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Digital Economy and Urban Low-Carbon Transition: Theoretical Model and New Mechanisms

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Abstract: Urban areas are at the forefront of economic activity and notably contribute to carbon emissions. Transforming cities to low-carbon models is imperative for addressing climate change. The digital economy (DE) has emerged as a pivotal force in driving global economic progress, offering unique benefits that support urban low-carbon transitions. Despite extensive research on the correlation between DE and urban low-carbon transformation (ULCT), there remains a gap in studies utilizing mathematical models to delve into the intrinsic mechanisms and deeper impacts. This research evaluates the influence of DE on ULCT by examining data from 283 prefecture-level and above cities in China, spanning from 2011 to 2019, through both theoretical frameworks and empirical testing. The analysis reveals that DE substantially fosters ULCT, a conclusion reinforced by rigorous robustness and endogeneity checks. Notably, DE's impact on ULCT is more significant in southern cities than in northern ones. Interestingly, while DE in the Yangtze River Delta and Chengdu-Chongqing urban clusters showed limited promotion of ULCT, it had the highest impact in the middle reaches of the Yangtze River. DE enhances ULCT through several pathways, including scale economy effect, heightened public environmental awareness effects, and increased income effects, contributing 6.64%, 9.84%, and 16.2%, respectively. Furthermore, the effects of public environmental awareness and income are particularly pronounced in southern regions, unlike in northern areas. This study not only expands the theoretical research on the relationship between the digital economy and urban low-carbon transition but also provides specific guidance and support for related policy formulation and implementation. This helps promote cities toward more environmentally friendly and sustainable development. Furthermore, the conclusions of this study have important reference value for other major polluting countries (such as the US, India, and Germany). Different countries and regions should formulate targeted low-carbon transition strategies based on their own DE development, income levels, and public environmental awareness. This will effectively promote urban low-carbon transitions, achieving a win-win situation for economic development and environmental protection.

Keywords: digital economy; urban low-carbon transformation; theoretical model; public environmental awareness effects; income effect

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1. Introduction

As a significant contributor to global carbon emissions, China accounted for approximately 30.66% of worldwide carbon emissions in 2020 [1]. It underscores China's extensive and challenging path to meet its carbon reduction goals. The Chinese government has explicitly proposed to "coordinate efforts to reduce carbon emissions, cut pollution, expand greenery, and promote growth, advancing ecological priority, conservation, intensive, and green low-carbon development". Low-carbon development has been elevated to an unprecedented level of importance. As the primary source of carbon emissions, achieving Urban Low-Carbon Transformation (ULCT) in cities is crucial for China's low-carbon economic transformation. Carbon emission efficiency considers multiple dimensions such as economic, social, ecological, and resource factors, as well as emission reduction, better reflecting the low-carbon development of Chinese-style modernization. It is crucial for achieving China's and even the global "dual carbon" goals [2]. Improving Urban Carbon Emission Efficiency (UCEE) and promoting low-carbon economic development has become an increasingly important issue for society, government, and academia [3,4].

The Digital Economy (DE) encompasses a range of economic activities that leverage digital technologies, devices, knowledge, and information as key production factors [5,6], It stands as one of the most dynamic, innovative, shared, and resilient forms of economic activity today. Compared to traditional industries such as energy, power, steel, petrochemicals, construction, and transportation, the digital industry inherently possesses green and low-carbon attributes. Nonetheless, the carbon emissions resulting from the production of digital hardware, the application of digital technologies, and the construction and operation of digital infrastructure have attracted widespread attention [7]; Regarding industrial digitization, the rapid development and innovative application of digital technologies can drive the transformation and upgrading of traditional industries, enhance output value, improve efficiency, and support low-carbon development. In digital governance, using digital technology clusters allows for more precise monitoring, analysis, prediction, and early warning of carbon emissions across regions and key industries. This enhances environmental regulatory decisions' accuracy, scientific foundation, and timeliness, providing robust support for precise and scientifically informed emission reductions [8]. The inherent connection between DE and carbon reduction is clear. However, when considering carbon emission efficiency—which balances carbon reduction with efficiency enhancement and other multidimensional factors—the impact of DE may be complex and uncertain. This complexity necessitates a comprehensive and systematic theoretical analysis framework for elucidation, as well as rigorous empirical methods for verification.

The literature pertinent to this study addresses three primary aspects. Firstly, concerning the scale of carbon emissions, numerous studies have developed comprehensive index systems to evaluate the impact of the DE on carbon emissions at various levels: national [9,10], urban [11–13], and provincial [14–16]. Such literature often uses carbon emission scale per unit of GDP to measure economic low-carbon transformation. Secondly, in terms of carbon emission efficiency, most literature uses the carbon emission efficiency index measured by the SBM and EBM models to measure economic low-carbon transformation and constructs comprehensive index systems to examine the impact of DE on UCEE [17–20]. Additionally, some literature examines the impact of certain aspects of DE, such as artificial intelligence [21], digital finance [22], and internet development [23], on carbon emission efficiency.

First, compared with similar literature [11–13], this study represents DE through digital technology and digital services, constructing a general equilibrium model that includes these elements to deeply reveal the intrinsic logic of DE's impact on ULCT. Second, compared with similar literature [17–20], this study extends the impact of DE on ULCT from the perspective of urban agglomeration heterogeneity. Third, while similar literature identifies energy consumption, energy intensity, urban greening, and technological innovation as mechanisms through which DE impacts ULCT [17–20], this study expands these mechanisms to include scale economy effects, public environmental awareness effects, and income effects, and examines the heterogeneity of these mechanisms between southern and northern cities. Fourth, this study uses multiple instrumental variables to effectively address the endogeneity problem of DE's impact on ULCT. Therefore, the study aims to furnish theoretical and empirical support for the role of DE in aiding China in achieving its "dual carbon" goals. By offering insights into the multifaceted effects of DE on low-carbon development, this research provides valuable guidance for policymakers and stakeholders dedicated to fostering sustainable and low-carbon urban growth.

2. Theoretical Model and Research Hypotheses

2.1. Theoretical Model

Compared with the existing theoretical models of DE's impact on ULCT, this study mainly includes the following three expansions: (1) In terms of setting the consumer utility function, this study mainly considers carbon emissions rather than environmental pollution, referring to the related research by Wen (2022) [24]. (2) Extending the endogenous economic growth model [25], this study expands endogenous technological progress to digital technological progress, endowing the production function with the theoretical connotation of DE. (3) Improving the green finance emission reduction effect model constructed by Wen (2022) [24], this study incorporates digital services into a general equilibrium model that includes carbon emissions, revealing the impact of digital services on carbon emission efficiency.

(1) Basic Setting of the Theoretical Model

① Consumer Utility Function

Assume all consumers are homogeneous and have the same preferences. In constructing the general equilibrium model, if the effect function considering environmental pollution is built, existing research typically incorporates environmental pollution into the consumer's effect function [26,27]. However, carbon emissions differ from pollutants in that they do not directly harm the human body but rather affect output levels through the greenhouse effect. Therefore, this paper refers to relevant theoretical model studies on carbon emissions [28,29] and does not consider the impact of carbon emissions on the utility function when constructing the consumer's utility function. The consumer's utility function is expressed as follows:

$$U = \frac{C(t)^{1-\sigma} - 1}{1-\sigma}, \sigma > 0 \tag{1}$$

where U represents the consumer utility function, $C(t)$ represents consumption at period t, and σ is the relative risk aversion coefficient.

② Production Function

To construct an economic growth model with environmental constraints, referring to existing literature [30], labor is not considered in the production function, i.e., labor is standardized to 1. Therefore, the production function can be expressed as:

$$\mathcal{Q}(t) = \Omega(E)Y(t) = \Omega(E)AK(T)^{\gamma}_{Y},\ \ 0 < \gamma < 1 \tag{2}$$

where t is the time variable representing period t, $Q(t)$ represents the output of period t under environmental constraints, and $Y(t)$ represents the output of period t without considering environmental constraints. E represents carbon emissions, and $\Omega(E)$ represents the output loss caused by the greenhouse effect due to carbon emissions, which is a nonlinear function of carbon emissions. A represents the level of technology, $K(t)$ represents the capital stock in period t, and γ represents the output contribution rate of capital. Although there is no consensus on the specific form of the $\Omega(E)$ function in existing research, most scholars believe it is a nonlinear increasing function of carbon emissions [24]. Referring to existing studies and considering real-world situations, this paper sets the function $\Omega(E)$ as an exponential function, i.e., $\Omega(E) = E(t)^{-\beta}$, where β represents the elasticity of output loss to carbon emissions. Thus, Equation (2) can be further expressed as:

$$Q(t) = \Omega(E)Y(t) = E\Big(t\Big)^{-\beta}AK(T)^{\gamma}_{Y}, 0 < \gamma < 1 \tag{3}$$

③ Carbon emissions and digital technology

Suppose carbon emissions are generated during the production process of enterprises and are expressed as follows:

$$E(t) = \frac{Y(t)}{H(t)} \tag{4}$$

where $E(t)$ represents the carbon emissions generated by enterprises during the production process in period t, and $H(t)$ represents emission reduction technology. Emission reduction technology is a key factor in reducing carbon emissions, and the rapid development of digital technology will become a significant driving force for emission reduction technology. Expanding endogenous technological progress to digital technology [31], while considering the openness and sharing characteristics of digital technology, assume that digital technology has spillover effects, thus further expressing emission reduction technology as follows:

$$H(t) = A_h K_H^{\mu} \tag{5}$$

where A_h represents the driving parameter of digital technology development on carbon reduction technology, and $K_H^{\mu}(\mu > 1)$ represents the capital investment in carbon reduction technology.

④ Carbon Emissions and Digital Services

With the continuous advancement of digital services, their role in the clean transformation of production activities has become increasingly significant. This paper examines digital finance as a representative of digital services and incorporates it into a general equilibrium model that includes carbon emissions. Current studies indicate that the development of digital financial services has significantly enhanced the efficiency of financial services, reduced financing constraints and costs for enterprises [32], and boosted corporate investment in innovation, thereby aiding in carbon reduction efforts. In particular, to support the green transformation and development of businesses, many specialized industries have benefited from interest-free loans, highlighting the impact of digital financial development on carbon reduction. Additionally, this impact of digital finance is independent of the market structure within the digital finance sector. To streamline the model and keep it in line with existing literature [33], it is assumed that the digital finance sector operates under perfect competition. Consequently, the profit function of the digital finance sector can be expressed as:

$$\pi_f = RK(t)_Y - rK(t) \tag{6}$$

where π_f represents the profit of the financial sector, R represents the marginal return, and r represents the capital price level. Meanwhile, digital financial institutions usually allocate a certain proportion of capital to support corporate carbon reduction, assuming the proportion is η, i.e.,:

$$\eta = \frac{K(t)_H}{K(t)} \tag{7}$$

where η represents the proportion of capital used for carbon reduction in the total capital, and $K(t)_H$ represents the capital used to support corporate carbon reduction. Here, η can represent the impact of digital services, represented by digital financial services, on carbon emissions. The larger the η, the higher the degree of support digital services provide for carbon reduction, thus facilitating carbon reduction.

(2) General Equilibrium Analysis of the Impact of the Digital Economy on Carbon Emission Efficiency

① Corporate Decision-Making

To simplify the formula, remove the time index t, and substitute Equations (4) and (5) into Equation (3), we get:

$$Q = A^{-\beta+1} A_h^{\beta} K_Y^{\gamma-\beta\gamma} K_H^{\beta\mu} \tag{8}$$

To simplify the model, referring to existing literature [24], set the price of the final product to 1. Under the condition of profit maximization, the marginal return of capital goods equals the price of capital goods, then:

$$Q_{K_Y} = R = (\gamma - \beta\gamma) A^{-\beta+1} A_h^{\beta} K_Y^{\gamma-\beta\gamma-1} K_H^{\beta\mu} \tag{9}$$

where, to achieve equilibrium, $\beta < 1$, indicating that the impact of the greenhouse effect caused by carbon emissions on output is relatively "moderate".

② Decision-Making of Digital Service Institutions

As previously assumed, in this model, digital finance is taken as a representative of digital services, and digital financial institutions are assumed to be perfectly competitive. In a perfectly competitive market, the condition that must be satisfied when profit is zero is:

$$\pi_b = R_Y K_Y - rK = 0 \tag{10}$$

Therefore, when this perfectly competitive market reaches equilibrium, we have:

$$R = \frac{1}{1-\eta} r \tag{11}$$

③ Consumer Utility Maximization

As shown by the consumer utility function in Equation (1), the consumer utility maximization can be expressed as:

$$\begin{gathered} max \int_0^\infty \frac{C^{1-\sigma}-1}{1-\sigma} e^{-\rho t} dt \\ s.t. \dot{a} = ra - C \end{gathered} \tag{12}$$

where a represents the wealth the consumer owns, and all wealth is deposited in financial institutions. With an interest rate of r, the interest income obtained is ra. C represents the consumer's consumption. It should also be noted that since the simplified model used in this paper does not consider the labor market, wages are not considered in the consumer's utility maximization function.

Further, by establishing the Hamiltonian function to solve the optimization problem of the above Equation (12), the Hamiltonian function can be expressed as:

$$H = \frac{C^{1-\sigma}-1}{1-\sigma} + \lambda_1 (ra - C) \tag{13}$$

From the static and dynamic first-order conditions of equation (13), we get:

$$r = \rho - \frac{\dot{U}_C}{U_C} \tag{14}$$

where ρ is the discount rate. The larger the value, the smaller the consumer's valuation of future consumption.

④ Market Equilibrium

Combining the market-clearing conditions of the above consumers, enterprises, and digital service sectors, we can obtain the market equilibrium conditions of the general equilibrium model in this paper:

$$(\gamma - \beta\gamma) A^{-\beta+1} A_h^{\beta} K_Y^{\gamma-\beta\gamma-1} K_H^{\beta\mu} = \left(\rho - \frac{\dot{U}_C}{U_C}\right) \frac{1}{1-\eta}. \tag{15}$$

Substituting Equation (15) into Equation (10) can further yield:

$$Q_{K_Y} = \left(\rho - \frac{\dot{U}_C}{U_C}\right) \frac{1}{1-\eta} \tag{16}$$

From Equation (16), it can be seen that at market general equilibrium, optimal growth is a function of the marginal return on capital, the marginal utility of consumers, and the discount rate. Combining Equation (16) and the production function, the expression for carbon emissions at market equilibrium can be further derived as follows:

$$E = (E/Q)^{\beta} = A^{\beta^2} A_h^{-\beta(1+\beta)} K^{-\beta\mu+\beta^2\gamma-\beta^2\mu} \eta^{-\beta\mu(1+\beta)} (1-\eta)^{\beta^2\gamma} \quad (17)$$

where E/Q represents carbon emission intensity, i.e., the amount of carbon emissions per unit of output. The smaller this value, the less carbon emissions are associated with each unit of output, which is more favorable for ULCT. From Equation (17), it can be seen that ULCT is related to the digital technology parameter A_h and the digital service parameter η. When the capital stock K is an unchanged exogenous variable, the larger the digital technology parameter A_h and the digital service parameter η, the more favorable it is for ULCT.

Hypothesis 1. *DE can promote ULCT*.

2.2. Research Hypotheses

DE helps promote the rapid expansion of production scale, forming diversified industrial clusters and generating scale economy effect (SCALE) [34]. First, from the perspective of production cost advantages, in the traditional economic era, the development of enterprises was restricted by production costs, their technological level, and management capabilities, limiting the long-term expansion of production scale [35]. With the rapid development of DE, its high growth will promote the formation of economies of scale by reducing marginal costs. According to Metcalfe's Law, the value of the DE network is proportional to the square of the number of network nodes. As internet platforms and users continue to increase, the value of the DE exhibits a trend of marginal increase [36]. With the rise in network nodes and users, marginal costs gradually approach zero. The characteristics of a large platform economy provide significant advantages in expanding enterprise scale, promoting the formation of production economies of scale, and extending the production possibility frontier [34]. This process reduces marginal production costs and intensifies the benefits of economies of scale. The formation of economies of scale and the expansion of the production possibility frontier decrease the average production costs for enterprises. This cost reduction is crucial for enhancing green production efficiency and fostering a green production model, thereby supporting ULCT.

Hypothesis 2. *DE promotes ULCT through SCALE.*

DE relies on digital technologies and new media, such as internet platforms and network media, mainly influencing public environmental awareness from three aspects: data, new media, and the network environment [37], facilitating public participation in environmental governance and supervision. First, the participation of data elements directly impacts achieving public attention and participation in environmental governance. As a new production factor, data elements have the integration effect of consolidating information and data from various aspects. For example, under the DE context, establishing various databases accelerates the liquidity and allocation efficiency of information and resources, enabling the public to receive more information. The transparency and timeliness of information in the DE era enhance the accuracy and credibility of information received by the public, reducing cognitive biases and helping the public make positive choices, thus stimulating public environmental awareness and leveraging the public environmental awareness effect brought by DE. The public environmental awareness effect acts like an "invisible hand", promoting green technological innovation [38]. On the one hand, with the development of DE and the gradual increase in public environmental awareness, green development will be fully practiced, thus promoting green technological innovation. On the other hand, the public environmental awareness effect acts as "soft supervision", urging the effective implementation of government environmental governance policies, enhancing government supervision from the perspective of policy implementation effects, and compelling enterprises to improve their green innovation levels, promoting ULCT.

The network environment created by the development of digital technology can also enhance public environmental awareness, generating public environmental awareness effects (PUBLIC). The network environment provides an interactive platform for the government to release environmental policies and for the public to express their demands for a better life. It can strengthen communication and interaction between the government and the public, promoting the penetration of the green development concept among the public. Generally speaking, a good network environment helps promote positive public behavior, whereas a closed information environment will adversely affect public behavior. Through extensive publicity in the network environment, the green development concept gradually takes root, and the public's awareness of environmental protection continuously strengthens, which helps actively guide the public to participate in low-carbon activities, contributing to improving carbon emission efficiency. Moreover, driven by DE, the network environment's strong penetration and wide coverage characteristics help the public make correct behavior choices. When the public feels that environmental pollution issues adversely affect their daily lives and health, they will use online platforms to demand that the government strengthen environmental regulation. Government measures to regulate corporate environmental practices are greatly influenced by public opinion. Public demands will prompt the government to pay close attention to environmental pollution issues, aiding in the effective and reasonable formulation of environmental regulation policies, thereby effectively regulating corporate carbon emissions and promoting ULCT.

Hypothesis 3. *DE promotes ULCT through PUBLIC.*

DE can affect income by increasing residents' disposable income. With the continuous development of digital technologies such as big data, industrial IoT, and blockchain, profound changes have occurred in production methods, management models, and service methods, reducing transaction friction and helping to lower transaction costs. According to microeconomic equilibrium theory, reducing transaction costs will help lower market equilibrium prices, further reducing consumer expenditures. With other costs remaining unchanged, reducing transaction costs can increase consumers' disposable income [39], bringing income effects (REVENUE) to consumers. As consumers' incomes increase, household consumption is positively correlated with disposable income, increasing household consumption capacity and consumption levels, which will help transform household consumption structures. On the one hand, in the consumption of necessities such as food, higher consumption levels will prompt households to prefer green food. On the other hand, according to Engel's law, as household income levels increase, the proportion of spending on necessities in household consumption expenditures will gradually decrease, and demand for service-oriented consumption will continuously increase, thereby promoting the growth of green consumption. As residents' consumption undergoes a green transformation and upgrade, it will compel enterprises to engage in green emission reduction, thereby benefiting ULCT.

DE provides employment opportunities for low-income or low-skilled people, increasing their income levels [40]. The development of digital technology has a dual impact on labor; while it replaces some jobs, it also creates many new job opportunities. However, since there is still a large amount of low-cost labor in China, the substitution effect of digital technology on the labor force is limited, and it has created many labor-intensive jobs such as food delivery workers. Specifically, on the one hand, the development of the DE has created many low-threshold job positions, which inherently have a certain ability to absorb labor; on the other hand, the DE has created many forms of flexible employment, providing opportunities for the unemployed or those who can only work part-time, thereby increasing the income levels of consumer groups who originally had difficulty earning wages, which helps narrow the income gap to some extent. The income gap and income levels of residents are important aspects affecting human capital. As residents' income levels increase and the income gap narrows, residents have the opportunity to receive better education and knowledge, which helps improve human capital levels. Furthermore, improving human capital levels will enhance green economic efficiency [41], providing an important guarantee for reducing pollution and benefiting ULCT.

Hypothesis 4. *DE can promote ULCT through REVENUE.*

3. Design of the Research

3.1. Setting Up the Model

This study constructs a panel fixed-effects model to identify the impact of *DE* on *ULCT*, as follows:

$$ULCT_{it} = \alpha_0 + \alpha_1 DE_{it} + \varphi X_{it} + \mu_i + v_t + \varepsilon_{it} \quad (18)$$

where *ULCT* is urban low-carbon transformation, *DE* is urban digital economy, and *X* is a series of control variables affecting *ULCT*. α_0 is the constant term, α_1 and φ represent the impact coefficients of variables *DE* and *X* on *ULCT*, respectively, μ_i is the individual fixed effect, v_t is the time fixed effect, and ε_{it} represents the random disturbance term.

3.2. Variable Definitions

(1) Explained variable. Referring to existing literature [42], the proposed EBM model, which includes both radial and SBM distance functions, is used to measure UCEE and assess ULCT. In the specific calculations, this study uses a non-oriented, variable returns to scale super-efficiency EBM model to measure UCEE. Referring to existing literature [43,44], the index system for UCEE is constructed from three aspects: input, expected output, and unexpected output (Table 1).

Table 1. UCEE Index System.

Indicator	Variable	Variable Description
Input Indicator	Land Input	Urban Construction Land Area (km^2)
	Labor Input	Total Urban Employment at Year-End (ten thousand people)
	Capital Input	Urban Capital Stock (ten thousand yuan)
	Energy Input	Total Consumption of Three Types of Energy (ten thousand tons of standard coal)
Expected Output Indicator	Economic Benefit Output	Urban GDP (ten thousand yuan)
	Environmental Benefit Output	Urban Built-up Area Green Coverage Rate (%)
	Social Benefit Output	Average Urban Employee Salary (yuan)
Unexpected Output Indicator	Carbon Emissions	Total Urban Natural Gas Carbon Emissions (ten thousand tons)
		Urban Liquefied Petroleum Gas Carbon Emissions (ten thousand tons)
		Urban Electricity Carbon Emissions (ten thousand tons)
		Urban Thermal Energy Consumption Carbon Emissions (ten thousand tons)
	Pollution Emissions	Total Urban Industrial Wastewater Discharge (ten thousand tons)
		Total Urban Industrial SO^2 Emissions (ten thousand tons)
		Total Urban Industrial Smoke (Dust) Emissions (ten thousand tons)

(2) Explanatory variables. The DE index system is constructed based on all aspects and dimensions of digital economy carriers, digital industrialization, and industrial digitalization. The specific indicator composition is shown in Table 2. Due to the lack of urban-level data on digital agriculture, the industrial digitalization indicators in the DE index system

are limited to industry and services. This study employs the entropy method and principal component analysis (PCA) to construct the DE index. Additionally, a robustness analysis is conducted using the DE index measured by PCA to ensure the reliability of the results.

Table 2. DE Index System.

Primary Indicators	Secondary Indicators	Indicator Attributes
Digital Economy Carrier Digital Industrialization	Number of Broadband Internet Access Users per 100 People (units)	+
	Number of Mobile Phone Users per 100 People at Year-End (units)	+
Industrial Digitalization Primary Indicators	Proportion of Employees in Computer Services and Software (%)	+
	Per Capita Telecom Business Revenue (ten thousand yuan)	+
Digital Economy Carrier	Digital Inclusive Finance Coverage Index (-)	+
	Digital Inclusive Finance Usage Depth Index (-)	+
	Digital Inclusive Finance Digitalization Degree Index (-)	+
	Number of Computers per 100 Employees in Industrial Enterprises (units)	+

(3) Control Variables. Referring to existing literature, this study selects 10 control variables that influence ULCT [44,45]. ① Temperature Change (CIM). The annual average temperature of each city is used to measure CIM. ② Transportation Infrastructure (INFRA). Per capita road area is used to measure INFRA. ③ Environmental Regulation (ER). The level of environmental regulation is captured through the removal rates of sulfur dioxide and industrial smoke (dust), as well as the comprehensive utilization rate of industrial solid waste. The entropy method calculates a composite index of ER [46]. ④ Openness (OPEN). The ratio of FDI stock to regional GDP measures urban openness. ⑤ Industrial Agglomeration (AGG). The location quotient of manufacturing employees is used to measure AGG. ⑥ Industrial Proportion (INDUSTR). The proportion of the secondary industry's added value to GDP is used to measure the INDUSTR. ⑦ Government Intervention (GOV). The proportion of fiscal expenditure excluding science and education to total fiscal expenditure is used to measure GOV. ⑧ Energy Utilization Efficiency (ENER). GDP per unit of energy consumption is used to measure ENER. ⑨ Urbanization (URB). The proportion of the urban year-end population to the regional year-end permanent population is used to measure URB. ⑩ Human Capital (HUMAN). The proportion of regular higher education students per ten thousand people is used to measure HUMAN.

3.3. Sample Selection

The primary sources of the original data for the variables are the "China Urban Statistical Yearbook", "China Energy Statistical Yearbook", "China Environment Yearbook", "China Industrial Statistical Yearbook", "China Science and Technology Statistical Yearbook", "China Labor Statistical Yearbook", and the EPS data platform. The digital inclusive finance data is also obtained from the Peking University Digital Finance Research Center. This research focuses on 283 cities at the prefecture level and above from 2011 to 2019, excluding those with substantial missing data. Missing values are supplemented and estimated using linear interpolation and Python data mining.

4. Empirical Results

4.1. Baseline Regression

Table 3 illustrates the baseline regression results assessing the impact of the DE on ULCT. Columns (1), (3), and (5) present regression outcomes without control variables, where column (3) accounts for city fixed effects, and column (5) includes both city and time fixed effects. The results indicate that, in the absence of control variables, the DE coefficient is significantly positive at the 1% level, suggesting a strong positive effect of DE on ULCT. Columns (2), (4), and (6) reveal the impact of DE on ULCT after incorporating control variables. Column (4) controls for city fixed effects, and column (6) adjusts for both city and time fixed effects. The consistent finding across these models is that the DE coefficient remains significantly positive at the 1% significance level. From the regression results in column (6), it is evident that a 1% increase in DE correlates with a 53.14% rise in UCEE, highlighting DE's significant role in promoting ULCT. Several factors may explain this positive impact. Firstly, DE facilitates urban green technological innovation by enabling the efficient allocation and widespread application of digital finance and technology, which drives innovation [47]. Secondly, digital technologies substantially benefit energy efficiency and environmental pollution control. They enhance pollution emission monitoring, improve corporate governance [48], and promote efficient energy use [49], all advancing ULCT. These findings substantiate Hypothesis 1, indicating the crucial role of DE in supporting sustainable urban development.

Table 3. Baseline Regression Results.

	(1)	(2)	(3)	(4)	(5)	(6)
DE	0.4155 ***	0.9053 ***	1.1293 ***	0.9951 ***	0.6015 ***	0.5314 ***
	(8.836)	(13.847)	(23.450)	(14.842)	(7.204)	(7.166)
CIM		0.0053 ***		−0.0218 ***		−0.0021
		(8.767)		(−5.469)		(−0.468)
INFRA		−0.0008		0.0007		0.0005
		(−1.366)		(0.681)		(0.587)
ER		−0.0051		−0.0050		0.0467 ***
		(−0.313)		(−0.279)		(2.789)
OPEN		−0.0035 **		0.0043 **		0.0030 **
		(−2.329)		(2.542)		(1.982)
AGG		−0.0174 **		−0.0799 ***		−0.0922 ***
		(−2.489)		(−7.078)		(−9.013)
INDUSTR		0.0001		0.0006		0.0042 ***
		(0.198)		(1.380)		(10.042)
GOV		0.2367 ***		−0.0493		−0.2190 ***
		(3.278)		(−0.608)		(−2.865)
ENER		0.0039 ***		0.0027 ***		0.0029 ***
		(29.945)		(19.049)		(23.162)
URB		0.0006 ***		0.0032 ***		0.0013 ***
		(2.896)		(12.190)		(5.014)
HUMAN		−0.0001 ***		−0.0001		-4.3×10^{-5}
		(−10.608)		(−1.249)		(−1.146)
Constant	0.6339 ***	0.2351 ***	0.5494 ***	0.7421 ***	0.6119 ***	0.5411 ***
	(98.993)	(3.528)	(92.245)	(8.693)	(61.092)	(5.768)
City Fixed Effects	NO	NO	YES	YES	YES	YES
Year Fixed Effects	NO	NO	NO	NO	YES	YES
N	2547	2547	2547	2547	2547	2547
R^2	0.0298	0.3665	0.7482	0.8021	0.7875	0.8423
Adj-R^2	0.0294	0.3638	0.7167	0.7764	0.7601	0.8212
F-value	78.0727	133.3253	549.8879	119.1182	51.9018	77.2688

Note: The values in parentheses are *t*-statistics of the parameter estimates; *** and ** are significant at the 1% and 5% levels, respectively.

A deeper analysis of the control variables' impact on ULCT, as indicated in column (6), provides several key insights. ER significantly promotes ULCT, suggesting that stringent

ER policies can compel enterprises to adopt green innovations, making ER a crucial driver of ULCT. OPEN also significantly affects ULCT, indicating that the "pollution haven hypothesis" does not apply to this study's sample. It suggests that increased openness, contrary to attracting polluting industries, supports low-carbon transformation. The impact coefficient of INDUSTR on ULCT is significantly positive, mainly due to the continuous increase in industrial output value, which has created economies of scale. The effect of ENER on ULCT is significantly positive, indicating that the improvement of ENER is a direct way to promote ULCT. URB has a positive effect on ULCT, which is due to the transition of urbanization development from a lower stage to a higher stage. Besides, it can be found that AGG and AGG have a significant negative effect on ULCT. The possible reasons are that after AGG enters the turning point, excessive agglomeration brings diseconomies of scale, and the improvement of AGG is not conducive to promoting energy conservation and emission reduction through market means, nor to the effective allocation of resources, thus hindering ULCT. In addition, INFRA, CIM, and HUMAN have no significant impact on ULCT.

4.2. Robustness Analysis

To validate the robustness of the regression results shown in Table 3, this study employs three distinct approaches: altering the DE measurement method, adjusting the carbon emission efficiency measurement method, and applying a different empirical model.

The DE index is initially recalculated using the principal component analysis method, and the model is re-estimated. These findings are displayed in column (1) of Table 4. Next, the SBM model is utilized to reassess ULCT and re-estimate the model. The results are presented in column (2) of Table 4. Lastly, the model is re-estimated using the dynamic panel system GMM estimation method, with the outcomes shown in column (3) of Table 4. The results across all three approaches indicate that the coefficient for the core explanatory variable, DE, remains significantly positive at the 1% significance level. This consistency across different methods reinforces the reliability of the baseline regression results. The findings conclusively demonstrate that DE significantly promotes ULCT, affirming Hypothesis 1.

Table 4. Regression Results Of Robustness Analysis.

	(1)	(2)	(3)
	Changing the Measurement Method of DE	**Changing the Measurement Method of ULCT**	**Changing the Empirical Model**
L.ULCT			0.6052***
			(38.871)
DE	0.2849 ***	0.8339 ***	0.4120 ***
	(3.857)	(7.393)	(9.923)
Constant	0.6001 ***	0.0851	−0.0957 **
	(6.422)	(0.732)	(−2.140)
N	2547	2492	2264
R^2	0.8325	0.8468	-
Adj-R^2	0.8100	0.8261	-
F/Wald	118.7385	79.6180	8332.85
P-AR(1)	-	-	0.0000
P-AR(2)	-	-	0.7241
P-sargan	-	-	0.1191

Note: Regression coefficients with *t* or z values in parentheses; *** and ** indicate significance at the 1% and 5% levels, respectively. Control variables, city fixed effects, and year fixed effects are already controlled.

4.3. Endogeneity Analysis

This study employs the instrumental variable method to address potential endogeneity issues in the model. First, the lagged value of DE by one period is used as an instrumental variable for IV-2SLS estimation. Second, historical data from 1984, including the number of fixed telephones per 100 people, the number of post offices per million people, and the postal business volume per person, are used to construct instrumental variables by interacting these historical metrics with time dummy variables for IV-2SLS estimation.

The rationale behind these instruments is twofold: on the one hand, historical telecommunication infrastructure influences the current application of internet technology through established technical levels and usage habits; on the other hand, it does not have a direct causal relationship with current economic development and urban carbon emission efficiency, thereby satisfying the condition of exogeneity.

The regression results of the endogeneity analysis are presented in Table 5. Columns (1) to (4) demonstrate that, after accounting for endogeneity issues, the coefficient of DE remains significantly positive at the 1% significance level. This indicates that the conclusions from the baseline regression results are robust. Additionally, the test results for the null hypothesis of "under identification of instrumental variables" show that the *p*-values of the Kleibergen-Paap rk LM statistics are all 0.000, which significantly rejects the null hypothesis. For the weak identification of instrumental variables, the Kleibergen-Paap rk Wald F statistics are all greater than the critical value at the 10% level of the Stock-Yogo weak identification test, confirming the validity of the chosen instrumental variables.

Table 5. Regression Results of Endogeneity Analysis.

	(1)	**(2)**	**(3)**	**(4)**
	Lag of DE by One Period	**Number of Post Offices per Million People in 1984**	**Number of Fixed Telephones per 100 People in 1984**	**Postal Business Volume per Person in 1984**
DIG	1.7759 ***	1.9476 ***	1.6076 ***	1.5799 ***
	(15.457)	(12.145)	(8.641)	(9.011)
Kleibergen-Paap rk LM statistic	839.257	387.693	272.819	306.055
	[0.000]	[0.000]	[0.000]	[0.000]
Kleibergen-Paap rk Wald F statistic	1448.080	61.293	39.853	45.713
	{16.38}	{33.84}	{33.84}	{33.84}
N	2264	2007	2007	2007
R^2	0.3559	0.3487	0.3832	0.3853
Adj-R^2	0.2598	0.2627	0.3018	0.3042
F	107.0499	97.8632	96.0064	96.9062

Note: Regression coefficients are z-values in parentheses, *** indicates significance at the 1% levels. Values in [ ] are *p*-values, and values in { } are the critical values for the Stock-Yogo weak identification test at the 10% level. Control variables, city fixed effects, and year fixed effects are already controlled.

Moreover, the analysis reveals that the promoting effect of DE on ULCT observed in the baseline regression results was underestimated due to the endogeneity problem in the model. This further validates the robustness and significance of the findings, reinforcing the positive impact of DE on ULCT.

4.4. Heterogeneity Analysis

4.4.1. Geographical Location Heterogeneity

Table 6 presents the effects of DE on ULCT in both southern and northern cities, as shown in columns (1) and (2), respectively. The findings indicate that the estimated coefficients of DE are significantly positive at the 1% level for both regions. However, the promoting effect of DE is more pronounced in southern cities.

Table 6. Model Regression Results of Geographical Location Heterogeneity.

	(1)	**(2)**
	Southern Cities	**Northern Cities**
DE	0.5086 ***	0.4692 ***
	(6.156)	(3.140)
Constant	0.3061 **	0.5369 ***
	(2.521)	(3.448)
N	1683	864
R^2	0.8578	0.8293
$Adj\text{-}R^2$	0.8381	0.8033
F	39.3619	32.3431

Note: The values in parentheses are *t*-statistics of the parameter estimates; *** and ** re significant at the 1% and 5% levels, respectively. Control variables, city fixed effects, and year fixed effects are already controlled. The notes for Tables 7 to 13 are consistent with this.

The economic structure of the regions can explain this difference. Southern cities predominantly feature service and high-tech industries, whereas northern cities rely more on traditional manufacturing and heavy industries. High-quality development of the DE is more readily achieved in service and high-tech sectors, which in turn more effectively facilitates the low-carbon transformation of southern cities. Consequently, the impact of DE on ULCT is stronger in the south, where the economic environment is more conducive to digital and low-carbon advancements.

4.4.2. City Cluster Heterogeneity

The regression results of city cluster heterogeneity, as presented in Table 7, reveal that DE significantly promotes ULCT in most city clusters, except for the Yangtze River Delta and Chengdu-Chongqing clusters. The magnitude of this promoting effect follows the order: Central Yangtze > Beijing-Tianjin-Hebei > Guangdong-Hong Kong-Macao. The intensity of DE's promoting effect on ULCT varies across these regions. The Central Yangtze city cluster experiences the most significant effect, likely due to its urgent need for economic transformation and strong policy support. In the Beijing-Tianjin-Hebei region, low-carbon transformation is driven by digital twin-city construction and enhanced industrial collaborative innovation. The Guangdong-Hong Kong-Macao Greater Bay Area benefits from green development, the digital economy, international cooperation, and green finance, which collectively contribute to substantial progress in low-carbon transformation. However, the specific magnitude of DE's promoting effect on ULCT is influenced by various factors, including the economic development level, industrial structure, and policy support intensity within each city cluster. These factors create a diverse landscape of DE's impact on low-carbon transformation across different regions.

Table 7. Heterogeneity Regression Results of Five Major City Clusters.

	Yangtze River Delta	Beijing-Tianjin-Hebei	Central Yangtze	Chengdu-Chongqing	Guangdong-Hong Kong-Macao
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
DE	0.2884	0.8030 **	1.0789 ***	−0.0959	0.4239 **
	(1.299)	(2.061)	(3.507)	(−0.265)	(2.003)
Constant	−0.5484	1.8884 ***	0.9221 *	−0.4264	−0.5510
	(−0.889)	(3.778)	(1.971)	(−0.851)	(−0.427)
N	243	117	234	144	135
R^2	0.8932	0.9291	0.9190	0.8803	0.8748
$Adj\text{-}R^2$	0.8688	0.9032	0.9001	0.8429	0.8338
F	9.4780	12.9121	26.1542	9.2076	8.8111

Note: The values in parentheses are t-statistics of the parameter estimates; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

4.5. Impact Mechanism Test

Drawing on the design of the mediation effect model from existing literature [50], this study uses the stepwise regression method to examine the influence mechanism of *DE* on *ULCT* based on the baseline model. First, the mechanism variable is taken as the dependent variable and *DE* as the independent variable to test the impact of the digital economy on the mechanism variable. Second, the mechanism variable is added to the baseline model, as shown in models (19) and (20).

$$MED_{it} = \alpha_0 + \alpha_1 DE_{it} + \varphi X_{it} + \mu_i + v_t + \varepsilon_{it} \quad (19)$$

$$ULCT_{it} = \gamma_0 + \gamma_1 MED_{it} + \gamma_2 DE_{it} + \varphi X_{it} + \mu_i + v_t + \varepsilon_{it} \quad (20)$$

MED represents the mechanism variable. The mechanism of the SCALE is measured by the economic agglomeration represented by the added value of non-agricultural industries per unit of administrative land area in cities [1]; Drawing on existing literature [51], the PUBLIC is measured using the number of times residents in various prefecture-level cities searched for the keyword "environmental pollution" on the Baidu search engine over the years; Drawing on existing literature [52], the logarithm of per capita income is used to represent the REVENUE. The meanings of the remaining variables are consistent with those in the baseline model. If DE influences ULCT through MED, then both the α_1 and γ_1 coefficients should be significant.

4.5.1. Scale Economy Effect

Table 8 presents the empirical test results of DE promoting ULCT through SCALE. Column (1) illustrates the impact of DE on SCALE, revealing that the estimated coefficient of DE is significantly positive and passes the 1% significance test. This indicates that DE significantly enhances SCALE. Column (2) reports the impact of both DE and SCALE on ULCT after controlling for other variables. The results show that the estimated coefficients of both SCALE and DE remain significantly positive. Notably, the estimated coefficient of DE is less than 0.5314, suggesting that SCALE partially mediates the relationship between DE and ULCT. The Sobel test results further indicate that the mediation effect of SCALE accounts for approximately 6.64% of the total effect. On the one hand, DE can take advantage of gradually decreasing marginal costs to reduce production costs, helping enterprises achieve scale production, and creating conditions for green production modes, thereby promoting ULCT. On the other hand, reducing marginal costs can help enterprises increase R&D investment, develop green products that meet consumer demands, and increase profits, providing financial support for clean production inputs, thereby promoting ULCT.

Table 8. Overall Test of DE's Scale Economy Effect.

	(1)	(2)
DE	0.5943 ***	0.4961 ***
	(2.998)	(6.761)
SCALE		0.0594 ***
		(7.622)
Constant	1.1069 ***	0.4753 ***
	(4.413)	(5.108)
N	2547	2547
R^2	0.9438	0.8463
Adj-R^2	0.9362	0.8256
F	15.7170	77.4718
Sobel Test	[Z = 2.790, p = 0.0052]	
Proportion of Mediation Effect	6.64%	

Note: The values in parentheses are t-statistics of the parameter estimates; *** indicates significance at the 1% levels.

Table 9 presents the test results of SCALE as an influencing mechanism in southern and northern cities. The results of columns (1) and (3) show that DE can generate scale economy effects in both southern and northern cities. The results of columns (2) and (4) find that SCALE partially mediates in both southern and northern cities. The reason for this is that southern cities typically have more advanced infrastructure and management levels, providing a better material foundation and conditions for the application of the digital economy. For instance, advanced intelligent traffic management systems and energy-efficient building facilities contribute to reducing carbon emissions and enhancing the low-carbon level of cities. In northern regions, particularly under cold climate conditions, energy consumption is usually higher. The intelligent application of digital technology can effectively reduce energy consumption and decrease carbon emissions. SCALE allows the cost of digital economy technologies to decrease with large-scale application, making it easier for northern cities to adopt and promote these technologies.

Table 9. Scale Economy Effect of DE in Southern and Northern Cities.

	Southern Cities		Northern Cities	
	(1)	(2)	(3)	(4)
DE	0.7546 ***	0.4756 ***	0.4198 ***	0.2838 *
	(2.661)	(5.807)	(4.255)	(1.961)
SCALE		0.0437 ***		0.4416 ***
		(5.826)		(8.336)
Constant	0.8799 **	0.2677 **	0.1876 *	0.4541 ***
	(2.111)	(2.226)	(1.824)	(3.040)
N	1683	1683	864	864
R^2	0.9448	0.8610	0.9581	0.8438
Adj-R^2	0.9371	0.8416	0.9517	0.8198
F	12.9474	39.7148	8.4377	38.1502

Note: The values in parentheses are t-statistics of the parameter estimates; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

4.5.2. Public Environmental Concern Effect

Table 10 presents the empirical test results of the public environmental concern effect as an influencing mechanism. Column (1) shows the impact of DE on PUBLIC. The results indicate that DE significantly enhances PUBLIC. Column (2) presents the test results of DE and PUBLIC on ULCT. The results show that PUBLIC plays a partial mediation role in the empowerment of PUBLIC by DE. Sobel test results report that this partial mediation effect accounts for approximately 9.84%. The rapid development of DE facilitates the public's access to comprehensive environmental information. Especially in the context of global climate change, digital platforms provide information channels for the public to deeply understand the Earth's environment, thereby helping to stimulate public environmental awareness. PUBLIC forms a "soft supervision" over enterprise production and government environmental policies, contributing to ULCT. Additionally, DE facilitates public participation in environmental governance. Through platforms provided by new media on the internet, the public not only accesses environmental information but also directly participates in environmental governance. For example, environmental protection activities provided by "Ant Forest" allow the public to participate in land protection and tree planting through online platforms, which helps reduce carbon emissions.

Table 10. Overall Test of DE's Public Environmental Concern Effect.

	(1)	**(2)**
DE	35.5917 ***	0.4495 ***
	(4.658)	(6.012)
PUBLIC		0.0014 ***
		(6.658)
Constant	32.1588 ***	0.4775 ***
	(3.378)	(5.138)
N	2511	2511
R^2	0.9288	0.8481
$Adj\text{-}R^2$	0.9193	0.8276
F	11.8054	75.4137
Sobel Test	[Z = 3.817, p = 0.0001]	
Proportion of Mediation Effect	9.84%	

Note: The values in parentheses are t-statistics of the parameter estimates; *** indicates significance at the 1% levels.

Table 11 presents the test results of PUBLIC as an influencing mechanism in southern and northern cities. The test results in columns (1) and (2) show that DE significantly promotes ULCT in the south by enhancing PUBLIC. The test results in columns (3) and (4) show that DE does not significantly impact PUBLIC, and PUBLIC is not established in northern cities. The reason for this may lie in the social and cultural backgrounds of northern cities, which might differ in the dissemination and promotion of environmental awareness. Cultural traditions and social values in different regions vary in their emphasis on environmental protection. The single technological dissemination of DE struggles to adapt to and change these deep-seated cultural factors.

The conclusions of this study reveal regional differences in PUBLIC between northern and southern cities in China, providing significant insights for other major polluting countries. Different countries and regions should develop targeted low-carbon transition strategies based on their environmental awareness and DE development. By enhancing public environmental awareness and participation, promoting green consumption, and adopting low-carbon lifestyles, urban low-carbon transitions can be effectively promoted, achieving a win-win situation for economic development and environmental protection.

The Indian government can draw on these conclusions by using DE methods (such as smartphone applications, social media, etc.) to increase public attention and participation in environmental issues. In areas with low environmental awareness, large-scale environmental education and publicity campaigns can be conducted to raise public awareness, supporting the development of the digital economy to promote low-carbon transitions.

Table 11. Test of DE's Public Environmental Concern Effect in Southern and Northern Cities.

	Southern Cities		Northern Cities	
	(1)	**(2)**	**(3)**	**(4)**
DE	52.0505 ***	0.4392 ***	−14.0965	0.3417 **
	(5.356)	(5.312)	(−1.201)	(2.212)
PUBLIC		0.0013 ***		0.0014 ***
		(6.002)		(2.827)
Constant	32.8166 **	0.2267 *	5.9020	0.4967 ***
	(2.309)	(1.890)	(0.506)	(3.239)
N	1665	1665	846	846
R^2	0.9275	0.8631	0.9391	0.8366
$Adj\text{-}R^2$	0.9174	0.8440	0.9297	0.8113
F	11.7246	40.4854	4.9202	30.2243

Note: The values in parentheses are *t*-statistics of the parameter estimates; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

4.5.3. Income Effect

Table 12 presents the regression results showing how DE affects ULCT through REVENUE. Column (1) displays the regression results of DE on REVENUE, indicating that DE significantly promotes REVENUE. Column (2) includes REVENUE as a control variable, and the results reveal that both DE and REVENUE have significant coefficients. Notably, the coefficient for DE decreases compared to the baseline regression model, suggesting that REVENUE partially mediates the relationship between DE and ULCT. According to the Sobel test, this partial mediation effect accounts for approximately 16.2%. DE reduces information asymmetry through information sharing, which enhances supply-demand matching in the labor market and helps workers obtain wage premiums. The increase in labor income levels leads to an upgrade in the consumption structure, increasing the scale and proportion of green consumption. This shift incentivizes enterprises to engage in green production, thereby promoting ULCT.

Table 13 presents the test results of REVENUE as an influencing mechanism in both southern and northern cities. Columns (1) and (2) focus on the effect of income on southern cities. The results show that the estimated coefficient of DE in column (1) is significantly positive, and both DE and REVENUE have significantly positive coefficients in column (2). This indicates that the income effect partially mediates DE's impact on ULCT in southern cities. In contrast, columns (3) and (4) present the test results for northern cities. The regression results in column (3) indicate that DE does not significantly impact REVENUE, suggesting that the income effect does not influence DE to promote ULCT in northern cities. The reason for this is that northern regions, due to their cold climate, have high energy consumption in winter because of heating needs. DE's REVENUE is unlikely to significantly change this large-scale energy consumption pattern in the short term, especially under the traditional high-carbon consumption model.

Table 12. Regression Results of Income Effect of DE.

	(1)	(2)
DE	0.4499 ***	0.4453 ***
	(4.467)	(6.190)
REVENUE		0.1913 ***
		(12.749)
Constant	10.5861 ***	−1.4843 ***
	(83.067)	(−8.116)
N	2547	2547
R^2	0.9841	0.8530
Adj-R^2	0.9819	0.8332
F	150.8431	89.4721
Sobel Test	[Z = 4.216, p = 0.0000]	
Proportion of Mediation Effect	16.20%	

Note: The values in parentheses are *t*-statistics of the parameter estimates; *** indicates significance at the 1% levels.

Table 13. Income Effect of DE in Southern and Northern Cities.

	Southern Cities		Northern Cities	
	(1)	(2)	(3)	(4)
DE	0.3536 ***	0.4564 ***	0.3168	0.4076 ***
	(3.670)	(5.581)	(1.621)	(2.814)
REVENUE		0.1476 ***		0.1944 ***
		(6.714)		(7.188)
Constant	10.5887 ***	−1.2565 ***	9.7957 ***	−1.3670 ***
	(74.767)	(−4.801)	(48.102)	(−4.486)
N	1683	1683	864	864
R^2	0.9906	0.8620	0.9802	0.8403
Adj-R^2	0.9893	0.8428	0.9772	0.8158
F	38.5593	40.9147	77.5360	35.9592

Note: The values in parentheses are *t*-statistics of the parameter estimates; *** indicates significance at the 1% levels.

The conclusions of this study provide important insights for other major polluting countries. Different countries and regions should develop targeted low-carbon transition strategies based on their economic development levels, industrial structures, and environmental policies. By increasing income levels and promoting green consumption and low-carbon lifestyles, urban low-carbon transitions can be effectively advanced, achieving a win-win situation for economic development and environmental protection. The Indian government can draw on these conclusions by formulating DE and low-carbon transition policies that consider regional economic development levels and industrial structures, thereby creating targeted policy measures.

5. Conclusions and Policy Implications

5.1. Conclusions

As the primary hubs of economic activity, cities are significant contributors to carbon emissions. Achieving low-carbon transformation in urban areas is crucial for addressing climate change. The DE, the new engine of global economic development, is facilitating this low-carbon transition with its unique advantages. This study examines the impact of DE on ULCT using data from 283 prefecture-level and higher cities in China, spanning from 2011 to 2019, through theoretical analysis and empirical testing.

The findings reveal that DE significantly promotes ULCT, a conclusion supported by robustness and endogeneity analyses. DE has a more substantial impact on ULCT in southern cities than in northern ones. Notably, DE did not significantly promote ULCT in the Yangtze River Delta and Chengdu-Chongqing city clusters. However, DE significantly advanced ULCT in other city clusters, with the impact magnitude ranked as follows: Central Yangtze > Beijing-Tianjin-Hebei > Guangdong-Hong Kong-Macao.

The study identifies three key mechanisms through which DE promotes ULCT: SCALE, PUBLIC, and REVENUE, with mediation effects of 6.64%, 9.84%, and 16.2%, respectively. It is important to note that the PUBLIC and REVENUE mechanisms are effective only in the southern region, not the northern region. These insights highlight the critical role of DE in driving sustainable urban development and provide a foundation for targeted policy interventions.

The conclusions of this study have significant managerial and academic implications. Firstly, the research indicates that DE has a more pronounced effect on promoting ULCT in southern cities, while the impact is less evident in the Yangtze River Delta and Chengdu-Chongqing urban agglomerations. This suggests that local governments should consider regional differences when formulating policies, prioritizing DE development in southern regions to achieve ULCT. For the Yangtze River Delta and Chengdu-Chongqing areas, alternative methods to promote ULCT should be explored, or the potential benefits of DE in these regions should be further investigated.

Secondly, to our knowledge, there are no existing studies that use rigorous mathematical models to depict the relationship between DE and ULCT. By integrating mathematical models with empirical testing, we address this gap. Moreover, previous literature has rarely focused on the impact mechanisms of DE on ULCT in southern and northern regions, particularly the mechanisms of SCALE, PUBLIC, and REVENUE. Therefore, the conclusions of this study expand on previous research, enriching the body of knowledge on DE and low-carbon transition.

5.2. Policy Implications and Research Limitations

5.2.1. Policy Implications

Given the significant impact of the DE on ULCT, the government should implement several targeted strategies to maximize this effect. Increasing investment in digital infrastructure, such as 5G networks, big data centers, and cloud computing platforms, will enhance the penetration and influence of the DE, thus supporting ULCT more effectively. Tailored approaches are necessary to address regional differences in DE's impact on ULCT. In southern cities, where the DE has a stronger impact, efforts should focus on leveraging DE to promote low-carbon transformation actively. In northern cities, the emphasis should be on integrating DE tools with traditional industries to drive low-carbon development. This includes adopting digital technologies to improve efficiency and reduce emissions in manufacturing and heavy industries. For city clusters like the Yangtze River Delta and Chengdu-Chongqing, where DE has not effectively promoted ULCT, a thorough analysis is needed to identify and address constraints such as industrial structure, energy mix, or policy environment. Potential policy measures might include optimizing industrial structures to favor cleaner industries, promoting clean energy sources, and enhancing low-carbon policies.

Public concern for environmental issues also positively impacts ULCT. The government should strengthen environmental protection campaigns through various media channels to raise public awareness. Encouraging public participation in low-carbon lifestyles by promoting green travel, energy saving, and waste reduction, as well as advocating for sustainable practices such as garbage classification and recycling, will further support ULCT. By implementing these strategies, the government can more effectively harness the DE to promote urban low-carbon transformation, achieving sustainable economic and environmental development.

SCALE, PUBLIC, and REVENUE are crucial mechanisms through which the DE promotes ULCT, with varying proportions of their mediation effects. Notably, the effect of public environmental concern and income is significantly established in the southern region but not in the northern region. The government should formulate targeted policies to utilize these effects better based on these findings. In the southern region, the government can enhance environmental education and publicity, leveraging DE tools and platforms to increase public concern for environmental protection and promote low-carbon lifestyles. Additionally, designing economic policies such as green consumption subsidies or tax incentives will guide and encourage consumers to choose low-carbon and environmentally friendly products and services, thereby effectively utilizing the income effect to promote low-carbon transformation. In contrast, in the northern region, where the PUBLIC and REVENUE are insignificant, the government should focus more on policy guidance and technical support. This includes promoting large-scale and intensive production practices to reduce energy consumption and emissions per unit product, thus achieving low-carbon transformation. Additionally, increasing investment in environmental protection infrastructure can raise societal environmental awareness, creating a more favorable environment for low-carbon transformation. By implementing comprehensive and targeted policy measures, the government can more effectively harness the DE to promote urban low-carbon transformation, achieving sustainable economic and environmental development.

5.2.2. Research Limitations

This study only covers data from 2011 to 2019. As time goes by, new development trends and influencing factors may emerge, so it is necessary to update the data to reflect the latest situation. Although this study identifies important influencing mechanisms such as SCALE, PUBLIC, and REVENUE, there may be other influencing mechanisms that have not been considered, such as policy support. In the future, other factors that may affect ULCT, such as the interaction between the policy environment and DE, can be further explored. Additionally, future research can compare China's ULCT situation with other countries, drawing on international successful experiences and practices to provide useful references for China's ULCT.

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