

Article

Exploring the Influence of Digital Economy Growth on Carbon Emission Intensity Through the Lens of Energy Consumption

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Abstract: Exploring the impact of new economic forms such as the digital economy (DE) on carbon emissions is crucial for China's "dual carbon" goals. This paper assesses the impact of the DE on carbon emission intensity (CI) from a 2011–2021 perspective on energy consumption in 30 provinces (Hong Kong, Macao, Taiwan, and Tibet are excluded) by using a double fixed-effects model for evaluating the DE. Based on the results from 2011 to 2021, (1) China's DE and CI differ spatially and temporally. In contrast to CI, DE shows a pattern of low in the northwest and high in the southeast. The changes are similar to Hu Huanyong's line, with considerable changes in the southeast, especially the coastal region. (2) Chinese DE's carbon control effects (−0.027) vary by region. A significant negative effect is seen in both the eastern and western regions, with the western region having the greatest negative effect (−0.030), and a positive but insignificant impact in the central region. (3) Total energy consumption (TEC), structure (EC) and efficiency (EI) are all pathways of its influence. Path changes in China are mainly dominated by dual paths (Accounting for over 47%), with fewer single and multiple paths. Among them, the main dual path types are TEC and EC in the east and central regions, TEC and EC, and EC and EI in the western regions; meanwhile, the paths are unchanged in most of the provinces in China, and the changed provinces are mainly in the west. Based on these findings, DE development policies based on regional energy consumption differentiation are crucial to reducing carbon emissions.



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Citation: Zhao, R.; Chen, H.; Liang, X.; Yang, M.; Ma, Y.; Lu, W. Exploring the Influence of Digital Economy Growth on Carbon Emission Intensity Through the Lens of Energy Consumption.

Sustainability **2024**, *16*, 9369. <https://doi.org/10.3390/su16219369>

Academic Editor: Adriana Del Borghi

Received: 12 September 2024

Revised: 9 October 2024

Accepted: 22 October 2024

Published: 29 October 2024



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Keywords: energy consumption; impact path; digital economy; measurement model; carbon emission intensity

1. Introduction

Currently, the world faces a major challenge in the form of climate change. In addition, extreme climate events caused by increasing greenhouse gases (mainly carbon dioxide) threaten human health, well-being and regional sustainability [1–3]. Therefore, reducing carbon emissions and controlling greenhouse gases are essential. In the global wave of green and low-carbon transformation, countries such as the United States, United Kingdom, and Japan have launched green industrial revolutions and zero-carbon emission initiatives [4]. As the largest emitter of carbon, how to achieve carbon neutrality has also become an important research area for China to address the current global climate change. The Chinese government can achieve high-quality, low-carbon development with unprecedented opportunities thanks to the arrival of the digital revolution [5]. There is currently a dual pressure on China's economic development: slowing growth and green transformation [6]; in order to gradually shift China to green and low-carbon development, it is urgent to use the huge dividends from the digital economy [7]. This field is important in addressing the issue of attaining carbon neutrality as the world moves toward a more sustainable economy. The digital economy's impact on emissions has become a crucial topic.

The digital economy is a new form of economic and social development that has emerged with the emergence of new technologies. It has a high degree of complexity, integration, and diversity, and has not yet formed a unified research paradigm. Therefore, different organizations and scholars in different fields have different views on the exploration of the connotations and characteristics of the digital economy [8]. Currently, there are mainly two methods for measuring the digital economy (DE): One is to delineate the parameters of the DE based on its fundamental concept, and then estimate it. For instance, certain academics have noted that the DE constitutes a significant portion of the production of digital goods and services [9]. Another approach is to choose metrics associated with the advancement of the DE and construct a DE index to comprehensively assess the DE, thereby enabling a more comprehensive and precise measurement of the DE. At present, domestic and foreign researchers mostly use this kind of measurement method. Some scholars have devised a digital economy assessment framework by choosing metrics related to both the accessibility of online infrastructure and the skills and behaviors of the populace [10]. Some scholars also measure three facets: the mobility of network and talent cultivation, the capacity of communication technology, and economic and technological foundations [11]. The EU's DESI selects five indicators to measure broadband access, human capital, digital technology integration, Internet service use, and digital public services [12]. In general, the current indicator system for measuring digital economy is inconsistent in structure, number and perspective. Therefore, it is particularly important to build an index system that can fully depict the DE based on prior research.

The essence of the relationship between the digital economy and carbon emissions lies in the intersection of technology and environment. Currently, the theoretical research mainly focuses on the question of "what framework to use to understand the impact of the digital economy on carbon emissions" [13]. It primarily centers around two key areas: first, the analysis of the relationship between the DE and CI. Some academics argue that the digitization process, or the advancement of one of its associated fundamental information sectors, will lead to a rise in energy consumption and subsequently an increase in CI [14,15], Lee and Brahmastre [16], Salahuddin and Alan [17], and Asongu et al. [18] conducted research using samples of 44 economies in the Association of Southeast Asian Nations, Australia, and Sub-Saharan Africa, and all concluded that the digital economy has a significant positive impact on carbon emissions. Some academics also argue that the DE could potentially have a mitigating effect on CI. This means that the advancement of the DE could lead to a reduction in CI. For instance, the greater penetration and utilization of the Internet, as well as increased investment in information and communication technology infrastructure, may contribute to a decrease in CI [14,19,20]. Lu W [21] conducted research on 12 Asian economies and found that the digital economy has a significant negative impact on carbon emissions. Many experts contend that the relationship between the DE and CI is non-linear [22,23]. A representative example is Li and Wang et al., who argue that there exists an "inverted U-shaped" correlation between the urban DE and carbon emissions in China, indicating that the DE initially raises carbon emissions and later decreases them [24,25], Asongu et al. [18] utilized a Generalized Method of Moments (GMM) model to discover a "inverted U" relationship in a sample of 44 Sub-Saharan African countries, while Fei et al. [26] also found the presence of an "inverted U" relationship in their sample. The second area of focus is the examination of how the DE influences the CI along various pathways. At present, most scholars' studies on the impact paths are only analyzed from several single paths. For example, some scholars [24,27,28] point out that energy consumption is a key factor in the DE's impact on carbon emissions. Some scholars [29,30] have individually examined the effects of the DE on carbon emissions through specific pathways, such as energy and industrial structures. Yan L et al. [31] highlighted the potential of the DE to influence people's everyday lives, as well as travel and entertainment, leading to a decrease in energy demand and a reduction in carbon emissions.

To sum up, the current body of literature on the DE, energy consumption, and CI provides a useful reference for subsequent research, but there are also shortcomings: (1) The

assessment criteria for the DE are not inclusive, often based on a singular indicator, limiting our comprehensive grasp of the DE; (2) Prior studies have predominantly concentrated on evaluating the influence of the DE on CI from a singular standpoint. Nevertheless, limited academics have taken into account various factors and spatial and temporal variations and utilized comprehensive approaches to gauge energy usage and scrutinize the mechanisms through which the DE impacts CI. Therefore, the decision to construct an indicator system that comprehensively represents the DE and explores the trajectory and transformations of the DE's influence on CI from the standpoint of energy consumption has emerged as a crucial issue in elucidating the mechanism of the DE's impact on CI.

To sum up, this paper uses 30 Chinese provinces (except Hong Kong, Macao, Taiwan, and Tibet) as case studies to investigate the impact of the DE on CI through energy consumption. This is achieved by constructing a DE evaluation system and applying econometric models like the double-fixed effect model. The study aims to offer theoretical support for reducing carbon emissions in China's energy consumption and achieving low-carbon development. Additionally, it aims to provide new cases of how DE can help in reducing carbon emissions.

2. Materials, Research Ideas and Methods

2.1. Data and Descriptive Statistics

- (1) Digital economy (DE). This text utilizes provincial data from China for the years 2011 to 2021 as the basis for research samples. The macroeconomic variables at the provincial level are sourced from the China Statistical Yearbook, with the data on digital inclusive finance development being derived from the "Peking University Digital Inclusive Finance Index". This article applies logarithmic processing to it, namely LnDE (Table 1).
- (2) Carbon emission intensity (CI). The total carbon emissions in the text are calculated based on the 2011–2021 provincial total carbon emissions data from the CEADs. These data includes various energy emissions and the final carbon emissions data are calculated using the IPCC sector accounting method [32–36]. The GDP data are sourced from the China Statistical Yearbook. To minimize data variability, certain data in this paper were subjected to logarithmic transformation.
- (3) Control variables are chosen based on the findings of Wang Xiangyan et al. [37] and Lei X et al. [38], and the data of five indicators are chosen, including population size (PS), income level (IL), opening to the outside world (OL), technological advancement (TA) and industrial composition (IC). Among them, PS is indicated by the total population of each province at the end of the year, while IL is indicated by the disposable income per capita of urban residents; OL is assessed based on the overall import and export volume of each province; TA is gauged by the number of approved patent applications; IC is determined by the proportion of the tertiary industry's added value to that of the secondary industry.
- (4) The intermediate variables are based on the research by WU et al. [37,39] and encompass three indicators, including total energy consumption (TEC), energy consumption structure (EC), and energy consumption efficiency (EI). Specifically, EC is represented by the ratio of coal consumption to TEC, and EI is represented by the ratio of TEC to GDP.
- (5) The remaining variable data used in this article (control variables, mediating variables, etc.) are sourced from the "China Statistical Yearbook", "China Energy Statistical Yearbook", and the statistical yearbooks of various provinces (Table 1).

2.2. Research Ideas and Methods

2.2.1. Research Ideas

This paper first references previous literature to construct an appropriate system of digital economic indicators for measuring the digital economy. Then, it employs econometric models such as the fixed effects model to investigate the impact mechanism and

path changes in the digital economy on carbon emission intensity from the perspective of energy consumption.

Table 1. Descriptive statistics of variables.

Variable	N	Mean	P50	SD	Min	Max
CI	330	0.170	0.131	0.115	0.0200	0.645
LnDE	330	−2.490	−2.400	1.004	−7.013	−0.297
PS	330	0.461	0.394	0.285	0.0570	1.268
IL	330	3.280	3.105	1.172	1.550	8.240
OL	330	0.145	0.0490	0.227	0.0005	1.092
TI	330	6.676	2.970	10.62	0.0500	87.22
IS	330	1.279	1.080	0.928	0.520	12.22
TEC	330	1.528	1.213	0.904	0.160	4.461
EI	330	0.754	0.594	0.427	0.176	2.189
EC	330	0.667	0.591	0.332	0.0130	1.848

2.2.2. Measurement of the DE

This article considers the definition and measurement methods of the digital economy, drawing on Li and Wang [24], and Cheng Y. et al.'s [4] methods and indicators. From the three aspects of digital economy infrastructure, digital economic industry scale, and digital technology innovation, six indicators including internet broadband access users, mobile phone users, Peking University's digital inclusive finance index, R&D expenditures of large-scale industrial enterprises, total telecommunications services, and technology contract transactions are selected to form a digital economy evaluation system for measuring the DE (Table 2).

Table 2. Assessment System for the DE.

L1 Indicators	L2	L3	Index Attribute
Digital economy	Digital Economy Infrastructure	Number of Internet broadband access users	+
		Number of mobile phone users	+
	Scale of digital economy industry	Total telecommunications business volume	+
		Peking University Digital Inclusive Finance Index	+
	Innovation in Digital Technology	R&D expenditure of industrial enterprises above designated size (\$10 ⁴)	+
		Technology market turnover (\$10 ⁸)	+

Referring to the studies of Zhao Xuan et al. [40], the indicators are standardized first, and then the entropy method is applied to determine the weights of the DE indicators, culminating in the DE index. The formula for calculation is as follows:

$$DE_i = \sum_{j=1}^m \omega_j \times x_{ij}^* (i = 1, 2, \dots, m) \quad (1)$$

where, DE_i represents the digital economy of province i ; x_{ij}^* denotes the standardized value of the data, while ω_j denotes the significance of indicator j . The value of DE_i is $[0,1]$, with a higher DE indicating a more advanced level of digital economy and vice versa.

2.2.3. Carbon Emission Intensity Measurement

Referring to the approach suggested by Feng et al. [41], the CI is determined by dividing the carbon emission by the actual GDP of each province. The formula for calculation is as follows:

$$CI_j = \frac{C_j}{G_j} \quad (2)$$

where, CI_j denotes the carbon emission intensity of province j ; C_j denotes the total carbon emissions of Province j (kgCO_2), and G_j denotes the GDP of Province j (yuan).

2.2.4. Researching the Influence of the DE on the CI

(1) The Influence of the DE on the CI

The impact of the DE on the CI can be comprehensively and accurately studied using the double-fixed effect model, which also solves the endogeneity problem and considers individual and temporal heterogeneity [25]. Thus, this study adopts a model based on double-fixed effects to examine the influence of the DE on the CI. The model settings are as follows:

$$CI_{it} = \alpha_1 + \beta_1 \text{LnDE} + \gamma_1 \sum \text{Control}_{it} + v_i + \mu_t + \epsilon_{it} \quad (3)$$

where, CI_{it} denotes the CI of province i in year t ; DE for the digital economy; Control_{it} is the value of each control variable for province i in year t ; α_1 , β_1 , γ_1 are the regression coefficients. v_i and μ_t represent the regional effect and time effect respectively. ϵ_{it} represents the random error.

(2) The influence path of the DE on the CI

The rapid development of the digital economy is profoundly transforming our production and lifestyle. Firstly, in terms of production, the development of the digital economy will optimize the production process, promote efficient flow of production, distribution, circulation, and consumption through data, which will not only help reduce energy consumption in processes such as conversion and transportation, but also facilitate energy efficient allocation and utilization, thereby potentially promoting energy conservation. Energy companies utilize digital technology to real-time collect production data for precise management of production energy consumption. By customizing energy usage plans based on supply side demands, excessive service can be avoided, thus promoting individual and household energy utilization rates, and potentially achieving energy savings and reduced environmental pollution. Next comes the lifestyle. The development of the digital economy is conducive to breaking the barriers of time and space, improving the level of resource inclusiveness, enhancing the convenience of people's lives, and meeting the diverse and personalized needs of the people. For example, with the improvement of Internet technology, some workers can choose to work from home, which not only helps to save energy consumption in office spaces, but also helps to reduce energy consumption caused by commuting. In addition, with the popularity of 5G communication technology and smartphones, the rise of various online sales platforms and video streaming platforms has changed people's traditional ways of shopping, learning, entertainment, and sports, as well as their energy use habits, thereby impacting energy consumption. However, it cannot be denied that the development of the digital economy may not always have a positive impact on energy consumption. For example, in the initial stage of digital economic development, the application of digital technology in various aspects has led to a decrease in the scale of energy consumption, an improvement in energy consumption structure, and an increase in energy consumption efficiency. However, as time goes on, the benefits of the decrease in the scale of energy consumption, the optimization of energy consumption structure, and the enhancement of energy consumption efficiency resulting from the changes in production and lifestyle brought about by the development of the digital economy gradually diminish. The total social demand for energy consumption may increase along with the development of the digital economy, leading to an increase in the scale of energy consumption.

At the same time, the maturity of the digital economy may also make it difficult to further optimize the energy consumption structure. The increase in energy consumption demand may lead to a need for coal to ensure a stable energy supply, resulting in a deterioration of the energy consumption structure and a drag on energy consumption efficiency, leading to its decline. However, the transformation of production and lifestyle by the digital economy not only influences energy consumption but also impacts carbon emissions. In other words, the impact of the digital economy on energy consumption will also extend to carbon emissions. In terms of production, the extensive application of digital technology in energy exploration, production, transportation, distribution, and usage will enable enterprises to build an efficient, clean, and low-carbon energy system, thereby reducing carbon emissions. In daily life, similar to the impact of the digital economy on energy consumption, the promotion and application of digital technology reduces CO₂ emissions resulting from various offline activities. At the same time, the improvement of digital communication technology contributes to the effectiveness of environmental protection propaganda, promoting the enhancement of people's awareness of carbon emissions reduction, and thereby reducing carbon emissions. Similarly, energy consumption is a major source of CO₂ emissions, and the impact of the development stages of the digital economy on energy consumption also translates to carbon emissions, which may not always have a positive effect. In addition, the impact may vary in different regions. Therefore, the specific impact pathways require further study.

In accordance with the model for mechanism testing proposed by Feng et al. [42], this text examines the path of the DE on CI from three angles: TEC, EC and EI. The calculation is based on Formula (3):

$$M_{it} = \alpha_2 + \beta_2 \ln DE + \gamma_2 \sum Control_{it} + v_i + \mu_t + \epsilon_{it} \quad (4)$$

where M_{it} represents the mediating variable of province i in year t , the remaining variables are consistent with the previous text. They are carried into TEC, EC and EI, respectively, for calculation.

3. Results

3.1. Space-Time Evolution of the DE and the CI

The year 2015 marks the transition from China's "12th Five-Year Plan" to the "13th Five-Year Plan", and the two plans differ significantly in their directives for DE development and carbon emission reduction goals. For the purpose of enhancing comparability, 2015 is selected as the midpoint in this study.

According to Figure 1, over time, China's overall level of China's DE has seen significant improvement. However, there has been a widening disparity in DE development among Chinese provinces. The number of high-value DE areas increased from 1 in 2011 to 16 in 2021, with the majority located in the southeastern region of China. The overall trend in China's DE shows a spatial pattern of low levels in the northwest and high levels in the southeast.

According to Figure 1a,b, the level of DE in most Chinese provinces remained low from 2011 to 2015. However, the number of low value DEs decreased, with the majority of distribution occurring in northwest China. Meanwhile, the number of medium and high-value DE areas increased, shifting from scattered distribution in the southeast coastal areas to concentrated distribution in southeast China. This was largely due to China being in the midst of its 12th Five-Year Plan, with a focus on upgrading technology industries related to the DE, increasing industrial integration and developing opportunities, thereby transforming China's information industry from large to strong, and developing the DE across all provinces in China. The eastern region of China, especially the southeast coastal region, relies on its superior geographical conditions to enable its DE to develop rapidly, thus differentiating itself from other regions.

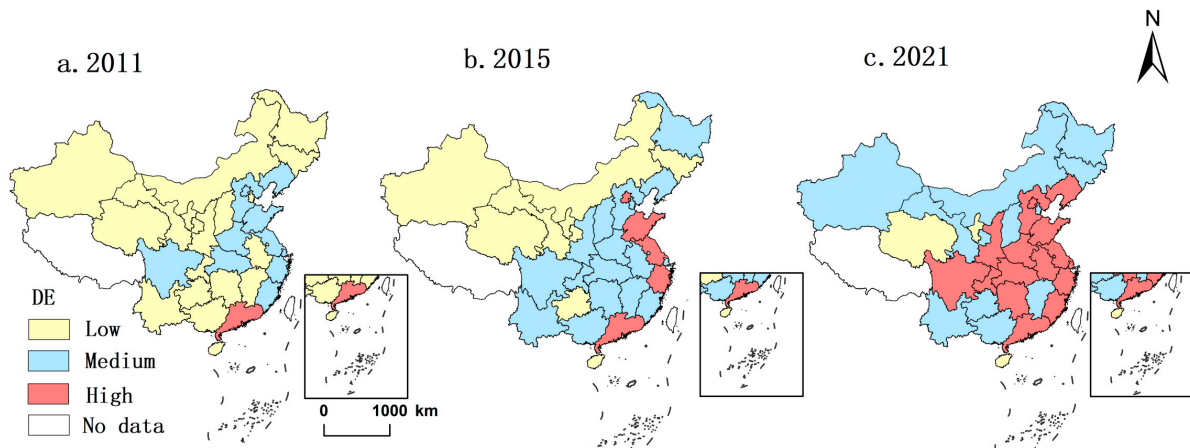


Figure 1. Geospatial and temporal transformation of China's DE.

When combined with Figure 1b,c, it becomes evident that the overall developmental level of the DE in all provinces of China has shown significant improvement from 2015 to 2021, with only a few provinces remaining in a relatively underdeveloped state. There has been a notable increase in the number of areas with medium and high value in the DE, resulting in a more concentrated distribution. The high-value area is concentrated in the southeast region. This is largely due to China's presence in the "13th Five-Year Plan" period, during which the country's DE has experienced a significant leap forward. Its growth rate has consistently remained high, with rapid advancements in digital industrialization and industrial digitization providing strong momentum for the sustainable and healthy development of the DE.

According to Figure 2, its change trend is opposite to that of the DE. Over time, the CI in China has primarily exhibited a decline. The provincial disparities in CI have narrowed in China. The count of regions with low CI has risen and they are increasingly concentrated in the southeast. China exhibits higher CI in the northwest and lower CI in the southeast.

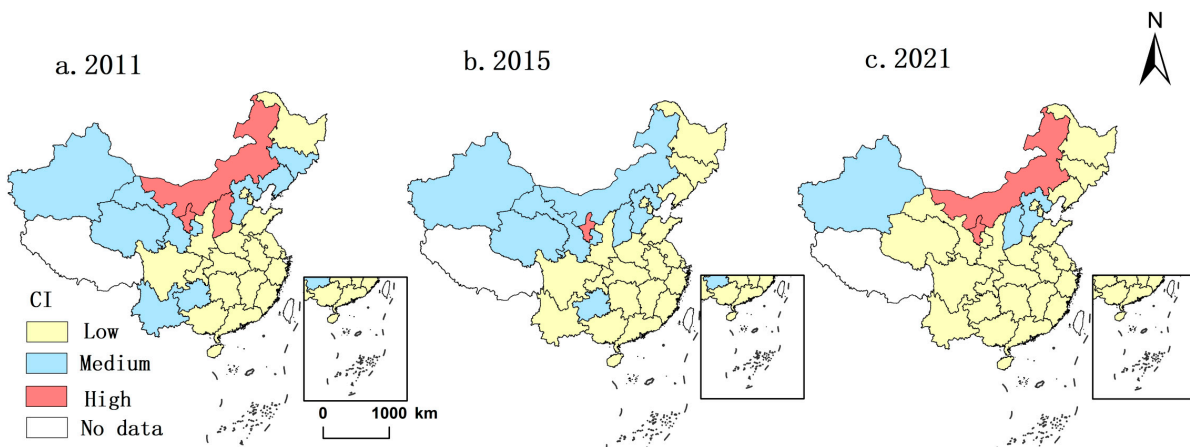


Figure 2. Geospatial and temporal transformation of CI in China.

Combined with Figure 2a,b, it can be seen that from 2011 to 2015, the number of regions in China with high CI has decreased. However, the CI of certain provinces has decreased, with most low-value CI regions located in the southeast. This can be primarily attributed to China's implementation of a comprehensive carbon emission control system during the "12th Five-Year Plan" period. Energy conservation and emission reduction have been emphasized as crucial focal points to optimize the economic structure, promote green, circular, and low-carbon development, and expedite the construction of an ecological civilization. Various provinces also actively and orderly promoted carbon emission reduction.

As the leading region of China's economy, the CI in the southeast is lower than that in the northwest.

Combined with Figure 2b,c, it can be seen that from 2015 to 2021, the number of regions with high carbon emission intensity in China has slightly increased, but overall, it is showing a downward trend. Guizhou, a region with a median carbon emission intensity, has decreased from the median to a low value, and the distribution range of low carbon emission intensity areas has further expanded and become more concentrated. During the "13th Five-Year Plan" period, China prioritized low-carbon development as a means to expedite scientific and technological innovation and institutional reform, enhance low-carbon leadership, drive energy and industrial revolution, facilitate supply side structural reform and consumer transition, and foster coordinated regional development. As a result, the majority of Chinese provinces achieved low carbon intensity.

3.2. Influence of the DE on the CI

The initial analysis focuses on the influence of the DE on the CI in 30 Chinese provinces from 2011 to 2021 at a national scale. Additionally, the study delves into the varying effects of the DE on the CI across the East, Central, and Western regions.

The magnitude of R^2 determines the explanatory power of the independent variable on the dependent variable. A small R^2 indicates that the factor is explained to a lesser extent by other factors and has a lower degree of linear correlation, indicating poor model fit. Based on columns (1)–(3) in Table 3, the model is initially examined to determine if control variables are included, and if provinces and years are controlled. The findings indicate that in (1), while statistically significant, the R-squared value is low, and the model's fit is poor; (2) It is statistically significant, with a significantly improved R-squared value, and a better model fit; (3) After controlling for variables and locking in the province and year, all models have an R^2 greater than 0.5, and the independent variables are generally significant at the 5% level. The model's performance is improved. It is evident that the coefficient of the DE displays a notably negative value, suggesting a significant inhibitory impact of the DE on the CI at the provincial level in China. This implies that each unit increase in the DE at the provincial level in China can lead to an average reduction of 0.027 units in the CI.

Table 3. The impact of the DE on the CI in China.

	National Level			Regional Level			
	(1) CI	(2) CI	(3) CI	(4) CI	(5) East	(6) Middle	(7) West
LnDE	−0.065 *** (0.005)	−0.030 *** (0.007)	−0.027 *** (0.008)		−0.013 ** (0.006)	0.012 (0.013)	−0.030 ** (0.012)
L.LnDE				−0.030 *** (0.005)			
R^2	0.319	0.965	0.966	0.760	0.672	0.561	0.732
Control variable	No	No	Yes	Yes	Yes	Yes	Yes
Province	No	Yes	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Given the known diversity of the impact of economic development on carbon intensity, we further examined the regional diversity. China was divided into three sub-regions, eastern, central, and western, each of which were brought into the regression model for the analysis. The effects of economic development on carbon intensity in these three regions were then obtained (columns (5)–(7) of Table 3). It is evident that the impact of economic development varies across the three regions. The eastern region and the western region are both significantly impacted by the DE, with the greatest negative impact in the western region (−0.030) and a slightly lesser impact in the eastern region (−0.013). Due to the rapid development of the digital economy in the eastern region, a mature technological innovation

system, stronger government participation and implementation of environmental policies, abundant high-tech human resources, and a relatively flat growth trend in urban low-carbon transformation and upgrading, environmental pollution has also been exacerbated to a certain extent [43], resulting in a weaker emission reduction effect compared to the western region. Despite the slower development of the DE in the western region, the coordinated development strategy, including the “Western development” initiative, has created a larger release space for DE dividends, leading to a stronger carbon emission reduction effect. The central region showed a positive effect (0.012) but it was not significant. The reason may be that although the economic development level in the central region is slightly higher than that in the western region, its carbon reduction effect is not significant compared to other regions because its energy resources are relatively abundant, and its economic and technological development level cannot support its green energy development, resulting in serious resource waste.

Despite the previous benchmark regression demonstrating the potential for the digital economy to reduce carbon emissions, it is important to acknowledge the possibility of bias in the results. In order to mitigate potential endogeneity issues, this article also employs the following testing methods: (1) On the one hand, this article draws on existing experience in building tools for digital economic development and uses the GMM estimation method to select the interaction terms of fixed telephone numbers per 100 people in each province and city in 1984 and broadband internet access users in each year as instrumental variables for the digital economy (Table 4, Column 4). On the other hand, we know that instrumental variable methods are one of the main ways to solve endogeneity. In addition to finding external instrumental variables, using lagged endogenous variables as instrumental variables is also very common in various disciplines of economics. Therefore, this article uses the lagged one-period digital economy as instrumental variables for endogeneity testing (Table 3, Column 4); (2) Taking into account the possible presence of extreme values in the selected samples, this paper employs tail reduction processing for all data (column 1 of Table 4); (3) The first half of this article utilizes the carbon emissions to GDP ratio as a measure of carbon emission intensity. However, given that the primary service target of production activities is consumers, the magnitude and direction of production activities in each region are influenced by residents’ consumption. Therefore, this article selects per capita carbon emissions as the explanatory variable and employs a fixed effects model to test robustness (Table 4, Column 2); (4) This article employs principal component analysis to re-evaluate the level of digital economy development in each province, and includes it as a new explanatory variable in the regression equation for examination (Table 4, Column 3). The aforementioned findings all point to the persistence of the carbon reduction impact of the digital economy, affirming the stability of the baseline regression results. To prevent potential multicollinearity issues among the variables, VIF tests were conducted in this study. The results indicated that the VIF values for all variables were below 10, with TEC, EC and EI both below 5. The reliable regression results were confirmed by the multicollinearity tests.

3.3. The Influence Path of the DE on the CI

This paper explores the evolution of the impact pathway of the DE on the CI in 30 Chinese provinces from 2011 to 2021, based on an analysis of the same.

3.3.1. The Spatial and Temporal Patterns of Energy Consumption

Combining the data and Figure 3, we can see that from 2011 to 2021, the overall trend in TEC in China is rising, with TEC-intensive regions becoming increasingly concentrated and showing a trend in spreading from the southeast to the northwest. Compared to TEC, EC in Chinese provinces is generally higher and trending upwards, with over 62% of the provinces mainly concentrated in the southeast, and the number of provinces has increased from 4 in 2011 to 6 in 2021. On the other hand, EI in Chinese provinces is generally showing a downward trend, with less than 20% of the provinces mainly concentrated

in the southeast. Although China has been implementing energy-saving and emission reduction policies during the “Twelfth Five-Year Plan” and “Thirteenth Five-Year Plan”, it is still mainly reliant on coal consumption, indicating a continuing strong demand for energy consumption.

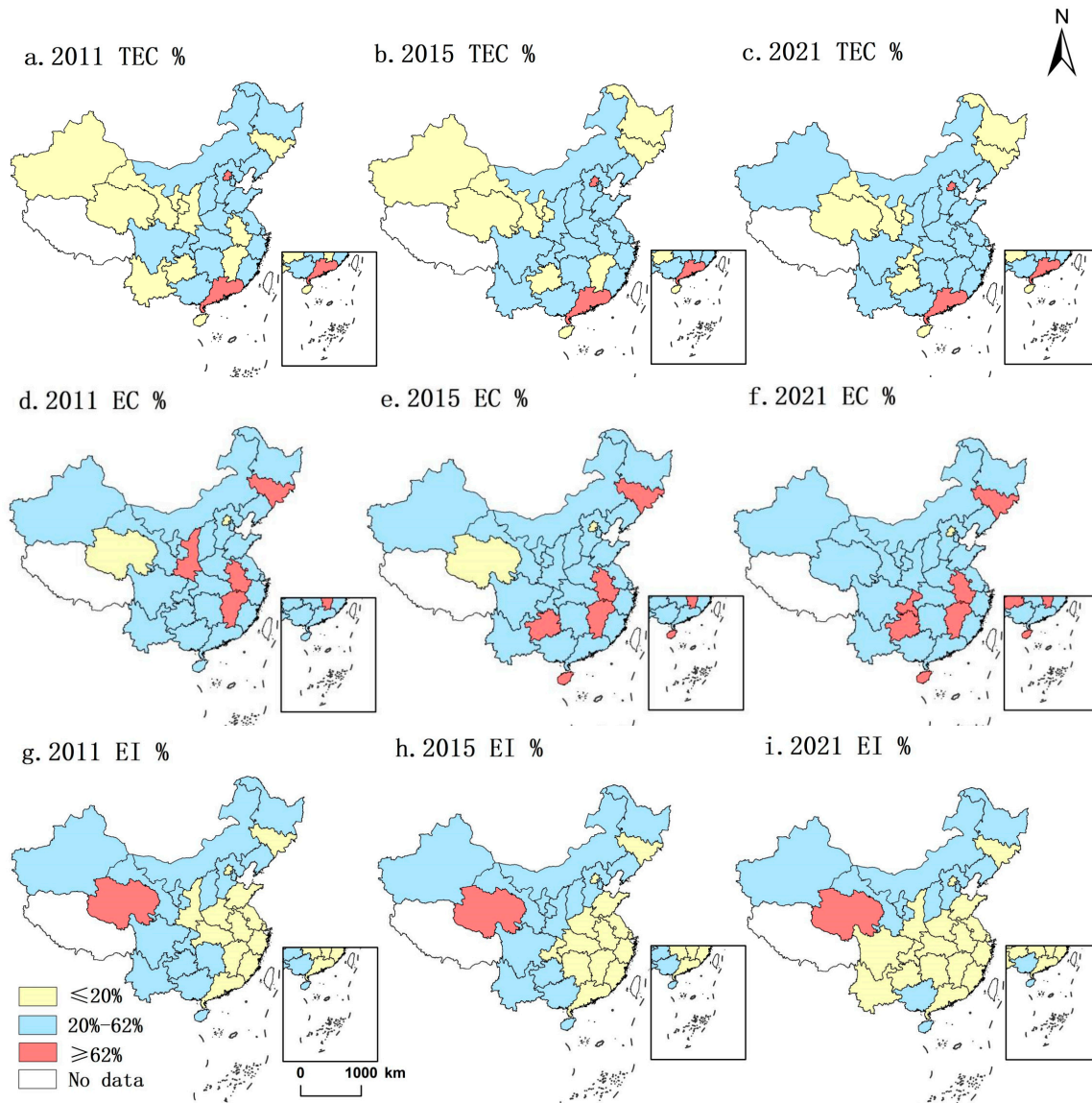


Figure 3. Spatial and temporal patterns of the three pathways of energy consumption in China.

3.3.2. The Specific Influence Path of the DE on the CI

China’s energy system is predominantly reliant on coal [44]. Not only does the TEC affect the CI, but also the change in EC and EI also have an effect. Therefore, in order to achieve the goal of coordinated economic, energy and environmental development, it is essential to clarify the effects of TEC, EC, and EI on CI. This paper explores the influence path of the DE on China’s CI at the national level and in the eastern, central, and western regions, as illustrated in Table 5.

According to Table 5, at the national level, the DE and TEC are significantly positive at the 1% level, while the DE and EC are significantly positive at the 10% level, and the DE and EI are significantly negative at the 1% level. This indicates that TEC, EC, and EI are all pathways through which the digital economy impacts carbon intensity. Overall, at the national level, although the digital economy follows the 3R principle of “reduce, reuse, recycle” in the circular economy, maximizing resource efficiency and enabling the low-

carbon transformation of the ecosystem, the “technology eager pioneer” phenomenon [45] and excessive investment in green resources may weaken the positive driving force of low-carbon economic transformation in the region [46], leading to an increase in TEC and EC. However, the development of the digital economy will lead to a series of green technology innovations, resulting in a decrease in EI.

Table 4. Robust Test.

	(1) Tail Reduction Processing	(2) Replace Explanatory Variables	(3) Replace Core Explanatory Variables	(4) GMM
LnDE	−0.041 *** (0.010)	−0.699 * (0.411)	−0.018 * (0.023)	−0.132 ** (0.02)
R ²	0.967	0.961	0.968	0.215
Control variable	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
AR (1)				0.002
AR (2)				0.705
Hansen				0.842

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Test results of the impact path of digital economy on China’s carbon emission intensity.

		LnDE	R ²	Control Variable	Province	Year
National	TEC	0.068 *** (0.023)	0.523	Yes	Yes	Yes
	EC	0.006 * (0.014)	0.486	Yes	Yes	Yes
	EI	−0.133 *** (0.021)	0.551	Yes	Yes	Yes
East	TEC	0.131 *** (0.040)	0.811	Yes	Yes	Yes
	EC	−0.061 ** (0.025)	0.703	Yes	Yes	Yes
	EI	0.003 ** (0.015)	0.718	Yes	Yes	Yes
Middle	TEC	−0.006 (0.063)	0.434	Yes	Yes	Yes
	EC	−0.035 (0.072)	0.270	Yes	Yes	Yes
	EI	0.045 (0.060)	0.780	Yes	Yes	Yes
West	TEC	−0.097 ** (0.045)	0.534	Yes	Yes	Yes
	EC	−0.041 * (0.026)	0.409	Yes	Yes	Yes
	EI	−0.120 ** (0.047)	0.573	Yes	Yes	Yes

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

From a regional perspective, TEC, EC and EI in eastern and western China are all paths that the DE affects CI, except for the central region. From the perspective of the eastern region, the DE and TEC are significantly positively correlated at the 1% level, while the DE and EC are significantly negatively correlated at the 5% level, and the DE and EI are significantly positively correlated at the 5% level. From the perspective of the western region, the DE is significantly negatively correlated with TEC, EC, and EI.

This indicates that the improvement of the level of digital economic development in the eastern region may lead to an increase in TEC and EI but will improve the EC level. On the other hand, the improvement of the level of digital economic development in the western region may have a reverse effect on TEC, EC, and EI. One possible reason is that the eastern region, being more developed than other regions, benefits from good geographical advantages and abundant resources, leading to a more rational flow of production factors and better development of the digital economy compared to other regions. This enables the eastern region to further enhance the low-carbon level of traditional industries and nurture new low-carbon industries, thus unleashing “structural dividends” and improving the quality and efficiency of its economic development, facilitating low-carbon transformation. However, its rapid development may result in higher overall energy consumption, leading to less obvious benefits from the digital economy compared to other regions. As for the western region, being a concentrated area for coal consumption, the improvement of its digital economy level will bring about changes in its original energy consumption structure and total amount. Moreover, in terms of energy trading, the enhancement of digital technology in the western region, to some extent, optimizes the signal transmission process between energy production and consumption, reducing inefficient losses during energy consumption and greatly improving energy allocation efficiency.

To sum up, TEC, EC and EI are all paths for the DE to affect CI. However, the impacts of various regions and different pathways vary. The potential reasons are as follows: despite China’s active promotion of energy conservation and emission reduction policies under the “12th Five-Year Plan” and “13th Five-Year Plan”, the country, with its predominant reliance on coal consumption, faces challenges in significantly altering its energy consumption structure. At the same time, the level of digital economy development in China continues to rise, leading to varying degrees of impact across different regions due to disparities in the level of digital economy development.

4. Discussion

4.1. DE and Spatial Change in CI

To better analyze the variations in the DE and CI across various stages and regions, this article categorizes the changes during the periods of 2011–2015 and 2015–2021 based on the classification standard for 2011–2021, and spatially represents them (Figure 4).

It is evident from Figure 4a,b that the overall the DE remained relatively stable from 2011 to 2015, and there was no significant change from 2015 to 2021. However, there was an increase in the number of provinces showing small and significant changes during this period, with the most noticeable increase being in the provinces with small changes. In 2015–2021, compared with 2011–2015, more provinces in China underwent shifts in the DE. The area of the DE change gradually gathered in the southeast of China, as opposed to being scattered at the outset. Compared with Figure 4a,b, the number of provinces with small changes in the DE in Figure 4c has further increased, and the number of provinces with large changes has also increased significantly. Most provinces in China have small changes in the DE, and the regions with large changes are mainly distributed in southeast China, and there are many and consistent areas with high values of change in the southeast coastal areas.

From Figure 4d, the overall change in carbon emission intensity from 2011 to 2015 was not significant, with only a few provinces experiencing substantial changes. As shown in Figure 4e, from 2015 to 2021, the overall carbon emission intensity remained largely unchanged, and the number of provinces with small changes did not increase. In comparison to the period from 2011 to 2015, there were no significant changes in the provinces with small changes in carbon emission intensity from 2015 to 2021, but they gradually shifted towards the southeast of China; the number of provinces with significant changes decreased to zero. Compared to Figure 4d,e, Figure 4f shows a further increase in the number of provinces with significant and small changes in carbon emission intensity, and they are gradually concentrated in the southeast of China.

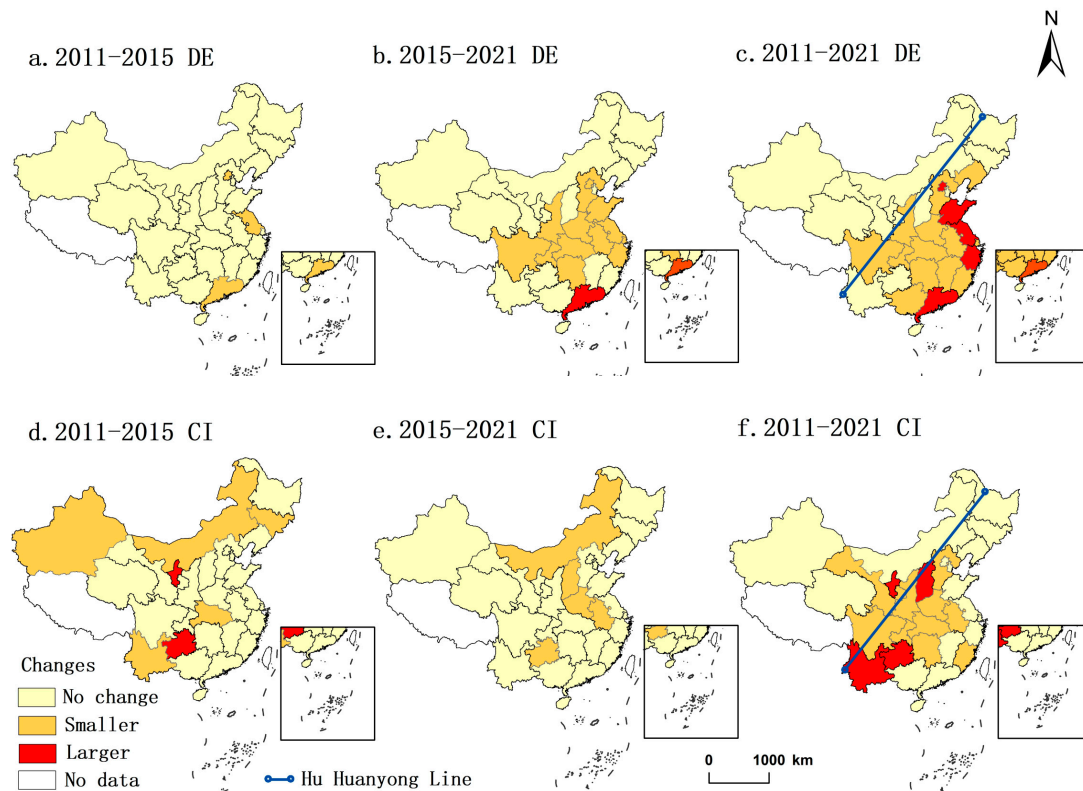


Figure 4. Changes in China's DE and CI.

It is evident that China's DE [47] and CI distribution changes align closely with Hu Huanyong's line. China is bounded by the Hu Huanyong Line, and its southeast is narrow and densely populated, while its northwest is vast and sparsely populated. The areas experiencing significant fluctuations in the DE and CI are predominantly located in southeastern China, particularly along the coastal regions in the southeast. Due to its unique geographical advantages, the southeast of China, particularly the coastal areas, took the lead in implementing special economic zones and became the vanguard of China's opening up. This also created a conducive environment for economic development. The rapid economic growth has led to a more diverse industrial structure and higher population density in the southeast compared to the northwest, which has further accelerated the development of the region. Additionally, the rapid development of the DE has also caused the CI of the southeast region to undergo more changes compared to the northwest.

4.2. The Change in the Impact Path of the DE on the CI

To investigate the changing impact path of the DE on the CI, we define the single influence path as the one accounting for more than 62%, the multi-influence path as the three paths that are more than 20%, and the remaining paths as the dual-dominant influence path, based on the known intermediary effect of the three intermediary variables. Further details of specific path changes are provided (Figure 5).

From Figure 5, from 2011 to 2021, the distribution pattern and number of provinces dominated by a single path changed little, only increasing from 7 in 2011 to 8 in 2021, showing scattered distribution as a whole. The provinces with a dominant TEC single path are primarily located in the eastern region, including Beijing and Guangdong. The provinces with a dominant EC single path are located in both the eastern and western regions, but are mainly concentrated in the central region, including Jilin, Anhui, and Jiangxi. The provinces with a dominant EI single path are mainly located in the western region, such as Qinghai. The provinces in China are predominantly characterized by dual-path and multi-path, with the number of dual-path and multi-path accounting for

more than 47% and 33%, respectively. The overall distribution pattern of the dual paths did not change much, but there were differences in their types. For example, the number of provinces dominated by TEC and EC dual paths gradually increased, concentrated in southeast China, especially in the southeast coastal areas, and basically met the Hu Huyong line. The number of provinces dominated by EC and EI dual paths is gradually decreasing and scattered in western China. The overall distribution pattern and quantity of multi-path have changed greatly, from 10 provinces clustered in northeastern China in 2011 to 7 provinces clustered in northern China in 2021.

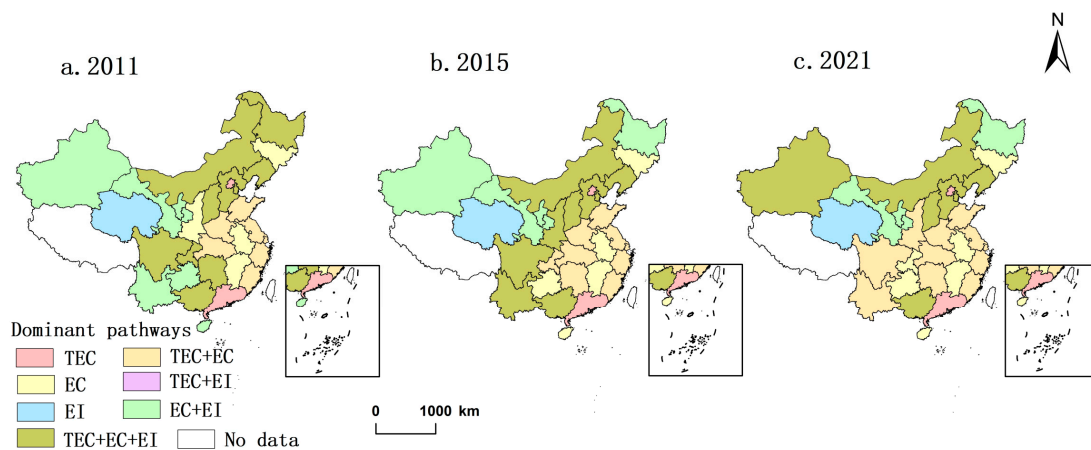


Figure 5. Path diagram of the impact of the DE on the CI.

In conclusion, the eastern and central regions of China are predominantly characterized by dual-path, specifically TEC and EC, single and multi-path are less, with TEC being the primary pathway in the eastern region and EC in the central region. In the western region, the main type of dual-path are TEC and EC, EC and EI, single and multi-path are less, and with the single pathway being mainly EI.

According to Figure 6a, from 2011 to 2015, the paths of most provinces did not change, and the other provinces that did change had more types of path changes and were scattered in the eastern region in space. Among them, many provinces changed from multi-path to TEC and EC dual path. According to Figure 6b, from 2015 to 2021, the number of provinces with no path change has slightly increased, while the remaining provinces that experienced changes in their paths showed a more concentrated and consistent type of path change, and they are relatively clustered in the western region in terms of spatial distribution. Among them, many provinces changed from multi-path to TEC and EC dual path. Based on Figure 6c, overall, from 2011 to 2021, the paths of the vast majority of provinces have not changed, while the types of path changes in the remaining provinces are diverse, and spatially concentrated in the western region. Among them, there are still many provinces with multiple paths that have changed to dual paths of TEC and EC, and these changes are also concentrated.

To sum up, the paths of most provinces in China remain unchanged, and the path change types of the remaining provinces that change gradually decrease over time and are relatively clustered in the western region in space. Among them, the main path change type is from multi-path to dual-path TEC and EC. The reason is that around 2015, the different national planning and policies for energy consumption changed the dominant path of China's provinces. Despite the slowing growth in energy consumption and increased use of clean energy compared to the "12th Five-Year Plan", China remains heavily reliant on coal and continues to have a large demand for it, making it difficult to achieve significant changes in the overall energy structure. During the planning period, China's coal energy development follows the overall requirements of "controlling the eastern part, stabilizing the central part, and developing the western part." Some provinces in western China have

given priority to energy development, and the proportion of some paths has increased, forming a trend dominated by two paths.

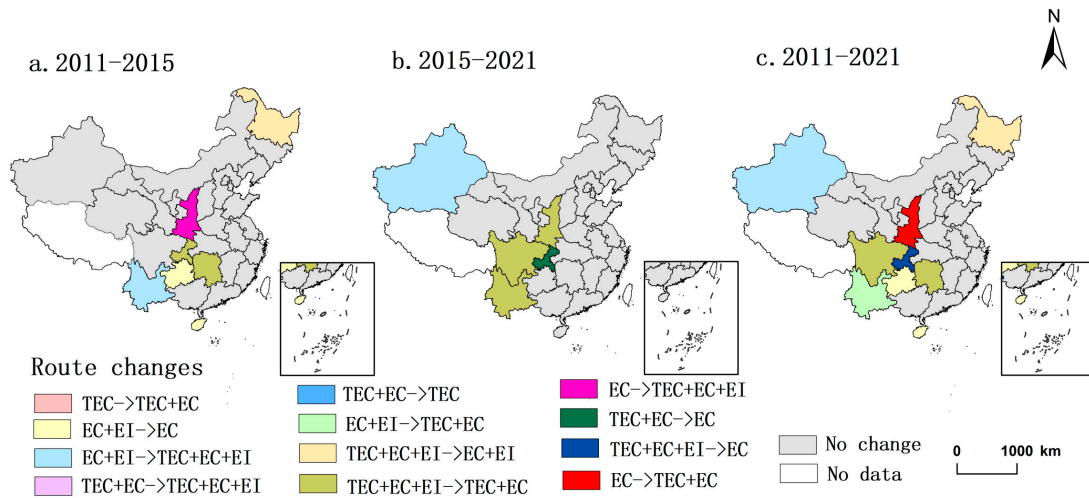


Figure 6. Path change chart of the DE's impact on CI.

4.3. Deficiency and Prospect

Additionally, this study has some limitations stemming from inadequate data sources and a restricted research timeframe. The following enhancements can be suggested for future research: (1) the assessment criteria for the development level of the DE outlined in this paper may not be sufficiently comprehensive. The DE refers to a range of economic activities that leverage modern information and communication technology as foundational resources, utilize information networks as important transmission platforms, and rely on digital information as a key production factor to enhance the efficiency and quality of economic operations, and continuously drive the optimization and upgrading of economic structures. It encompasses two main categories: “digital industrialization” and “industrial digitalization” [48]. Some academics have embraced this categorization approach and assessed the DE using the growth accounting framework. Going forward, we can draw upon scholars’ representations of the DE and select more inclusive indicators for evaluation. (2) Further research into pathways is necessary. Firstly, this paper only examines the influence of the DE on the CI through the lens of energy usage. Apart from energy consumption, other dimensions have been analyzed by researchers. For instance, academics have highlighted that the DE will have an indirect impact on the progress of low-carbon city performance by fostering innovation in green technology [49]. Additionally, some scholars have noted that the advancement of the DE can diminish CI by enhancing and refining the industrial framework [50]. Therefore, future studies can be further combined with other aspects to explore the possible impact path. Secondly, In the selection of control variables, the education level, technological innovation index, or energy policy indicators may also have an impact, and it should be considered to include them in future research. (3) This paper solely examines its influence at the provincial level, and additional research may be undertaken in prefecture-level cities to more comprehensively explore its impact across diverse urban areas, thus offering more nuanced theoretical underpinning for the development of localized carbon emission reduction policies.

5. Conclusions

Based on the existing literature, the text aims to establish a holistic assessment system for the development status of the DE in 30 provinces in China (Hong Kong, Macao, Taiwan, and Tibet are excluded) from 2011 to 2021, and utilizes an econometric model to examine the impact of energy consumption. The paper further explores the changes in impact pathways and spatial disparities among the DE, energy consumption, and CI from a temporal and spatial perspective. The specific research findings are as follows:

Firstly, from 2011 to 2021, the spatio-temporal heterogeneity and opposing trends in China's DE and CI were evident. The DE showed a low overall trend in the northwest and a high trend in the southeast, while CI exhibited a high trend in the northwest and a low trend in the southeast. The distribution of change areas for both indicators closely followed the Hu Huanyong Line, with significant changes concentrated in the southeast of China, particularly in the coastal areas.

Secondly, the advancement of China's DE has a notable impact on carbon control (-0.027), exhibiting regional disparities. Both the eastern and western regions demonstrate a prominent decrease, with the most substantial decrease observed in the western region (-0.030), followed by the eastern region (-0.013), and a minor, yet insignificant increase in the central region.

Thirdly, TEC, EC, and EI are all pathways that influence the DE and CI. In China, the change in paths is mainly dominated by dual paths (Accounting for over 47%), and there are few single paths and multi-paths. The primary dual path types in the eastern and central regions are TEC and EC, while in the western region they are mainly TEC and EC, as well as EC and EI. Meanwhile, the majority of provinces in China maintain their existing paths, with the main changes occurring in the western region.

Based on the findings of this study, we have put forward targeted policy recommendations. The specific suggestions are as follows:

Firstly, grasp the direction of digitization, networking, and intelligentization, promote the digitization of industries such as manufacturing, services, and agriculture, use new internet technologies to build internationally competitive digital economic infrastructure, guide the integration of platform economy, sharing economy, service economy, and real economy, and effectively promote the upgrade of the digital economy. At the same time, it is necessary to fully understand that there is an unbalanced interaction between the economic structure, resource endowment, market size, and policy environment in the eastern, central, and western regions of China, and the long-term existence of unbalanced regional development is an objective fact. We should avoid exacerbating the "digital divide", which would intensify the imbalance in regional digital economic development and the irrationality of carbon reduction tasks.

Secondly, the government should allocate digital resources reasonably and strengthen planning guidance based on the actual development and spatial characteristics of the digital economy in different regions, forming a system of complementary and coordinated development. Tailored carbon reduction policies should be formulated according to the actual development of different regions. For example, the eastern region should leverage its development advantages to interact with the central and western regions through information sharing and technology exchange, establishing communication and cooperation mechanisms to gradually form an open and collaborative cross-regional energy-saving and emission-reduction system. The central and western regions should optimize their energy structure and improve energy efficiency while considering their regional development reality and learning from advanced technological means. This will ensure the consistency and effectiveness of emission reduction actions nationwide, gradually forming an open, collaborative, and intelligent regional emission reduction coordination mechanism.

Thirdly, in response to regions where the trend of carbon reduction is still not obvious, the government should develop coordinated policies based on the integration of the region, focusing on industrial adjustment, energy consumption, traffic control, etc., to ensure the realization of emission reduction targets. It will help to promote the quality, structure, scale, speed, efficiency, and safety of low-carbon economic development, and coordinate the advancement of carbon reduction, green expansion, and growth, unleashing the regional advantages of the digital economy in improving carbon emissions and promoting the formation of a new integrated pattern of regional carbon reduction and green expansion.

Author Contributions: Conceptualization, R.Z. and X.L.; methodology, R.Z.; software, M.Y. and Y.M.; validation, M.Y.; data curation, Y.M. and W.L.; writing—original draft preparation, R.Z.; writing—review and editing, R.Z., H.C. and X.L.; supervision, H.C. and X.L.; funding acquisition, X.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 42171256.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data for measuring the digital economy comes from the China Statistical Yearbook, and the development data of digital inclusive finance comes from the “Peking University Digital Inclusive Finance Index”. The carbon emission data comes from the China Carbon Accounting Database (CEADs), while indicators such as GDP and control variables are sourced from the China Statistical Yearbook, China Energy Statistical Yearbook, and provincial statistical yearbooks.

Acknowledgments: We would like to express our gratitude to all those who helped us during the writing of this article.

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

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