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Has Information Infrastructure Reduced Carbon Emissions?—Evidence from Panel Data Analysis of Chinese Cities

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Abstract: Human activities have increased greenhouse gas emissions since the Industrial Revolution, and "emission peaking" and "carbon neutrality" have become serious concerns at this point. The role of information infrastructure in reducing carbon emissions is a critical issue that has received little attention and needs to be addressed. Using panel data from 289 cities in China between 2011 and 2017, this research empirically explores the impact of information infrastructure on urban carbon emission intensity and the mechanism behind this effect. We discover that the construction of information infrastructure significantly reduces urban carbon emissions, and this finding holds true after a series of robustness tests. The mechanism is optimization of industrial structure, agglomeration of producer service industries, and innovation of green technologies. According to the heterogeneity test, the carbon emission reduction is greater in mega cities with higher technological levels and larger urban scales, as well as large cities with better traditional infrastructure. The present work's findings give empirical support for promoting green and low-carbon development and mitigating global warming.

Keywords: construction of information infrastructure; new infrastructure; carbon emission

1. Introduction

Global demand for fossil fuels as a result of economic expansion increases greenhouse gas emissions, specifically carbon dioxide, and the resulting global warming and El Nino phenomena have begun to imperil the development of human civilisation. China has experienced a rapid economic growth since the Reform and Opening Up. This has placed significant pressure on the country to reduce its CO_2 emissions. China's CO_2 emissions accounted for 27% of global emissions in 2019, surpassing the total emissions of OECD countries and making China as the world's largest carbon emitter. China's industrial sector accounts for more than 70% of total emissions (Data are obtained from http://www.tanpaifang.com (15 February 2022)). Chinese government, in line with the Paris Agreement, has proposed a goal of reaching emission peak by 2030 and reducing carbon emissions per unit of GDP by 60–65% by 2030. It is critical to find a low-carbon development path that balances economic growth and carbon reduction.

Under China's "dual circulation" development pattern,"new infrastructure" has emerged as a new engine for economic. The national 14th Five-Year Plan defines the measures for information infrastructure construction (IIC), leading the path of new technologies such as artificial intelligence, block chain, and big data. The Ministry of Industry and Information Technology (MIIT) released the "Communications Industry Statistical Bulletin 2021", which indicates that China's information infrastructure continues to evolve and upgrade, with the total number of mobile communication base stations nationwide reaching 9.96 million by 2021, including 5.9 million 4G base stations and 1.425 million 5G base stations; 5G investment totaled 184.9 billion yuan, accounting for 45.6% of total investment. Total broadband Internet access ports now exceed 931 million. The next generation of information infrastructure, as the bearer of information in the digital economy, is crucial for redesigning the modern economic system. During the COVID-19 epidemic, information infrastructure, in particular, was important in revitalizing enterprises. A crucial issue is whether information infrastructure can help cities reduce carbon emission intensity (CEI). If so, does this effect differ by city? Additionally, what are the strategies for carbon reduction? Due to a paucity of pertinent research, our present work has practical importance.

There are three major types of studies relevant to carbon emission reduction being hampered by information infrastructure: the first type concerns carbon emission. Numerous studies have been conducted to measure the carbon emissions produced by various sectors and regions [1–3] and also the factors that affect carbon emissions. Economic growth, financial development, technological advancement, and reorganization of the energy sector all contribute significantly to carbon emissions [4–7]. Government regulations and policies have suppressed carbon emissions [8–10]. There is no consensus on whether urbanization accelerates or retards carbon emissions, as different approaches of urbanization may affect energy demand [11–13]. The second type of literature focuses on the environmental consequences of transportation infrastructure. High-speed railway reduces fossil fuel consumption and carbon emissions, but this effect is offset by the scale effect of passenger [14–16]. Additionally, high-speed railway indirectly reduces pollution emissions by promoting knowledge spillover and factor mobility in a way that strengthens enterprises' energy-saving and emission-reducing technologies [17]. The third type of literature is concerned with the macroeconomic and microeconomic consequences of information infrastructure. While the development of information infrastructure facilitated by information communication technology (ICT) has benefited employment structure, export, and economic growth [18–21], but excessive informatization also results in labor mismatch and resource waste, lowering the labor share of national income [22].

This present work uses panel data from 289 cities in China from 2011 to 2017 and examines the impact of IIC on CEI, in terms of direct impact, heterogeneity, and mechanism. The present work's contributions are reflected in three areas. First, this present work, instead of focusing on the economic effects of IIC on total factor productivity (TFP) and urban innovation levels, focuses on effect of IIC on CEI. Second, our research is enriched based on regional technology, city scale, and traditional infrastructure construction. Thirdly, this present work provides empirical evidence for the continued development of the digital economy and provides a theoretic foundation to achieve the "dual carbon" goal – "emission peak and carbon neutrality".

The remainder of the present work is organized as follows: Section 2 reviews relevant literature on similar topics; Section 3 presents the empirical design and data description, describing the econometric model's and data selection; Section 4 presents the empirical results and analysis, focusing on the model's basic regression results, robustness, and heterogeneity; and Section 5 examines the mechanism by which information infrastructure contributes to the reduction of urban carbon emission intensity; Section 6 concludes the paper.

2. Literature Review

2.1. Impact of Information Infrastructure on Carbon Emissions

The impact of IIC on CEI is mostly manifested as follows: First, the information technology industry, as represented by 5G, artificial intelligence, and big data, possesses its own environmentally friendly properties and contributes to a smaller negative externalities. The information technology business, dominated by Internet information service enterprises, places a higher premium on environmental benefits than traditional manufacturing industries. Meanwhile, the growth of information infrastructure facilitates the "dematerialization" and "virtualization" of economic operations, reducing carbon emissions associated with conventional energy use [23]. Second, IIC reduces CEI by penetrating digital technologies and disseminating knowledge and information to conventional sectors, which not only increases added value but also reduces energy consumption and carbon emissions. Additionally, the IIC frequently comes with knowledge and information spillover, which in turn promotes penetration. This network externality increases enterprise informational investment motivation and disincentivizes high-pollution operations [24,25]. Thirdly, the IIC nurtures a carbon emissions trading market, thereby resulting in carbon emissions reductions. Since 2011, when the National Development and Reform Commission issued the Notice on the Pilot Project of Carbon Emission Trading, several pilot cities have begun carbon emission trading [26], and information technology overcomes technical challenges associated with emission detection, reporting, and verification in the carbon trading market. Carbon trading allows energy-efficient enterprises to sell excess emission rights to other businesses, rewarding them to boost their energy efficiency and emission reduction efforts.

2.2. Information Infrastructure Reduces Carbon Emissions by Optimizing Industry Structure

Optimizing and upgrading industrial structure is a critical component of low-carbon economic development [27], because it entails resource optimization and reconfiguration. The information infrastructure provided by the Internet, artificial intelligence, and big data has improved factor allocation and facilitated urban resource reconfiguration [28].

From a macro perspective, information infrastructure enabled by information technology transforms data into a new factor of production, accelerating the growth of the Internet, artificial intelligence, big data, and other emerging industries, while also promoting factor reallocation, and industrial structure optimization [29].

From a meso-industry perspective, information infrastructure integrates information technology into the production methods and business processes of traditional manufacturing industries [30], promoting the transformation of manufacturing industries into high-value-added fields and the upgrading of traditional service industries. Additionally, information infrastructure eliminates barriers to information exchange between industries through data resources and digital technology, enabling specialized division of labor within industries and mutual coupling between industries. It also promotes the evolution of industries away from natural resources and labor-intensive toward knowledge- and technology-intensive industries, and facilitates the flow of resources from resource-intensive to resource-intensive industries.

From the perspective of micro enterprises, information infrastructure fosters the adoption of information technologies, such as the Internet of Things (IOTs), big data, and cloud computing, which can not only improve enterprise information sharing, but also assist entrepreneurs' decision-making, and thus enable the rational and effective allocation of resources.

2.3. Information Infrastructure Reduces Carbon Emissions by Producer Services Agglomeration

According to new geo-economic theory, upstream and downstream enterprises tend to convene under the influence of scale economies due to transportation costs [31], and pollution-intensive enterprises in cities are forced to relocate due to cost pressure, which also promotes the agglomeration of producer services [32]. Additionally, agglomeration increases competition, and service specialization and labor division are imminent, resulting in a high cost for manufacturing companies to pursue individualized breakthroughs such as design and R&D. As a result, manufacturing firms outsource them to service firms with more specialized producer [33], resulting in industrial clusters with producer service industries clustered around manufacturing industries [34]. This agglomeration of intermediate services and products effectively deploys economies of scale by integrating more low-carbon production technologies and services into the industrial value chain, approaching high-value-added and low-pollution modes of production [33,35].

ICT-based information infrastructure helps firms overcome spatial distances, connects upstream and downstream in the industrial chain, and propels the evolution of production operation modes toward greater efficiency and sustainability. The production service industry bridges the gap between industries [36], and ICT facilitates information dissemination between clusters of production service industries and manufacturing firms, thereby reducing information asymmetry between them [37]. When intermediary services can be transmitted via ICT and the manufacturing industry outsources pollution control and emission reduction, manufacturing companies can concentrate on core business development and achieve production linkage. Since intermediate services can be transmitted via ICT and the manufacturing industry outsources pollution , manufacturers can concentrate on core business.

Information infrastructure promotes green and low-carbon transformation by speeding up the market development and technology diffusion of producer service sectors within the agglomeration. Specifically, as a result of big data, data, technology, talent, and other elements are gradually transported and clustered into high-end producer services, resulting in the formation of a knowledge-intensive transmission network. As a result, low-end production with high pollution and energy consumption will be continuously eliminated. The technology spillover effect generated by the agglomeration of high-end producer service industries promotes the agglomeration production and continuously improves the information exchange, as well as the cost of information transmission and transaction, etc., thereby achieving green development of producer service industries.

2.4. Information Infrastructure Reduces Carbon Emissions by Enhancing Green Technology Innovation Capabilities

In terms of technical progress, the remainder of the economic growth rate other than capital and labor factors of production is referred to as total factor productivity, which assumes that each factor's productivity changes in the same proportion and is also referred to as neutral technical progress, according to the Solow surplus as measured by the Solow C-D production function [38]. Later, some researchers claim that businesses would try to raise total factor productivity to maximize profit, and that as a result, the productivity of each factor will not always change in the same proportion in this process, resulting in technological progress bias [39]. Studies have demonstrated that biased technical advancement contributes to carbon emission reduction [40], that is, the development and deployment of information infrastructure represented by information and communication technology provides a technological approach for carbon emission reduction.

Through economies of scale and technical spillover, information infrastructure, as a critical component of the digital economy, contributes to the growth of green technology. On the one hand, according to Metcalfe's law and the law of diminishing marginal cost of network, the marginal cost of hardware inputs such as information infrastructure tends to decrease as user size increases, resulting in significant economies of scale. The information infrastructure, centered on the Internet and information technology, continuously distributes the information technology spillover to the traditional industrial sector, lowering R&D costs, promoting industry development toward intelligence and greening, and increasing industry added value. On the other hand, the advantages of intelligent network platforms in super large-scale information transmission and sharing of technical research results accelerate the speed of frontier technology spillover [41], generate incremental effects of technical rewards, and accelerate the re-innovation of knowledge and technology. Additionally, information infrastructure effectively removes the obsticles in information exchange, facilitates the transfer and flow of knowledge and technology between regions [42], and contributes to the reduction of uncertain innovation risks associated with enterprise technology exchange and cooperation as a result of information asymmetry.

2.5. Literature Gap

There are two main differences that distinguishes our research from other studies on carbon emissions and sustainability. First, a great number of research have examined the effect of transportation infrastructure (high-speed rail) on carbon emissions [14,15], and the results on carbon emission reduction are inconsistent. While this article investigates the effect of information infrastructure on carbon emissions. Second, some studies have argued that information infrastructure plays a critical role in a low-carbon economy, but they focus on developed countries [23,24] and ignore the heterogeneity, mechanism of action, and relationship between information infrastructure and carbon emissions. China's rapid economic development, as the world's largest developing country, has resulted in regional development imbalances; thus, this article examines the impact of information infrastructure on urban carbon emission intensity by developing a fixed-effects model using 289 Chinese cities as a sample from 2011 to 2017. These findings not only contribute to the current literature, but also merit special attention from policy makers.

3. Materials and Methods

3.1. Identification Strategies

To investigate the effect of information infrastructure on CO_2 emissions, we set the basic regression model as follows.

$$CEI_{i,t} = \alpha + \beta IIC_{i,t} + \lambda X_{i,t} + u_i + \mu_t + \varepsilon_{i,t}, \quad (1)$$

where $CEI_{i,t}$ denotes the carbon emission intensity of city i in year t; $IIC_{i,t}$ measures the information infrastructure construction of city i in year t; $X_{i,t}$ is a set of control variables; α denotes the intercept term; λ denotes the coefficient of the control variables. u_i and μ_t denote the area fixed effects and time fixed effects; $\epsilon_{i,t}$ is the error term. The coefficient β is the essential statistic that captures the net effect of information infrastructure on carbon emissions. A significant negative β indicates a reduction in carbon emission intensity as a result of improved information infrastructure, which effectively reduces carbon dioxide produced per unit of GDP in the context of the digital economy. Otherwise, the impact of information infrastructure is negligible if β is not significant or positive.

3.2. Variables

3.2.1. Dependent Variable (Carbon Emission Intensity, CEI)

This article discusses the industrial carbon emissions of cities, inspired by a relevant study [43]. Three sources of industrial energy are employed in cities: natural gas, liquefied petroleum gas (LPG), and electricity. China has an abundant supply of coal, which powers the majority of the country's electricity generation. CO_2 emissions come from a variety of sources, both direct and indirect. Direct emissions are caused by the consumption of natural gas and liquefied petroleum gas (LPG), whereas indirect emissions are caused by the consumption of electricity in urban industries. Additionally, CEI is the ratio of regional CO_2 emissions to GDP, which can be calculated as

$$CE = C_1 + C_2 + C_3 \kappa E_1 + \gamma E_2 + \phi(\eta E_3) \quad (2)$$

$$CEI = CE/GDP \quad (3)$$

where CE denotes the total CO_2 emissions; CEI denotes the carbon emissions intensity of the area; C_1, C_2 denote the CO_2 emissions from natural gas and LPG, and C_3 is the CO_2 emissions from the whole society's electricity consumption; E_1, E_2, E_3 denote the consumptions of natural gas, LPG, and industrial electricity; κ, γ denote the CO_2 emission factors of natural gas and LPG, ϕ denotes the greenhouse gas emission factor of coal power fuel chain, and η is the proportion of coal power generation to total generation. CO_2 emission factors come from IPCC National Greenhouse Gas Emission Guidelines and Japan Energy Economics Institute, where the carbon emission coefficients of natural gas, oil and coal (104t carbon / 104t standard coal) are 0.449, 0.568 and 0.756 respectively.

3.2.2. Core Independent Variable (Information Infrastructure Construction, IIC)

Scholars have already measured indicators of information infrastructure based on telecommunication network, information service, post, Internet user count, and telecommunication service pricing [25,44], as well as MIIT's pilot cities for the "broadband China" strategy. The methods outlined above do not take into account the state of the information infrastructure. However, the methodologies discussed above cannot capture the regional information infrastructure accurately. The purpose of this present work is to extend the connotation of information infrastructure indicators by using principal component analysis (PCA) to weight the indicators while taking regional and temporal aspects into account.

Four indicators are used to determine the quality of each city's information infrastructure [45]: internet penetration (the number of Internet users per 100 people), employees employed in computer services and software (the percentage of urban employees employed in computer services and software), the total number of telecommunications services per capita, and mobile phone penetration (the number of mobile phone users per 100 people). The original data of the above indicators are obtained from "China City Statistical Yearbook" (Supplementary Materials). The index system was created using principal component analysis (PCA). The aforementioned indicators were standardized and downscaled using PCA to produce the complete index of information infrastructure, denoted by IIC.

3.2.3. Control Variables

The control variables are as follows: fixed asset investment ($invest$), expressed as the ratio of the city's total fixed asset investment to regional GDP; foreign real investment (FDI), expressed as the ratio of actual foreign capital used to regional GDP, with actual foreign capital used converted at the current year's mid-price of the RMB/USD exchange rate; financial development level (fin), expressed as the proportion of the city's year-end RMB loans balance of financial institutions to the regional GDP, urbanization rate ($urban$), expressed as the population share of the municipal district; government intervention ($expenditure$), expressed as the ratio of the city's general public budget expenditure to the regional GDP.

3.2.4. Data Source

This present work examines the effect of information infrastructure construction on carbon emissions using a panel of 289 prefecture-level cities in 29 provinces in China from 2011 to 2017. The data come from publicly accessible sources such as the China City Statistical Yearbook, the EPS data platform, and the China Research Data Service Platform. We cross-reference the data above with the city's identifying code. Additionally, some variables were standardized to eliminate the magnitude effect, and data winsorization was used to avoid the effect of outliers or extreme values on the research results. Table 1 contains the descriptive statistical analysis of the variables used in this present work.

Table 1. Variables and descriptive statistics.

Variables	Variable Symbols	50th Percentile	Min.	Max.	Standard Deviation
Carbon emissions intensity	CEI	−0.3000	−1.4500	6.2000	1.0000
Information infrastructure edvelopment index	IIC	−0.2500	−1.5400	14.6200	1.0000
Foreign direct investment	FDI	0.0100	0.0002	0.1900	0.0200
Financial development	fin	1.2400	0.3700	8.8700	0.6600
Fixed Asset Investment	$invest$	0.7600	0.0900	2.2000	0.2900
Percentage of population in urban areas	$urban$	0.3000	0.0500	1.0000	0.2400
Government intervention	$expenditure$	0.0700	0.0100	1.2700	0.0500
Technology	tec	11.8200	8.1300	16.0800	1.0200
City size	$citysize$	5.9300	3.0000	8.1300	0.7000
Traditional infrastructures	$infra$	6.9300	3.9500	9.8500	0.9700

4. Results

4.1. Basic Regression Results

To control regional macroeconomic disparities and regions that do not change over time, this research employs a double fixed-effects model to experimentally examine the association between "information infrastructure—carbon intensity." Table 2 summarizes the results of the basic regression, column (1) is the result of the regression analysis with only regional information infrastructure as the independent variable without control variables, and column (2) is the result of the regression with control variables included. The estimated coefficients of IIC on CEI are significantly negative at the 1% level, indicating that the IIC bears a significant impact on reducing regional carbon emission. The results show that the more developed the information infrastructure, the more advanced the informatization and digitalization technology, which enables industry to transition to low-carbon manufacturing while increasing enterprise resource utilization efficiency.

Additionally, Table 2 restricts the CEI at the 50% quantile and assesses the utility of various levels of information infrastructure in terms of CEI reduction. The results of column (3) and (4) in Table 2 indicate that the estimated coefficient for information infrastructure is −0.2557 in the group with high carbon emissions per unit of GDP, which is significant at 1% level; and −0.0428 in the group with low carbon emissions, which is also significant at 1% level but significantly less than that of the high carbon emissions group. This confirms that IIC allows for a greater elasticity in high-carbon areas but not in low-carbon places.

Table 2. Basic model: effect of IIC on CEI.

Variables	(1) CEI	(2) CEI	(3) Low CEI	(4) High CEI
IIC	−0.1629 ***	−0.1055 ***	−0.0428 ***	−0.2557 ***
	(0.0161)	(0.0201)	(0.0075)	(0.0588)
FDI		−5.5150 ***	0.6378	−7.0109 ***
		(1.0064)	(0.4416)	(1.8102)
fin		0.1255 ***	−0.0086	0.2462 ***
		(0.0366)	(0.0172)	(0.0631)
$invest$		0.0436	0.2373 ***	0.1669
		(0.0738)	(0.0362)	(0.1159)
$urban$		−0.6220 ***	−0.1530 ***	−0.5253 ***
		(0.0812)	(0.0421)	(0.1326)
$expenditure$		1.7957 ***	−0.8547 ***	1.0448 **
		(0.3215)	(0.2717)	(0.4107)
Observations	1604	1604	793	809
Adjusted R-squared	0.5926	0.6184	0.4536	0.4890
year FE	YES	YES	YES	YES
provincename FE	YES	YES	YES	YES

t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by * , **, *** for 10%, 5%, and 1%.

4.2. Heterogeneity Analysis

On a full-sample basis, the preceding study shown that IIC helps significantly to carbon intensity abatement. To prevent any omission bias and to provide a more nuanced understanding of the boundary conditions for this mitigation, this present work compares mitigation by regional technology level, city size, status of traditional infrastructure construction.

4.2.1. Heterogeneity in Technology

For cities, disparities in technical innovation can result in disparities in the industrialization of digital applications, such as heterogeneity in financial and industrial development, which can result in disparate effects of IIC on CEI. We divide the sample into low- and high-technology groups according to the city's technology expenditure to verify the heterogeneous effect of IIC on carbon emission reduction.

The estimated coefficient IIC fails the significance test in the low technology level group of model (1) and (2) in Table 3, indicating that there is no significant mitigation of

CEI due to IIC in low-tech regions. This is primarily due to a lack of regional technology supply, which makes it difficult to obtain high-quality technology support for information infrastructure and stalls the effect of information infrastructure in low-carbon industries. The estimated coefficient of IIC in the group of high technology level cities in model (3) and (4) of Table 3 are both significant at the 1% level. The findings imply that IIC considerably reduces urban CEI in high-technology cities. One plausible answer is that more technology results in increased innovation, and IIC results in the creation of industries that support technical innovation and green, low-carbon industries.

Table 3. Heterogeneity analysis: technology.

Variables	Regional Technology Level			
	Low-Tech		High-Tech	
	(1)	(2)	(3)	(4)
IIC	−0.0587	−0.0769	−0.1203 ***	−0.0584 ***
	(0.0659)	(0.0641)	(0.0253)	(0.0162)
Controls	NO	YES	NO	YES
Observations	800	800	803	803
Adjusted R-squared	0.6195	0.6758	0.5959	0.6268
F statistics	0.7950	6.2280	22.7000	7.5020
year FE	YES	YES	YES	YES
province FE	YES	YES	YES	YES

Columns (1) and (2) indicate the regression results for low level of technology; columns (3) and (4) indicate the regression results for high level technology. When Controls is NO, it indicates that the control variables are not controlled; when Controls is YES, it indicates that the control variables are controlled. t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% respectively.

4.2.2. Heterogeneity in City Size

Cities of various sizes differ significantly in terms of resource endowment and economic development, which may affect the effectiveness of urban information infrastructure in reducing CEI. In general, larger cities serve as the political and economic hubs or test sites for major development strategies. In comparison to smaller cities, larger cities not only benefit from policy and financial support due to their administrative rank and economic scale, but also from their gathering of talents, information, capital, and other factor resources, resulting in the variability of information infrastructure across cities of various sizes. This present work, based on the State Council's Notice on Adjusting the Criteria for City Classification (Guo Fa [2014] No. 51), defines cities as follows: those with a permanent urban population of less than 500,000 are classified as small cities; those with a permanent urban population of more than 500,000 but less than 1 million are classified as medium cities; those with a permanent urban population of more than 1 million but less than 5 million are classified as large cities; those with a permanent urban population of more than 5 million but less than 10 million are mega-cities; and those with more than 10 million are super cities. We divide the sample into three subgroups based on the classification criteria above: mega and super cities, large cities, and medium and small cities.

In the subgroups of mega and super cities and large cities in columns (1)–(4) of Table 4, the estimated coefficients of IIC are all significantly negative at 5% levels, indicating that the reduction in CEI due to IIC is greater in larger cities. the likely explanation is that larger cities, by virtue of their information agglomeration and economic scale, provide the framework for IIC, thereby improving the resource allocation and supporting technology-driven, green, and low-carbon economic development. In columns (5) and (6) of Table 4, the estimated coefficients of IIC are not significant in the subgroups of medium-sized and small cities. Small and medium-sized cities are typically ordinary cities with lower administrative levels and economic management authority, making it more difficult to promote innovative businesses through preferential policies such as land and fiscal taxes. They also lack the endogenous power for green and low-carbon development, as well as the technological and financial resources that IIC requires, resulting in IIC's failure to reduce CEI.

Table 4. Heterogeneity analysis: city size.

Variables	City Size					
	Mega and Super Cities		Large Cities		Medium and Small Cities	
	(1)	(2)	(3)	(4)	(5)	(6)
IIC	−0.1420 ***	−0.0972 ***	−0.1242 ***	−0.0582 **	−0.0934	−0.0918
	(0.0326)	(0.0331)	(0.0309)	(0.0258)	(0.0690)	(0.0738)
Controls	NO	YES	NO	YES	NO	YES
Observations	75	75	727	727	800	800
Adjusted R-squared	0.7492	0.8044	0.6209	0.6507	0.5999	0.6590
F statistics	18.99	7.381	16.18	6.028	1.832	5.666
year FE	YES	YES	YES	YES	YES	YES
province FE	YES	YES	YES	YES	YES	YES

Columns (1) and (2) indicate the regression results for mega and super cities; columns (3) and (4) indicate the regression results for large cities; columns (5) and (6) indicate the regression results for medium and small cities. When Controls is NO, it indicates that the control variables are not controlled; when Controls is YES, it indicates that the control variables are controlled. t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

4.2.3. Heterogeneity in Traditional Infrastructure Development

The information infrastructure with the Internet and big data as important symbols depends to a certain extent on the development of traditional infrastructure. Traditional infrastructure serves as the catalyst and enabler for the development of information infrastructure, while information infrastructure enables the expansion and extension of traditional infrastructure. The normal operation of social services, urban management, and manufacturing in traditional infrastructure imposes stringent requirements on data collection and analysis mining, whereas information infrastructure enables traditional infrastructure to leverage artificial intelligence algorithm frameworks and development platforms to increase facility and service efficiency, reduce unit energy consumption, and achieve green and low-carbon development. To investigate the heterogeneous effect of traditional infrastructure on the carbon emission reduction effect of information infrastructure, this present work uses the city's actual paved road area as a proxy for traditional infrastructure and divides the sample into a poor and a better traditional infrastructure group.

The regression coefficient of IIC in columns (1) and (2) of Table 5 is not statistically significant. The results indicate that the carbon emission reduction effect of information infrastructure is correlated with the level of traditional infrastructure. In cities with insufficient infrastructure, urban public service facilities such as airports, high-speed railroads, and highways would also be insufficient, and the terrain is frequently undulating, making information infrastructure more difficult to construct. Thus labor and technology flow both contribute to development. The regression coefficient of IIC in column (3) and (4) of Table 5 is significant at the 1% level, indicating that in cities with better traditional infrastructure, information infrastructure improves the allocation efficiency as well as operation and service efficacy, and accelarate the flow of production factors. This is a bonus for emission reduction.

Table 5. Heterogeneity analysis: traditional infrastructure.

Variables	Traditional Infrastructure			
	Poor Traditional Infrastructure		Better Traditional Infrastructure	
	(1)	(2)	(3)	(4)
IIC	0.0465	0.0357	−0.1543 ***	−0.0773 ***
	(0.0724)	(0.0688)	(0.0338)	(0.0290)
Controls	NO	YES	NO	YES
Observations	780	780	824	824
Adjusted R-squared	0.6169	0.6666	0.6449	0.6850
F statistics	0.4130	4.4420	20.8800	9.7050
year FE	YES	YES	YES	YES
province FE	YES	YES	YES	YES

Columns (1) and (2) indicate the regression results for cities with poor traditional infrastructure; columns (3) and (4) indicate the regression results for cities with better traditional infrastructure. When Controls is NO, it indicates that the control variables are not controlled; when Controls is YES, it indicates that the control variables are controlled. t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

4.3. Robustness Tests

To further enhance the robustness of the basic model, this article conducts the following tests: reconstruction of dependent variable, adding a "$latitude * year$" interaction term, exclusion of outliers in the observations, and use of instrumental variables.

4.3.1. Reconstructing the Dependent Variables

Given that industrial activities generate both carbon dioxide and sulfur dioxide, the independent variable is reconstructed using sulfur dioxide emission intensity, i.e., "the proportion of industrial sulfur dioxide emissions in regional GDP," to assess its robustness. As shown in Table 6, the robustness test indicates that the estimated coefficient of information infrastructure is significant at the 5% level, implying a consistence with the aforementioned basic findings.

4.3.2. Adding a "$Latitude * Year$" Interaction Term

Regional differences and time trends may influence urban carbon emission intensity. Although the region and time fixed effects have been controlled in the basic model, it is still worthwhile to investigate how their interplay influences the carbon emission reduction effect of information infrastructure. After adding the interaction term of city latitude and year ($latitude * year$) to the basic regression, the results in column (2) of Table 6 show that the estimated coefficient of IIC is −0.1049, which is still significantly negative at the 1% level, indicating that the carbon emission reduction effect of information infrastructure is robust, while the coefficient of the interaction term $latitude * year$ is 1.7714, which is significant at the 1% level, showing the higher the latitude, the greater the carbon emission intensity, echoing the pattern of "strong in the south, weak in the north" of China's unbalanced economic development.

4.3.3. Elimination of Outliers

We winsorize all variables at the 5th and the 95th percentile to avoid the effect of outliers and misreported data. According to the results in Table 6 (3), IIC has a coefficient of −0.1970 after the winsorization process, which is significant at the 1% level, showing that information infrastructure continues to have a substantial impact, which is consistent with the findings in previous section.

Table 6. Robustness test.

	Reconstructing the Dependent Variable	Interaction Term	Drop Outliners	Instrument Variables	
	Industrial Pollutant Emissions	*CEI*	*CEI*	1st Stage	2nd Stage
	(1)	(2)	(3)	(4)	(5)
IIC	−0.0578 ** (0.0243)	−0.1049 *** (0.0199)	−0.1970 *** (0.0278)		−0.2404 *** (0.0581)
latitude ∗ *year*		1.7714 *** (0.3550)			
L.IIC				0.3638 *** (0.0263)	
Durbin–Wu–Hausman					32.61
Anderson canon. corr. LM statistic					169.068
Cragg-Donald Wald F					187.816
Controls	YES	YES	YES	YES	YES
Observations	1590	1604	1604	1343	1343
Adjusted R-squared	0.4342	0.6241	0.6294	0.6396	0.0677
year FE	YES	YES	YES	YES	YES
province FE	YES	YES	YES	YES	YES

t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, *** for 10%, 5%, and 1% .

4.3.4. Instrumental Variable Regression

The previous regression results may face endogeneity problem, other unobservable factors may affect the carbon emission intensity, including institutional and cultural factors that are difficult to quantify. This may result in omitted variables or biased estimated coefficients. Additionally, cities with a higher CEI may struggle to attract talent in science, technology, and information industries, which in turn impedes the information infrastructure. As a result, this article incorporates one-period lags of core independent variables as instrumental variables, a widely used technique for mitigating endogeneity bias produced by omitted variables and reverse causation. On the one hand, information infrastructure construction exhibits some dynamic continuity; that is, the previous period's information infrastructure development lays the framework for the present period's information infrastructure construction. Through affecting the present period's information infrastructure building, the previous period's IIC, on the other hand, will affect present CEI. As a result, this article employs the lagged period of IIC as an instrumental variable and re-estimates the model using the two-stage least squares method (2SLS).

Table 6 presents the results of 2SLS regression. The estimated coefficient of IV in the first-stage regression in column (4) is 0.3638 and significant at the 1% level, indicating that the information infrastructure in the previous period lays the foundation for current period. The estimated coefficient of IIC in the second-stage regression in column (5) is −0.2404 and is significant at the 1% level, indicating that the carbon reduction due to information infrastructure construction is still significant. In addition, the instrumental variable test shows that the model does not bother unidentifiable and weak instrumental variables, the Durbin-Wu-Hausman statistic is 32.61 with a p-value of 0.000, rejecting that the independent variables are all exogenous, so the basic regression model can be considered endogenous at the 1% statistical level; Anderson canon. corr. LM statistic statistic is 169.068 with a p-value of 0.0000, rejecting the original hypothesis of non-identifiability; Cragg-Donald Wald F statistic value is 187.816, which is greater than 10 (rules-of-thumb value) and passes the weak instrumental variable test. It can be seen that when the potential endogeneity problem is alleviated, the information infrastructure significantly reduces the carbon emission intensity, and the regression results of the instrumental variables remain consistent with the previous findings, indicating that the selected instrumental variables are robust, which corroborate the hypothesis of this present work.

5. Mechanism Test

We have showed in previous sections that information infrastructure would suppress carbon emission intensity, but that is only the overall impact, behind which the black box of the mechanism is yet clear. We further explore the mechanism with respect to industrial structure optimization, producer service industry agglomeration, and green technology innovation.

5.1. Industrial Structure Effect

As the underlying foundation of the digital economy, information infrastructure provides a supporting role to promote industrial digitization. Information infrastructure, as the carrier of big data information, has significant positive externality, the more users, the more utility of information value, as information infrastructures are not mutually exclusive. Industrial structure optimization and transformation and upgrading constitute the main parts of low carbon economic. Due to the limited connection between service industry and traditional manufacturing industry, data isolation leads to business isolation between industries, which can be lubricated by information infrastructure through data transmission and information exchange that reduce information asymmetry and accelerate the flow of capital, technology and labor factors. With information infrastructure construction, the degree of tertiary industry development and whether the ratio of industries is reasonable and coordinated, can information infrastructure promote the optimization of industrial structure? Can it break through the industrial barriers to widen the industrial chain?

To test the industrial structure optimization from information infrastructure, we use the share of tertiary industry in GDP (Per3) and the ratio of tertiary industry to secondary industry (Ris) as proxy variables of industrial structure. Column (1) of Table 7 tests the effect of information infrastructure on the tertiary industry in GNP, and the regression coefficient of IIC is 1.7414, which is significant at 1% level. Column (2) of Table 7 tests the influence of information infrastructure on the relationship between the ratio of tertiary and secondary industries in the industrial structure, and the regression coefficient is 0.0573 and is significant at the 1% level. The results show that information infrastructure is positively related to the optimization of industrial structure, and the investing in information infrastructure construction promotes the optimization of industrial structure.

The mechanism by which information infrastructure reduces CEI by optimizing industrial structure lies in the following: on one hand, industrial structure optimization comes from the inter-industry resource reallocation within cities. The information infrastructure triggers knowledge spillover effects, facilitates the evolution of industries from natural resources and labor to knowledge- and technology-intensive industries, promotes the flow of resources from industries with a low degree of professional division of labor to those with a higher one, and promotes specialized division of labor coupling between industries. At the same time, the investment in information infrastructure unleashed a number of new industries and generated "creative destruction", which has boosted the proportion of service industry inputs and increased the demand for service industry products. On the other hand, the optimization of industrial structure can be a result of the reallocation of resources among cities. The popularity of network and the speed of information services make information more transparent, which intensifies competition and requires more harshly on the city's industrial layout and the capability of resource allocation. At the same time, information infrastructure reduces the cost of information collection from physical level, smooths the cross-regional integration of capital, manpower, and technology resources, improves resource allocation and supply chain, and thus promotes the re-integration and layout of industries and provide favorable conditions for the transformation to a low-carbon economy.

Table 7. Mechanism test: industrial structure effect.

VARIABLES	(1) Per3	(2) Ris
IIC	1.7414 ***	0.0573 ***
	(0.4525)	(0.0201)
FDI	14.1929	−1.3140
	(26.4008)	(1.1630)
fin	11.3327 ***	0.4524 ***
	(1.2154)	(0.0635)
$invest$	0.3285	−0.0017
	(1.9815)	(0.1096)
$urban$	−11.7734 ***	−0.4887 ***
	(2.1301)	(0.0945)
$expenditure$	−2.9557	−0.0247
	(11.8952)	(0.5675)
Observations	1603	1603
Adjusted R-squared	0.5346	0.4731
F statistics	30.78	19.39
year FE	YES	YES
province FE	YES	YES

t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

5.2. Producer Service Industry Agglomeration Effect

Manufacturing enterprises outsourced the intermediate manufacturing to specialist producer service manufacturers, which formed an agglomeration of the production service industry. This agglomeration realizes economies of scale in the production of intermediate services and products, embeds more low-carbon production technologies and services into the manufacturing, and embraces higher value-added and low-pollution production. Can information technology industry represented by cloud computing and big data accelerate the integration of high value-added service and manufacturing industries, so as to improve total factor productivity and reduce carbon emissions?

For this reason, we construct a producer services agglomeration model based on producer services specialization agglomeration index (SA_i) and diversification agglomeration index (DA_i), inspired by a relevant study [46], to measure the agglomeration patterns of specialized and diversified producer service. Among these, the SA_i of the production service sector indicates the degree to which the production service industry is specialized relative to the rest of the country. DA_i reflects the region's concentration of diverse production services. The index is constructed in the following manner: The index is constructed as follows,

$$SA_i = \sum_s \left| \frac{E_{is}}{E_i} - \frac{E'_s}{E'} \right|, \tag{4}$$

$$DA_i = 1/\sum_{s=1}^{n} (E_{is} - E_s), \tag{5}$$

where SA_i denotes the producer service industry specialization concentration index for city i, DA_i denotes the producer services diversification index for city i. E_{is} denotes the employed population in some producer services industry s, E_i denotes the total employments in city i. The symbols with an apostrophe indicate the corresponding indicator other than city i. E_s denotes the the employment in producer services s as a percentage of total employment all across the country.

According to the employment statistics of urban industries in China, seven industries in 19 industries are merged to represent producer services [35]: transportation, warehousing and postal services, information transmission computer services and software, wholesale and retail, finance, leasing and commercial services, scientific research and technical services, environmental governance and public facilities management.

The regression coefficient of IIC in column (1) of Table 8 is 0.1443, and it is significant at 1% level. The regression results show that information infrastructure significantly promotes the professional agglomeration of producer services. New business type with information technology and cloud computing enables producer service agglomeration and manufacturing industry, which breaks through their spatial limitations and helps outsourcing the intermediate services, pollution control and emission reduction. As a result, companies can thus concentrate on their core business and speed their transition to green manufacturing. The information infrastructure provides a favorable technology carrier to promote the knowledge spillover and technology transfer between different industries in the specialized agglomeration of producer service industries and form a development path of "high value-added and low pollution". The regression coefficient of information infrastructure in column (2) of Table 8 is not significant, indicating a weak relationship between information infrastructure and diversified agglomeration in producer services. The reason may be the effect of the heterogeneity in industry segments on the diversified agglomeration, that is, a large proportion of low-end producer services may dampen the spillover of information infrastructure technology and weaken carbon emission reduction.

Table 8. Mechanism test: agglomeration effect.

VARIABLES	**(1)** **SA**	**(2)** **DA**
IIC	0.1443 **	−0.0016
	(0.0711)	(0.0013)
FDI	−5.0130	−0.0082
	(3.0868)	(0.0434)
fin	−0.3981 **	0.0046
	(0.1895)	(0.0037)
$invest$	−0.0598	0.0143
	(0.2085)	(0.0103)
$urban$	0.2590	0.0025
	(0.2593)	(0.0052)
$expenditure$	0.8285	0.0021
	(0.8660)	(0.0373)
Observations	1558	1558
Adjusted R-squared	0.2239	−0.0054
F statistics	2.502	0.691
year FE	YES	YES
province FE	YES	YES

t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

5.3. Green Technology Innovation Effect

Carbon emission intensity is the carbon emission per unit of GDP, which is a concept about efficiency, and therefore pertaining to technological innovation. The higher the technological innovation capacity of cities, the more they can lead low-carbon technologies and environmental technologies, which curbs carbon emissions. From Metcalfe's law, the marginal cost of information infrastructure and other hardware inputs will decrease with the expansion of user scale, resulting in significant economies of scale. Can the information infrastructure continuously release the technological spillover bonus of information technology, enhance green technology and thus reduce the carbon emission intensity?

Patent invention from R&D activities can reflect the development of urban innovation. We use the number of green inventions applied for that year (gpatent) and the number of green utility models applied for that year (ppatent) as the proxy variables of green technology innovation, and take logarithm of these variables to test the impact of information infrastructure on green technology innovation. Among them, green invention patents and green utility model patents are obtained by excluding non-green technology invention patents from the international green patent classification.

The estimated coefficients of IIC in the regression results of Table 9 are 0.4684 and 0.3955, and both are significant at the 1% level, indicating that information infrastructure improves the green technology innovation in cities. The improved information infrastructure implies a better accessibility of information network which, due to the decreasing marginal network cost, reduces the cost of network-mediated technology innovation information transmission and enhances the flow of innovation factors and diversified information between regions. Information technology keeps generating technology bonus from an increasing information infrastructure investment, which promotes the green technology in cities, thus providing a feasible path to reduce the CEI during the industrial development.

Table 9. Mechanism test: technological innovation effect.

VARIABLES	(1) Gpatent	(2) Ppatent
IIC	0.4684 ***	0.3955 ***
	(0.1100)	(0.0904)
FDI	22.8569 ***	19.1619 ***
	(3.9742)	(3.2008)
fin	0.9406 ***	0.8801 ***
	(0.1501)	(0.1388)
$invest$	−0.8993 ***	−0.8705 ***
	(0.2508)	(0.2309)
$urban$	0.5746	0.2836
	(0.4065)	(0.3764)
$expenditure$	−4.5364 *	−4.3129 *
	(2.6849)	(2.6042)
Observations	1573	1578
Adjusted R-squared	0.6313	0.6840
F statistics	46.75	46.31
year FE	YES	YES
province FE	YES	YES

t-statistics based on standard errors clustered at the city level are reported beneath each coefficient estimate. Significance levels are indicated by *, **, *** for 10%, 5%, and 1%.

6. Discussion and Conclusions

6.1. Discussion

Global warming is a growing problem that is inextricably linked to human economic activity. The paper's contributions are reflected in three areas. First, the present work, instead of focusing on the economic effects of IIC on total factor productivity (TFP) and urban innovation, focuses on effect of IIC on CEI. Second, our research is enriched as performed based on regional technology, city scale, and traditional infrastructure construction. Thirdly, the present work provides empirical evidence for the digital economy and provides a theoretic foundation to achieve the "dual carbon" goal—"emission peak and carbon neutralit".

However, the present work has some limitations. First, the sample of this study is from one single country, and future studies could extend the study to more countries, especially developing countries. Information infrastructure could be a double-edged sword for carbon emission reduction. Due to the fact that some developing countries are at a low economic level and are subject to stringent environmental regulations, the excessive investment of information infrastructure may have a serious "green paradox" effect, impeding economic development. Second, environmental pollution is not solely due to CO_2 emissions; future research will include other greenhouse gases. Additionally, due to data availability, we conducted empirical testing using 2011–2017 urban panel data. If more global data were available, the findings of this study would need to be empirically tested again to ensure their robustness. Finally, the existing model can be developed further by incorporating additional exogenous variables such as environmental policies, corruption, and green technology innovation.

6.2. Conclusions

We examines the impact of information infrastructure on urban carbon emission intensity by constructing a fixed-effects model using 289 cities in China as a research sample from 2011–2017. It is found that: (1) Information infrastructure construction significantly reduces urban carbon emission intensity. This indicates that the more developed the information infrastructure, the more advanced the digitalization technology, which enables the transformation of industry to low-carbon manufacturing and increase resource utilization efficiency. This conclusion still holds after a series of robustness tests. (2) The present work on the mechanism of information infrastructure construction to reduce carbon emission intensity shows that information infrastructure achieves the purpose of carbon emission suppression through the paths of industrial structure optimization, producer service industry agglomeration, and green technology innovation. (3) It is discovered that the impact of information infrastructure construction on carbon emission intensity is heterogeneous. The carbon emission reduction effect is greater in mega and super cities, large cities. The carbon emission reduction effect are not significant in the subgroups of medium-sized and small cities. In other words, information infrastructure, with the Internet and big data as key symbols, is contingent on the traditional infrastructure, technology supply, and economic scale of cities. Disparities in initial resource endowment will affect the quality and effectiveness of information infrastructure in supporting low-carbon industries.

The findings not only provide theoretical analysis of how information infrastructure affects carbon emission reduction, but also deserve special attention from policymakers in China: first, this study finds that information infrastructure plays an important role in carbon emission reduction. Thus, it is critical to keep promoting emerging businesses such as big data, cloud computing, and artificial intelligence in order to reap the benefits of the digital economy. Information technology innovation, as a impetus for common construction and sharing of innovation platforms, enhances the city's innovation. Second, regional diversities, such as city size, technology level, and traditional infrastructure construction, should be considered when formulating policies for information infrastructure construction. Due to the uneven initial endowment of cities' resources, a single investment in information facilities may not reduce carbon emissions. For less developed cities, efforts should be made to improve traditional infrastructure, foster a healthy business environment and attract scientific talent to create a favorable environment for information infrastructure. Removing barriers to production factors flow and optimizing element allocation are necessary to maximize the technology spillover impact of information infrastructure across areas.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/buildings12050619/s1. For the reference of potential researchers, the main urban economic indicators in 2011 and 2017 are added.

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