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Assessing the Static and Dynamic Efficiency of Digital Economy in China: Three Stage DEA–Malmquist Index Based Approach

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Abstract: The digital economy, a new economic form, has become an essential economic development engine in various countries. Recently, less research has been conducted on the efficiency of the digital economy, with the majority of studies instead concentrating on the industrial size of the digital economy. Therefore, to quantify and analyze the efficiency of China's digital economy from 2013 to 2020 from both a static and dynamic perspective, this research utilized a three-stage DEA model and the Malmquist index. The findings demonstrated that after excluding external environmental factors, the scale efficiency value, integrated technical efficiency value, and pure technical efficiency value all significantly increased. This confirmed that external environmental factors uniquely influence the efficiency of the digital economy. The efficiency of the digital economy varies by location, with the eastern region tending to perform the best, and the central region tending to perform the worst. The efficiency decomposition results demonstrated that the positive growth trend of the efficiency of the digital economy is primarily due to technological advancement. Overall, there is a lot of room for growth in China's digital economy. Each province and city should combine their own capabilities to accelerate digital construction.

Keywords: digital economy; efficiency; three stage DEA; Malmquist index; SFA regression model

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1. Introduction

Since 2020, the world has been affected by the pandemic, and the traditional industrial economy has been hit hard. Against this backdrop, economic powerhouses, such as China, the United States, and Russia, as well as some countries in the Asian–African region, are promoting national economic recovery through digital transformation [1–5]. In recent years, the rapid development of information technology has had a wide impact on people's lives. China's 14th Five-Year (2021–2025) Plan proposes to promote a comprehensive digital economy (DE), adhering to a sustainable development path. As an emerging economy, the DE has a wider scope and a deeper impact than ever before. In 2021, China made a new breakthrough in the development of the DE. The size of the DE reached RMB 45.5 trillion, with a nominal growth of 16.2% year-on-year [6]. The DE has now become an important engine driving China's progress toward becoming a modernized country.

Currently, China's DE is second only to the United States' DE in size. However, the sheer size of a DE does not necessarily reflect a high level of DE efficiency. It is therefore crucial to objectively measure the efficiency of the DE in China. Some current scholars have used the traditional BCC-DEA (variable returns to scale-data envelopment analysis), DEA-SBM (Slacks-Based Model), and DEA-Tobit models to study the efficiency of DEs. However, most scholars have not considered the influence that both environmental factors and random factors have on the efficiency of DEs. It is worth noting that, due to the vast land area of China, there are certain differences in economic bases and policy conditions between provinces and cities. Therefore, whether external environmental factors and stochastic factors have significant effects on the efficiency of the DE is currently a question that needs to be addressed.

The main aims of this paper was to determine the development status of DE efficiency in each region of China, and to determine whether there were regional differences. This paper focused on the DE efficiency of 30 Chinese provinces and cities from both static and dynamic perspectives, and proposes corresponding recommendations based on the analysis results. Firstly, an input–output index system for the DE was constructed. The indicators were selected from four aspects: labor input, capital input, economic output, and technical output. Secondly, a three-stage DEA model was used to statically analyze the efficiency of the DE, and a stochastic frontier regression model was used in the second stage to remove the external environmental effects and random disturbances. Finally, the Malmquist index model was used to analyze the dynamic changes in the DE efficiency of 30 Chinese provinces and cities.

The remainder of the paper is structured as follows: The second part presents a literature review. The third part presents the research content of this paper, including two aspects of model selection and indicator selection. The fourth part presents an empirical analysis. The fifth part discusses the results of the study. The sixth part draws conclusions, proposes recommendations, and discusses limitations and future work.

2. Literature Review

The DE has been developing for decades. Tapscott, the "father of the digital economy", wrote a book in 1996 titled "*The Digital Economy*", which focuses on the process of DE development [7]. Hungerland et al. stated that 'big data' and 'artificial intelligence' are the keywords representing the next round of the digital revolution, and that they are foundational to the concept of the DE [8]. Bo believes that the Internet will drive the economy in the future and that it is already integral to people's lives [9]. In recent years, scholars have realized the importance of objectively measuring the level of development within the DE. A review of the relevant literature reveals that the level of development of the DE is divided into three main areas.

The first area concerns the measurement of the level of development of China's DE. Itkonen believes that a relevant statistical system is the best way to measure the development of the DE [10]. Sidorov et al. proposed a comprehensive index model of functional networks based on the extent of DE growth in regions of different sizes [11]. Bilozubenko et al. used a cluster analysis to compare indicators of DE development in EU countries in order to identify the most important issues for closing the global digital gap [12]. Fu et al. used the entropy value method to construct a system of indicators, encompassing digital infrastructure, digital industrialization, and penetration rate [13]. Although there is currently no consensus on the metrics best suited to measure the development level of the DE, most scholars have provided a comprehensive measure of the DE comprising multiple dimensions [14–16].

The second area concerns the impact of the development of the DE on society. Currently, the DE has become an integral part of people's daily lives and plays a role in all walks of life. China is at a stage where the income gap between urban and rural areas is large, but research has shown that the DE can promote the coordinated development of urban–rural integration [17]. Cui et al. believe that the DE has now become a driving force of high-quality economic development and that it can break down trade barriers between different regions [18]. Zhou et al. showed that the DE has become a huge driver of sustainable business growth. In addition to this, they maintain the DE can play a positive role in the ecosystem [19]. Wu et al. argue that the DE can improve the environment and reduce $PM_{2.5}$ emissions [20]. Lee et al. have showed that the DE has a mitigating effect on carbon emissions in the transportation sector [21].

The third area concerns the study of the efficiency level of a DE. Most studies on the efficiency of the DE use the DEA model, which was developed by the famous American operators Charnes and Cooper [22]. The DEA model is a linear programming model that represents a ratio of outputs to inputs. It has a wide range of applications in healthcare, ecology, technology innovation, and business. Cheng et al. used a traditional DEA model to

measure the efficiency of the DE in Chinese provinces, and the results showed that there was indeed regional heterogeneity in the efficiency the DEs between different Chinese provinces [23]. The DEA model has the advantage of not requiring a specified production function, and likewise avoids the influence of subjective factors [24]. It also has the following disadvantages: Firstly, the closer the total number of decision units is to the total number of inputs and outputs and indicators, the more the technical efficiency reading obtained by the DEA method deviates from the actual amount. Secondly, the DEA method is not suited to comparing technically efficient units. If the effects of random factors in the system are not considered, the technical efficiency results of the DEA method will be affected when there are special points in the sample [25]. In light of these disadvantages, researchers have made the following modifications to the traditional DEA method: Firstly, since environmental factors may have an impact on efficiency values, Coelli proposed a DEA-Tobit regression model [26]. For an example of this, Li has used the DEA-Tobit model to explore the efficiency of China's DE development [27]. Secondly, when assessing efficiency, traditional DEA models do not take into account input–output slack, which may lead to biased estimates of DE efficiency due to radial and perspective decisions. For this reason, Tone has proposed the use of a DEA-SBM model [28]. Zhao et al. used this DEA-SBM model to comprehensively measure the industrial efficiency of China's DE [29]. Zhao also used the SBM-DEA method to measure the regional efficiency of DE industries in both China and the United States [30]. Zhang et al. measured the total factor efficiency of the DE in Latin American countries using an SBM model designed to include non-desired outputs [31]. Finally, Fried proposed a three-stage DEA model that can eliminate the influence of various factors, such as that of the external environment, on the true efficiency [32]. Ye used such a three-stage DEA method to measure the relationship between the efficiency of DE development inputs and the development of commerce and distribution in Zhejiang Province, identifying significant regional differences [33]. While the three-stage DEA model has had a broad impact on various industries, such as transportation, agriculture, and health services industries, it has been relatively seldom applied to the digital economy [34–36]. In this paper, a three-stage DEA model has been used to analyze China's DE from 2013 to 2020. Since the DEA model can only measure static efficiency, it cannot examine the trend of decision unit efficiency over time. On this basis, in order to measure the efficiency of the DE from both static and dynamic perspectives, a three-stage DEA–Malmquist model has been used in this paper.

In summary, this paper uses a three-stage DEA model to study the efficiency of China's DE. In addition, a review of the literature revealed that current scholars mainly conducted research from a static perspective, and that analyses of the dynamic changes in the efficiency of the DE were lacking; therefore, this paper also introduces the use of a Malmquist index based on the three-stage DEA model to measure China's DE from both static and dynamic perspectives. Based on the results of this study, targeted countermeasures have been proposed to support the balanced development of DE efficiency across provinces and municipalities.

3. Methodology and Data

3.1. Methods

The traditional DEA model is a non-parametric statistical estimation method that is widely used to assess technical efficiency. Two of the most classic DEA models are the 'assuming constant returns to scale' model (CCR) and the 'assuming variable returns to scale' model (BCC) [37]. The BCC model can break down the combined efficiency into pure technical efficiency and scale efficiency. The BCC model has increasing or decreasing returns to scale, while the CCR model can only account for technical efficiency with constant returns to scale. The BCC and CCR models are also called VRS and CRS, respectively. However, in the traditional DEA model, external environmental factors and random interference factors affect actual efficiency values. Therefore, Fried proposed the famous three-stage DEA model. The aim of the three-stage DEA model is to determine how to remove environmental factors and random disturbance factors. In the three-stage DEA model, the first stage uses the

BCC-DEA model with variable returns to scale in order to calculate the efficiency of each province. In this paper, the input-oriented BCC has been used to assess the level of DE efficiency, for the following reasons: First, examining the local government's regulation of digital economy inputs allows for more flexibility than controlling both output outcomes and quality does. Second, the BCC model does not impose rigid restrictions on the size of assessment objects and is more consistent with practical research, as shown in Equation (1):

$$\begin{matrix} \text{Min}\left[\theta - \varepsilon(\sum_{j=1}^{m} s^{-} + \sum_{r=1}^{s} s^{+})\right] \\ s.t. \begin{cases} \sum_{i=1}^{n} x_{ij}\lambda_i + s_{ij}^{-} = \theta x_{0j}, j = 1 \ldots m, \\ \sum_{i=1}^{n} y_{ir}\lambda_i - s_{ir}^{+} = y_{0r}, r = 1 \ldots s, \\ \sum_{i=1}^{n} \lambda_i = 1, i = 1 \ldots n, \\ \lambda_i \geq 0, s_r^{+} \geq 0, s_j^{-} \geq 0 \end{cases} \end{matrix} \quad (1)$$

In Equation (1), n is the number of decision units; x_{ij} denotes the j-th input element of the i-th decision unit; y_{ir} denotes the r-th output element of the i-th decision unit; the numbers of j and r are m and s, respectively; s_{ij}^{-} and s_{ir}^{+} are the slack variables of x_{ij} and y_{ir}, respectively; λ_i is the weight variables; θ is the efficiency values, which take values between 0 and 1; and ε is the quantity approaching 0.

Stage 2: China's land is vast, and the resource environment and economic level of its provinces and cities have great variability. The DE efficiency values calculated in the first stage are subject to bias due to environmental and stochastic factors. Therefore, a stochastic frontier model (SFA) is used, with the slacks in the input variables used as explanatory variables and three environmental variables used as explanatory variables. A regression equation is then established to remove environmental and random factors, and the final adjusted input variables can be obtained. The specific expression method is as follows:

$$S_{ij}^{-} = f^{j}(z_i; \beta_j) + \nu_{ij} + \mu_{ij} \quad (2)$$

In Equation (2): f^{j} is the functional form corresponding to the slack variables; z_i is the environment variable; β_j is the coefficient of the environment variable; $\nu_{ij} + \mu_{ij}$ is the mixed error term; ν_{ij} is the random perturbation; and μ_{ij} is the management inefficiency. The adjusted formula is Equation (3):

$$x_{ij}^{A} = x_{ij} + [\max f^{j}(z_i; \beta_j) - f^{j}(z_i; \beta_j)] + [\max\{\nu_{ij}\} - \nu_{ij}] \quad (3)$$

In Equation (3) x_{ij}^{A} is the adjusted input value; $\max f^{j}(z_i; \beta_j) - f^{j}(z_i; \beta_j)$ is adjusted for the external environment; and $\max\{\nu_{ij}\} - \nu_{ij}$ is adjusted for random disturbances. The above adjustment allows each decision unit to be influenced by the same external environment, eliminating their influence.

Stage 3: The operation steps in this stage are roughly the same as those in stage 1, except the two original inputs are replaced with the adjusted inputs, and then used in the BCC-DEA model to calculate the true efficiency values, as demonstrated in Figure 1.

Traditional DEA models measure the static relative efficiency of different decision units within a fixed period. The Malmquist index can measure the dynamic changes of the efficiency of a decision unit in different periods. Combining these two evaluation methods, the DEA model and the Malmquist index model, can provide a more comprehensive measure of the efficiency of a DE. Therefore, this paper introduces the Malmquist index model in combination with the three-stage DEA model. The specific steps of the three-stage DEA–Malmquist index study were as follows: Firstly, the original inputs and outputs were calculated using the traditional DEA–Malmquist index model to obtain the change in the total factor productivity before adjustment. Secondly, the optimized inputs were calculated using the DEA model and the SFA model. Finally, the DEA–Malmquist index model was again used to calculate the adjusted inputs and the original outputs, so as to obtain the adjusted total factor productivity.

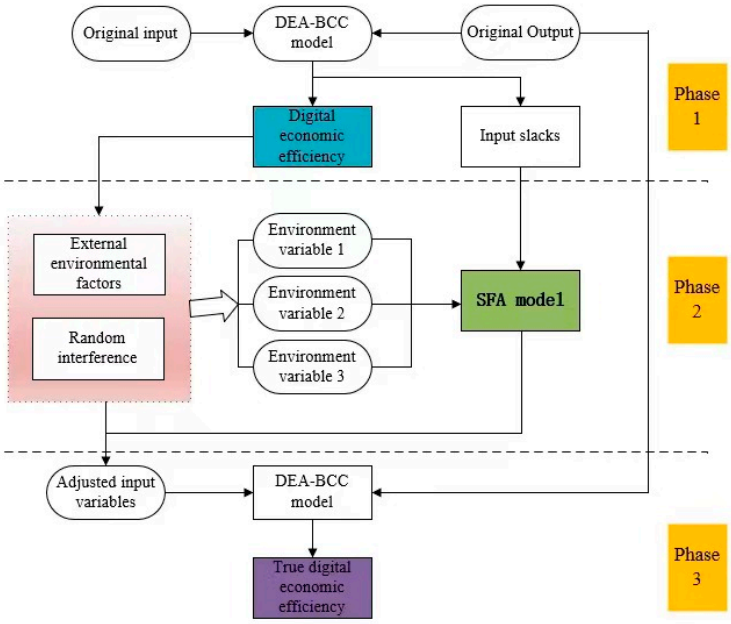


Figure 1. Three-stage DEA model.

The Malmquist index was first proposed by Malmquist in 1953 [38]. Caves et al. constructed a Malmquist index for measuring productivity changes using the ratio of distance functions, inspired by the Malmquist scaling factor [39]. Therein, x^t and y^t are the inputs and outputs in period t, respectively; x^{t+1} and y^{t+1} are the inputs and outputs in period $t+1$, respectively; and the change is called the productivity change. The formula is as follows:

$$\begin{aligned} M_t(x^t, y^t, x^{t+1}, y^{t+1}) &= \frac{D_c^t(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)}, \\ M_{t+1}(x^t, y^t, x^{t+1}, y^{t+1}) &= \frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^{t+1}(x^t, y^t)} \end{aligned} \tag{4}$$

In empirical analyses, researchers commonly use a DEA-based Malmquist index constructed by Färe et al., which uses the geometric mean of two Malmquist production indices to calculate the change in productivity [40]. This Malmquist index measures the change in the total factor productivity from period t to $t+1$. The formula is shown below.

$$M(x^t, y^t, x^{t+1}, y^{t+1}) = (M_t \times M_{t+1})^{1/2} = \left[\frac{D_c^t(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)} \cdot \frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^{t+1}(x^t, y^t)} \right]^{1/2} \tag{5}$$

If $M > 1$, this indicates that the total factor productivity is growing; if $M < 1$, this indicates that the total factor productivity is declining. The Malmquist index can, in turn, be broken down as follows.

$$\begin{aligned} M(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_v^{t+1}(x^{t+1}, y^{t+1})}{D_v^t(x^t, y^t)} \times \left[\frac{D_v^t(x^t, y^t)}{D_v^{t+1}(x^t, y^t)} \cdot \frac{D_v^t(x^{t+1}, y^{t+1})}{D_v^{t+1}(x^{t+1}, y^{t+1})} \right]^{1/2} \times \\ \left[\frac{D_c^t(x^{t+1}, y^{t+1}) / D_v^t(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t) / D_v^t(x^t, y^t)} \cdot \frac{D_c^{t+1}(x^{t+1}, y^{t+1}) / D_v^{t+1}(x^{t+1}, y^{t+1})}{D_c^{t+1}(x^t, y^t) / D_v^{t+1}(x^t, y^t)} \right]^{1/2} \\ TFP = TE \times TP = PTE \times SE \times TP \end{aligned} \tag{6}$$

In Equation (6), the meanings of the letters appearing in the formula are shown in Table 1.

Table 1. Letter symbol meaning.

Symbols	Explanation
TPF	Indicates the total factor productivity.
TE	Indicates the comprehensive technical efficiency.
PTE	Indicates the pure technical efficiency.
TP	Indicates the technical progress.
SE	Indicates the scale efficiency.
C	This is the efficiency level with CCR.
V	This is the efficiency level with BCC.
$D^t(x^t, y^t)$,$D^t(x^{t+1}, y^{t+1})$	They are the distance functions of the decision units at t and $t + 1$, respectively, when the data at time t is used as the reference.

3.2. Data

3.2.1. Indicator Selection

According to the available research results and data [41], the following variables have been selected as input–output indicators in this paper, as shown in Table 2: First, input indicators included the labor input and capital input. The number of employed persons in urban units of the digital industry was selected to measure the labor force participation in the digital industry. The total fixed asset investment in the digital industry was selected as the indicator of capital input, while the digital fixed asset investment reflects the national support for the digital sector, to a certain extent. Second, the output indicators were selected, and they were selected based on two aspects: economic output and technical output. For the former, the software industry's revenue has been used as an economic output indicator, as it can reflect the output scale of the DE to a certain extent. The Digital Inclusive Finance Index was selected as a technical output indicator. 'Digital inclusive finance' represented the application of Internet technology in the financial field with the help of computer processing, data communication and other related technologies, so that the Digital Inclusive Finance Index could reflect the development of digital technology [42].

Table 2. Input and output indicator system.

Indicator Type	Indicator Meaning	Specific Indicator	Indicator Source
Input	Labor	Employment in urban units of digital industry	White Paper on the Development of China's Digital Economy
	Financial	Total fixed asset investment in digital industry	White Paper on the Development of China's Digital Economy
Output	Economic	Software industry income	China Statistical Yearbook
	Technological	Digital Inclusive Finance Index	Peking University Digital Finance Research Center
Environmental variables	Economic	Gross domestic product	China Statistical Yearbook
	Scientific Research	Fiscal expenditure on science and technology	China Statistical Yearbook
	Market	Total retail sales of social consumer goods	China Statistical Yearbook

3.2.2. Selection of Environmental Variable Indicators

The external environment is an objective factor that affects the efficiency of the digital economy, but it cannot be controlled. When assessing the efficiency of the digital economy, it is crucial to consider the impact of external environmental factors. By reviewing and collating relevant literature, we found that some scholars selected indicators based on the level of economic development, the level of urbanization, the capacity of market consumption, and the number of patent applications [43,44]. In contrast, this paper selected indicators from economic research, scientific research, and market environments, and did so based on the availability and rationality of the data as represented by gross domestic product, fiscal expenditure on science and technology, and the total retail sales of social consumer goods, respectively. The descriptive statistics of the variables are shown in Table 3.

Table 3. Descriptive statistics of each variable.

Indicator	Unit	Mean	Std. Dev.	Min	Max
Total fixed asset investment in digital industry	100 million yuan	136.36	118.61	3.98	550.06
Employment in urban units of digital industry	10 thousand	13.06	15.99	0.80	92.30
Software industry income	10 thousand yuan	17,356,115.3	28,092,013.27	8743.96	157,372,908.00
Digital Inclusive Finance Index	_	253.87	68.59	118.01	431.93
Gross Domestic Product	100 million yuan	21,498.0682	16,263.32328	1978.76732	73,075.67068
Fiscal Expenditure on Science and Technology	100 million yuan	109.829726	125.4953439	6.942581864	785.2626539
Total retail sales of social consumer goods	100 million yuan	8736.21154	6762.221242	544.08162	29,071.37952

This paper selected the panel data of 30 Chinese provinces covering the period of 2013–2020 for empirical analysis. Due to the lack of data for Hong Kong, Macao, Taiwan, and Tibet, they were not included in the study. The original data in this paper were obtained from the China Statistical Yearbook, and the White Paper on China's Digital Economy Development. The Digital Inclusive Finance Index was built using data from the Digital Finance Research Center of Peking University. All price-related indicators in this paper have been adjusted based on the 2013 price index, excluding the effect of inflation.

4. Results

4.1. Correlation Analysis

Before calculating the efficiency of DE, a correlation test was conducted on the input–output indicators to ensure that there are specific correlations between them. Using SPSS22.0 software to calculate the Pearson correlation test matrix, it was concluded that there is a significant positive correlation between the input and output variables. Therefore, we concluded that an efficiency analysis can be performed on the previously selected indicators, as shown in Table 4.

Table 4. The correlation coefficient of input-output variables.

	Software Industry Income	Digital Inclusive Finance Index	Total Fixed Asset Investment in Digital Industry	Employment in Urban Units of Digital Industry
Software industry income	1			
Digital Inclusive Finance Index	0.451 **	1		
Total fixed asset investment in digital industry	0.567 **	0.406 **	1	
Employment in urban units of digital industry	0.884 **	0.388 **	0.484 **	1

** indicate that corresponding variables are significant at significance levels of 5%.

4.2. Results of the First Phase of Analysis

This study used the DEA-BCC model with both input-oriented and variable returns to scale in the first stage. DEAP 2.1 software was then used to calculate the combined technical efficiency of 30 Chinese provinces and cities from 2013 to 2020, with the results of this shown in Table 5. The values in the table are efficiency values, and when the efficiency value is equal to 1, this indicates that the province or city reached the efficiency frontier surface, i.e., the efficiency achieves the best value. The closer the efficiency value is to 1, the more efficient the DE.

Table 5. The DE efficiency by province and city in China from 2013 to 2020.

Region	2013	2014	2015	2016	2017	2018	2019	2020	Mean
Beijing	0.940	0.372	0.392	0.466	0.425	0.407	0.490	0.784	0.535
Tianjin	1.000	1.000	1.000	0.941	0.908	0.902	0.842	0.995	0.949
Hebei	0.196	0.143	0.168	0.179	0.213	0.170	0.140	0.106	0.164
Shanxi	0.208	0.197	0.167	0.248	0.550	0.378	0.348	0.300	0.300
Inner Mongolia	0.151	0.167	0.193	0.207	0.223	0.162	0.171	0.174	0.181
Liaoning	1.000	1.000	0.985	1.000	0.638	0.430	0.412	0.497	0.745
Jilin	0.343	0.318	0.338	0.363	0.382	0.452	0.277	0.403	0.360
Heilongjiang	0.182	0.174	0.177	0.188	0.189	0.132	0.138	0.136	0.165
Shanghai	0.795	0.547	0.828	0.629	0.745	0.797	0.767	1.000	0.764
Jiangsu	0.776	0.899	1.000	1.000	1.000	0.971	0.827	0.968	0.930
Zhejiang	0.788	0.674	0.809	0.727	0.699	0.839	0.686	0.858	0.760
Anhui	0.173	0.172	0.180	0.196	0.224	0.218	0.244	0.283	0.211
Fujian	1.000	1.000	1.000	1.000	1.000	0.924	1.000	1.000	0.991
Jiangxi	0.214	0.222	0.164	0.210	0.225	0.208	0.201	0.229	0.209
Shandong	0.826	0.815	0.988	0.894	0.790	0.967	0.871	0.872	0.878
Henan	0.348	0.192	0.186	0.173	0.164	0.129	0.113	0.095	0.175
Hubei	0.500	0.404	0.455	0.453	0.463	0.467	0.313	0.367	0.428
Hunan	0.244	0.243	0.263	0.267	0.294	0.310	0.258	0.366	0.281
Guangdong	0.673	0.738	0.870	0.778	0.741	0.618	0.583	0.748	0.719
Guangxi	0.178	0.198	0.202	0.234	0.245	0.218	0.358	0.353	0.248
Hainan	0.712	0.698	0.653	1.000	1.000	1.000	1.000	1.000	0.883
Chongqing	0.618	0.796	1.000	1.000	1.000	1.000	1.000	1.000	0.927
Sichuan	0.575	0.533	0.528	0.487	0.473	0.578	0.506	0.526	0.526
Guizhou	1.000	1.000	0.646	0.440	0.388	0.319	0.310	0.288	0.549
Yunnan	0.141	0.186	0.282	0.212	0.277	0.262	0.272	0.244	0.235
Shaanxi	0.164	0.111	0.184	0.103	0.147	0.127	0.140	0.130	0.138
Gansu	0.274	0.319	0.294	0.319	0.477	0.337	0.358	0.336	0.339
Qinghai	1.000	1.000	1.000	1.000	0.835	0.857	0.860	0.961	0.939
Ningxia	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Xinjiang	0.291	0.284	0.266	0.315	0.400	0.296	0.290	0.300	0.305
Mean	0.544	0.513	0.541	0.534	0.537	0.516	0.493	0.544	0.528

The overall efficiency of China's DE development between 2013 and 2020 showed a good performance, with a mean value of 0.528 for comprehensive technical efficiency, which does lag behind the efficiency frontier surface of 0.472 and thus has much room for improvement. From the perspective of each province, the top five provinces and cities are Ningxia, Fujian, Tianjin, Qinghai, and Jiangsu. Among them, Fujian, Tianjin, and Jiangsu are located in the eastern part of China; they are strategically located and economically developed, so their DEs are better developed. Ningxia and Qinghai belong to relatively economically poor regions in China, but they still rank among the top regions in China regarding digital economy efficiency. A further analysis revealed that Ningxia Autonomous Region maintained a comprehensive technical efficiency value of 1 for a long time throughout the period of 2013–2020, indicating that the region led in both pure technical efficiency and scale efficiency. The main reason for this is that a relatively economically developing region makes the best use of digital input resources and, thus, receives better returns. The table above shows preliminary estimates of China's DE efficiency values for 2013–2020. However, the development of the DE may have been affected by external environmental factors and random disturbances, which may have led to higher or lower efficiency values. Therefore, it is necessary to make further adjustments and to measure the efficiency of China's DE after removing the influence of external environmental factors and random disturbances.

4.3. Analysis of the External Environment of Digital Economy Development Efficiency

In the second stage of the three-stage DEA model, the SFA method was applied to calculate the influence of environmental factors on the efficiency values, reduce the

errors in the first stage, and analyze the real digital economy efficiency in China. The slack variable was the difference between the actual input value calculated in the first stage and the target value. A maximum likelihood estimation was performed using FRONTIER 4.1 software, with two input slack variables used as explanatory variables and three external environmental variables used as explanatory variables. The results of the SFA model manipulation are shown in Table 6. Significance tests found that most of the environmental variables were significant, and it can be seen from Table 6 that each of the three environmental variables had different effects on the slack variables.

Table 6. Results of the second phase of analysis.

Environment Variable	Financial	Labor
Constant	−11.995836 ***	−0.11326818
	(−11.995848)	(−0.41421638)
Gross domestic product	0.0022286175	0.000072277341 **
	(1.2622553)	(2.0818534)
Fiscal expenditure on science and technology	0.11165376	−0.0050884214 **
	(1.0833973)	(−2.1907933)
Total retail sales of social consumer goods	−0.011277366 ***	−0.0001547671 **
	(−2.7788939)	(−2.1040214)
Sigma squared	12,710.589	14.904716
	(12710.589)	(3.3293068)
Gamma	0.83495621 ***	0.92875796 ***
	(19.594055)	(44.02234)
Log likelihood function	−1276.6204	−407.06643
LR test	248.73587 ***	415.36481 ***

***, ** indicate that corresponding variables are significant at significance levels of 1%, 5%, respectively.

As can be seen from Table 6, the LR one-sided error test was significant at the 5% level; the gamma values were 0.83495621 and 0.92875796, and they converged to 1, indicating that the model was set up reasonably and that the external environment had a significant effect on the efficiency values. Therefore, the original input quantity should be rationalized to reduce the interference of the external environment. If the coefficient is positive, there is a positive correlation between the external environment and the slack variables, which is detrimental to the improvement of the efficiency of the DE. If the coefficient is negative, there is a negative correlation between the external environmental factors and the slack variables, which is beneficial to the improvement of the efficiency of the DE. The results of the analysis of the effect of each of the environmental variables on the slack variables were as follows.

(1) The economic environment coefficient of the input variables was significantly positive for the economic environment. This indicated that the level of regional economic development does not contribute to improving the efficiency of the DE, probably because regions with higher levels of economic growth have a siphon effect, which attracts more enterprises and talents. If the input indicators are not reasonably allocated, then redundancy will occur.

(2) The coefficient of the science and technology innovation environment of the input variables was significantly negative, which indicated that the science and technology innovation environments play a role in improving the efficiency of the digital economy. The main reason for this is that the high-technology development can improve the digital industry's efficiency, which, in turn, can reduce unnecessary human and material investments. Therefore, the provinces should improve their financial investment in science and technology, which will be beneficial to enhancing the efficiency of the DE in each province.

(3) The coefficient of the market consumption environment of input variables was significant and negative, which indicated that a good consumption environment can reduce input redundancy, which, in turn, can improve digital economy efficiency.

Thus, improving the living standards of the population can improve the efficiency of China's DE.

4.4. The Third Stage of Analysis

In the third stage of DEA analysis, the DE efficiency of 30 Chinese provinces and cities from 2013 to 2020 was remeasured using DEAP 2.1 software. The optimized efficiency values are shown in Table 7. By observing the data in the table, it can be seen that, after excluding the effects of environmental factors and random perturbations, there were some differences in the efficiency values before and after adjustment, indicating that the construction of the SFA model was meaningful for the second-stage estimation. In the overall analysis, the adjusted annual average value of China's DE efficiency was 0.681; this is higher than the average efficiency in the first stage of 0.153, which is 0.319 behind the production frontier. This indicated that the efficiency value of the first stage has been underestimated.

Table 7. Average efficiency before and after the optimization of China's digital economy from 2013 to 2020.

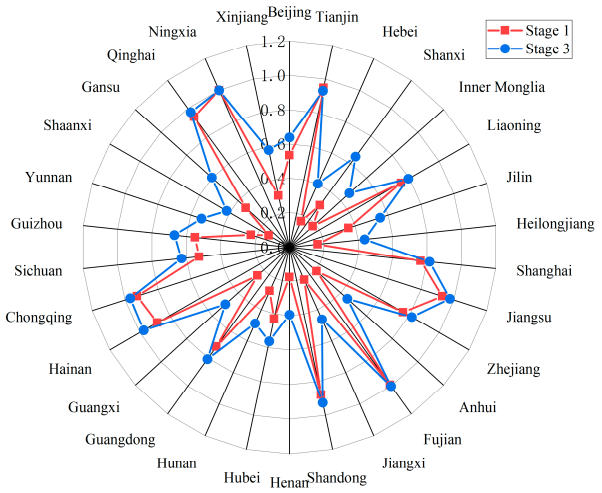
Area	Region	Results of Stage 1			Results of Stage 3		
		TE	PTE	SE	TE	PTE	SE
East	Beijing	0.535	1.000	0.535	0.639	1.000	0.639
	Tianjin	0.949	1.000	0.949	0.931	0.998	0.933
	Hebei	0.164	0.184	0.899	0.402	0.424	0.964
	Shanghai	0.764	1.000	0.764	0.815	1.000	0.815
	Jiangsu	0.930	1.000	0.930	0.976	1.000	0.976
	Zhejiang	0.760	1.000	0.760	0.817	1.000	0.817
	Fujian	0.991	1.000	0.991	1.000	1.000	1.000
	Shandong	0.878	0.950	0.927	0.926	0.973	0.952
	Guangdong	0.719	0.979	0.735	0.808	0.991	0.816
	Hainan	0.883	1.000	0.883	0.974	1.000	0.974
Central	Shanxi	0.300	0.350	0.848	0.651	0.695	0.932
	Anhui	0.211	0.275	0.783	0.450	0.489	0.891
	Henan	0.175	0.204	0.871	0.396	0.412	0.962
	Hubei	0.428	0.460	0.927	0.563	0.601	0.929
	Hunan	0.281	0.293	0.957	0.489	0.510	0.966
West	Inner Mongolia	0.181	0.227	0.826	0.466	0.498	0.905
	Chongqing	0.927	0.939	0.984	0.968	0.976	0.992
	Sichuan	0.526	0.542	0.971	0.628	0.653	0.964
	Guizhou	0.549	0.559	0.976	0.670	0.702	0.950
	Yunnan	0.235	0.249	0.942	0.535	0.576	0.929
	Guangxi	0.248	0.286	0.878	0.500	0.538	0.923
	Jiangxi	0.209	0.297	0.742	0.462	0.507	0.904
	Shaanxi	0.138	0.185	0.796	0.420	0.436	0.943
	Gansu	0.339	0.356	0.957	0.604	0.670	0.908
	Qinghai	0.939	0.958	0.979	0.972	0.989	0.983
	Ningxia	1.000	1.000	1.000	1.000	1.000	1.000
	Xinjiang	0.305	0.324	0.950	0.578	0.610	0.952
North-east	Liaoning	0.745	0.749	0.993	0.794	0.813	0.971
	Jilin	0.360	0.363	0.991	0.551	0.580	0.963
	Heilongjiang	0.165	0.172	0.959	0.437	0.468	0.926
East mean		0.757	0.911	0.837	0.829	0.939	0.889
Central mean		0.279	0.316	0.877	0.510	0.541	0.936
West mean		0.466	0.494	0.917	0.650	0.680	0.946
North-east mean		0.423	0.428	0.981	0.594	0.620	0.953
National mean		0.528	0.597	0.890	0.681	0.737	0.926

The third-stage efficiency values of all regions were more significant than the first-stage values. This indicates that the external environment had some influence on the efficiency values of each region in China, resulting in the underestimation of DE efficiency. A further analysis revealed that the external environment interfered the most with the

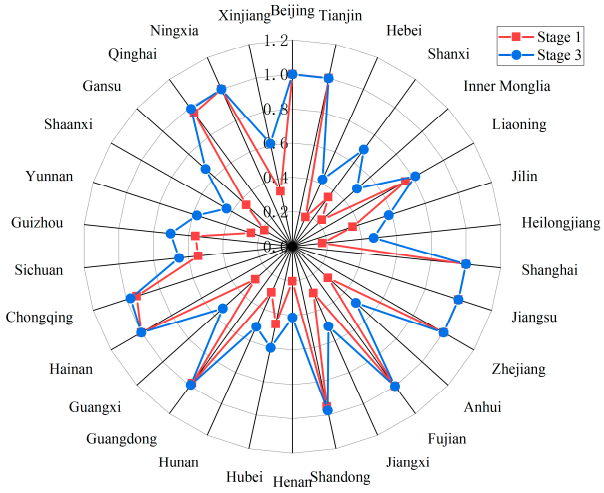
efficiency value in the central region. This indicates that the central region should improve the external environment while developing their DE. The regional rankings of the adjusted combined technical efficiency values for the digital economy were (in descending order): east, west, northeast, and central. This showed regional heterogeneity in the efficiency of China's DE and an uneven development of the regional DE. After a further investigation, it was found that the degree of DE development in different regions and DE industry talent mobility may be causally related; economically developed regions with good information and data infrastructures provide more jobs related to the DE, and they are more likely to attract a large inflow of talented people. In addition, a continued inflow of talent in digital-economy-related industries led to increased productivity, thus continuing to drive the region's digital economy.

Interprovincial analysis: After adjusting the efficiency values of the DE, the gap between the provinces was reduced. Two provinces have production frontiers in the first and third stages, namely Ningxia and Fujian, with Ningxia reaching the efficiency frontier surface in both the first and third stages, which indicates that external environmental factors and random disturbances do not affect it. In contrast, the efficiency value of Fujian Province increased from 0.990 to 1 and likewise reached the efficiency frontier, indicating that the influence of the external environment results in the underestimation of the scale efficiency of Fujian Province and thus does not reflect the real situation.

In addition, as shown in Figure 2, the combined technical efficiency obtained after excluding environmental factors was mainly caused by the change of pure technical efficiency, which may be because environmental factors are related to digital technology and management in different regions. As a result, environmental factors have been adjusted to have a more significant impact on pure technical efficiency and a relatively low impact on scale efficiency. Only Tianjin has three optimized efficiency values, slightly lower than the first stage. After optimization, the remaining provinces and municipalities have higher efficiency values than before. Regarding scale efficiencies, only those of Tianjin, Liaoning, Heilongjiang, Guizhou, Yunnan, and Gansu Provinces became smaller after optimization, with the scale efficiency values of the remaining provinces instead improving to some extent.

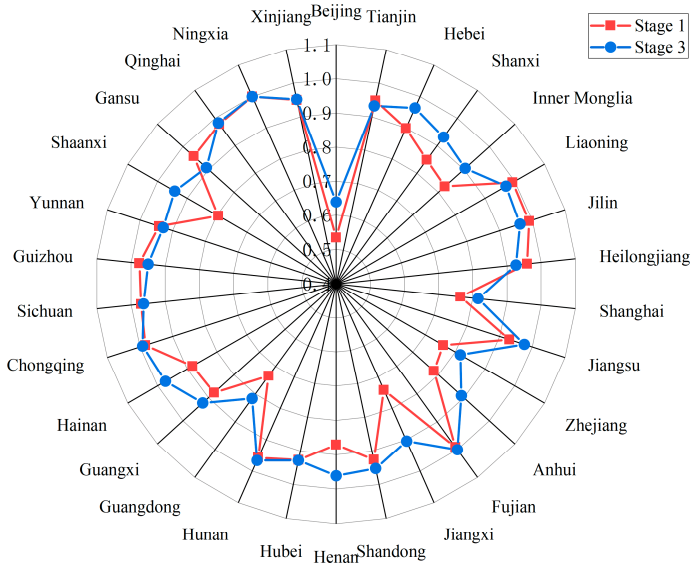


(**a**) Comprehensive Technical Efficiency



(**b**) Pure Technical Efficiency

Figure 2. *Cont.*



(**c**) Scale Efficiency

Figure 2. The radar charts in (**a**–**c**) represent comprehensive technical efficiency, pure technical efficiency, and scale efficiency, respectively.

4.5. Analysis of Malmquist

Thus far, this paper has studied the efficiency of China's DE from 2013 to2020 from a static perspective. In order to have a more comprehensive understanding of the dynamic changes in the efficiency of the digital economy in each province and city, a three-stage Malmquist index model is introduced in the following section of the paper to study the dynamic efficiency changes in each province and city. The results are shown in Table 8.

Table 8. The DEA-Malmquist index of the digital economy efficiency in China and its decomposition.

Area	Region	Results of Stage 1					Results of Stage 3				
		TE	TP	PTE	SC	TFP	TE	TP	PTE	SC	TFP
East	Beijing	0.897	0.805	1.000	0.897	0.722	0.999	0.980	1.000	0.999	0.979
	Tianjin	0.927	0.833	1.000	0.927	0.772	1.000	1.219	1.000	1.000	1.218
	Hebei	0.969	0.852	0.949	1.021	0.825	0.85	1.167	0.845	1.006	0.992
	Shanghai	1.036	0.781	1.000	1.036	0.809	0.984	1.019	1.000	0.984	1.003
	Jiangsu	1.026	0.856	1.025	1.001	0.878	1.000	1.114	1.000	1.000	1.114
	Zhejiang	0.865	0.876	1.000	0.865	0.757	1.000	1.102	1.000	1.000	1.101
	Fujian	1.000	0.804	1.000	1.000	0.804	1.000	1.038	1.000	1.000	1.038
	Shandong	0.965	0.87	0.966	0.998	0.839	0.987	1.110	0.987	1.000	1.095
	Guangdong	0.934	0.823	1.000	0.934	0.769	0.976	1.08	0.989	0.987	1.055
	Hainan	1.046	0.865	1.000	1.046	0.905	1.000	1.099	1.000	1.000	1.099
Central	Shanxi	1.066	0.819	0.959	1.112	0.873	0.968	1.075	0.973	0.995	1.041
	Anhui	0.871	0.850	0.924	0.943	0.740	0.863	1.245	0.889	0.97	1.074
	Henan	0.824	0.821	0.789	1.045	0.677	0.835	1.019	0.835	1.001	0.852
	Hubei	0.907	0.877	0.937	0.968	0.796	0.895	1.176	0.900	0.995	1.053
	Hunan	0.95	0.854	0.986	0.963	0.811	0.901	1.263	0.898	1.003	1.138

Table 8. *Cont.*

Area	Region	Results of Stage 1					Results of Stage 3				
		TE	TP	PTE	SC	TFP	TE	TP	PTE	SC	TFP
West	Inner Mongolia	1.042	0.869	1.129	0.923	0.905	0.902	1.237	0.899	1.003	1.116
	Chongqing	0.928	0.865	0.966	0.961	0.804	0.909	1.292	0.909	1.001	1.174
	Sichuan	0.957	0.843	0.999	0.958	0.806	1.008	1.163	1.005	1.003	1.173
	Guizhou	0.930	0.870	0.932	0.998	0.809	0.936	1.149	0.932	1.004	1.075
	Yunnan	0.796	0.790	0.809	0.984	0.629	0.910	1.001	0.916	0.994	0.912
	Guangxi	1.073	0.839	1.039	1.033	0.900	0.944	1.197	0.945	0.999	1.130
	Jiangxi	0.961	0.832	0.936	1.027	0.800	0.886	1.148	0.925	0.958	1.017
	Shaanxi	0.975	0.769	0.846	1.152	0.749	0.914	1.088	0.919	0.995	0.995
	Gansu	1.018	0.848	1.033	0.986	0.863	0.961	1.159	0.954	1.007	1.113
	Qinghai	0.979	0.785	1.000	0.979	0.769	0.997	1.071	1.000	0.997	1.068
	Ningxia	1.000	0.893	1.000	1.000	0.893	1.000	1.136	1.000	1.000	1.136
	Xinjiang	1.021	0.887	1.027	0.994	0.905	0.944	1.189	0.948	0.995	1.122
Northeast	Liaoning	1.171	0.842	1.170	1.001	0.986	0.915	1.012	0.923	0.992	0.926
	Jilin	1.099	0.856	1.098	1.001	0.941	0.937	1.207	0.923	1.015	1.131
	Heilongjiang	1.038	0.860	1.033	1.005	0.894	0.879	1.209	0.886	0.992	1.062
National mean		0.976	0.841	0.985	0.992	0.821	0.943	1.132	0.947	0.997	1.067
East mean		0.967	0.837	0.994	0.973	0.808	0.980	1.093	0.982	0.998	1.069
Central mean		0.924	0.844	0.919	1.006	0.779	0.892	1.156	0.899	0.993	1.032
West mean		0.973	0.841	0.976	1.000	0.819	0.943	1.153	0.946	0.996	1.086
Northeast mean		1.103	0.853	1.100	1.002	0.940	0.910	1.143	0.911	1.000	1.040

It is only in Liaoning province that the Malmquist total factor productivity index in the third stage was lower than in the first stage, indicating that the DE in this province received "false growth" due to the environmental impact. In addition, the average value of the Malmquist index after optimization was 1.067, compared with 0.821 before optimization. The growth rate average was 24.6%, for which technical progress increased from 0.841 to 1.132, pure technical efficiency decreased from 0.985 to 0.947, and scale efficiency increased from 0.992 to 0.997. Therefore, the primary contributing values of total factor productivity were found to be technical progress and scale efficiency. From the perspective of each province, the top five Malmquist index values in the third stage were 1.218 for Tianjin, 1.174 for Guangxi, 1.173 for Chongqing, 1.138 for Hunan, and 1.136 for Ningxia, all of which exceed 1, which indicates that the efficiency of local digital economy development maintained a growth trend during this period. The bottom five were Henan, Guizhou, Liaoning, Beijing, and Hebei; the growth rates of these provinces lag behind those of the overall national level, indicating that there are specific bottlenecks which have been causing a relatively slow development rate in the DE of these provinces.

From a regional perspective, the total factor productivity of each region was greater than 1, indicating that the efficiency of China's DE is in a positive growth trend. The specific analysis was used to determine the growth rate ranking of each region from the highest to the lowest: the western region, the eastern region, the north-eastern region, and the central region. Since the static efficiency value of the DE in the western region was lower than that in the eastern region, there is more room for progress and faster efficiency growth in the western region. In the efficiency decomposition results, the mean values of total factor productivity and technological progress were more significant than 1, indicating that total factor productivity was mainly influenced by technological progress. If the input of technological progress increases, then the corresponding total factor productivity will increase.

5. Discussion

The results of the three-stage DEA study showed that external environmental variables do affect the efficiency of the DE. After excluding the effects of environmental variables and random errors, the combined technical efficiency, pure technical efficiency, and scale

efficiency increased by 15.3%, 14%, and 3.6%, respectively. The results show that there was a significant difference between the efficiency estimates obtained from the traditional DEA model and the actual efficiency values, which has led to an underestimation of the true efficiency values. Therefore, while a DE is developing rapidly, it is important to build a good external environment. The current average value of China's DE efficiency is 0.681, which still has a lot of room for improvement. At the same time, there was regional variability in DE efficiency [45,46]; there was a stepwise spatial distribution, with the best in the east, medium in the west and north-east, and the worst in the central region, which had unbalanced regional efficiency values. The average efficiency value for the eastern region was 0.829, which is much higher than the national average efficiency value. The main reason for this is that provinces and cities such as Shanghai, Beijing and Zhejiang have developed economies and convenient transportation, which can attract more digital talents and corporate investments [47]. In addition, there are famous Internet companies in the eastern region, such as Alibaba, Tencent, and Jingdong. The average efficiency value of the central region was 0.510, which is a lot lower than that of the eastern region. A further analysis revealed that the low mean efficiency value in the central region was mainly due to pure technical efficiency. In this region, Anhui and Henan had the lowest pure technical efficiency values at 0.489 and 0.412, respectively. The above two provinces and cities are located in the plains of China and are mainly agricultural. Although the sizes of the DE in both Henan and Anhui were above 0.9, the lower level of technology and management led to a comprehensive technical efficiency that was lower than that in the other provinces and cities.

From the adjusted Malmquist index model, the mean value of total factor productivity in China is greater than 1. This indicates that the efficiency of the digital economy showed an increasing trend during the study sample period. Due to the external environment, only Liaoning Province experienced "false growth". In contrast, the rest of the provinces and cities improved their adjusted total factor productivity. So, the average value of total factor productivity in China is greater than 1. A further analysis revealed that the western region ranked first in terms of its total factor productivity value of 1.086. Although the static efficiency values in the west were lower than those in the east, local governments in the west have been strengthening the DE in recent years. Based on the index decomposition, the combined technical efficiency and pure technical efficiency of the eastern region were mostly close to 1 or equal to 1. The central region performed the worst, with no province having an efficiency value equal to 1. In terms of the efficiency of technological progress, all regions had efficiency values greater than 1. This indicates that technological progress is an important factor driving the rapid development of the DE. The current scale efficiency values of 30 Chinese provinces and cities were close to 1 or greater than 1, indicating that the current overall level of scale efficiency in China is high. An analysis from both static and dynamic perspectives revealed that pure technical efficiency was the main factor constraining the development of China's DE. Therefore, Chinese provinces and cities should improve their technology management to promote the high-quality development of the DE.

6. Conclusions

In today's globalized economy with modernized artificial intelligence, rapid economic growth relies heavily on the successful development of digital information technology. Digital technology has driven the economic revolution and given rise to the DE, which has become a fundamental concept in China's economic development [48]. Due to the vast land area of China, there are differences in economy, culture, and education in each province and city. Therefore, the impact of external factors should be taken into account when calculating the efficiency of China's DE. In this paper, a three-stage DEA model was used to eliminate environmental and stochastic factors to obtain the real DE efficiency values. Since the three-stage DEA measures the DE from a static perspective, the Malmquist index model was introduced based on the three-stage DEA model. The three-stage DEA–Malmquist index model was used to measure the dynamics of the DE of 30 Chinese provinces and

cities. The results of the study show that the economic environment, the STI environment, and the market consumption environment all have significant effects on the efficiency of the DE. Among them, the economic environment played a suppressive role, and the science and technology innovation environment and the market consumption environment played a positive role. Therefore, this paper makes the following recommendations at the national and regional levels:

China's vast territory and various uncertainties have led to the uneven development of regional digital economy efficiency. First, strategic planning should be actively promoted for the development of the DE, and financial and credit support policies should be developed for industries related to the DE. Second, the development of the DE industry should be comprehensively coordinated, and the overall efficiency of the DE industry should be promoted. Finally, the common construction and sharing of digital industry information resources should be promoted, interconnections between regions should be strengthened, and the regional gaps in the development of DE industries should be reduced. At the regional level, when analyzed from a static perspective, the eastern region was found to have the highest efficiency value. However, when analyzed dynamically using the Malmquist index, the western region was found to top the list over the eastern region. Therefore, the eastern region should allocate resources rationally and focus on the development of science and technology innovation capabilities. For the central and western provinces, the introduction of talents to the DE industry should be increased, a comprehensive talent training system should be established, and limited resources should be fully used. Each region should consider its own situation; give full play to its resource advantages; and make reasonable use of the established benefits of its local geographical location, natural resources, and economic and social conditions.

However, this paper did have the following limitations in its research process: The first limitation was the short time span. Since data on China's DE are missing from before 2013, this paper examined the period of 2013–2020. Future studies should increase the time span. The second limitation was the selection of input–output indicators. Due to the imperfection of the current DE indicator system, many indicators cannot measure the development of DE comprehensively. In this paper, the input indicators were selected from two dimensions, namely, labor input and capital input, and more dimensions must be studied in the future. The third limitation was that the Malmquist index cannot really measure efficiency in a dynamic sense, so the estimation of dynamic efficiency must be studied in the future [49–52]. The fourth limitation was that this paper allowed testing whether there was a significant difference between the efficiency values of the first and third stages. In order to assess the difference between the first and third stages with statistical precision, the most common test is the S-Z test [53]. Since the current knowledge of the authors on this area is lacking, this will be the direction of future research.

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