frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 28 June 2024
DOI 10.3389/fenvs.2024.1414034

OPEN ACCESS

EDITED BY
Zhaoyang Han,
Nanjing Forestry University, China

REVIEWED BY
Muhammad Saeed Meo,
Sunway University, Malaysia
Ángel Acevedo-Duque,
Autonomous University of Chile, Chile

*CORRESPONDENCE
Qiguang An,
wangyk@mail.sdufe.edu.cn

RECEIVED 08 April 2024
ACCEPTED 04 June 2024
PUBLISHED 28 June 2024

CITATION
Wang Y, An Q, Xie Q and Wang R (2024), The impact of new digital infrastructures on urban carbon emissions-An empirical study from Chinese cities.
Front. Environ. Sci. 12:1414034.
doi: 10.3389/fenvs.2024.1414034

The impact of new digital infrastructures on urban carbon emissions-An empirical study from Chinese cities

Yongkai Wang[1], Qiguang An[1]*, Qian Xie[2] and Ruoyu Wang[1]

[1]School of Statistics and Mathematics, Shandong University of Finance and Economics, Jinan, China, [2]Department of Reproductive Medicine, Central Hospital Affiliated to Shandong First Medical University, Jinan, China

Introduction: In the digital era, new digital infrastructures (NDIs) play a pivotal role in fostering economic growth and technological innovation. However, their ecological impact, particularly on carbon dioxide emissions, remains underexplored. Addressing this gap holds significant practical and theoretical value.

Methods: Utilizing panel data from 283 Chinese cities spanning 2009 to 2020, this study employs a two-way fixed-effects model to empirically assess the influence of NDIs on urban carbon emissions (UCE). Additionally, a mediation effect model is used to examine the mechanisms of this influence.

Results: The findings reveal that: (1) NDIs significantly mitigate UCE levels, a conclusion supported by robustness tests involving instrumental variables and the exogenous policy shocks of smart city pilot programs; (2) NDIs primarily impact UCE through two channels: the digital economy and green technology innovation; and (3) heterogeneity analysis indicates that NDIs predominantly curb carbon emissions in cities with lower administrative levels, while positively contributing to UCE intensity in higher administrative level cities. Notably, NDIs substantially reduce UCE in non-old industrial cities, with a negligible effect in old industrial cities.

Discussion: This research expands the understanding of the economic-environmental implications of NDIs, offering valuable insights for policymakers regarding NDIs' environmental impacts. It also provides strategic guidance for urban low-carbon transitions in the big data era.

KEYWORDS

new digital infrastructures, carbon emissions, digital economy, green technology innovation, difference-in-difference model

1 Introduction

Climate change, driven by factors such as carbon emissions and rising temperatures due to human energy consumption, poses a significant environmental challenge, profoundly affecting human health and wellbeing. Addressing issues like climate change requires collective action and widespread participation across society. According to BP, a leading global oil company, the demand for global primary energy surged by 5.8% in 2021. Concurrently, carbon dioxide emissions from energy use, industrial processes, exhaust flaring, and methane emissions increased by 5.9%, totaling 3.39 billion tons of carbon dioxide. Additionally, the global demand for natural gas rose by 5.3% in the same year. These trends have heightened international concern over climate change and environmental issues. In response, over 200 countries have ratified the Paris Agreement, aiming to limit the global average temperature increase to below 2°C above pre-industrial levels, with ambitions to keep it under 1.5°C.

As the world's largest carbon emitter, China accounts for approximately 28.8% of global carbon emissions (Liu et al., 2015). Consequently, China bears significant responsibility in addressing climate change and reducing carbon emissions. China has dedicated substantial efforts to carbon reduction and has implemented various legislative measures to promote energy conservation and emission reduction. Following the Paris Climate Conference in 2007, China formulated and released its first national plan to address climate change, the "National Climate Change Programme" (Heggelund, 2007). At the Copenhagen Climate Conference in 2009, China committed to reducing its carbon emissions per unit of GDP by 40%–45% by 2020 (Dalmedico and Aykut, 2013). In September 2020, China announced the dual carbon goals of peaking carbon dioxide emissions before 2030 and achieving carbon neutrality by 2060. Currently, China's efforts in carbon emission reduction have been practical and substantial. However, given the enormous volume of carbon emissions, China requires more effective strategies to fulfill its emission reduction commitments. In the context of this ambitious "dual-carbon" target, the development of strategies for reducing UCE has become a critical agenda for the Chinese government and society.

In 2021, the Chinese government issued the "Implementation Plan for the Peak Carbon and Carbon Neutral Targets", elevating the construction of NDIs to a national and strategic priority. These NDIs, guided by innovative development concepts and driven by technological advancements, focus on digital transformation, intelligent upgrading, and integrated innovation. They primarily encompass 5G base stations, big data centers, artificial intelligence, industrial internet, and new energy vehicle charging infrastructure. Unlike traditional industrial infrastructures, NDIs are inherently energy-intensive, necessitating continuous energy investment and consequently leading to increased energy consumption (Bashroush et al., 2022; Hao et al., 2022). The relationship between the development of NDIs and UCE remains a topic of debate. Some studies highlight a "carbon lock-in effect" in NDIs, where carbon dioxide emissions persist throughout their lifecycle (Seto et al., 2016). Conversely, other studies suggest that NDIs can reduce UCE by improving energy efficiency (Hong et al., 2023) and facilitating industrial restructuring (Ren et al., 2021). This paper aims to explore the complex relationship between NDIs and UCE, seeking to ascertain whether the construction of NDIs promotes or inhibits UCE, understand the underlying mechanisms, and identify any heterogeneity in its impact. Addressing these questions is crucial not only for China's green development and its dual-carbon objectives but also provides significant practical and theoretical insights for global efforts to mitigate UCE.

This paper conducts an empirical evaluation of the impact of NDIs on UCE in China. Utilizing a two-way fixed-effects model, this study analyzes data from 283 prefecture-level cities spanning the years 2009–2020. The novel contributions of this research are threefold. Firstly, from a research perspective, this study diverges from the prevalent focus on the effects of transportation infrastructure on employment, economic growth, and the environment. Instead, it concentrates on the environmental implications of NDIs, specifically their influence on UCE intensity. Secondly, regarding research content, this paper acknowledges the diversity in city characteristics, including administrative levels, industrial foundations, and developmental scales. It examines the heterogeneity of impacts across various city types, particularly distinguishing between old industrial cities and others. Furthermore, it explores the mechanisms through which NDIs affect UCE, emphasizing the roles of the digital economy and green technological innovation. Thirdly, from a practical standpoint, the study provides empirical evidence supporting the intensified development of NDIs. It contributes a scientific basis for national policies aimed at achieving China's dual-carbon goals, underscoring the strategic importance of NDIs in China's transition to a low-carbon economy.

The remainder of this paper is structured as follows: Chapter 2 presents the literature review and theoretical analysis, offering a comprehensive review of existing studies and establishing the theoretical framework underpinning this research. This chapter sets the academic context of the study and identifies the gaps that the current research aims to fill. Chapter 3 details the research design, including model specifications, descriptions of the data sources, and analytical techniques used in the empirical evaluation. Chapter 4 presents the results of the empirical analysis, providing a data-driven exploration of the impact of NDIs on UCE. Chapter 5 delves deeper into the underlying mechanisms and examining the heterogeneity in the impacts of NDIs on UCE across different city types. Chapter 6 engages in a critical discussion of the findings, situating them within the broader scholarly discourse and highlighting their theoretical and practical implications. Chapter 7 synthesizes the key insights from the study, drawing conclusions and offering policy recommendations based on the empirical evidence. Finally, Chapter 8 discusses the limitations of the study and suggests directions for future research.

2 Literature review and theoretical analysis

2.1 Literature review

As global environmental challenges intensify, scholarly attention to carbon emissions research has significantly increased, resulting in a substantial body of theoretical and empirical studies. The existing literature relevant to this paper can be broadly classified into two primary categories:

The first category includes literature focused on carbon emissions, particularly emphasizing the quantification of emission levels across various regions and industries and examining factors influencing these emissions. This body of work encompasses a diverse range of studies using different methodologies and perspectives. (1) Regional and industrial carbon emission measurement: Shaari et al. (2021) utilized the panel ARDL method to explore the impact of rural population growth on

CO2 emissions across several developing countries. Their findings revealed that while increases in energy use and economic growth elevate CO2 emissions in the long term, rural population growth does not lead to changes in CO2 emission levels. Yao et al. (2016) analyzed panel data from China's provincial-level industrial sector using the meta-frontier non-radial Malmquist CO2 emission performance index to assess changes in CO2 emission performance and its driving forces. This study is instrumental in understanding regional emission dynamics. (2) Predictive modeling of carbon emission trends: Fatima et al. (2021) employed a nonlinear ARDL model and wavelet analysis to examine the asymmetric and time-varying effects of global energy prices on China's CO2 emissions. Kong et al. (2022) developed a system dynamics model to forecast China's carbon emissions, indicating that China is unlikely to meet its 2030 carbon peaking target, underscoring the challenges in emission reduction. (3) Empirical estimation using remote sensing data: Wang et al. (2022) devised a model to estimate carbon emissions from construction land in Chengdu, China, integrating remote sensing data and emission statistics. This approach represents a technological advancement in emission measurement. (4) Policy impact analysis: Chen and Mu (2023) explored the effect of carbon trading policies on total carbon efficiency in China using a DID model. Similarly, Yu et al. (2022) applied producer theory and the DID method to analyze the impact of China's carbon trading system on agricultural green total factor productivity. These studies offer valuable insights into policy effectiveness. Additionally, several other studies (Meo et al., 2023; Cheng et al., 2018; Lu et al., 2016; Shi et al., 2017; Chaudhry et al., 2022) have examined carbon emissions from different perspectives using varied methodologies, contributing to a more comprehensive understanding of the issue. Collectively, these studies not only enhance the measurement and understanding of carbon emission levels but also provide critical insights into the effectiveness of policies and practices aimed at managing and reducing emissions.

The second category of literature primarily addresses the economic effects of traditional infrastructure, notably transportation infrastructure. This body of work can be further subdivided into two main areas: the impact on technological innovation and the environmental implications. (1) Impact on technological innovation: Studies in this area generally concur that transportation infrastructure positively influences the level of technological innovation, albeit with regional variations in impact. For example, Wang et al. (2018) analyzed data from Chinese firms (1998–2007) to explore the impact of highway infrastructure on corporate innovation. Their findings demonstrate a significant correlation between increased road density and enhanced innovation levels in companies. Similarly, Dong et al. (2020), examining city panel data from China (2006–2015), found that the introduction of high-speed railroads, by shortening inter-city commuting times, facilitates increased research output, particularly in larger cities. (2) Environmental impact of transportation infrastructure: The environmental impact, especially concerning carbon dioxide emissions, is a crucial aspect of this category. According to the International Energy Agency, approximately a quarter of global CO2 emissions in 2018 were attributable to transportation. Churchill et al. (2021) investigated the impact of transportation infrastructure on CO2 emissions using a 150-year dataset from OECD countries. Their results suggest that transportation infrastructure significantly contributes to the increase in CO2 emissions, with economic growth and population acting as mediators. Furthermore, Krantz (2017) reported that about 30% of Sweden's annual CO2 emissions are associated with the development of transportation infrastructure. Collectively, these studies highlight the dual role of transportation infrastructure in both fostering technological innovation and contributing to environmental challenges. They emphasize the necessity to balance the positive economic effects with the potential environmental costs associated with the development of transportation infrastructure.

Despite the growing importance of NDIs, only a limited number of studies have focused on their environmental effects, particularly in the context of UCE. The existing literature in this area is divided. One perspective suggests that NDIs substantially increase carbon emissions, posing a challenge to environmental sustainability. (1) Energy intensity of NDIs: It is commonly understood that NDIs are inherently energy-intensive. Andrae and Edler (2015) projected that by 2030, the electricity consumption in data centers could increase up to fifteen-fold, accounting for 8% of the global demand. This projection underscores the significant energy requirements of emerging digital technologies. (2) Energy consumption *versus* efficiency in 5G networks: Madlener et al. (2022) argued that the surge in energy consumption due to the deployment of 5G networks could potentially offset gains in energy efficiency. According to their analysis, the net result is an overall increase in energy consumption. (3) Empirical findings from Chinese cities: Tang and Yang (2023) conducted an empirical study using panel data from 215 Chinese cities. Their findings reveal that digital infrastructure notably increases total carbon emissions, *per capita* carbon emissions, and carbon intensity in these cities. (4) Energy consumption from digital devices: The advent of the big data era, corresponding with the development of NDIs, has led to an increased use and demand for digital devices. The operational, standby, and replacement phases of these devices are particularly energy-intensive, contributing to heightened energy consumption and carbon emissions (Asongu et al., 2018). These studies collectively indicate that while NDIs hold immense potential for innovation and economic growth, they also present significant environmental challenges. Specifically, they contribute to increased energy consumption and carbon emissions, which are critical considerations in the context of global sustainability efforts.

The second perspective in the literature posits that NDIs can play a pivotal role in reducing UCE. This viewpoint is supported by a range of empirical studies: Dong et al. (2022) analyzed the impact of information infrastructure on greenhouse gas (GHG) emissions using panel data from 281 Chinese cities. Their study concludes that information infrastructure significantly enhances urban GHG emission performance. The key mechanisms identified include technological innovation and industrial structure upgrading. Wu et al. (2021) employed the Slack-Based Measure (SBM) model alongside OLS, spatial Durbin model, mediating effect model, and DID model to evaluate the energy-saving and emission-reduction efficiency of Internet development, using city-level data from China. Their findings indicate that Internet development markedly improves energy-saving and emission-reduction efforts. Luo and Yuan (2023) utilized the 'Broadband China' policy as a quasi-natural experiment to examine the impact of network infrastructure construction on energy saving and emission reduction. Analyzing data from 263 Chinese cities with a DID model, they found that network infrastructure construction enhances energy utilization rates via green technology innovation and energy efficiency, thereby reducing carbon emission intensity. Nie et al. (2023) explored the influence of digital infrastructure on urban green innovation using a two-way fixed-effects model based on panel data from 280 Chinese cities. Their results suggest that digital infrastructure fosters economic agglomeration, supports the growth of digital inclusive finance, and heightens public environmental awareness. These factors collectively contribute to promoting urban green innovation. These studies collectively illustrate that NDIs, through various channels, can significantly contribute to improving energy efficiency and reducing UCE. They underscore the multifaceted role of NDIs in fostering a more sustainable urban environment.

An examination of the existing literature reveals two key insights regarding the relationship between NDIs and UCE. Firstly, there is no definitive consensus on this relationship; it remains a subject of considerable debate within the academic community. The divergent findings and perspectives in the literature underscore the complexity and multifaceted nature of this topic. Secondly, a notable gap in current research is the insufficient focus on the specific impact of China's NDIs development on UCE. Most studies have not thoroughly explored the internal transmission mechanisms driving these impacts, nor have they adequately examined the potential heterogeneity in these effects. This lack of detailed investigation into the nuances of China's context, especially considering its status as a major global player in both NDIs development and UCE, highlights a significant area for further research. Therefore, this paper seeks to bridge these gaps by providing a comprehensive analysis of the relationship between NDIs and UCE in China. It aims to elucidate the internal mechanisms at play and investigate the existence of heterogeneous impacts across different urban contexts. This approach not only contributes to the academic discourse but also offers practical insights for policymakers and stakeholders involved in urban planning and environmental sustainability. By doing so, the paper provides a more nuanced understanding of how China's NDIs development intersects with UCE, offering both theoretical and practical contributions to the field.

2.2 Theoretical analysis and research hypotheses

In recent years, the rapid development of NDIs, exemplified by big data, 5G, artificial intelligence, and the industrial internet, has had a significant impact on the level of UCE. This paper aims to elucidate the transmission mechanism of NDIs' impact on UCE from the perspectives of the digital economy and green technology innovation, subsequently proposing corresponding research hypotheses.

Existing empirical studies indicate that the construction of NDIs can effectively reduce UCE, significantly lower haze concentrations, and improve environmental quality (Zhu et al., 2023; Xiao et al., 2024). Additionally, the construction of NDIs facilitates the interconnection of governments, enterprises, and individuals, leading to changes in production and distribution processes, and improvements in efficiency. As NDIs expand, governments at various levels are increasingly striving to build smart and digital governments. The shift of government affairs and public services from offline to online platforms reduces the need for travel and the use of paper and other office supplies, thereby decreasing energy consumption and carbon emissions. In the realm of production, NDIs construction aids enterprises in optimizing their production processes, factor allocation, and energy usage, contributing to energy savings and emission reductions (Lin and Zhou, 2021). Furthermore, within the circulation sector, NDIs ensure the efficient operation of logistics systems, thus enhancing goods circulation efficiency. This enhancement, in turn, reduces energy consumption in the distribution chain, paving the way for low-carbon development. Based on these observations, this paper posits the following research hypothesis:

Hypothesis 1: The implementation of NDIs can effectively reduce UCE.

NDIs can reduce the level of UCE by promoting the development of the digital economy. It is well-established that NDIs not only improve total factor productivity (Tang and Zhao, 2023) but also drive the rapid growth of the digital economy, a fact supported by numerous studies (Zha et al., 2022; Sun and Chen, 2023). Characterized by high innovation, strong penetration, and wide coverage, the digital economy impacts energy consumption and carbon emissions by reducing search, matching, and transaction costs. Most empirical studies indicate that the development of the digital economy can effectively inhibit carbon emissions and improve carbon emission performance (Ma et al., 2022; Zhang et al., 2022). The in-depth development of the digital economy has led to various new modes and business forms, such as mobile payments and the sharing economy, which influence energy consumption and carbon emissions by altering consumer consumption habits. The platform economy aggregates numerous merchants and consumers, reshaping the shopping process through online selection and purchasing, thereby reducing energy consumption associated with consumer travel. Additionally, it enables merchants and producers to more accurately gauge consumer demand, allowing timely adjustments to production and sales plans. This reduces production waste and saves costs, consequently lowering energy consumption in the production process. Moreover, the sharing economy, by enhancing the utilization rate of social resources and avoiding redundant production of goods, contributes to energy savings and emission reduction in the real economy. Based on this understanding, the following research hypothesis is proposed:

Hypothesis 2: NDIs can curb the level of UCE by fostering the digital economy.

The construction of NDIs can reduce the level of UCE by fostering green technological innovation. NDIs can effectively promote green technology innovation (Liu and Ma, 2020; Li et al., 2024). Recent studies indicate that NDIs has a significant positive effect on substantive green innovation (Han et al., 2024). On one hand, leveraging the technical advantages of big data, artificial intelligence, and other related technologies, NDIs fundamentally overcome the spatial and temporal constraints on factor flow. Technologies such as 5G and the Internet significantly accelerate the speed of information dissemination and facilitate knowledge exchange and sharing through instant messaging, telecommuting, and other means, thereby enhancing the efficiency of technological innovation (Xu et al., 2021). On the other hand, existing literature has established that technological innovation can help reduce the level of UCE (Zhu et al., 2021; Cheng et al., 2021). Green technology, which encompasses technologies aimed at reducing ecological load and improving resource utilization efficiency, plays a crucial role. The innovation and advancement in green technology are effective methods for improving energy utilization efficiency and reducing carbon emission intensity. Green technology is increasingly being incorporated in enterprise production and residential life. It enables the adoption of advanced energy-saving and clean production processes, replacing older, high-energy-consumption, and high-pollution methods. This shift promotes the green transformation of industrial structures and the green upgrading of energy consumption. Furthermore, advancements in green technology in the energy sector accelerate the development and utilization of clean, renewable, and new energy sources. This is conducive to the low-carbon transformation of the energy consumption structure, thus reducing resource and energy consumption at both the production and consumption ends, and achieving control at the source. Based on this understanding, the following research hypothesis is proposed:

Hypothesis 3: NDIs can reduce UCE by promoting green technological innovation.

3 Research design

3.1 Modeling

As a commonly used method in environmental economics, the two-way fixed effects model is widely employed in studies examining the impact of infrastructure and policy interventions on environmental outcomes. This paper draws on relevant research (Ran et al., 2023) and adopts the two-way fixed effects model to empirically test the impact of NDIs on UCE. The specific model is set up as follows:

$$UCE_{i,t} = \alpha_0 + \alpha_1 NDI_{i,t} + \lambda X_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{1}$$

where $UCE_{i,t}$ represents the level of UCE in city i in year t, $NDI_{i,t}$ denotes the level of NDI in city i in year t, $X_{i,t}$ is the set of control variables; μ_i signifies the city fixed effect, δ_t is the time fixed effect, and $\varepsilon_{i,t}$ represents the random error term. The coefficient α_1 measures the effect of NDIs on UCE, a negative value of α_1 that is statistically significant would indicate that NDIs can inhibit the level of UCE.

The two-way fixed effects model is chosen for several reasons: First, control for unobserved heterogeneity. This model accounts for unobserved heterogeneity that may remain constant within cities and across different cities over time, such as city-specific policy environments or economic trends, which can influence UCE levels. Second, by including both city and time fixed effects, the model can better distinguish the impact of NDIs on UCE from other confounding factors that vary across cities and over time. This enhances the causal interpretation of the results, thereby improving the robustness and credibility of the study's conclusions. Finally, the two-way fixed effects approach is widely used in empirical research on environmental economics and urban development. The application of this model in our study aligns with previous research on the environmental impacts of infrastructure and policy interventions. For instance, Liu and Zhu (2024) used a two-way fixed effects model to analyze the impact of green finance on the intensity and efficiency of carbon emissions, which is consistent with the empirical strategy employed in this paper.

3.2 Definition of variables

3.2.1 Explained variables

To measure the level of UCE, various methods exist. In this study, carbon emission intensity is chosen as the explained variable. The Open-Data Inventory for Anthropogenic Carbon Dioxide (ODIAC), a high-resolution global emission data product, provides detailed spatial resolution of carbon dioxide emissions from fossil fuel combustion. This data is published by the National Institute for Environmental Studies (NIES) of Japan and is available for download from the Center for Global Environmental Research website. We utilize the ODIAC data to compile panel data of total carbon emissions for each city in China from 2009 to 2020. The data is summarized by region, and the ratio of total carbon emission to regional GDP is used as a proxy variable for the carbon emission intensity of cities. Additionally, for the purpose of robustness testing, *per capita* carbon emission is also employed.

3.2.2 Core explanatory variables

Accurately portraying the NDIs of each city presents a significant challenge in current research. As NDIs is a relatively new concept, there is no uniform evaluation method established in the academic world. As previously mentioned, NDIs is an infrastructure system driven by technological innovation and based on the information network. Given the Internet's crucial role in its construction and development, this paper, drawing on related research (Shen et al., 2023), employs the logarithm of Internet access ports as a proxy variable for NDIs. This method is considered to have a certain level of rationality. Additionally, text analysis methods have been widely used for indicator measurement. With reference to related studies (Wu et al., 2022), this paper utilizes the frequency percentage of words such as '5G', 'big data', and 'data centers' in government work reports, as well as regional *per capita* telecommunication business income, as alternate proxy variables for NDIs. These measures are used in a robustness test to provide a more comprehensive understanding of NDIs' portrayal. The inclusion of words frequency and telecommunication business income offers an innovative approach to capturing the essence and scale of NDIs development within different urban contexts.

3.2.3 Mediating variables

The mediating variables in this paper are the digital economy and green technology innovation. In terms of the digital economy, this study follows the approach used by Wei et al. (2022). Four

TABLE 1 Variable definitions.

Variable	Symbol	Definitions
urban carbon emissions	UCE	The ratio of total carbon emission to regional GDP, utilize the ODIAC data to compile panel data of total carbon emissions for each city
new digital infrastructures	NDIs	The logarithm of Internet access ports
Government investment in science and technology	X1	The proportion of government expenditure on science and technology within the total general budget expenditure
Urbanization level	X2	The ratio of the urban resident population to the city's total population
Population density	X3	The logarithm of the number of people per square kilometer
Level of economic development	X4	The logarithm of the GDP *per capita*
Level of financial development	X5	The ratio of loan balances of financial institutions to GDP
Industrial structure	X6	The ratio of the value added of the tertiary industry to that of the secondary industry
Fiscal autonomy	X7	The ratio of local budget revenues to local budget expenditures
digital economy	Digit	Measured by a development index derived from principal component analysis of four standardized indicators related to internet usage, software employment, telecommunication services, and cell phone ownership
green technology innovation	Innov	Quantified by the logarithm of the number of green utility model patent applications, compiled based on the WIPO Green Patent List classification

Data sources: the Center for Global Environmental Research (https://db.cger.nies.go.jp/dataset/ODIAC/DL_odiac2022.html)), the State Intellectual Property Office (SIPO) (https://www.cnipa.gov.cn/col/col61/index.html), the China Stock Market & Accounting Research Database (CSMAR) (https://data.csmar.com), the China Statistical Yearbook, the China Urban Statistical Yearbook.

indicators are selected: the number of Internet broadband access users per 100 people, the proportion of computer software employees among urban employees, the total amount of telecommunication services *per capita*, and the number of cell phones per 100 people. These four indicators are then standardized, and their dimensionality is reduced using the principal component analysis method to derive the digital economy development index. Regarding the level of green technology innovation, it is quantified by the logarithm of the number of green utility model patent applications. The data for these applications are compiled after filtering the classification numbers in accordance with the WIPO Green Patent List. This method ensures that the measurement accurately reflects the volume and significance of green technological innovations, as indicated by the patent applications in this category.

3.2.4 Control variables

In reference to existing studies, this paper selects the following city-level control variables: Government investment in science and technology (X1): This is measured by the proportion of government expenditure on science and technology within the total general budget expenditure. Urbanization level (X2): This is quantified by the ratio of the urban resident population to the city's total population. Population density (X3): This is calculated by taking the logarithm of the number of people per square kilometer. Level of economic development (X4): This is determined by taking the logarithm of the GDP *per capita*. Level of financial development (X5): This is measured using the ratio of loan balances of financial institutions to GDP. Industrial structure (X6): This is quantified by the ratio of the value added of the tertiary industry to that of the secondary industry. Fiscal autonomy (X7): This is measured by the ratio of local budget revenues to local budget expenditures. Each of these variables has been chosen for its relevance and potential impact on the study's outcomes. By including these control variables, the paper aims to account for various factors that might influence the relationship between NDIs and UCE. Detailed definitions and explanations of all variables are provided in Table 1.

3.3 Data sources

This paper utilizes panel data from 283 prefecture-level cities in China, spanning the years 2009–2020. The sources of this data are diverse and comprehensive: Carbon emission data is obtained from the Center for Global Environmental Research. Data on green technology innovation is sourced from the State Intellectual Property Office (SIPO). Other city-level variables are primarily derived from the China Statistical Yearbook, the China Urban Statistical Yearbook, and the China Stock Market & Accounting Research Database (CSMAR). In cases where the data had missing values, linear interpolation was employed to estimate and fill in these gaps. The descriptive statistics for each variable are presented in Table 2, providing a detailed overview of the data characteristics and their distribution. This data collection and preparation method offers a solid foundation for the subsequent analysis, ensuring that the study is based on accurate and representative data reflecting the various dimensions of the research topic.

4 Results of empirical analysis

4.1 Benchmark regression

Table 3 reports the results of the baseline regression examining the impact of NDIs on UCE. Column (1) of the table displays the net

TABLE 2 Descriptive analysis of variables.

	Variables	Obs	Mean	Std. Dev	Min	Max
Explained variable	UCE	3,396	0.514	0.405	0.044	4.416
Explanatory variable	NDIs	3,396	4.663	1.078	1.115	7.77
Control variable	X1	3,396	1.616	1.628	0.057	20.683
	X2	3,396	54.977	15.062	18.493	100
	X3	3,396	5.73	0.973	1.659	9.42
	X4	3,396	10.625	0.619	8.41	13.056
	X5	3,396	0.979	0.619	0.116	9.622
	X6	3,396	0.986	0.557	0.109	5.348
	X7	3,396	0.458	0.225	0.054	1.541
Mediating variables	Innov	3,396	4.173	1.713	0	9.302
	Digit	3,396	0.227	1.154	−1.0201	12.571

TABLE 3 Benchmark regression results of the impact of NDIs on UCE.

	(1)	(2)	(3)
	UCE	UCE	UCE
NDIs	−0.1296***	−0.1541***	−0.0689***
	−(−40.75)	−(−7.81)	−(−3.77)
X1			−0.0008
			−(−0.33)
X2			0.0021***
			(2.80)
X3			−0.1815***
			−(−6.50)
X4			−0.2866***
			−(−19.23)
X5			0.09***
			(15.37)
X6			0.0431***
			(4.30)
X7			0.0925*** (2.70)
Constant	1.1189*** (44.22)	1.2337*** (18.15)	4.6157*** (21.28)
City Fixed	No	Yes	Yes
Year Fixed	No	Yes	Yes
N	3,396	3,396	3,396
R^2	0.1875	0.1938	0.2170

Note: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; values in parentheses are t values.

effect of NDIs without incorporating any control variables or fixed effects. In Column (2), both city fixed effects and year fixed effects are added. Column (3) further includes city-level control variables in the analysis. Across all regression results, the coefficients are negative and statistically significant at the 5% level. This consistent pattern indicates that NDIs significantly reduce UCE, thereby promoting low-carbon urban development. Consequently, Hypothesis 1, which posits that NDIs effectively curb UCE, is substantiated by these findings. These results not only validate the hypothesized relationship between NDIs and UCE but also provide empirical evidence supporting the role of NDIs in facilitating sustainable urban growth.

4.2 Robustness tests

To ensure the reliability of the core findings, this paper undertakes a series of robustness tests, which primarily involve replacing the explained variables and the core explanatory variables, as detailed below:

First, replacing the explained variables: Considering the differences in economic development levels across various regions, this study replaces the previously used UCE intensity with *per capita* carbon emissions (PCE), accounting for regional population disparities. Additionally, sulfur dioxide emissions, a common indicator for measuring environmental pollution, are used to reflect regional environmental pollution levels. In this robustness test, urban sulfur dioxide emission intensity (USE) is calculated by dividing sulfur dioxide emissions by the gross regional product and is used instead of carbon emission intensity. The regression results, presented in columns (1) and (2) of Table 4, show that the coefficients of NDIs are significantly negative at the 1% level, aligning with the benchmark regression results. Second, replacing the core explanatory variables: In line with existing studies, two alternate explanatory variables are employed. The word frequency share of government work reports on NDI (WFS) is used as one explanatory variable, and urban *per capita* telecommunication business income (CTI) is used as a proxy variable for NDIs. The regression results, displayed in columns (3) and (4) of Table 4, indicate that the coefficients are significantly negative, thereby affirming the robustness of the paper's core

TABLE 4 Robustness test.

	(1)	(2)	(3)	(4)
	PCE	USE	UCE	UCE
NIC	−0.1437*** (−3.26)	−44.1743*** (−8.64)		
WFS			−0.0570**	
			−(−2.45)	
CTI				−0.0917*** (−3.00)
cons	9.4784*** (18.14)	63.2393 (1.04)	4.5223*** (20.89)	4.5432*** (21.02)
Control Variables	Yes	Yes	Yes	Yes
City Fixed	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Observations	3,396	3,396	3,384	3,396
R^2	0.0619	0.2451	0.1930	0.1935

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; values in parentheses are t values.

findings. These robustness tests validate the stability and reliability of the study's conclusions, demonstrating that the observed relationship between NDIs and UCE remains consistent under various analytical conditions.

4.3 Endogenous processing

4.3.1 Instrumental variable

In reality, carbon emissions are influenced by a myriad of factors, and the control variables in this study do not encompass all the relevant factors. Consequently, the issue of endogeneity due to omitted variables is likely to arise. Furthermore, there exists a bidirectional relationship between NDIs and UCE: while NDIs significantly impacts carbon emissions, the level of UCE can also influence the construction of NDIs, indicating potential reverse causality.

To address these concerns, this paper employs the instrumental variable method for an endogeneity test. Drawing on the studies by Ivus and Boland (2015) and Feng et al. (2007), this study calculates the land topographic relief degree (LTRD) of China using ArcGIS. LTRD reflects the complexity of local terrain, which affects the installation and deployment of NDIs. Generally, higher LTRD indicates greater costs and difficulties in NDIs construction, thereby satisfying the relevance condition as an instrumental variable. Additionally, as a natural factor, LTRD is not directly related to UCE, fulfilling the exogeneity requirement. Moreover, considering that LTRD is constant and does not change over time, a two-stage least squares (2SLS) regression was conducted. This regression utilized the product of LTRD and the number of Internet users in the country in the previous year as an instrumental variable, following the approach of Ji and Yang (2020). This methodology provides a robust way to mitigate the endogeneity concerns and substantiate the reliability of the findings in this study.

The instrumental variables regression results are detailed in columns (1) and (2) of Table 5. The findings from the first stage of the regressions reveal that the coefficients on the instrumental variables are significantly positive and successfully pass the weak instrumental variables test. In the second stage of the regression, the results demonstrate that the coefficients of the core explanatory variables, which are the focus of this paper, are significantly positive. This indicates that NDIs have a substantial inhibitory effect on UCE, confirming the hypothesis that employing instrumental variables can effectively mitigate endogenous problems. Meanwhile, Table 5 employs the Anderson canonical correlation LM statistic for identification tests. The *p*-values for these statistics are indicated within pointed brackets. Additionally, the Cragg-Donald Wald F statistic is used for the weak instrumental variable (IV) test. The critical values derived from the Stock-Yogo test are displayed within square brackets. These values represent the critical thresholds at the 10% significance level. This approach ensures that the instruments used in the study are both valid for identification and not weak, thereby providing robustness to the regression results. This rigorous statistical analysis is crucial for validating the instruments used in the regression models. By passing these tests, the study's methodology is strengthened, ensuring that the findings are based on reliable and valid statistical procedures.

Furthermore, this study also utilizes the lagged one-period data of NDIs as an instrumental variable for an endogeneity test. The corresponding results are presented in columns (3) and (4) of Table 5. These results similarly show that the coefficients of the instrumental variables are significantly positive in the first-stage regression and pass the weak instrumental variable test. The second-stage regression results further confirm that the coefficients of the core explanatory variables are significantly positive, reinforcing the conclusion that NDIs exert a significant inhibitory effect on UCE. This consistency in results underlines the effectiveness of using instrumental variables to address the issue of endogeneity in this context.

4.3.2 Exogenous policy shocks

In addition to the IV-2SLS estimation, this paper identifies exogenous policy shocks as quasi-natural experiments and

TABLE 5 Estimation of instrumental variables.

	IV1 (LTRD)		IV2 (Lagged)	
	Stage1	Stage2	Stage1	Stage2
IV1	0.0003*** (19.71)			
IV2			0.5776*** (40.83)	
NIC		−0.4826*** (−8.55)		−0.1170*** (−3.91)
cons	3.7275*** (14.65)	6.0296*** (18.65)	1.5036*** (6.98)	4.5325*** (16.42)
Control variables	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
City Fixed	Yes	Yes	Yes	Yes
N	3,396	3,396	3,113	3,113
Anderson canon. corr. LM statistic	378.67 <0.0000>		1158.79 <0.0000>	
Cragg-Donald Wald F statistic	388.29 [16.38]		1667.42 [16.38]	

employs the difference-in-difference (DID) model to further address the endogeneity issue. The construction of NDIs is influenced by a variety of factors. In December 2012, China issued the "Circular on Carrying Out National Smart City Pilot Work," which emphasizes informatization infrastructure as a key component of smart city development. This directive provides a feasible metric for measuring NDIs in this study. Utilizing the smart city pilot policy as a proxy for NDIs help mitigate the issues arising from mutual causality between variables. The smart city initiative, focusing on urban innovation and the enhancement of intelligent and comprehensive development through NDIs construction and improvement, is rooted in digitalization. It is a crucial policy measure for boosting digital infrastructure capacity. Importantly, this policy is not directly linked to carbon emissions. Consequently, this study considers smart city construction as a quasi-natural experiment for empirical testing. This approach allows for a more accurate assessment of the relationship between NDIs and UCE, strengthening the validity of the study's findings.

The Ministry of Housing and Urban-Rural Development has announced three batches of national smart city pilots. Following the approach of Beck et al. (2010), this article constructs a multi-temporal DID model to assess the policy's impact on UCE. The specific model settings are as follows:

$$UCE_{i,t} = \alpha_0 + \alpha_1 Smart_{i,t} + \gamma X_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{2}$$

In this model, $Smart_{i,t}$ represents the smart city pilot variable, which is set to 1 from the current year onward if the city is approved as a smart city pilot, and 0 otherwise. Other variables retain the same definitions as in Equation 1. Table 6 reports the baseline regression results of the impact of smart city pilots on UCE. Column (1) displays the policy effects without including control variables, while column (2) incorporates city-level control variables. The estimation results reveal that the coefficients of the national smart city pilot policy are significantly negative, both with and without the addition of control variables. This finding suggests that NDIs have a significant effect on reducing carbon emissions, even after addressing endogeneity through the use of exogenous policy shocks. These results provide further evidence supporting the conclusions drawn earlier in the paper.

TABLE 6 Impact of smart cities on UCE.

	(1)	(2)
	UCE	UCE
Smart	−0.0465*** (−5.03)	−0.0372*** (−4.63)
cons	0.7059*** (94.95)	4.5179*** (20.93)
Controls	No	Yes
City Fixed	Yes	Yes
Year Fixed	Yes	Yes
N	3,396	3,396
R^2	0.0412	0.1888

Note: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$; values in parentheses are t values.

5 Further analysis

5.1 Mechanism analysis

The benchmark regression and a series of robustness tests conducted in this study affirm that NDIs can effectively reduce UCE. The critical question arises: through what mechanisms does this policy achieve its effect? As theorized earlier, the construction of NDIs is believed to suppress UCE by promoting the development of the digital economy and green technology innovation. To empirically test these two mechanisms, this paper employs the mediation effect model, aiming to validate Hypothesis 2 and Hypothesis 3. The specific model is structured as follows:

$$Med_{i,t} = \gamma_0 + \gamma_1 NDI_{i,t} + \theta X_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{3}$$

TABLE 7 Results of mechanism tests.

	UCE (1)	Mechanism I		Mechanism II	
		Digit (2)	UCE (3)	Innov (4)	UCE (5)
NIC	−0.0689*** (−3.77)	0.2102*** (2.60)	−0.0658*** (−3.60)	0.1846*** (2.74)	−0.0667*** (−3.64)
Med			−0.0151*** (−3.72)		−0.0122** (−2.50)
control variables	Yes	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes	Yes
fixed time	Yes	Yes	Yes	Yes	Yes
N	3,396	3,396	3,396	3,396	3,396
R^2	0.1938	0.3124	0.2093	0.7170	0.2198

Note: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; values in parentheses are t values.

$$UCE_{i,t} = \mu_0 + \beta_1 NDI_{i,t} + \beta_2 Med_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{4}$$

In this model, $Med_{i,t}$ represents the mediating variables, which include the digital economy and green technology innovation. The descriptions of the other variables remain consistent with those outlined in the previous section. The causal stepwise regression method is applied, where model (3) and model (4) are estimated based on the significantly negative fitting coefficient of NDIs in the baseline model (1). This approach involves examining if the parameters of NDIs in model (3) and the mediating variables in model (4) are significant. The results of this mediating effect test are presented in Table 7.

Columns (2) and (3) of Table 7 report the path mechanisms by which NDIs influences UCE from the perspective of the digital economy. The results indicate that NDIs significantly fosters the development of the digital economy, characterized by high innovation, strong penetration, and extensive coverage. The digital economy effectively reduces search, matching, and transaction costs, achieving the objective of UCE reduction by innovating consumption modes and altering consumption habits. Columns (4) and (5) of Table 7 present the path mechanisms that examine the role of green technology innovation. The findings reveal that NDI promotes green technology innovation, which in turn achieves UCE reduction goals by enhancing energy use efficiency and improving production processes.

These results confirm Hypotheses 2 and 3. They demonstrate that NDIs not only catalyzes the growth of the digital economy and green technological innovation but also significantly contributes to the reduction of UCE through these channels. This underscores the multifaceted impact of NDIs in driving sustainable urban development.

5.2 Heterogeneity analysis

5.2.1 Municipal administrative level

In China, the productivity level and resource allocation efficiency across cities are highly correlated with their administrative levels. Cities of higher administrative status, such as municipalities, provincial capitals, and sub-provincial cities, typically enjoy more benefits in terms of factor appropriation, local tax burden, and technological innovation capacity. These advantages facilitate the promotion of NDIs development. Referring to previous research (Yan et al., 2023), this paper classifies 49 larger cities, including municipalities and provincial capitals, as high-level cities, while the rest are considered low-level cities.

The results, as shown in columns (1) and (2) of Table 8, indicate that in low-level cities, the impact of NDIs on UCE is significantly negative. In contrast, in high-level cities, the impact of NDIs on UCE appears to be positive. This divergence can be attributed to the scale of NDIs construction in high-level cities, which is often larger, leading to substantial carbon emissions from infrastructure such as 5G base stations and data centers. Additionally, the initial stage of NDIs construction tends to be energy-intensive, resulting in significant carbon emissions. The carbon emission reduction effects through pathways like the digital economy and green technological innovation have not yet been fully realized in these cities. Consequently, the overall effect in high-level cities is an increase in UCE, as the inhibitory impact on carbon emissions is weaker at this stage.

5.2.2 Industrial development base

The industrial bases among Chinese cities vary greatly, influenced by initial resource endowments and historical national strategies. In 2013, to facilitate coordinated adjustment and transformation of industries in old industrial bases, the National Development and Reform Commission (NDRC) issued the "National Plan for Adjustment and Transformation of Old Industrial Bases (2013–2022)." This plan identified 95 prefectural-level cities as old industrial bases. Characteristically, these cities often exhibit low industrial levels, haphazard development, high energy intensity, and significant environmental pollution (Shi and Li, 2020).

Accordingly, this paper divides the sample cities into old industrial cities and non-old industrial cities to conduct separate regression analyses. The results, as presented in columns (3) and (4) of Table 8, indicate that the impact of NDIs on UCE in non-old industrial cities is significantly negative. Conversely, in old industrial cities, the impact of NDIs on UCE is positive, leading to an increase in UCE levels. This outcome is likely due to the industrial structure in old industrial cities being predominantly characterized by high-

TABLE 8 Heterogeneity analysis.

	Administrative level		Industrial base	
	(1)	(2)	(3)	(4)
	High-level	Low-level	Old industrial	Non-old industrial
NIC	0.0326** (2.35)	−0.0753*** (−3.40)	0.0135 (0.37)	−0.0598*** (−3.52)
Constants	1.4439*** (9.46)	5.5579*** (19.49)	1.8032*** (3.96)	4.4647*** (21.63)
control variable	Yes	Yes	Yes	Yes
City Fixed	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
N	588	2,808	1140	2,256
R^2	0.2823	0.1933	0.1268	0.1899

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; values in parentheses are t values.

energy-consuming and high-carbon-intensity industries. These cities exhibit strong path dependency in their economic growth, offering limited scope for emission reduction in the short term. Additionally, old industrial cities are often situated in regions like the northeast and northwest, which experience net population outflows and lack economic vitality. The financial dependence of these cities on central government transfer payments, coupled with insufficient local fiscal resources, further constrains the energy-saving and emission-reduction effects of NDIs.

6 Discussion

This study investigates the impact and mechanisms of NDIs on UCE within the context of China. As the world's largest carbon emitter, reducing China's carbon emissions is crucial for achieving global carbon reduction goals. In the context of the global push for green and sustainable development, the findings of this study provide valuable insights into the relationship between NDIs and UCE. They also offer a theoretical foundation and policy recommendations for reducing UCE in the digital era. Thus, these findings merit further in-depth discussion.

Firstly, the primary regression model of this paper reveals a significant negative correlation between NDIs and UCE. This indicates that NDIs can substantially reduce UCE, a conclusion that aligns with most existing research results (Liu, 2023; Wang and Shao, 2024). This consistency underscores the validity and persuasiveness of the chosen variables and research methodology. In recent years, China has escalated its construction and investment in NDIs. This development has fostered the in-depth application of technologies such as artificial intelligence, the industrial internet, and blockchain, leading to innovative application scenarios and new industrial forms. It has tapped into new drivers of economic growth and facilitated the optimization and upgrading of traditional industries known for high energy consumption, pollution, and low efficiency. Consequently, NDIs play a critical role in pollution and carbon reduction, providing empirical evidence and a model for green development for other countries worldwide.

Secondly, the construction and development of NDIs often depend on various factors, which may also influence UCE simultaneously. Therefore, this paper uses the smart city pilot policy as an exogenous policy shock to examine the impact of NDIs on UCE, effectively addressing endogeneity issues. The results of this study are consistent with previous research (Qian et al., 2023; Zhang and Wu, 2023), indicating that the smart city pilot policy can effectively reduce UCE and has a positive effect on reducing urban smog pollution. Robustness tests, including replacing dependent and independent variables and handling endogeneity with instrumental variables, further demonstrate the robustness and credibility of the research conclusions.

Thirdly, the mediating effect analysis conducted in this paper reveals that NDIs influences the level of UCE through the digital economy and green technology innovation. As previously theorized, these two pathways are potent drivers for reducing UCE. This finding aligns with the conclusions of numerous existing studies (Li et al., 2023; Ma and Lin, 2023). In the modern era of big data, many countries are focusing on digital government and smart city initiatives as key directions for future development. These initiatives necessitate the increased construction of new types of infrastructure. However, it is important to acknowledge that building NDIs requires substantial capital investment. In the short term, its effect on reducing UCE may not be immediately apparent. Indeed, in the initial stages of construction, carbon emissions may temporarily increase due to high energy consumption. Nonetheless, the mechanism paths identified in this paper provide compelling evidence that UCE can be effectively reduced through the digital economy and green technology innovation, ultimately leading to a decrease in UCE.

Fourthly, the heterogeneity analysis of this paper shows that the development of NDIs has a significant negative impact on UCE in cities with lower administrative levels. In contrast, in cities with higher administrative levels, the development of NDIs has not yet demonstrated the ability to reduce UCE and may even contribute positively to it. This unique finding may be due to the larger scale of NDIs construction in higher-level cities, which is often energy-intensive in the initial stages, leading to increased carbon emissions. During the early stages of NDIs construction, the carbon reduction effects of the digital economy and green technology innovation have not yet been fully realized, resulting in a positive impact on UCE. This finding

10.3389/fenvs.2024.1414034

provides valuable theoretical support for government and policymakers to formulate targeted policy recommendations. Green development and emission reduction policies should not be one-size-fits-all but should be adjusted according to the heterogeneity of cities, providing targeted approaches to address these environmental challenges.

7 Conclusions and recommendations

Utilizing urban-level panel data from China from 2009 to 2020, this paper investigates the impact of NDIs on UCE, their transmission mechanisms, and the heterogeneity among cities of varying administrative levels and industrial bases. The study uncovers several key findings: (1) NDIs can significantly reduce the level of UCE, and this conclusion holds after a series of robustness tests. (2) NDIs mainly affect the level of UCE through two pathways: the digital economy and green technology innovation. (3) The heterogeneity analysis shows that NDIs reduce the carbon emission level in cities with low administrative levels and non-old industrial cities, while their inhibitory effect on UCE has not yet appeared in high administrative level cities and old industrial cities. Based on the above discussion and conclusions, this paper puts forward the following policy recommendations:

Firstly, promoting the construction and development of NDIs. Governments should vigorously promote and enhance the construction of NDIs, focusing on increasing their coverage and penetration. Specific measures include investing in developing infrastructures related to big data, 5G, artificial intelligence, and the industrial internet. Establish platforms for information disclosure and sharing to guide more information resources into the production sector. These actions will amplify the impact of NDIs in urban governance, green manufacturing, intelligent management, and the formation of new industries and modes, ultimately contributing to the reduction of UCE.

Secondly, promoting the digital economy and green technology innovation. Leverage NDIs to foster the growth of the digital economy and green technological innovation, which are critical pathways for reducing UCE. Governments should focus on nurturing talent, particularly in the fields of the digital economy and artificial intelligence. This can be achieved through educational programs, incentives for R&D, and policies that encourage innovation. Utilize big data, the Internet, and other information technologies to promote the integration of talent, capital, and technology. Strengthening these areas will contribute to lower carbon emissions.

Thirdly, tailoring policies to urban heterogeneity. Develop differentiated policies that consider the unique characteristics of cities with varying administrative levels and industrial bases. For high administrative level cities, focus on further technological innovation and lifestyle changes to reduce carbon emissions. For old industrial cities, prioritize upgrading traditional industries and altering energy structures. Implement targeted measures such as tax incentives, subsidies for green projects, and support for clean energy initiatives.

8 Limitations and future recommendations

This paper primarily investigates the impact of NDIs on UCE, exploring the mechanisms of the digital economy and green technology innovation. However, carbon emissions in one region may affect emissions in another, underscoring the need for further analysis of the spatial spillover effects of NDIs on UCE. This will be a major focus of future research. Additionally, the study has certain limitations and shortcomings, which also provide directions and goals for future research:

Firstly, regarding the selection of core explanatory variable indicators, although the current indicators have a degree of rationality, relying on a single indicator could lead to issues such as weak representativeness. In future studies, we plan to strengthen our theoretical analysis and methodological exploration to identify more comprehensive and representative evaluation indicators. Secondly, the sample research period of this paper, spanning from 2009 to 2020, is constrained by the availability of data. In recent years, the Chinese government has significantly increased policy support and investment in NDIs construction. Updating the data to include more recent years could provide a deeper and more nuanced understanding of the relationship between NDIs construction and UCE. Thirdly, this study predominantly focuses on the macro-urban level. However, county areas, as more fundamental economic units, play a crucial role in both economic development and carbon emission reduction. Therefore, future research extending to the county level and more micro perspectives will be an important direction to explore. Such research could yield valuable insights into the localized impacts of NDI and environmental policies.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

YW: Data curation, Methodology, Writing–original draft, Software. QA: Conceptualization, Funding acquisition, Investigation, Writing–review and editing. QX: Investigation, Resources, Writing–review and editing. RW: Formal Analysis, Methodology, Writing–original draft.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This research was funded by Shandong Province Social Science Planning Fund Program, grant number [23CJJJ20].

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Andrae, A. S., and Edler, T. (2015). On global electricity usage of communication technology: trends to 2030. *Challenges* 6 (1), 117–157. doi:10.3390/challe6010117

Asongu, S. A., Le Roux, S., and Biekpe, N. (2018). Enhancing ICT for environmental sustainability in sub-Saharan Africa. *Technol. Forecast. Soc.* 127, 209–216. doi:10.1016/j.techfore.2017.09.022

Bashroush, R., Rteil, N., Kenny, R., and Wynne, A. (2022). Optimizing server refresh cycles: the case for circular economy with an aging moore's law. *Ieee Trans. Sustain. Comput.* 7 (1), 189–200. doi:10.1109/tsusc.2020.3035234

Beck, T., Levine, R., and Levkov, A. (2010). Big bad banks? The winners and losers from bank deregulation in the United States. *J. Finance* 65 (5), 1637–1667. doi:10.1111/j.1540-6261.2010.01589.x

Chaudhry, I. S., Nazar, R., Ali, S., Meo, M. S., and Faheem, M. (2022). Impact of environmental quality, real exchange rate and institutional performance on tourism receipts in East-Asia and Pacific region. *Curr. Issues Tour.* 25 (4), 611–631. doi:10.1080/13683500.2021.1894101

Chen, Y., and Mu, H. (2023). Natural resources, carbon trading policies and total factor carbon efficiency: a new direction for China's economy. *Resour. Policy* 86, 104183. doi:10.1016/j.resourpol.2023.104183

Cheng, G., Zhao, C., Iqbal, N., Gulmez, O., Isik, H., and Kirikkaleli, D. (2021). Does energy productivity and public-private investment in energy achieve carbon neutrality target of China? *J. Environ. Manage.* 298, 113464. doi:10.1016/j.jenvman.2021.113464

Cheng, Z. H., Li, L. S., Liu, J., and Zhang, H. M. (2018). Total-factor carbon emission efficiency of China's provincial industrial sector and its dynamic evolution. *Renew. Sust. Energ. Rev.* 94, 330–339. doi:10.1016/j.rser.2018.06.015

Churchill, S. A., Inekwe, J., Ivanovski, K., and Smyth, R. (2021). Transport infrastructure and CO2 emissions in the OECD over the long run. *Transp. Res. D-Tr. E.* 95, 102857. doi:10.1016/j.trd.2021.102857

Dalmedico, A. D., and Aykut, S. C. (2013). *After Copenhagen, revisiting both the scientific and political framings of the climate change regime. Global change, energy issues and regulation policies.* Berlin: Springer, 221–237. doi:10.1007/978-94-007-6661-7_11

Dong, F., Li, Y., Qin, C., Zhang, X., Chen, Y., Zhao, X., et al. (2022). Information infrastructure and greenhouse gas emission performance in urban China: a difference-in-differences analysis. *J. Environ. Manage.* 316, 115252. doi:10.1016/j.jenvman.2022.115252

Dong, X. F., Zheng, S. Q., and Kahn, M. E. (2020). The role of transportation speed in facilitating high skilled teamwork across cities. *J. Urban Econ.* 115, 103212. doi:10.1016/j.jue.2019.103212

Fatima, T., Abd Karim, M. Z., and Meo, M. S. (2021). Sectoral CO2 emissions in China: asymmetric and time-varying analysis. *J. Environ. Plann. Man.* 64 (4), 581–610. doi:10.1080/09640568.2020.1776691

Feng, Z., Tang, Y., Yang, Y. Z., and Zhang, D. (2007). The relief degree of land surface in China and its correlation with population distribution. *J. Geogr.* 62 (10), 1073–1082.

Han, D. R., Zhu, Y., Diao, Y. X., Liu, M., and Shi, Z. Y. (2024). The impact of new digital infrastructure construction on substantive green innovation. *Manag. Decis. Econ.* doi:10.1002/mde.4236

Hao, Y., Li, Y., Guo, Y. X., Chai, J. X., Yang, C. X., and Wu, H. T. (2022). Digitalization and electricity consumption: does internet development contribute to the reduction in electricity intensity in China? *Energ. Policy* 164, 112912. doi:10.1016/j.enpol.2022.112912

Heggelund, G. R. (2007). China's climate change policy: domestic and international developments. *Asian Perspect.* 31 (2), 155–191. doi:10.1353/apr.2007.0017

Hong, J. J., Shi, F. Y., and Zheng, Y. H. (2023). Does network infrastructure construction reduce energy intensity? Based on the "Broadband China" strategy. *Technol. Forecast. Soc.* 190, 122437. doi:10.1016/j.techfore.2023.122437

Ivus, O., and Boland, M. (2015). The employment and wage impact of broadband deployment in Canada. *Can. J. Econ.* 48 (5), 1803–1830. doi:10.1111/caje.12180

Ji, Y., and Yang, Q. (2020). "Can the high-speed rail service promote enterprise innovation? A study based on quasi-natural experiments" [J]. *World Econ.* 43 (2), 147–166. doi:10.19985/j.cnki.cassjwe.2020.02.008

Kong, H. J., Shi, L. F., Da, D., Li, Z. J., Tang, D. C., and Xing, W. (2022). Simulation of China's carbon emission based on influencing factors. *Energies* 15 (9), 3272. doi:10.3390/en15093272

Krantz, J. (2017). *Reducing carbon dioxide emissions in transportation infrastructure projects [D].* Sweden: Lulea University of Technology.

Li, C. M., Wen, M. Y., Jiang, S. X., and Wang, H. X. (2024). Assessing the effect of urban digital infrastructure on green innovation: mechanism identification and spatial-temporal characteristics. *Hum. Soc. Sci. Commun.* 11 (1), 320. doi:10.1057/s41599-024-02787-y

Li, W., Xu, X., Huang, S., Cheng, T., Liu, M., and Zhang, C. (2023). Assessment of green technology innovation on energy-environmental efficiency in China under the influence of environmental regulation considering spatial effects. *Sci. Rep.* 13 (1), 20789. doi:10.1038/s41598-023-47786-2

Lin, B., and Zhou, Y. (2021). Does the Internet development affect energy and carbon emission performance? *Sustain. Prod. Consump.* 28, 1–10. doi:10.1016/j.spc.2021.03.016

Liu, C., and Ma, Q. (2020). Research on the influence of network infrastructure construction on total factor productivity growth: a quasi-natural experiment of "Broadband China" pilot policy. *Chin. J. Popul. Sci.* 3, 75–88.

Liu, L. W., Chen, C. X., Zhao, Y. F., and Zhao, E. D. (2015). China's carbon-emissions trading: overview, challenges and future. *Renew. Sust. Energ. Rev.* 49, 254–266. doi:10.1016/j.rser.2015.04.076

Liu, W. J., and Zhu, P. (2024). The impact of green finance on the intensity and efficiency of carbon emissions: the moderating effect of the digital economy. *Front. Env. Sci-Switz.* 12. doi:10.3389/fenvs.2024.1362932

Liu, Y. (2023). Impact of industrial robots on environmental pollution: evidence from China. *Sci. Rep.* 13 (1), 20769. doi:10.1038/s41598-023-47380-6

Lu, Y. J., Cui, P., and Li, D. Z. (2016). Carbon emissions and policies in China's building and construction industry: evidence from 1994 to 2012. *Build. Environ.* 95, 94–103. doi:10.1016/j.buildenv.2015.09.011

Luo, S., and Yuan, Y. (2023). The path to low carbon: the impact of network infrastructure construction on energy conservation and emission reduction. *Sustain* 15 (4), 3683. doi:10.3390/su15043683

Ma, Q., Tariq, M., Mahmood, H., and Khan, Z. (2022). The nexus between digital economy and carbon dioxide emissions in China: the moderating role of investments in research and development. *Technol. Soc.* 68, 101910. doi:10.1016/j.techsoc.2022.101910

Ma, R. Y., and Lin, B. Q. (2023). Digital infrastructure construction drives green economic transformation: evidence from Chinese cities. *Hum. Soc. Sci. Commun.* 10 (1), 460. doi:10.1057/s41599-023-01839-z

Madlener, R., Sheykhha, S., and Briglauer, W. (2022). The electricity- and CO2-saving potentials offered by regulation of European video-streaming services. *Energ. Policy* 161, 112716. doi:10.1016/j.enpol.2021.112716

Meo, M. S., Nathaniel, S. P., Khan, M. M., Nisar, Q. A., and Fatima, T. (2023). Does temperature contribute to environment degradation? Pakistani experience based on nonlinear bounds testing approach. *Glob. Bus. Rev.* 24 (3), 535–549. doi:10.1177/0972150920916653

Nie, C., Zhong, Z., and Feng, Y. (2023). Can digital infrastructure induce urban green innovation? New insights from China. *Clean. Technol. Envir.* 25, 3419–3436. doi:10.1007/s10098-023-02605-0

Qian, L., Xu, X. L., Zhou, Y. J., Sun, Y., and Ma, D. L. (2023). Carbon emission reduction effects of the smart city pilot policy in China. *Sustain* 15 (6), 5085. doi:10.3390/su15065085

Ran, Q., Yang, X., Yan, H., Xu, Y., and Cao, J. (2023). Natural resource consumption and industrial green transformation: does the digital economy matter? *Resour. Policy* 81, 103396. doi:10.1016/j.resourpol.2023.103396

Ren, S. Y., Hao, Y., Xu, L., Wu, H. T., and Ba, N. (2021). Digitalization and energy: how does internet development affect China's energy consumption? *Energ. Econ.* 98, 105220. doi:10.1016/j.eneco.2021.105220

Seto, K. C., Davis, S. J., Mitchell, R. B., Stokes, E. C., Unruh, G., and Ürge-Vorsatz, D. (2016). Carbon lock-in: types, causes, and policy implications. *Ann. Rev. Env. Resour.* 41, 425–452. doi:10.1146/annurev-environ-110615-085934

Shaari, M. S., Abidin, N. Z., Ridzuan, A. R., and Meo, M. S. (2021). The impacts of rural population growth, energy use and economic growth on CO2 emissions. *Int. J. Energy Econ. Policy* 11 (5), 553–561. doi:10.32479/ijeep.11566

Shen, K., Lin, J., and Fu, Y. (2023). Network infrastructure construction, information accessibility and the innovation boundaries of enterprises. *China Ind. Econ.* 418 (1), 57–75. doi:10.19581/j.cnki.ciejournal.2023.01.014

Shi, D., and Li, S. (2020). Emissions trading system and energy utilization efficiency -Measurement and empirical evidence for prefecture-level and above cities. *China Ind. Econ.* 09, 5–23. doi:10.19581/j.cnki.ciejournal.2020.09.001

Shi, Q., Chen, J. D., and Shen, L. Y. (2017). Driving factors of the changes in the carbon emissions in the Chinese construction industry. *J. Clean. Prod.* 166, 615–627. doi:10.1016/j.jclepro.2017.08.056

Sun, J. W., and Chen, J. Z. (2023). Digital economy, energy structure transformation, and regional carbon dioxide emissions. *Sustain* 15 (11), 8557. doi:10.3390/su15118557

Tang, J. J., and Zhao, X. (2023). Does the new digital infrastructure improve total factor productivity? B. *Econ. Res.* 75 (4), 895–916. doi:10.1111/boer.12388

Tang, K., and Yang, G. (2023). Does digital infrastructure cut carbon emissions in Chinese cities? *Sustain. Prod. Consump.* 35, 431–443. doi:10.1016/j.spc.2022.11.022

Wang, G. J., Peng, W. F., Xiang, J. Y., Ning, L. A., and Yu, Y. A. (2022). Modelling spatiotemporal carbon dioxide emission at the urban scale based on DMSP-OLS and NPP-VIIRS data: a case study in China. *Urban Clim.* 46, 101326. doi:10.1016/j.uclim.2022.101326

Wang, L. H., and Shao, J. (2024). The energy saving effects of digital infrastructure construction: empirical evidence from Chinese industry. *Energy* 294, 130778. doi:10.1016/j.energy.2024.130778

Wang, X., Xie, Z. A., Zhang, X. B., and Huang, Y. P. (2018). Roads to innovation: firm-level evidence from People's Republic of China (PRC). *China Econ. Rev.* 49, 154–170. doi:10.1016/j.chieco.2017.12.012

Wei, S. W., Du, J. M., and Pan, S. (2022). How the digital economy promotes green innovation-empirical evidence from Chinese cities. *Finance Econ.* 11, 10–20. doi:10.13762/j.cnki.cjlc.20220308.001

Wu, H., Xue, Y., Hao, Y., and Ren, S. (2021). How does internet development affect energy-saving and emission reduction? Evidence from China. *Energ. Econ.* 103, 105577. doi:10.1016/j.eneco.2021.105577

Wu, K., Fu, Y., and Kong, D. (2022). Does the digital transformation of enterprises affect stock price crash risk? *Financ. Res. Lett.* 48, 102888. doi:10.1016/j.frl.2022.102888

Xiao, X., Liu, C., and Li, S. X. (2024). How the digital infrastructure construction affects urban carbon emissions-A quasi-natural experiment from the "Broadband China" policy. *Sci. Total Environ.* 912, 169284. doi:10.1016/j.scitotenv.2023.169284

Xu, L., Fan, M., Yang, L., and Shao, S. (2021). Heterogeneous green innovations and carbon emission performance: evidence at China's city level. *Energ. Econ.* 99, 105269. doi:10.1016/j.eneco.2021.105269

Yan, N., Sun, Y., Lin, S., Wang, J., and Wu, T. (2023). The impact of high-speed rail on SO2 emissions-based on spatial difference-in-differences analysis. *Sci. rep-UK* 13 (1), 22835. doi:10.1038/s41598-023-49853-0

Yao, X., Guo, C. W., Shao, S., and Jiang, Z. J. (2016). Total-factor CO2 emission performance of China's provincial industrial sector: a meta-frontier non-radial Malmquist index approach. *Appl. Energ.* 184, 1142–1153. doi:10.1016/j.apenergy.2016.08.064

Yu, D. S., Liu, L. X., Gao, S. H., Yuan, S. Y., Shen, Q. L., and Chen, H. P. (2022). Impact of carbon trading on agricultural green total factor productivity in China. *J. Clean. Prod.* 367, 132789. doi:10.1016/j.jclepro.2022.132789

Zha, Q. F., Huang, C., and Kumari, S. (2022). The impact of digital economy development on carbon emissions — based on the Yangtze River Delta urban agglomeration. *Front. Env. Sci.* 10. doi:10.3389/fenvs.2022.1028750

Zhang, L. W., and Wu, C. Q. (2023). The impact of smart city pilots on haze pollution in China-an empirical test based on panel data of 283 prefecture-level cities. *Sustain* 15 (12), 9653. doi:10.3390/su15129653

Zhang, W., Liu, X., Wang, D., and Zhou, J. (2022). Digital economy and carbon emission performance: evidence at China's city level. *Energ. Policy* 165, 112927. doi:10.1016/j.enpol.2022.112927

Zhu, K. J., Xiang, G. C., and Yang, S. M. (2023). Will mismatched new infrastructure investment cause air pollution crisis? Environmental impact analysis based on the coupling degree of digital economy and new infrastructure investment. *Pol. J. Environ. Stud.* 32 (5), 4429–4445. doi:10.15244/pjoes/165910

Zhu, R., Zhao, R., Sun, J., Xiao, L., Jiao, S., Chuai, X., et al. (2021). Temporospatial pattern of carbon emission efficiency of China's energy-intensive industries and its policy implications. *J. Clean. Prod.* 286, 125507. doi:10.1016/j.jclepro.2020.125507