The Impact of City Network Status on Carbon Emission Efficiency-based on Data from Three Major Urban Agglomerations

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Abstract: Based on the data from 2006 to 2020 of the three major urban agglomerations of Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta, this paper constructs a "structure-relationship-performance" framework to explore the impact of city network status on carbon emission efficiency. The study uses the gravity model, super-efficiency SBM model and Tobit model, combined with the instrumental variable method, to reveal the mechanism by which network status improves carbon emission efficiency through value chain reorganization, digital infrastructure, green finance and market development. The results show that point centrality, betweenness centrality and proximity centrality significantly positively affect carbon emission efficiency, the Pearl River Delta and Yangtze River Delta have significant effects, and Beijing-Tianjin-Hebei inhibits the efficiency of marginal cities due to its core-edge structure. The study proposes a governance path of network optimization and cross-domain coordination, providing a policy basis for the coordination of "dual carbon" goals and urbanization.

Keywords: Urban Network; Carbon Emission Efficiency; Urban Agglomeration; Green Finance; Digital Infrastructure

1. Introduction

The biggest challenge facing human beings in the 21st century is global climate change. In 2023, the global average temperature will increase by 1.1°C from that of pre-industrial levels, and the 1.5°C goal of the Paris Agreement is facing pressure of time. Over 130 nations worldwide have put forward carbon neutrality targets, and China has clarified its "dual carbon" strategy in 2020 [1]. Urban regions contribute more than 70% of worldwide carbon dioxide emissions, and urban agglomeration carbon emission efficiency is significant to double carbon targets. The policymaking has evolved from single city emission mitigation to intercity cooperation [2]. The "14th Five-Year Plan" Energy Conservation and Emission Reduction Plan focuses on urban agglomeration low-carbon development planning, and we are in a pressing need to study the coupling mechanism between urban networks and carbon emission efficiency.

Typical urban studies adopt a hierarchical structure, while informatization and globalization introduced urban network theory, focusing on mobility and connectivity [3]. Urban networks are a multi-center, flat structure created by cross-domain elements flow, and resource allocation and environmental management are optimized by functional complementarity and synergy [4]. It has been found that urban networks influence environmental performance by means of knowledge spillover and technology diffusion, but still there exists a theoretical gap in carbon emission efficiency in the way of network status.

China's Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta urban agglomeration are cases to be studied. The China Yangtze River Delta has low carbon emission efficiency, while Beijing-Tianjin-Hebei has immense pressure to cut emissions owing to its energy structure constraints. The network development of these three urban agglomeration urban complexes differs strongly: the Yangtze River Delta has a multi-center structure, the Pearl River Delta depends on industry chain division of labor, while that of Beijing-Tianjin-Hebei has a core-periphery nature. Current studies have neglected urban network locational character spatial spillover effects on carbon emission efficiency [5].

The subject of this paper specifically addresses urban networks' relation to carbon emission efficiency and urban agglomeration network heterogeneity mechanisms. Theoretically, a structure-relationship-performance system model is built to enrich urban network theory's environmental economic connotation; practically, it offers a foundation for coordinating urban agglomeration optimization and cross-field carbon compensation mechanisms, assisting in coordinating emission reductions and efficiency management models in networks. There are both academic and policy implications from this piece of work.

2. Literature Review

The measurement of regional low-carbon development has a core indicator of carbon emission efficiency, categorized into "single factor" and "full factor" measurement modes. In early years, carbon emission intensity per unit of GDP was primarily used, while later on, the DEA model was employed to include multiple factors like energy, capital, and labor [6]. Drivers include both structural drivers (economic development level, industry structure, energy structure) as well as technical drivers (green technology innovation, technology spillover of foreign investment, environmental regulation). More recent years have dealt with spatial spillover effects, but these are generally restricted to geographic adjacency, while a networked association mechanism remains inadequate [7].

Urban network theory shatters the conventional hierarchical structure and focuses on the non-hierarchical relationship established by factor flow. In China, urban networks are expressed as economic networks (enterprise division of labour), facility networks (high-speed rail, informatization) and government networks (cross-sector policy coordination) [8]. Urban networks influence regional development by reconfiguring resources (spillover of knowledge and technology) and generating functions (cross-regional environment governance), but the mechanism through which they influence carbon emission efficiency has not yet been institutionalized.

Studies on the urban agglomerations of Beijing-Tianjin-Hebei, Yangtze River Delta, as well as Pearl River Delta indicate that the decoupling of carbon emission efficiency and output value in Beijing-Tianjin-Hebei manufacturing industry tends to be relatively stable, inter-provincial differences are considerable in Yangtze River Delta, and the Pearl River Delta has a trend of first accelerating then slowly increasing carbon emissions [9]. The core city networks of both Beijing-Tianjin-Hebei and Yangtze River Delta are of high density, while relationship intensity among cities differs significantly; the Pearl River Delta network tends to be homogeneous.

Progress has been made by existing studies in measuring carbon emission efficiency, urban network theory, and urban agglomeration empirics: breaking through the constraints of one index and establishing a multi-dimensional system of evaluation; interpreting the synergetic mechanism of factor flow and function; accumulating data on urban agglomeration carbon emissions to serve as a basis for policy design [10]. The work unifies economic, geographic, and public management concepts using DEA models, social network analysis, et al., and suggested industrial optimization recommendations are partially put into practice.

However, the research emphasizes the internal mechanism of a single region, has no cross-regional comparison framework, and lacks a systematic synergistic relationship between urban network structure and carbon emission efficiency. The innovation of this work: firstly, it crosses urban network theory and environmental economics to design a "structure-association-performance" framework to disclose the mechanism of network status influencing carbon emission efficiency through digital infrastructure, green finance, and market development; secondly, it synthesizes the gravity model, super-efficiency SBM model, and Tobit model, applies the instrumental variable approach to reveal the dynamic effect of the network; thirdly, based on comparing the three main urban agglomerations, investigates the heterogeneity of network impacts, suggests a "network optimization + cross-domain coordination" governing approach to serve as a foundation of carbon emission governing, green financial system, and facilitate coupling of "dual carbon" and urbanization [11].

3. Theoretical Basis and Hypothesis Research

The network status of a city affects carbon emission efficiency through multiple paths. First, the improvement of network status promotes the reorganization of the value chain, promotes the matching of production segmentation with urban resource endowments, amplifies the effects of economies of scale and technological accumulation, and improves economic performance and carbon emission efficiency. Second, the development of urban networks enriches the types of intermediate products, avoids diminishing returns on capital, enhances the ability to utilize diversified intermediate products, and improves the efficiency of unit energy output. Third, network status optimizes spatial accessibility, reduces resource interaction costs, accelerates the diffusion of low-carbon technologies, optimizes the topological structure of logistics networks, reduces transportation energy consumption, and promotes the low-carbon transformation of industries. Theoretical hypothesis 1: The improvement of the network status of cities promotes the improvement of total factor carbon emission efficiency.

Secondly, cities with high point centrality give priority to the layout of efficient transportation and digital infrastructure through frequent factor flow demand, attract digital industry investment, and promote the construction of data centers and smart energy systems. Digital infrastructure significantly reduces energy consumption and carbon emissions by enabling the low-carbon transformation of industries, promoting the diffusion of green technology innovation, and optimizing resource allocation. Theoretical hypothesis 2: Point centrality promotes carbon emission efficiency by improving the level of digital infrastructure.

Secondly, cities with high intermediary centrality act as resource allocation hubs, gather financial capital and institutional innovation capabilities, and promote the development of the green financial system. Green finance improves regional carbon emission efficiency by optimizing capital allocation, stimulating low-carbon technology innovation, and promoting energy structure transformation. Hub cities drive surrounding green financial innovation through network communication effects and form a low-carbon collaborative network. Theoretical hypothesis 3: Intermediary centrality promotes carbon emission efficiency by improving the green finance index.

Finally, cities with high proximity centrality reduce transaction costs and enhance the role of market mechanisms by virtue of resource accessibility and information communication efficiency. The improvement of market development promotes enterprises to adopt energy-saving technologies, promote the diffusion of market-based emission reduction tools, and achieve carbon emission efficiency optimization by optimizing resource allocation, strengthening price constraints and competitive pressure. Theoretical hypothesis 4: Proximity centrality improves carbon emission efficiency by promoting market development.

4. Research methods

4.1 Gravity Model

This paper uses the gravity model to describe the economic spatial correlation between cities. The gravity model is more suitable for total data and has more advantages in describing the dynamic evolution trend of space. This paper draws on its calculation formula as follows:

$$y_{ij}=K_{ij}\frac{\sqrt{P_iG_i}\sqrt{P_jG_j}}{D_{ij}^2} \tag{1}$$

$$K_{ij}=\frac{C_i}{C_i+C_j} \tag{2}$$

$$D_{ij}=\frac{d_{ij}}{g_i-g_j} \tag{3}$$

In the formula: i and i represent cities; y_{ij} represents the intensity of economic connection between city i and city j; Krepresents the proportion coefficient; P represents the permanent population; G represents the regional GDP; D_{ij} represents the friction distance. According to the Todaro population migration model, the geographical distance is represented by the shortest kilometer distance d_{ij} between city i and city j, and the economic distance is represented by the per capita GDP differenceg_i-g_j.

4.2 Measurement of City Network Status

The city network status can be measured by three indicators: point centrality, betweenness centrality, and proximity centrality

The point centrality indicator can measure the degree of external radiation and the degree of external radiation received by each city. The higher the point centrality, the more attention the city receives, and the more central it is in the network. The point centrality calculation formula is

$$C_D(i)=\frac{l(i)}{n-1} \tag{4}$$

Where: C_D is the point degree centrality, $l(i)$ is the number of regions directly associated with region i; n is the number of members in the network

The betweenness centrality index is the number of times a city appears on the shortest path between two other cities. The higher the betweenness centrality, the stronger the control ability of the city. The formula for calculating betweenness centrality is

$$C_B(i)=\frac{2\sum_{j<k}r_{jk}(i)/r_{jk}}{(n-1)(n-2)} \tag{5}$$

Where: C_B is the betweenness centrality, r_{jk} is the number of shortcuts between region j and region k; $r_{jk}(i)$ is the number of shortcuts between region j and region k that pass through region i. The proximity centrality index measures the influence of a city by analyzing the sum of the shortest distances between a city and all other cities. The greater the proximity centrality, the shorter the shortcut distance from the city to other cities. The calculation formula for proximity centrality is:

$$C_C(i)=\frac{n-1}{\sum_j D_{ij}} \tag{6}$$

Where: $C_C(i)$ is the closeness to the center, D_{ij} is the spherical distance between city i and city j.

4.3 Measurement of Urban Carbon Emission Efficiency

This paper uses a combination of the window model and the super-efficiency SBM model in data envelopment analysis (DEA) to measure the total factor carbon emission efficiency ($UCEE$) of the three major urban agglomerations from 2006 to 2020. Among them, the window model can not only realize the horizontal comparison of economic efficiency between different cities at a specific time point, but also realize the vertical comparison of economic efficiency of the same city at different time points; the super-efficiency SBM model not only takes into account the slack characteristics of input and output variables, but also makes those cities at the efficiency frontier in the traditional DEA model more distinguishable.

Consider an input-output panel data with $N(i=1,2,\cdots,N)$ and a year span of $T(t=1,2,\cdots T)$, where each city uses m types of inputs x to produce s types of outputs y. If a window starts at time point k $(1\le k\le T)$ and has a width of d $(1\le d\le T-k)$, then the input matrix x_{kd} and output matrix y_kd of the city in this window are:

$$x_{kd}=[x_1^k,x_2^k,\cdots,x_N^k,x_1^{k+1},x_2^{k+1},\cdots,x_N^{k+1},\cdots,x_1^{k+d},x_2^{k+d},\cdots,x_N^{k+d}]^T \tag{7}$$

$$y_{kd}=[y_1^k,y_2^k,\cdots,y_N^k,y_1^{k+1},y_2^{k+1},\cdots,y_N^{k+1},\cdots,y_1^{k+d},y_2^{k+d},\cdots,y_N^{k+d}]^T \tag{8}$$

Where: $x_i^t=[x_i^{1t},x_i^{2t}\cdots,x_i^{mt}]$ and $y_i^t=[y_i^{1t},y_i^{2t}\cdots,y_i^{st}]$ represent the m-dimensional input vector and s-dimensional output vector of city i in year t (t=k，k+1，⋯，k+d) respectively. On this basis, the input and output matrices of each window are brought into the non-guided super-efficiency SBM model to obtain the total factor carbon emission efficiency of all cities in the window period. The total factor carbon emission efficiency of all cities in each window is calculated in the same way, and then the average efficiency of each city at the same time point in different windows is calculated, and finally the average efficiency value is used to measure the carbon emission efficiency of the city at each time point. The window width is set to 3 years (d= 3), so the number of windows is 14. According to the principle of data availability, this paper adopts the total factor carbon emission efficiency of major energy consumption, where the expected output indicator is the actual GDP of the city, and the non-expected output indicator is the carbon emission of the city; the input indicators include the total energy consumption, actual fixed capital stock, and labor force of the city. The definition method of input and output indicators is shown in Table 1.

Table 1. Measurement Indicators of Total Factor Carbon Emission Efficiency of Cities

First-level indicators	Second-level indicators	Definition
Input indicators	labor	Number of employees in various cities over the years
	capital	Expressed in terms of capital stock. The capital stock adopts the perpetual storage method, and the formula is: $K_{i,t}=K_{i,t-1}(1-\delta_{i,t})+I_{i,t}$ Where: $K_{i,t}$ represents the capital stock of city i in year t (100 million yuan); $\delta_{i,t}$ represents the capital depreciation rate, which is calculated at 9.6%; $I_{i,t}$ represents the capital flow (100 million yuan)
	energy	The direct energy consumption of cities mainly includes natural gas and liquefied petroleum gas, and the indirect energy consumption mainly includes

		electricity consumption. Due to the different units, the energy consumption is converted into standard coal. Referring to the "General Rules for Calculating Comprehensive Energy Consumption", the conversion coefficients are 1.33 kg tec/m3, 1.7143 kg tec/kg, and 0.1229 kg tec/(kW · h) respectively.
Expected output Unexpected output	City GDP	GDP at constant 2006 prices
Expected output Unexpected output	Urban carbon emissions	Urban carbon emissions include carbon emissions from direct energy sources such as natural gas and liquefied petroleum gas, as well as carbon emissions from indirect energy sources such as electricity and heat.

4.4 Panel Tobit Model

Based on the STIRPAT theoretical framework, this paper explores the multi-dimensional impact of network centrality on urban carbon emission efficiency. The STIRPAT framework can analyze the combined impact of various human activities and has flexible scalability. It has been widely used to explore the driving factors of energy consumption carbon emissions and has produced a large number of results. Considering that the total factor carbon emission efficiency of the city is merged data, the use of ordinary least squares regression will produce biased estimation results. Based on the above analysis, this paper attempts to use the Tobit double fixed effect model, but in view of the multicollinearity between the individual fixed effect and the core explanatory variables, this study uses the time fixed effect Tobit model to estimate the impact of urban network status on carbon emission efficiency. The empirical model is set as follows

$$UCEE_{it}=\alpha_0+\alpha_1 NP_{it}+\sum_l \varphi_1 Ctrl_{it}^l+T_i+\varepsilon_{it} \quad (9)$$

In the formula: i represents the city; t represents the year; $UCEE$ represents the city's total factor carbon emission efficiency; NP represents the city's network centrality; Ctrl represents the control variable; l represents the coding of the control variable; α_0 represents the constant term; α_1 is the core parameter that reflects the impact of the city network structure on the total factor carbon emission efficiency; φ_1 represents the fitting coefficient of the lth control variable; T_i represents the time effect; ε is the error term.

Table 2. Control Variables and Definition Methods

Variable	Symbol	Definition	Influence mechanism
Urbanization rate	Urban	Urban permanent population/total permanent population	Agglomeration economy has a carbon reduction effect, while energy consumption growth increases carbon emissions, and high-energy consumption sectors increase carbon emissions
Industrial structure	*Indust*	Value added of the tertiary industry/value added of the secondary industry	Structural optimization improves efficiency, and high-energy consumption sectors increase carbon emissions
Foreign direct investment	FDI	Logarithm of actual foreign investment	Pollution haven effect
Government investment	Gov	Fixed asset investment/general government expenditure	Improve efficiency by improving infrastructure
Green technology innovation	GIN	Logarithm of total green patent authorizations	Improve energy utilization efficiency and reduce carbon emissions through green technology innovation
Energy consumption structure	ES	Electricity consumption/total energy consumption	Improve carbon emission efficiency by improving energy structure

This paper takes the city's total factor carbon emission efficiency (UCEE) as the explained variable and uses the DEA window model and the super-efficiency SBM model to measure it. The core explanatory variable is the network status (NP), which is characterized by degree centrality, betweenness centrality, and proximity centrality. Based on the extended STIRPAT model, six control variables, including urbanization rate, industrial structure, foreign direct investment, government intervention, green technology innovation, and energy consumption structure, are included to comprehensively consider the impact of economic structure, innovation ability, and economic incentives on carbon emission efficiency, as shown in Table 2.

4.6 Data Source

This paper uses the headquarters-branch data set of A-share listed companies to construct the urban economic connection network. Enterprise connections are quantitative analysis based on panel data at the city level. The urban agglomerations selected are the Yangtze River Delta urban agglomeration, the Pearl River Delta urban agglomeration, and the Beijing-Tianjin-Hebei urban agglomeration. The data comes from the China City Statistical Yearbook, with 2006 as the base period. The data source is the China City Statistical Yearbook, and missing values are filled using interpolation. Carbon emissions are converted according to the IPCC inventory method. The specific formula is as follows:

$$C_i=\sum_{j=1}^{n} \theta_j \times \delta_{ijl} \times \alpha_j \quad (10)$$

In the formula: C represents carbon emissions; i、j、l represent cities, energy types and years respectively; n represents energy type; θ represents the energy conversion coefficient of 10,000 tons of standard coal; δ represents energy consumption; α represents the carbon dioxide emission coefficient of each energy.

5. Empirical Results and Analysis

5.1 Characteristic Facts

From 2006 to 2020, as shown in Figure 1, the network density of the Yangtze River Delta urban agglomeration in China increased from 0.2436 to 0.2507, the network density of the Pearl River Delta urban agglomeration increased from 0.2333 to 0.2595, and the network density of the Beijing-Tianjin-Hebei region decreased from 0.2628 to 0.2373, with a high network level. The networks of the three urban agglomerations all show obvious core-edge characteristics.

At the same time, the carbon emission efficiency of the three major urban agglomerations has been significantly improved overall, as shown in Figure 2. The carbon emission efficiency of the Pearl River Delta urban agglomeration is significantly higher than that of the Yangtze River Delta urban agglomeration and the Beijing-Tianjin-Hebei urban agglomeration, followed by the Yangtze River Delta urban agglomeration, and the Beijing-Tianjin-Hebei urban agglomeration is the last. At the same time, the carbon emission efficiency of the three major urban agglomerations has fluctuated upward.

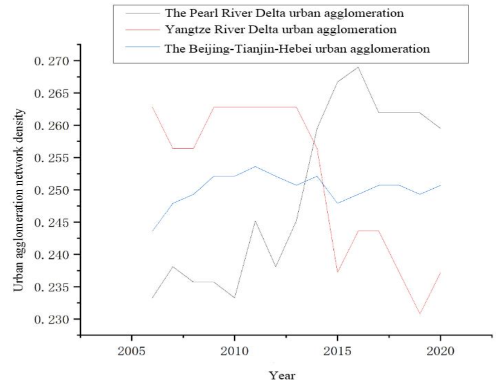

Figure 1. Network Density of the Three Major Urban Agglomerations from 2006 to 2022

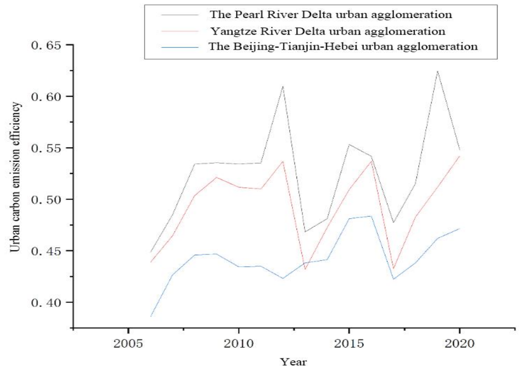

Figure 2. Carbon Emission Efficiency of the Three Major Urban Agglomerations from 2006 to 2022

5.2 Benchmark Regression Results

To avoid collinearity, this paper analyzes point centrality, betweenness centrality, and proximity centrality in turn. The benchmark regression shows that point centrality is positive and significant, and the number of links improves carbon emission efficiency; betweenness centrality is positive and significant, with the highest coefficient, and the bridging function enhances efficiency; proximity centrality is positive and significant at the 1% level, and network distance optimizes efficiency. Among the control variables, Urban and Industry are negatively significant, and urban expansion and industrial reverse upgrading reduce efficiency; Gov and ES are positive and significant, and infrastructure investment and clean energy improve carbon emission efficiency.

Table 3. Benchmark Regression Results of Panel Tobit Model

Variables and Statistics		(1)		(2)		(3)
Degree		0.237***				
		(3.48)				
Betweenness				1.199***		

				(3.88)		
Closeness						0.522***
						(3.84)
Urban		-0.205**		-0.185**		-0.216***
		(-2.48)		(-2.28)		(-2.61)
Indust		0.021		0.026		0.025
		(0.99)		(1.20)		(1.15)
FDI		0.241		0.344		0.269
		(0.69)		(0.99)		(0.77)
Gov		0.002		0.004		0.003
		(0.49)		(0.71)		(0.54)
GIN		-0.018**		-0.023**		-0.020**
		(-2.08)		(-2.49)		(-2.22)
ES		-0.044		-0.035		-0.047
		(-0.97)		(-0.77)		(-1.04)
Individual Effect		yes	yes	yes	yes	yes
Time Effect		yes	yes	yes	yes	yes
Observations		914		914		914

Note: The values in brackets are standard errors; *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

5.3 Robustness Test and Endogeneity Test

5.3.1 Robustness test

The robustness test adopts the measurement method of changing carbon emission efficiency. Although the super-efficiency SBM model can rank and compare decision-making units at the efficiency frontier, this method regards carbon dioxide emissions as an input factor. In fact, carbon dioxide is an undesirable output of the economic system. In the presence of undesirable outputs, technologies with more good (expected) outputs and less bad (unexpected) outputs relative to less resource inputs should be considered effective. To this end, this paper adopts a method combining the window model and the undesired output SBM model to re-measure the urban carbon emission efficiency and conduct regression analysis. The results are shown in the table:

Table 4. Robustness Test Results of the Transformation Carbon Emission Efficiency Measurement Method

Variables and Statistics	(1)	(2)	(3)
Degree	0.220***		
	(3.57)		
Betweenness		1.191***	
		(4.20)	
Closeness			0.480***
			(3.89)
Control variables	yes	yes	yes

Note: The values in brackets are standard errors; *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively; the selection of control variables is consistent with column (2) in Table 3, and all regressions include individual effects, time effects and constant terms; to save space, the regression results of control variables, individual effects, time effects and constant terms are not reported, the same below.

5.3.2 Endogeneity test

To control reverse causal endogeneity, this paper uses the city network status (L.Degree, L.Between, L.Closeness) lagged by one year for regression. Table 6 shows that the coefficient of the lag term is significantly positive, indicating that the positive impact of network status on carbon emission efficiency is still robust after alleviating endogeneity.

In order to alleviate the endogeneity problem (such as reverse causality and omitted variables), this paper adopts the instrumental variable method and selects the natural logarithm of the coastline length as the instrumental variable. It is determined by geographical endowment and has no direct correlation with carbon emission efficiency, satisfying exogeneity; coastal cities rely on ports to attract factor flows and enhance network status, satisfying strong correlation. The regression results show that the length of the coastline has a significant positive impact on point centrality, betweenness centrality, and proximity centrality, and the weak instrumental variable test confirms strong explanatory power.

Table 5. Robustness Test Results of spatial Lag Model

Variables and Statistics	(1)	(3)	(5)
L.Degree	0.201***		
	(2.76)		
L.Betweenness		1.100***	

		(3.36)	
L.Closeness			0.425***
			(2.94)
Control variables	yes	yes	yes

Table 4 estimates show that network status significantly promotes carbon emission efficiency, with point centrality coefficients of -1.110601***, betweenness centrality of -7.949422***, and proximity centrality of -2.407101***, and reduces carbon emission intensity by optimizing connections, resource allocation, and technology diffusion. The results are robust, confirming that the network status driven by geographical endowment improves carbon efficiency and provides a basis for coordinated urban emission reduction.

Table 6. Robustness Test Results of the Two-Step IV-Tobit Model

	Degree	UCEE	Betweenness	UCEE	Closeness	UCEE
Coastline	0.0299978***		0.0041909***		0.0138405***	
	(6.62)		(3.72)		(6.11)	
Degree		-1.110601***				
		(-3.99)				
Betweenness				-7.949422***		
				(-2.99)		
Closeness						-2.407101***
						(-3.78)
Control variables	yes	yes	yes	yes	yes	yes
F	60.89***		65.32***		64.72***	
Endogeneity test		38.89***		38.89***		54.97***

6. Test Analysis

6.1 Mechanism Analysis

The regression results in Table 7 show that the city's network status significantly affects carbon emission efficiency. Point centrality has a positive effect on the level of digital infrastructure, with coefficients of 216.505*** and 396.498***. Highly connected cities such as Shanghai attract digital infrastructure investment through frequent exchanges, optimize 5G and industrial Internet construction, and use digital technology to enable low-carbon transformation and resource allocation in industries, reduce energy consumption, and improve carbon efficiency, verifying theoretical hypothesis 2. Intermediary centrality has a positive impact on the green finance index, with coefficients of 0.195*** and 0.179***. Hub cities such as Beijing gather financial resources, promote innovation in tools such as green credit and bonds, guide funds to low-carbon industries, promote technological upgrades and energy transformation, and improve carbon efficiency, verifying theoretical hypothesis 3. The proximity to the centrality has a positive effect on the market development degree, with coefficients of 3.379*** and 3.233***. Cities with high accessibility, such as Guangzhou, optimize market rules. The carbon trading market forces enterprises to reduce emissions through price mechanisms. Competitive pressure promotes technological research and development, improves carbon efficiency, and verifies theoretical hypothesis 4.

Table 7. Mechanism Analysis Results

Variables and statistics	(1)		(2)		(3)	
Degree	216.505***	396.498***				
	(4.62)	(7.42)				
Betweenness			0.195***	0.179***		
			(2.96)	(2.72)		
Closeness					3.379***	3.233***
					(5.58)	(5.26)
Control variables	yes	no	yes	no	yes	no

Note: (1) DIP digital infrastructure level (2) GFI green finance index (3) Market market development level

6.2 Heterogeneity Analysis

The three major urban agglomerations are regressed separately

This paper uses regression tests on the Pearl River Delta, Yangtze River Delta, and Beijing-Tianjin-Hebei urban agglomerations to reveal the regional heterogeneity of network status on carbon emission efficiency, as shown in Table 8. The Pearl River Delta's point centrality (0.475, t=3.77), intermediary centrality (3.215, t=5.57), and proximity centrality (0.948, t=3.79) have a significant positive impact on carbon efficiency, and industrial chain division of labor and efficient accessibility promote low-carbon synergy. The Yangtze River Delta's point centrality (0.235, t=2.17) and proximity centrality (0.593, t=2.71) are positively significant, and the effect of intermediary centrality (1.497, t=2.61) is weak. The multi-center structure and high-speed rail network optimize the emission reduction synergy, but administrative barriers restrict synergy. The point centrality (-0.313, t=-2.86), intermediary centrality (-0.448, t=-1.10), and proximity centrality (-0.506, t=-2.37) of Beijing-Tianjin-Hebei showed negative effects, and the core-periphery structure led to resource agglomeration and inhibited the low-carbon transformation of peripheral cities.

Table 8. Test Results of Regional Heterogeneity

Variables and statistics	Pearl River Delta urban agglomeration			Yangtze River Delta urban agglomeration			Beijing-Tianjin-Hebei urban agglomeration		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Degree	0.475***			0.235**			-0.313***		
	(3.77)			(2.17)			(-2.86)		
Betweenness		3.215***			1.497***			-0.448	
		(5.57)			(2.61)			(-1.10)	
Closeness			0.948***			0.593***			-0.506**
			(3.79)			(2.71)			(-2.37)

7. Conclusion

Based on the panel data of Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta from 2006 to 2020, this study examines the impact of urban network status on carbon emission efficiency through the "structure-relationship-performance" framework. The results show that network status promotes carbon efficiency through value chain reorganization, intermediate product diversification, and spatial accessibility optimization. The point centrality (0.237), intermediary centrality (1.199), and proximity centrality (0.522) have significant effects, and the instrumental variable method verifies that the conclusion is robust. Point centrality strengthens digital infrastructure, intermediary centrality improves green finance, and proximity centrality promotes market development. The Pearl River Delta relies on the division of labor in the industrial chain, the Yangtze River Delta achieves emission reduction through a multi-center structure, and the core-periphery structure of Beijing-Tianjin-Hebei inhibits the efficiency of peripheral cities. This study crosses network theory and environmental economics, proposes a path of network optimization and institutional collaborative governance, and helps the coupling of "dual carbon" and urbanization.

This study reveals that the network status of cities promotes carbon emission efficiency through digital infrastructure, green finance, and market development, and emphasizes the synergistic effect of "structure-relationship" attributes on emission reduction. The intermediary centrality has the greatest impact (1.199), and hub cities optimize resource allocation through green financial innovation. The Pearl River Delta relies on the division of labor in the industrial chain to achieve positive effects, the emission reduction potential of the multi-center structure of the Yangtze River Delta has not been fully released, and the core-periphery structure of Beijing-Tianjin-Hebei inhibits the efficiency of peripheral cities due to administrative barriers. The study makes up for the limitations of traditional environmental economics and suggests that policies need to take into account both network optimization and institutional coordination.

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