, the level of energy efficiency in China has garnered significant attention [1]. While the Chinese government has taken steps to enhance regional energy efficiency, challenges related to economic structure and technology have led to energy efficiency levels that are still lower than those in developed countries [2]. In 2022, China's energy efficiency was recorded at 0.132 tons of standard coal per thousand dollars of GDP, substantially higher than the global average of 0.108 tons. This figure is 1.43 times that of Germany and 1.55 times that of the United States [3].

Since its initial introduction by Canadian scholar Don Tapscott in 1996, the concept of the "digital economy (DE)" has been the subject of extensive research, focusing on its relationship with energy efficiency [4]. Existing studies indicate a shift in the evaluation methods of the DE from a singular indicator approach to a comprehensive indicator framework [5]. However, a unified set of comprehensive evaluation indicators for the DE has yet to be established [6]. Furthermore, numerous studies suggest that the relationship between the DE and energy efficiency is linear, with most research concluding that the DE positively influences energy efficiency [7]. In contrast, a minority of studies have identified a nonlinear relationship between the two [8]. Additionally, the common method for evaluating regional total factor energy efficiency (TFEE) is the data envelopment analysis (DEA) model; however, this model requires improvements regarding undesirable outputs and the assessment of full efficiency values [9]. According to the China Academy of Information and Communications Technology, the scale of China's DE continued to experience rapid growth in 2022, accounting for over 36% of China's GDP [10]. The development of the DE plays a significant role in enhancing energy efficiency in China.

In comparison to the existing research, this study introduces innovations in its indicator system, research methods, and research perspective. The evaluation indicator system for the development of the digital economy (DE) in Chinese cities is based on the "Four Transformations Framework" outlined in the "China Digital Economy Development Report (2020)" published by the China Academy of Information and Communications Technology. Additionally, the study employs an improved data envelopment analysis (DEA) model, specifically the Super-SBM-Undesirable model, to evaluate the TFEE of 280 cities in China. Finally, it utilizes the system generalized method of moments model (SGMM model) with the inclusion of the squared term of the DE and threshold regression model (TR model) to empirically analyze the nonlinear relationship between the DE and energy efficiency.

The structure of this paper is organized as follows: Section 2 reviews the existing literature. Section 3 provides a theoretical analysis and presents the research hypotheses. Section 4 outlines the evaluation indicator system, research methods, and data sources. Section 5 presents the empirical analysis, and Section 6 discusses it. Finally, Section 7 summarizes the research conclusions and offers policy recommendations.

2. Literature Review

In summarizing the existing research on energy efficiency, we classify it into single-factor energy efficiency (SFEE) and TFEE based on the number of input factors [11]. The measurement of SFEE generally involves calculating the proportion of output to energy usage. However, this measure overlooks the influence of technology, capital, labor, and environmental factors, leading more scholars to focus on TFEE [12]. For instance, Filippini and colleagues used the SFA model to calculate the TFEE across 49 states in the United States [13]. Nikbakht, aiming to avoid underestimating energy efficiency, employed the DEA model to assess the TFEE of countries in the Gulf region [14]. Similarly, Li et al. calculated the TFEE of 30 provinces in China based on an improved DEA model [15].

The primary factors influencing regional TFEE include economy, industry, technology, urbanization, openness to international markets, and environmental regulations. For instance, Ohene-Asare studied African countries and employed a three-stage framework model to reveal a bidirectional causal relationship between TFEE and the economic level [16]. Yu et al. employed a spatial model to analyze the factors of energy efficiency in China, concluding that optimizing the industrial structure significantly enhances regional TFEE. Conversely, due to China's relatively low rate of technology transfer, investments in technological invention have not had a notable impact on regional TFEE [17]. Cheng et al. employed the DID model to assess both the direct and indirect effects of new urbanization on urban TFEE, finding that new urbanization significantly boosts urban TFEE by promoting innovation, industrial, and structural effects [18]. Additionally, Wu et al. chose the spatial Durbin model to reveal that environmental regulations have a U-shaped impact on China's TFEE [19].

Among the existing research results, only a few scholars have studied regional TFEE from the perspective of the DE. Initially, scholars measure the level of the regional DE through single indicators such as the size of Internet users, online consumption, and digital finance to examine the correlation between the DE and regional energy efficiency. For example, Wu et al. employed the Durbin model to discover that the development of regional Internet not only directly enhances local energy efficiency, but also improves the energy efficiency of neighboring areas [20]. Yang et al. found that digital finance has facilitated effective resource allocation, resulting in more than a 15% increase in regional energy efficiency [21]. With growing interest in the DE, scholars have begun directly constructing regional DE evaluation indicator systems to study its impact on regional

TFEE. Most of these studies conclude that the DE promotes regional TFEE. Liu et al., using the Tobit model and quantile regression model, found that the DE significantly improves China's TFEE, although notable regional differences exist [22]. Xu et al. found that the DE can significantly enhance green TFEE. Furthermore, in more economically developed cities with relatively scarce natural resources, the DE plays an even more beneficial role in improving green TFEE [23]. Shahbaz et al., using panel data from 72 countries, studied the DE's impact on green energy production and consumption. Their results indicate that the DE positively affects energy transition and promotes renewable energy adoption by enhancing governmental governance capabilities [24]. Conversely, some studies suggest that the DE may inhibit regional TFEE. Zhang et al. analyzed the mutual influence paths between the DE, energy efficiency, and carbon emissions. The results show that the growth of the DE does not contribute to promoting energy efficiency and may even inexplicitly increase carbon emissions [25]. Chen's research also found that as the development of the DE continues, there will be a rebound effect on energy consumption. This results in increased energy use while diminishing regional energy efficiency [26]. Some scholars have discovered that the DE exhibits nonlinear characteristics in relation to regional TFEE. Zhou et al. examined energy consumption per unit of GDP as a measure of energy efficiency and discovered a double-threshold effect in the relationship between the DE and energy efficiency. This finding indicates an "N-shaped" pattern; while there are fluctuations in the middle, the overall impact is positive [27].

To sum up, the exploration of the relationship of the DE on regional TFEE is still in its infancy, with the DE emerging as a new driver for regional economic growth. Current research indicates a shift from single-index methods to comprehensive-index methods for evaluating DE levels. However, the comprehensive evaluation index system for the DE remains exploratory, and no widely accepted system has yet been developed. Furthermore, existing studies suggest that the DE's impact on regional TFEE is generally considered linear, with most studies indicating a positive effect on regional TFEE. The DEA evaluation model is commonly used to assess regional TFEE, yet it requires enhancements to address issues such as accounting for unexpected outputs and achieving full efficiency values.

In light of the above, this paper aims to build an index system for China's urban DE by drawing on the China Digital Economy Development Report (2020) issued by the Chinese government. This system will encompass four dimensions: digital industry, industrial digitization, digital governance, and data valorization. Furthermore, leveraging Tone's SBM model and Andersen's super-efficiency evaluation model, this paper proposes the construction of a DEA model tailored to evaluating the TFEE of Chinese cities—the Super-SBM-Undesirable model [28,29]. Additionally, the paper will employ the SGMM model and TR model to study the nonlinear effect of the DE on TFEE, thereby broadening the perspective on enhancing urban TFEE. Finally, this research aims to assist the government in formulating and adjusting DE development policies, maximizing its positive effects on energy efficiency, and promoting regional sustainable development.

3. Theoretical Analysis and Research Hypothesis

From existing research and development practices, the impact of the DE on energy efficiency encompasses two contrasting effects: a suppressive effect and a promotive effect. The specific impact mechanism is shown in Figure 1.

Firstly, the DE can positively influence regional TFEE by optimizing resource allocation, reducing transaction costs, enhancing management precision, and enabling informed decision-making. By optimizing resource allocation and improving production efficiency, information economics suggests that through big data analytics, cloud computing, and IoT technologies, enterprises can more accurately align resources with production needs, thereby minimizing energy waste [30]. For instance, shared mobility platforms like Didi Chuxing employ big data technology and geolocation systems to analyze passengers' demand hotspots and travel patterns, enabling highly efficient matching between vehicles and users. This resource allocation method minimizes vehicle idle time, optimizes capacity distribution, and reduces the total energy consumption and carbon emissions per trip. Secondly, the reduction in transaction costs plays a crucial role. Transaction cost theory suggests that the functioning of firms and markets incurs various transaction costs, such as those associated with information search, negotiation, supervision, and enforcement [31]. However, in the DE, advancements in information technology have significantly reduced these costs. For example, traditional offline market transactions require a significant amount of time and effort to gather information about products, prices, and quality. This increases transaction costs for both consumers and merchants. In contrast, e-commerce platforms such as Taobao and JD.com provide extensive product information and convenient price comparison features, which greatly reduce the time and costs associated with searching for information. Furthermore, refined management theory posits that by focusing on details and precise data management, the efficiency of an organization or system can be enhanced [32]. Digital technologies facilitate this refined management in critical areas—such as transportation, buildings, energy, and environmental protection—through smart city platforms, effectively reducing energy consumption and pollution emissions. For example, in smart agriculture, digital technologies allow for the precise management of water, fertilizers, and pesticides. This is achieved by monitoring factors such as soil moisture, weather conditions, and crop growth. Unlike traditional management methods, which often take a broad approach, this precision strategy significantly reduces the waste of water and pesticides. As a result, it conserves resources and decreases the energy consumption associated with agricultural activities. Lastly, data-driven decision theory suggests that making decisions based on extensive objective data can effectively reduce subjective biases and enhance the scientific rigor of decisions [33]. Thus, in the manufacturing sector, big data analytics is crucial in implementing predictive maintenance, which helps companies minimize resource waste due to equipment failures. For instance, automotive manufacturers leverage big data to monitor the operational status of their production equipment. This allows them to detect early signs of faults and schedule maintenance in advance. By adopting this approach, they effectively prevent production interruptions and reduce energy waste caused by equipment downtime, ultimately enhancing the overall energy efficiency of the production line.

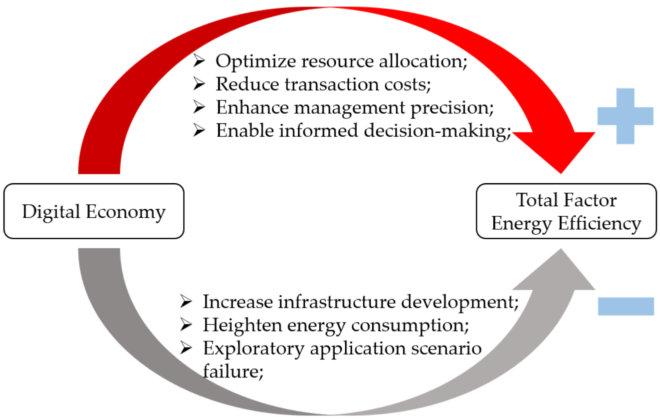

Figure 1. The promotion and inhibition mechanism of the DE on TFEE.

Secondly, the DE may negatively impact regional TFEE through increased infrastructure development, heightened energy consumption, and exploratory failures in application scenarios. Initially, input–output theory indicates that in the early stages of emerging industry development, the high costs of infrastructure investment can raise total factor production costs [34]. In particular, deploying a smart grid involves significant equipment investments, which can result in high energy consumption during the initial construction and testing phases. In Shanghai, for instance, the implementation of a smart grid project included the installation of smart meters for every household and commercial user. This led to a temporary increase in overall energy consumption within the power system. During the construction phase, before the full-scale adoption of the smart grid, this surge in energy demand limited improvements in the region's Total Final Energy Efficiency (TFEE). Additionally, the energy rebound effect theory suggests that although technological advancements can improve energy use efficiency, they may also result in an overall increase in energy consumption [35]. For instance, a smart city project has installed thousands of sensors to monitor traffic, environmental conditions, and energy usage. However, the operation and maintenance of these devices require a continuous power supply, which increases the energy demands of urban infrastructure. This, in turn, negatively impacts the region's Total Final Energy Efficiency (TFEE). Moreover, the energy demands of these new digital infrastructures are significantly higher than those of traditional industry infrastructures. Finally, the theory of innovation failure posits that unsuccessful technological innovations can result in wasted resources and financial losses [36]. As an emerging industry, the DE requires extensive exploratory applications. However, the failure of new application models or technologies—such as smart grids or energy-saving management systems—may lead to ineffective investments that not only fail to achieve energy-saving goals but also contribute to inefficient energy consumption. For example, in a smart street lighting project, Nanjing experimented with different sensors and control systems. However, due to a flawed design, the system did not respond effectively to the actual demand. As a result, many streetlights remained on when they were not needed, leading to unnecessary energy consumption. The subsequent removal and replacement of the equipment further exacerbated the energy waste.

In summary, this paper proposes the following research hypothesis: In China, the DE has a significant impact on urban TFEE, and a potential nonlinear relationship may exist between the two.

4. Research Design

4.1. DE Evaluation

4.1.1. Evaluation Index System for Urban DE

This paper draws on the Four Modernizations framework proposed by the Chinese government in the China Digital Economy Development Report and constructs an evaluation index system for the DE. The evaluation index system covers four dimensions: digital industry, industrial digitization, digital governance, and data valorization, and considers the availability of data. The chosen variables are indicated in Table 1 [37].

Table 1. The evaluation index system of China's urban DE.

Target Layer	Dimension Layer	Indicator Layer
Digital economy	Digital industry	Scale of digital industry practitioners Per capita telecommunications business volume Number of electronic information manufacturing enterprises Number of broadcasting and television industry enterprises Number of Internet and related service enterprises
	Industrial digitization	Agricultural Digitalization Index Industrial Digitization Index Service Industry Digitization Index
	Digital governance	Government Website Development Index Number of pilot projects for smart cities
	Data valorization	Number of data trading institutions Number of open government data platforms

4.1.2. Evaluation Method for DE

Drawing upon the established literature, the entropy method emerges as a commonly adopted approach for assessing the extent of the DE. As an objective weighting technique, the entropy method remains uninfluenced by subjective biases, thereby yielding outcomes of relatively high accuracy and reliability [38]. Hence, this paper opts to employ the entropy method in evaluating the DE status across 280 Chinese cities. The computational procedure of the entropy method is delineated as follows.

First, standardize each indicator in the DE evaluation index system, as shown in Formulas (1) and (2).

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (\text{x is a positive indicator.}) \tag{1}$$

$$x'_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (\text{x is a negative indicator.}) \tag{2}$$

Secondly, calculate the entropy estimate of each variable according to Formula (3). Here, p_{ij} represents the ratio of the j-th data under variable i, and N represents the total number of samples. Entropy is used to measure the uncertainty of the value of the indicator to be evaluated.

$$E_i = -\frac{p_{ij}\ln(p_{ij})}{\ln(N)} \quad p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}} \tag{3}$$

Thirdly, calculate the weights of each indicator according to Formula (4). Here, k represents the number of indicators included in the evaluation index system.

$$w_i = \frac{1 - E_i}{k - \sum_{i=1}^{k} E_i} \tag{4}$$

Finally, normalize the weights of all indicators.

4.2. TFEE Evaluation

4.2.1. Evaluation Index System for TFEE

This paper draws on the urban TFEE evaluation index system by Honma and Borozan, selecting seven major evaluation indicators around the "energy-economy-environment" triple system [39,40]. Furthermore, the evaluation indicators are classified according to the inputs, desired outputs, and undesired outputs, as shown in Table 2. The aim is to objectively evaluate the TFEE level of Chinese cities by using inputs and outputs as the mainline, with energy, labor, capital, economy, and pollutant emissions as the basic elemental units.

Table 2. The input–output index of TFEE.

Target Layer	Criterion Layer	Indicator Layer
Input	Energy	Total energy consumption
	Labor force	Employment scale
	Capital	fixed capital stock
Output	Expected output	GDP
	Unexpected output	Industrial CO_2 emissions
		Industrial SO_2 emissions
		Discharge amount of industrial waste water

4.2.2. Evaluation Method for TFEE

This paper expands on Tone's SBM-Undesirable model by incorporating the super-efficiency DEA model created by Andersen and Petersen to formulate the Super-SBM-Undesirable evaluation model. The SBM-Undesirable evaluation model proposed by Tone is illustrated in Equation (5).

$$\min\rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1 + \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^{g+}}{y_{rk}} + \sum_{t=1}^{q_2}\frac{s_t^{b-}}{y_{tk}}\right)} \tag{5}$$

$$\text{s.t.}\begin{cases} X\lambda + s^- = x_k \\ Y^g\lambda - s^{g+} = y_k^g \\ Y^b\lambda + s^{b-} = y_k^b \\ s^-, s^{g+}, s^{b-}, \lambda \geq 0 \end{cases}$$

In Equation (5), ρ represents the TFEE value of the decision-making unit (DMU). λ denotes the weight vector, while k signifies the k-th evaluated city. m represents the total number of cities being evaluated. The variables q_1 and q_2 indicate the total number of expected output indicators and undesirable output indicators, respectively. Additionally, x, y^g, and y^b represent the input values, expected output values, and undesirable output values, accordingly. The slack variables s^-, s^{g+}, and s^{b-} correspond to inputs, expected outputs, and undesirable outputs, respectively.

The numerator and denominator of the objective function reflect the actual input and output values of the DMU, scaled proportionally to the production frontier, representing input inefficiencies and output inefficiencies. As shown in Equation (5), the SBM-Undesirable model directly incorporates slack variables for both inputs and outputs into the objective function. This allows for a direct measurement of the gap between variable slackness and the optimal production frontier. This approach addresses the slackness issues of inputs and outputs present in traditional DEA models, while also resolving the comprehensive technical efficiency evaluation problem under undesirable outputs.

The core idea of the super-efficiency DEA evaluation model developed by Andersen and Petersen is to exclude the evaluated DMU from the reference set. This means that the efficiency of a DMU is derived from the frontier constituted by other DMUs. As a result, the efficiency value of an efficient DMU will be greater than 1, allowing for the differentiation of efficient DMUs. Based on this principle, the Super-SBM-Undesirable model, derived from the SBM-Undesirable evaluation model and the super-efficiency evaluation model, is presented in Equation (6). The meanings of the characters in Equation (6) are consistent with those in Equation (5).

$$\min\rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^{g+}}{y_{rk}} + \sum_{t=1}^{q_2}\frac{s_t^{b-}}{y_{tk}}\right)} \tag{6}$$

$$\text{s.t.}\begin{cases} \sum\limits_{j=1,j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik} \\ \sum\limits_{j=1,j\neq k}^{n} y_{rj}^g\lambda_j + s_r^{g+} \geq y_{rk}^g \\ \sum\limits_{j=1,j\neq k}^{n} y_{tj}^b\lambda_j - s_t^{b-} \leq y_{tk}^b \\ 1 - \frac{1}{q_1+q_2}\left(\sum\limits_{r=1}^{q_1}\frac{s_r^{g+}}{y_{rk}} + \sum\limits_{t=1}^{q_2}\frac{s_t^{b-}}{y_{tk}}\right) > 0 \\ s^-, s^{g+}, s^{b-}, \lambda \geq 0 \\ i = 1,2,\ldots,m;\ r = 1,2,\ldots,q;\ j = 1,2,\ldots n (j \neq k) \end{cases}$$

From the above, it is evident that the Super-SBM-Undesirable evaluation model constructed in this paper possesses three notable characteristics. First, it effectively measures the slack variables of inputs and outputs. Second, it fully considers and effectively addresses the issue of undesirable outputs. Lastly, it allows for the further evaluation and analysis of efficient DMUs. Therefore, compared to traditional DEA models, the Super-SBM-Undesirable model provides a more authentic and accurate assessment of regional TFEE.

4.3. Model Settings

4.3.1. Determine Variables

Through the organization of research results on TFEE, we have found that various factors influence TFEE, including economics, population, industry, technology, energy, policy, etc. [41,42]. Considering the common characteristics of TFEE development in Chinese cities, this paper selects five major influencing factors, as shown in Table 3.

Table 3. Explanation of regression model variables.

Variable		Variable Definition	Symbol
Interpreted variable	Total factor energy efficiency	Evaluation results of urban TFEE.	TFEE
Core explanatory variable	Digital economy level	Evaluation results of the urban DE.	DEL
	The square of digital economy level	The square of the evaluation results of the urban DE.	DEL^2
Control variables	Economic development	Per capita GDP.	PGDP
	Industrial structure	The portion of the secondary industry.	IS
	Technological innovation	The proportion of scientific and technological expenditures to fiscal expenditure.	TL
	Environmental regulations	The comprehensive index of pollutant emissions.	ER

Interpreted variable: TFEE is selected as the dependent variable. The TFEE of 280 Chinese cities is evaluated based on the aforementioned urban TFEE evaluation index system and the Super-SBM-Undesirable model.

Core explanatory variable: DEL and DEL^2 are selected as the core explanatory variable. The DEL of Chinese cities are evaluated based on the aforementioned urban DE evaluation index system and the entropy method.

Control variables: (1) Choose PGDP to reflect the economic conditions of the city. The effect of economic advancement on urban TFEE includes both promoting and inhibiting effects. A higher economic level is usually accompanied by more technological investment and innovation activities, making it easier to optimize resource utilization and develop alternative energy sources. There is also a higher awareness and requirement for environmental protection and sustainable development, effectively promoting urban TFEE [43]. On the other hand, economically developed areas may have high energy-consuming traditional industries, higher levels of consumption, and lifestyles that lead to more environmental pollution issues, thus inhibiting urban energy efficiency to some extent [44]. (2) The portion of the secondary industry is chosen to indicate the features of the city's industrial structure. Compared to agriculture and service industries, industrial production requires more energy consumption and emits more pollutants. By vigorously developing clean energy and high-technology industries and weakening the growth of energy intensive firms, urban TFEE can be effectively improved [45]. (3) Select the indicator of the share of scientific and technological expenses to fiscal expenses to evaluate the level of urban technological invention. IS is pivotal in developing the TFEE of cities by improving production efficiency, energy utilization, and reducing pollution emissions, thereby achieving continuous improvement in urban energy efficiency [46]. (4) Using a comprehensive index of pollutant emissions to reflect the intensity of ER. The appropriate intensity of ER can urge enterprises to reduce energy consumption, suppress high energy-consuming industries, accelerate technological innovation, improve enterprise management levels, and stimulate market demand, all of which have significant impacts on improving urban TFEE [47].

4.3.2. SGMM Model

The system generalized method of moments model (SGMM model) effectively addresses the endogeneity issue between explanatory variables and the error term in panel data. It overcomes the biases that may arise from ordinary least squares and fixed effects models, while also enhancing estimation efficiency by estimating both the differenced and level equations. Therefore, this paper constructs a SGMM model using the variables presented in Table 3 to analyze the relationship between the DE and TFEE [48]. As shown in Formula (7), i denotes the i-th city and t represents the t-th year. α_i indicates the intercept term, μ_{it} is the error term, ε_{it} represents the city effect, and δ_{it} denotes the time effect. The meanings of TFEE, DEL, DEL^2, PGDP, IS, TL, and ER are consistent with those in Table 3.

$$TFEE_{it} = \alpha_i + \beta_1 TFEE_{it-1} + \beta_2 DEL_{it} + \beta_3 DEL_{it}^2 + \beta_4 PGDP_{it} + \beta_5 IS_{it} + \beta_6 TL_{it} + \beta_7 ER_{it} + \mu_{it} + \varepsilon_{it} + \delta_{it} \quad (7)$$

4.3.3. TR Model

To strengthen the examination of the hypothesis regarding the nonlinear relationship of the DE on TFEE, this paper adopts Hansen's TR model to investigate how the DE influences TFEE across various developmental stages. The model employs the DEL as the threshold indicator to construct the TR model, as represented by Equations (8) and (9) [49]. Here, η represents the threshold value of the model.

$$TFEE_{it} = \alpha_i + \beta_1 DEL_{it} + \beta_2 PGDP_{it} + \beta_3 IS_{it} + \beta_4 TL_{it} + \beta_5 ER_{it} + \mu_{it} + \varepsilon_{it} + \delta_{it}(DEL \leq \eta) \quad (8)$$

$$TFEE_{it} = \alpha_i + \beta_1 DEL_{it} + \beta_2 PGDP_{it} + \beta_3 IS_{it} + \beta_4 TL_{it} + \beta_5 ER_{it} + \mu_{it} + \varepsilon_{it} + \delta_{it}(DEL > \eta) \quad (9)$$

4.4. Data Interpretation

This paper selects a research sample comprising 280 Chinese cities spanning from 2011 to 2022 (excluding Hong Kong, Macau, Taiwan, and Tibet due to data limitations). Interpolation methods are applied to address a small amount of missing data. We obtained enterprise-related data based on the CSMAR data base. Other data sources include the following: China Urban Statistical Yearbook, China Statistical Yearbook, China Economic Net, etc. Table 4 presents a comprehensive list of various statistical indicators for the sample data, including the mean, standard deviation, minimum, and maximum values. These statistics offer insights into the basic characteristics and distribution of the sample data.

Table 4. Variable description statistical results.

Variable	Mean	Std. Dev.	Maximum	Minimum
TFEE	0.531	0.153	1.217	0.074
DEL	0.175	0.105	0.783	0.046
DEL^2	0.126	0.086	0.613	0.002
PGDP	0.354	0.312	2.569	0.058
IS	0.458	0.117	0.914	0.089
TL	0.005	0.022	0.064	0.000
ER	0.136	0.197	0.682	0.000

To avoid false regression, this article uses three testing methods to perform unit root tests on all variables, as shown in Table 5 [50]. The stability of ER is poor and did not pass the 1% significance test. After first-order differencing, ER passed the 1% significance test and was found to be a stationary sequence. Therefore, this paper utilizes the processed stationary variables for the calculations of the SGMM model and the TR model to ensure the reliability of the model estimates. Furthermore, to maintain consistent sequence lengths for all variables, we apply lagging to the remaining variables.

Table 5. Unit root test results.

Variable	LLC Test	ADF Test	IPS Test
TFEE	0.0000	0.0000	0.0000
DTFEE	0.0000	0.0000	0.0000
DEL	0.0000	0.0000	0.0000
DDEL	0.0000	0.0000	0.0000

Table 5. *Cont.*

Variable	LLC Test	ADF Test	IPS Test
DEL^2	0.0000	0.0000	0.0000
$DDEL^2$	0.0000	0.0000	0.0000
PGDP	0.0000	0.0039	0.0000
DPGDP	0.0000	0.0000	0.0000
IS	0.0007	0.0022	0.0000
DIS	0.0000	0.0000	0.0000
TL	0.0000	0.0000	0.0000
DTL	0.0000	0.0000	0.0000
ER	0.0552	0.0681	0.0000
DER	0.0000	0.0000	0.0000

5. Results

5.1. Multicollinearity Test

This study employs the variance inflation factor (VIF) method to examine the multicollinearity among the explanatory variables [51]. The results of the analysis are presented in Table 6. The findings indicate that the mean VIF is 2.62 ($0 < VIF < 10$, suggesting the absence of multicollinearity). Moreover, the VIF values for both core explanatory variables and control variables remain below 10. Therefore, it can be concluded that there is no multicollinearity issue among the explanatory variables in this study.

Table 6. Results of multicollinearity test.

Variable	VIF	1/VIF
DEL	2.17	0.46
DEL^2	2.54	0.39
PGDP	2.96	0.34
IS	2.31	0.43
TL	3.42	0.29
ER	2.33	0.43
Mean VIF	2.62	

5.2. Results of the SGMM Model

The regression results of the SGMM model are presented in Table 7. First, the p-value of the AR(1) test is less than 0.05, while the p-value of the AR(2) test is greater than 0.1. This indicates the presence of first-order autocorrelation and the absence of second-order autocorrelation. The SGMM model passes the autocorrelation tests. The Hansen test yields a p-value greater than 0.1, suggesting that there are no issues of over-identification. Thus, employing the SGMM model to study the impact of the DE on TFEE is valid.

Table 7. SGMM model regression results.

Variable	Coefficient
DEL	−0.764 ***
DEL^2	1.347 ***
PGDP	−0.874 ***
IS	−0.632 ***
TL	1.628 **
ER	1.247 ***
Hansen Test	0.147
AR(1) Test	0.000
AR(2) Test	0.217

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

The impact coefficients of DEL and DEL^2 on TFEE are -0.764 and 1.347, respectively, indicating a "U-shaped" effect of DEL on TFEE. The influence of the DE level on TFEE varies across different stages, which can be divided into four distinct phases, as illustrated in Figure 2.

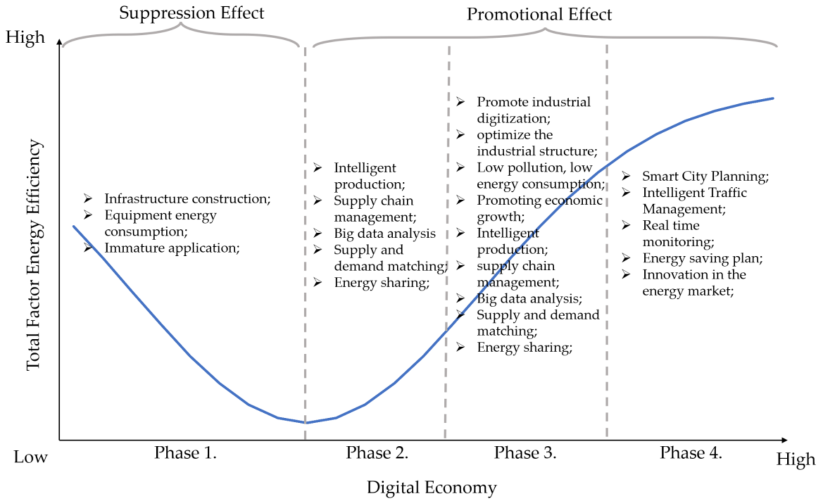

Figure 2. Impact path diagram.

Firstly, there is a stage of inhibitory effect. In the budding stage of the DE, the rapid expansion of the digital industry and industrial digitization has resulted in a rapid growth in the scale of electronic infrastructure, and energy consumption has also increased accordingly. Additionally, the enhancement of DE necessitates substantial energy usage, including the energy consumption of digital equipment, the energy demands of data centers, the energy use of information and communication networks, data transmission, and the energy consumption associated with cloud computing. Finally, DE technology applications are in the exploration stage, and only a few scenarios for improving energy efficiency have been discovered. Therefore, in the budding stage of the DE, the inhibitory effect of the DE on urban TFEE significantly outweighs its promoting effect [52].

Secondly, there is a stage of a promoting effect. After the initial development stage of the DE, basic digital infrastructure and technological foundations are gradually established, and traditional industries are better able to adapt to digital transformation. At this point, the scale of the DE is approaching the critical point, and the promoting effect of TFEE gradually exceeds the inhibitory effect. Mainly, industrial digitization promotes enterprises to achieve intelligent production and supply chain management, optimize production plans and supply chain scheduling, and avoid energy waste and resource idleness. Moreover, industrial digitization provides support for big data analysis and artificial intelligence technology, helping enterprises optimize energy utilization strategies and production decisions. Finally, industrial digitization promotes supply–demand matching and energy sharing among enterprises, avoiding urban energy surplus and imbalance, and improving urban TFEE [53].

Thirdly, there is a stage of an expanding promoting effect. With the continuous development of industrial digitization, urban digital industries are gradually improved, promoting rapid improvement in urban TFEE. The digital industry provides technology, products, services, and solutions for industrial digitization, accelerating the construction of urban industrial digitization. On the other side of the shield, the electronic industry can ensure the transformation of production structures from high energy consumption to environmentally friendly practices. Furthermore, it drives the shift in urban industrial focus towards technology-intensive industries, optimizes the urban industrial structure, and achieves improvements in energy efficiency. Finally, the digital industry, with technological upgrading as the key path, has strong penetration and multiplier effects, which can significantly drive urban economic growth [54].

Fourthly, there is a stage of slowing down the promoting effect. With the gradual maturity of industrial digitization and digital industries, their promoting effect on TFEE gradually weakens. However, the rise of digital governance and data monetization further promotes the improvement of urban TFEE. First and foremost, the construction of digital government and smart cities enhances urban planning and development. It facilitates intelligent traffic management and optimization, along with the real-time monitoring of urban energy consumption and emissions, effectively reducing energy use and pollutant emissions in urban operation and management. Furthermore, data monetization refers to the process of converting data into commercial value. By analyzing and applying data effectively, it can be utilized profitably. Data monetization can significantly enhance urban energy efficiency and sustainability by developing personalized energy-saving strategies, fostering innovation in the energy market, and other methods [55].

Further exploration revealed that when the value of DEL was equal to 0.284, the relationship between DEL and TFEE reversed. That is, when DEL exceeds 0.284, TFEE increases with the rise in DEL. A spatio-temporal analysis of 280 prefecture-level and higher cities in China found that since 2011, cities like Shenzhen, Dongguan, Shanghai, Beijing, and Guangzhou have surpassed a DEL of 0.284. Subsequently, cities like Hangzhou, Nanjing, Suzhou, Ningbo, Xiamen, Zhuhai, and Urumqi also exceeded this level. According to the Digital Economy Blue Book published by the Chinese Academy of Social Sciences, from 2011 to 2022, China's DE grew at an average annual rate of 11.2%. In the early stages, the demand for new digital infrastructure in cities expanded significantly, with few digital technology conversion results and limited practical applications, leading to a decline in urban TFEE. However, as infrastructure improved and application scenarios matured, the DE effectively prevented urban energy waste and resource idleness, even enhancing the urban industrial structure. For example, in 2011, Wuxi's DEL was 0.201 and its TFEE was 0.725. As the DE continued to develop, TFEE fluctuated and declined. By 2014, Wuxi's DEL had increased to 0.341 and its TFEE had dropped to 0.607. Subsequently, Wuxi's TFEE increased continuously with the growth of DEL. By 2022, Wuxi's DEL had risen to 0.472 and its TFEE had increased to 0.929.

Specifically discuss the impact of the four control variables on TFEE. Firstly, the coefficient of PGDP is -0.874, suggesting that PGDP significantly inhibits TFEE. The improvement of urban economic levels often requires more industrial activities and environmental pollution, resulting in a decrease in TFEE. The coefficient of IS is negative, meaning that if IS rises by a unit, TFEE will reduce by 0.632 units. Prove that the impact of IS on TFEE is negative. The more emphasis is placed on the development of the secondary industry, the more high energy-consuming enterprises within the city and the more pollutants are emitted. The coefficient of TL is positive, which means that if TL enlarges by a unit, TFEE will rise by 1.628 units. Prove that TL can promote the improvement of TFEE. The more advanced technology is, the less the energy consumption per unit output, effectively reducing fossil energy consumption and improving urban TFEE. The coefficient of ER is also positive, meaning that if ER grows by a unit, TFEE will improve by 1.247 units. This demonstrates that ER can effectively promote the improvement of TFEE. The more complete the environmental laws and regulations are, the more attention the government pays to urban environmental quality. Therefore, implementing stringent environmental laws can effectively enhance the energy efficiency of organizations and reduce waste emissions.

5.3. Robustness Test

To assess the robustness of the SGMM model, this paper conducts several robustness checks by modifying the measurement methods for the explanatory variable, incorporating additional control variables, and refining the sample range [56]. Firstly, the measurement method for the DE is changed from the entropy method to principal component analysis. The regression results are presented in column (1) of Table 8. Secondly, foreign direct investment (FDI) is included as an additional control variable, with the corresponding regression results shown in column (2) of Table 8. Finally, data from municipalities directly under the central government and provincial capitals are excluded from the sample, and the regression results for this adjustment are displayed in column (3) of Table 8. The findings from all three robustness tests indicate a U-shaped relationship between the DE and TFEE, which aligns with previous conclusions. This suggests that the SGMM model developed in this paper offers a stable explanation of the relationship between the DE and TFEE across various conditions.

Table 8. The robustness test results of the SGMM model.

Variable	(1) Change the Measurement Method of the Explanatory Variable TFEE	(2) Add Control Variable TFEE	(3) Narrow the Sample Range TFEE
DEL	−0.431 ***	−0.915 ***	−0.652 ***
DEL^2	0.857 ***	1.703 ***	1.219 ***
FDI		−0.272 **	
Controls	Yes	Yes	Yes
Hansen Test	0.176	0.203	0.139
AR(1) Test	0.000	0.000	0.000
AR(2) Test	0.187	0.237	0.207

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

5.4. Results of the TR Model

To enhance the reliability of the conclusions drawn from the aforementioned SGMM model, this paper employs a more sophisticated econometric method for hypothesis testing, specifically the TR model [57]. The objective is to investigate whether the variable DEL exhibits a significant threshold effect, thereby determining the nonlinear relationship between DEL and TFEE. The advantage of this method lies in its ability to identify different threshold points within the data, thereby providing a more detailed depiction of the complex relationships between variables. Initially, this paper uses the Bootstrap method for threshold effect testing, obtaining more robust statistical results through multiple sampling. The resulting F-statistic and p-value are presented in Table 9. According to the results, the threshold variable DEL fails to pass the double and triple threshold tests at the 1% significance level, indicating that the correlation of DEL and TFEE does not meet the significance criteria across multiple threshold values. However, DEL shows significance in the single threshold test, indicating that at a specific threshold value, DEL significantly affects TFEE. Specifically, this suggests that when DEL reaches a certain critical point, its mechanism of impact on TFEE may undergo significant changes.

Table 9. Threshold test (bootstrap = 1000 1000 1000).

Threshold Variable	Scenarios	Fstat	Prob.
DEL	Single	108.55	0.000
	Double	32.51	0.171
	Triple	24.12	0.328

Table 10 details the single threshold estimates and their 95% confidence intervals, with a specific estimate of 0.304. This result indicates that when DEL reaches a particular value, the impact of DEL on TFEE undergoes a significant change, further supporting our hypothesis of the threshold effect. The provision of the confidence interval enhances the credibility of this estimate, as it accounts for sample variability, providing a range of possible values and thus increasing the robustness and interpretability of the outcomes.

Table 10. Threshold estimation results (level = 95).

Scenario	Threshold	Lower	Upper
Single	0.304	0.277	0.327

Finally, the computational results of the TR model are presented in Table 11. These results clearly illustrate the complex relationship between DEL and TFEE, confirming the significant impact of DEL on TFEE under specific conditions.

Table 11. Single threshold regression results.

Variable	Coefficient
PGDP	−0.316 **
IS	−0.211 ***
TL	2.033 ***
ER	0.418 **
DEL $(\text{DEL} \leq 0.304)$	−1.224 ***
DEL $(\text{DEL} > 0.304)$	1.407 ***
Cons	0.262 ***
R-squared	0.873
Prob > F	F = 0.000

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

Considering the computational results of the TR model as demonstrated in Table 11, significance tests at the 1% level are passed regardless of whether the threshold variable is above or below 0.304. This indicates that the model possesses high statistical reliability and significance. Specifically, this means that whether the chosen threshold variable is above or below 0.304, the model robustly explains the impact of DEL on TFEE.

Furthermore, when DEL is below 0.304, the coefficient is −1.224, suggesting a negative correlation between DEL and TFEE. Specifically, within this range, as DEL increases, TFEE decreases gradually, indicating that an increase in DEL negatively affects TFEE, thereby diminishing efficiency. This negative correlation suggests that at lower levels of DEL, an increase in DEL may lead to inefficient resource utilization or other adverse effects, thereby restraining TFEE.

However, when DEL is above 0.304, the coefficient changes to 1.407, indicating a positive correlation between DEL and TFEE within this range. In other words, as DEL increases in this interval, TFEE gradually rises. This positive correlation suggests that at greater levels of DEL, an increase in DEL positively impacts TFEE, potentially enhancing TFEE through improved resource utilization efficiency, technological advancements, or other positive effects. This finding indicates that DEL may play different roles at various stages of economic development. For economies with high DEL, increasing DEL could indeed contribute to enhancing TFEE.

Overall, both the SGMM and TR models indicate a U-shaped association connecting DEL and TFEE. Such a U-shaped association reveals the complexity and nonlinear nature of DEL's impact on TFEE. For policymakers, this conclusion provides crucial insights, highlighting the need to carefully consider the different levels of DEL and their varying impacts on TFEE when formulating policies. This approach ensures that appropriate measures are taken to optimize TFEE levels in urban settings.

6. Discussion

We conducted a multi-faceted analysis of the mechanisms by which the DE affects TFEE using the SGMM and TR models. The study reveals a "U-shaped" relationship between the DE and TFEE. To enhance the generalizability and practical value of our research, we compared our findings with the existing literature to uncover differences and analyze their underlying causes. Based on this analysis, we propose rational hypotheses to expand the application scenarios of the DE in enhancing energy efficiency.

Firstly, a comparison and analysis of the results reveal that in the SGMM model, the impact of the DE on TFEE exhibits a significant "U-shaped" relationship. This finding is further supported by the results from the threshold regression model, which identifies a specific threshold value of −2.08. Beyond this threshold, the positive effect of Digital Experience (DE) on total factor energy efficiency (TFEE) begins to emerge. Methodologically, the system generalized method of moments (SGMM) model emphasizes dynamic characteristics, making it well suited for exploring causal relationships in time series data. In contrast, the threshold regression model pinpoints the nonlinear turning point in the DE's impact on TFEE. The consistent results from both models validate each other, confirming that the turning point effect of DE in enhancing TFEE is both significant and robust. Furthermore, our research provides a new perspective on the nonlinear relationship between DE and TFEE, contrasting with previous studies. For example, Zhang et al. found that the digital economy (DE) can enhance China's total factor energy efficiency (TFEE) by promoting economic growth, urbanization, and investment in research and development, based on a mediation effect model [58]. However, Zhao et al., using dynamic panel models and the Durbin model, discovered that the DE has negative effects and spatial spillover effects on China's green TFEE [59]. The "U-shaped" relationship offers a meaningful explanation for these conflicting conclusions and provides valuable support for the development of the digital economy (DE). For instance, cities like Shenzhen and Shanghai, which have reached a high level of DE development, have already surpassed the threshold value, making the positive effects of the DE on total factor energy efficiency (TFEE) evident. In contrast, regions with relatively lower levels of development may still fall on the left side of the "U-shaped" curve, where energy efficiency has not yet experienced significant improvements. Finally, based on the "U-shaped" relationship between the DE and TFEE, we propose the following three hypotheses. These hypotheses integrate relevant theories to further explore the applicability of this relationship in various scenarios and its performance under different conditions. This approach will enhance the generalizability and explanatory power of our conclusions, as well as clarify how varying conditions affect our research findings. Ultimately, this will provide valuable insights for policy-making. (1) We propose a hypothesis regarding urban development, suggesting that cities at different stages of development occupy various positions on a "U-shaped" curve and experience differing levels of impact. Developed cities, which exhibit higher levels of development effectiveness (DE), may be positioned in the ascending phase on the right side of the curve. In contrast, smaller cities might still be located on the left side or at the bottom of the curve. This hypothesis facilitates a deeper analysis of regional differences in the relationship between DE and total factor energy efficiency (TFEE). For example, developed cities, with their advanced digital infrastructure, may have already made strides in energy efficiency. In contrast, smaller cities may need to accelerate their digital economic development in order to enter the phase of efficiency enhancement. This hypothesis can inform policy-making in various cities, encouraging smaller ones to expedite their digital transformation to improve energy efficiency. (2) The hypothesis regarding differences in industrial structure suggests that a city's industrial composition can affect the "U-shaped" relationship between digital economy (DE) and total factor energy efficiency (TFEE). For instance, cities with a higher proportion of industrial activities may require more time and a greater level of DE development to move from the lower part to the ascending phase of the "U" curve. In highly industrialized cities, an initial decline in energy efficiency may occur due to digitization. However, as smart manufacturing and the industrial internet advance, the development of DE will ultimately lead to improvements in energy efficiency. This hypothesis can inform industrial upgrading policies tailored to different types of cities. Heavy industrial cities should prioritize the development of the industrial internet and smart manufacturing. In contrast, cities with a significant service sector need to enhance energy efficiency management within their digital service industries. (3) Hypotheses based on the level of policy support demonstrate that the strength of government policy support influences the curvature of the "U-shaped" relationship. High-intensity policy support (such as financial subsidies and technical assistance) can shorten the bottom phase of the "U" curve, enabling energy efficiency to rise more quickly. In environments with strong policy support, the negative effects of the DE are mitigated, while its positive effects accelerate. For example, government investment in digital infrastructure can speed up a city's transition from the bottom to the right side of the "U" curve. This hypothesis provides valuable guidance for policymakers, suggesting that policy interventions can shorten the efficiency downturn phase and expedite the positive impact of the DE on energy efficiency.

7. Conclusions and Policy Implication

7.1. Conclusions

The DE is a product of the information society and the network era, characterized by innovation, low energy consumption, and sharing. It provides a new pathway to enhance TFEE. Existing research has predominantly explored the linear relationship between the DE and TFEE [60]. This research broadens the perspective by examining the influence of the DE on TFEE through a linear lens. Empirical analysis using sample data from 280 cities in China reveals the following findings: (1) Results from the SGMM model indicate a U-shaped association connecting the DE and TFEE across Chinese cities. (2) The TR model further confirms the U-shaped impact of the DE on TFEE, identifying a threshold at 0.304. (3) Economy and industrial structure significantly inhibit TFEE improvement, while technology and environmental regulations significantly promote TFEE. These findings underscore the complex dynamics involved in how the DE influences TFEE, highlighting the need for nuanced policy considerations that account for both inhibitory and promoting factors across different urban contexts.

7.2. Policy Implications

Recently, the Chinese government has been actively promoting the development of the DE. Key measures include advancing information infrastructure construction, introducing supportive digital industry policies, accelerating the openness of government data, and enhancing information security infrastructure. However, the impact of the development of the DE on the TFEE of cities varies at different stages, so the government should develop policies tailored to the specific stages of the DE [61]. In the initial stage, emphasis is placed on supporting the establishment of information structure and exploring electronic technology application scenarios [62]. In the later stage, more focus is placed on industrial digitalization upgrades, expanding the digital industry, data governance, and data valorization [63].

In the initial phases of development, due to the rapid expansion of demand for information infrastructure and the early stage of digital technology application scenarios, the inhibitory impact of the DE on TFEE outweighs its promotional effects. Therefore, for cities like Guyuan, Dingxi, and Liupanshui that are still in the nascent stages of the DE, it is crucial for the government to expedite the establishment of urban information structure and explore the practical applications of electronic technologies. First, it is not possible to rely solely on the government to complete the construction of information infrastructure. The government, enterprises, and society should work together to form a joint force. Social capital needs to be introduced to accelerate urban information infrastructure construction, enabling it to quickly enter the promoting effect stage. Secondly, in the construction of information infrastructure, energy-saving and environmentally friendly technologies and equipment should be adopted and intelligent monitoring systems and energy-saving equipment should be introduced to reduce energy consumption. Furthermore, the reasonable planning of the layout and design of data centers and the adoption of technologies, such as distributed data centers or edge computing, can reduce data transmission distances and energy loss. Finally, by establishing a digital energy innovation fund, strengthening the industry–university–research cooperation mechanism, and promoting talent training and exchange, the effective promotion of the application of digital technology in improving energy efficiency and the transformation of industry–university–research can be achieved.

In the later stages of digital economic development, industrial digitization, the digital industry, digital governance, and data valorization effectively promote enterprises to achieve intelligent production and supply chain management, promote urban industrial structure transformation, and accelerate the planning and construction of smart cities. The promoting effect of the DE on TFEE far outweighs the inhibitory effect. Firstly, accelerate industrial digitization upgrade. The government needs to formulate policies to support industrial digitization, including tax incentives, financial subsidies, etc., to encourage enterprises to increase digital investment and innovation. Establish industrial digitization service platforms and promote industry–university–research cooperation to provide enterprises with information consultation, technical support, and training services for digital transformation, promoting innovative applications and the implementation of electronic technology in industries. Secondly, promote the vigorous growth of the electronic industry. The government needs to build a favorable digital industry ecosystem, including improving relevant laws, regulations, and policy support. Actively cultivate digital industry clusters and innovation parks, provide excellent venues and infrastructure, promote the aggregation of enterprise resources, and innovate development. Strengthen the coordinated cooperation of the digital industrial chain, promote technological innovation and cooperation between upstream and downstream organizations, and form a solid industrial ecosystem. Next, promote urban digital governance. Construct a sound digital governance infrastructure to enhance data collection and processing capabilities. Promote the opening and sharing of government department data, and establish unified data standards and platforms. Strengthen the digital governance capacity building of civil servants and government personnel, and conduct training and educational activities to enhance their digital skills and awareness of information. Finally, promote data valorization. Strengthen data security and privacy protection measures, establish a sound data management system and legal framework, use encryption technology, and identity authentication to protect data security and personal privacy. The government can incentivize enterprises and research institutions to explore digital technology application scenarios by establishing special funds. This initiative can facilitate the utilization of data in urban operations, healthcare, tourism, consumption, and other sectors, thereby unlocking the full potential value of data.

7.3. Limitations

This paper found that the influence of the DE on the TFEE of Chinese cities follows a “U-shaped” pattern. The study directly determined the control variables in the testing model by referencing existing research results and did not conduct an evaluation of the impacting factors of TFEE in China. Additionally, our team did not compare China with developed countries or other developing countries. The impact of the DE on TFEE may vary depending on the development environment and level of different countries. Particularly for developed countries, the effect of the DE on TFEE may signify a double threshold effect. Hence, the DE may primarily have an inhibitory influence on TFEE, then transition to a promoting effect, and finally revert to an inhibitory effect.

In the next stage, our team will focus on emerged countries such as the United States, Germany, and Japan and will further examine whether the impact of the DE on TFEE exhibits a double threshold effect by constructing TR models, smooth transition autoregressive models, and other econometric models. In this process, control variables for the econometric model will be determined through an evaluation of the impacting factors of TFEE to ensure the accuracy and interpretability of the testing model.

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