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Has digital policy improved urban carbon emission efficiency? Quasi-natural experiment based on national big data comprehensive pilot zone

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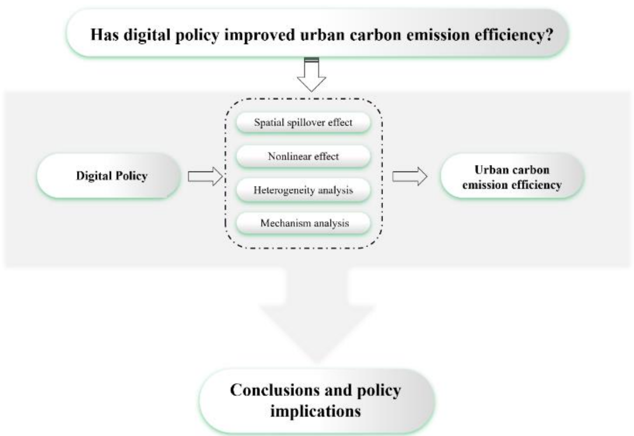
Graphical abstract



Abstract

In the context of the current technological revolution and industrial transformation, the digital economy has emerged as a strategic imperative. It is essential to investigate the influence of digital policies on urban carbon emission efficiency and to elucidate the underlying mechanisms. Such research can provide both theoretical underpinnings and empirical evidence for the evaluation and refinement of digital policy frameworks. This paper utilizes panel data at the city level within China, employing the National Big Data Comprehensive Pilot Zone (NBDZ) as a proxy for digital policy. The study employs the Meta-frontier Non-radial Directional Distance Function (MFNDDF) method to quantify carbon emission efficiency. Furthermore, it leverages the Difference-in-Differences (DID) model to assess the impact and mechanisms of digital policy on enhancing urban carbon emission efficiency. The study finds: (1) NBDZ significantly promote urban carbon emission efficiency, a conclusion that remains valid after undergoing placebo tests and controlling for interference from other policies. (2) Non-linear regression results indicate that the marginal effects of the NBDZ are dynamically changing and exhibit a decreasing trend at different levels of urban carbon emission efficiency. (3) Heterogeneity tests reveal that NBDZ significantly foster the energy transition development in the eastern region, non-resource-dependent cities, and large cities, but their impact is not pronounced in the central and western regions and resource-dependent cities. (4) Spatial effect tests indicate that the implementation of the NBDZ has not led to predatory behaviors towards neighboring cities. On the contrary, this pilot policy has, to some extent, promoted the spatial diffusion of technological innovation in pilot cities, playing a positive role in "demonstrating and facilitating coordinated development." (5) The mechanism of action suggests that NBDZ can influence the development of energy transition by enhancing the level of human capital and technological innovation. This research contributes nuanced insights that inform policymakers, practitioners, and scholars about the strategic design and scaling of digital policy in diverse urban contexts.

Keywords: digital economy; carbon emission efficiency; difference-in-difference; national big data comprehensive pilot zone

1. Introduction

Within the broader context of a global shift towards green and low-carbon development, nations are proactively adopting "carbon neutrality" strategies to mitigate their environmental impact (Lu *et al.* 2025). China, as one of the world's leading energy consumers, confronts substantial challenges in reducing its carbon emissions (Cheng *et al.* 2020). According to data from the National Bureau of Statistics, there has been a marked escalation in China's total energy consumption, rising from 1.47 billion tonnes of standard coal in 2000 to 5.41 billion tonnes of standard coal in 2022 (refer to **Figure 1** for a detailed illustration). Furthermore, data from the International Energy Agency (IEA) indicate that China's carbon dioxide emissions constitute approximately 33% of the global total. Carbon emission efficiency is a critical indicator of the economic implications of decoupling CO2 emissions from economic growth, and the inefficiency of carbon emissions poses a threat to the sustainability of economic development

(Baiardi and Morana 2021). Consequently, the Chinese government is vigorously pursuing a development model that balances economic growth with the reduction of carbon emissions. For instance, the government has articulated its goal to peak carbon dioxide emissions by 2030 and to achieve "carbon neutrality" by 2060 (Gao *et al.* 2024a; Wang and Shao 2025).

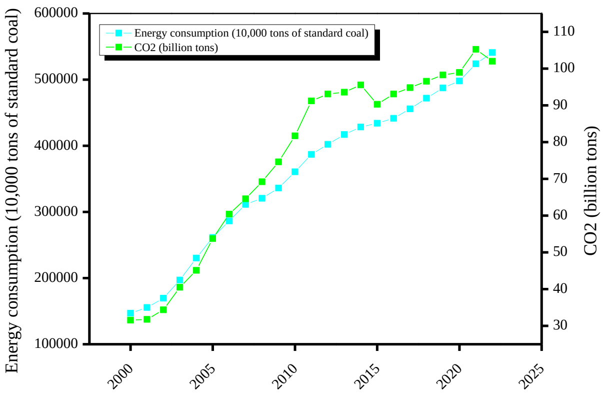


Figure 1. Energy consumption and CO2 emission

In recent years, Information and Communication Technologies (ICT), including the Internet, big data, cloud computing, and artificial intelligence, have experienced global proliferation. These emerging technologies have been integrated into various economic activities as pivotal factors of production, thereby giving rise to a novel economic paradigm: the digital economy (Zhu *et al.* 2022). The advent of the digital economy has increasingly positioned it as a critical catalyst for both economic growth and energy conservation (Arvin *et al.* 2021; Kim *et al.* 2021). As a novel economic and social structure, China's digital economy has been progressing steadily. Estimates suggest that the scale of China's digital economy has been expanding, increasing from 2.7 trillion yuan in 2005 to 50.2 trillion yuan in 2022. Concurrently, the digital economy's share of GDP has been on the rise, reaching 41.5% in 2022 (as depicted in **Figure 2**). With the robust growth of the digital economy, data has emerged as a new factor of production, serving not only as a foundational and strategic resource but also as a novel impetus for modern economic development. In light of this, major industrialized nations have been launching big data development strategies in succession.

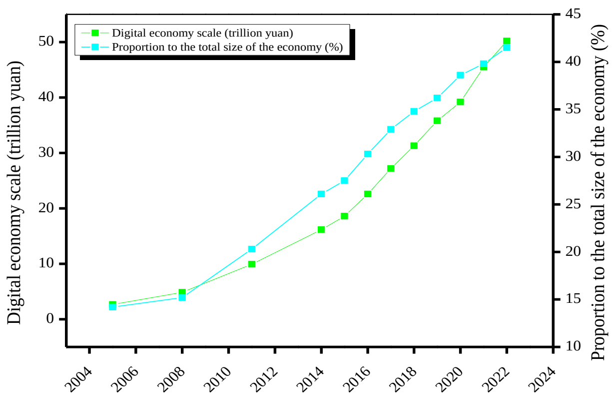


Figure 2. Scale and proportion of digital economy

The Chinese government has accorded substantial importance to the advancement of the big data industry. In 2014, the concept of big data was introduced in the government work report for the first time, marking a significant policy milestone. Subsequently, in 2015, the State Council promulgated the "Action Outline for Promoting the Development of Big Data," which designated big data as a strategic national priority. This outline proposed a comprehensive strategy that included the establishment of national big data pilot zones to foster innovation and development in this sector. Building on this foundation, in 2020, the State Council's "Opinions on Building a More Perfect Market-oriented Allocation System for Factors of Production" formally acknowledged data as a factor of production, underscoring its role in the modern economic framework. The establishment of big data pilot zones has facilitated extensive exploration in critical areas such as data resource management, sharing, integration of data centers, and the application of data resources. The implementation of these pilot zones serves a dual purpose: it not only propels the development of the big data industry but also seeks to deepen the exploration and utilization of data as a strategic element. This initiative is aimed at enhancing the synergy between the digital economy and the real economy, thereby driving overall economic transformation and growth.

While scholars generally concur that digital technology possesses substantial potential for enhancing energy efficiency (Haldar and Sethi 2022), the extant literature on the nexus between digital technology and carbon emissions is characterized by a divergence of opinions. This divergence primarily stems from the competing substitution and cost effects associated with digital technologies. The academic discourse can be broadly categorized into three prevailing perspectives: "positive," "negative," and "non-linear" (Xu *et al.* 2022). Moreover, the absence of a standardized methodology for quantifying the digital economy's scale has resulted in significant variation in estimates across different scholars, introducing potential biases into research findings. Consequently, the question arises: As a quintessential digital policy, does the NBDZ exert a significant influence on urban carbon emission efficiency? If affirmative, what are the mechanisms underlying this impact?

Addressing the aforementioned inquiries is pivotal for enhancing our comprehension of the energy-saving and emission-reduction effects associated with the development of the digital economy. Such an exploration is not merely advantageous for more effectively catalyzing the growth of the digital economy; it also carries substantial practical significance. This significance is evident in the thorough investigation of governance methods for emission reduction and the formulation of pertinent policies aimed at mitigating emissions. By elucidating these aspects, we can contribute to a more informed and strategic approach to environmental sustainability within the context of digital economic advancement.

Compared to existing studies, this paper's marginal contributions are primarily reflected in three areas: First, using urban-level sample data, it systematically examines for the first time the policy effects of the NBDZ on urban carbon emission efficiency, providing new evidence and a useful supplement to related studies on digital policies. Second, it cleverly uses the formal implementation of the NBDZ by the Chinese government in 2016 as an exogenous shock to serve as a quasi-natural experiment. Based on urban panel data, a DID model is constructed, addressing issues of variable endogeneity and data measurement, thus offering a new empirical approach for related research. Third, this paper further applies the Spatial Durbin Model with DID (SDM-DID) and quantile model to analyze the spatial spillover and nonlinear effects of the NBDZ on urban carbon emission efficiency, thus providing a more comprehensive analysis of the policy effects of this pilot policy. Finally, based on empirical results, it offers valuable policy recommendations for decision-making bodies aiming to achieve energy transition targets.

The subsequent sections of this study are systematically organized as follows: The second section offers an exhaustive review of pertinent literature and the formulation of hypotheses. The third section elucidates the research design employed in this paper. The fourth section details the empirical findings. Finally, the concluding section synthesizes the study's findings and discusses their implications for policy-making.

2. Literature review and hypotheses development

2.1. Literature review

The extant literature on carbon emission efficiency predominantly centers on two dimensions: measurement methodologies and determinant factors (Pan *et al.* 2020; Xu *et al.* 2022). Initially, the predominant approach employed by scholars to assess carbon emission efficiency was the single ratio method (Ang 1999). Although the single indicator measurement method is simple, it results in errors because it does not consider the substitution effects of other production factors. Consequently, subsequent studies have conducted comprehensive measurements of carbon emission efficiency by constructing an input-output evaluation indicator system (Dissanayake *et al.* 2020; Wang and Shao 2022). For instance, Wang and Shao (2022) employed the Meta-frontier and Nonradial Directional Distance Function (MFNDDF) methods to assess the carbon emission efficiency across 260 Chinese cities. Their findings suggest that, while the average carbon emission efficiency showed a general upward trend over the study period, there remains a notable discrepancy from the optimal level of efficiency. Xiao *et al.* (2023) utilized the Super-EBM model to calculate the carbon emission efficiency for 136 countries spanning from 2000 to 2019, revealing substantial variability in efficiency among different nations and regions. Gao *et al.* (2021) applied the Slacks-Based Measure (SBM) model to measure the embodied carbon emissions within 28 industrial sectors in China from 2005 to 2017, uncovering significant heterogeneity in carbon emission efficiency across various sectors. In a similar vein, Guo *et al.* (2023) employed the SBM model to evaluate the carbon emission efficiency of the pig farming industry across 30 provinces in China. Chandra *et al.* (2020) leveraged both Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) methods to comprehensively assess the levels of carbon emission efficiency in German cities.

Regarding the determinants of carbon emission efficiency, the existing scholarly literature has established the influence of economic growth, population expansion, foreign trade, technological innovation, and urbanization on this metric (Wang *et al.* 2019; Acheampong *et al.* 2020; Brini 2021). Meng and Niu (2012) dissected the absolute change in carbon emission efficiency into the cumulative annual absolute impacts of various influencing factors across different industrial sectors, concluding that the contribution of technological innovation significantly surpasses that of adjustments in industrial structure. Sun *et al.* (2019) posited a positive correlation between a country's position index in the Global Value Chain (GVC) and its carbon emission efficiency, suggesting that nations with higher GVC positions tend to exhibit greater efficiency in carbon emissions. Li *et al.* (2022c), in their study of Belt and Road Initiative countries, identified energy efficiency as the primary factor contributing to disparities in carbon emission efficiency. Guang *et al.* (2023) examined the impact of energy allocation distortions on carbon emission efficiency, utilizing measurements of these distortions as a basis for their analysis.

The digital economy, emerging as a novel economic paradigm subsequent to the agricultural and industrial economies, has garnered extensive scholarly attention. Current research endeavors within the domain of the digital economy are predominantly concentrated on elucidating its core essence, methods of quantification, and its transformative impact on traditional economic growth trajectories. Tapscott (1996) initially introduced the concept of the digital economy in his seminal work, "The Digital Economy," positing that within this new economic paradigm, the flow of information is transmuted into a digital format, thereby equating the digital economy with the new economy at large. The digital economy is generally delineated into two scopes: a narrow and a broad definition. In its narrowest interpretation, the digital economy primarily pertains to the industrialization of data, that is, the conversion of data into an industry (Guo and Lian 2020). Conversely, a broader perspective encompasses not only the industrialization of digital data but also the profound integration of digital technologies with traditional and real economies, which is to say, the digitalization of industries (Han *et al.* 2022). As for the quantification of the digital economy, a unified methodology has yet to be established; research predominantly centers on assessments of both absolute and relative magnitudes.

Initial assessments of the digital economy were predicated on the information technology sector. In 2002, the U.S. Department of Commerce introduced the "Digital Economy Industry Classification Standard," which offered a more systematic approach to calculating the value added by digital industries. Li *et al.* (2022a) gauged the developmental level of the digital economy across two dimensions: internet development and digital financial inclusion. They employed principal component analysis to derive a composite index reflecting the overall development of the digital economy. Fan and Wu (2021) devised a digitalization index system that included metrics for production digitization, consumption digitization, and circulation digitization. The weighting of these indicators was primarily ascertained through a combination of principal component analysis and expert scoring methods, thereby facilitating a comprehensive measurement of the digital economy's level. Concurrently, Han *et al.* (2022) utilized input-output table data to estimate the scale of the digital economy across various Chinese provinces. Their findings indicate a general upward trend in the scale of the digital economy at the provincial level in China.

As a pivotal element of economic development, the digital economy's proportion is expanding, thereby acting as a catalyst for economic growth. Specifically, the digital economy contributes to economic growth primarily by enhancing productivity, fostering industrial restructuring, and optimizing resource allocation (Liu 2019). In a similar vein, Berkhout and Hertin (2004) determined that the digital economy spearheads the transformation and upgrading of industrial structures through the digitalization of industry and the industrialization of digital technologies, thereby creating new opportunities for economic growth. Additionally, research by Ghasemaghaei and Calic (2019) indicates that the digital economy can elevate the quality and efficiency of traditional factors of production, such as labor and capital, ultimately bolstering economic growth.

As scholarly inquiry advances, an increasing number of researchers are directing their attention towards the implications of digital economy development for green and low-carbon transitions (Wang and Shao 2024). For instance, Hampton *et al.* (2013) posit that the internet, leveraging big data and cloud computing capabilities, can integrate and analyze environmental datasets pertaining to air, soil, and water quality. This integration and analysis enhance the efficacy of environmental governance by providing a more comprehensive understanding of ecological conditions. Johansson *et al.* (2015) discovered that the internet has broadened the avenues for public engagement in environmental conservation efforts, thereby elevating environmental protection awareness and facilitating more robust monitoring. Erdmann and Hilty (2010) conducted a study on the internet's impact on carbon emissions across various scenarios, with their findings suggesting that the internet has a substantial mitigating effect on carbon emissions. Li and Wang (2022) employed the SDM and panel threshold model to investigate the relationship between the digital economy and carbon emissions. Their research revealed an inverted U-shaped relationship, indicating a complex interplay between the digital economy's growth and its impact on carbon emissions. These findings underscore the potential for the digital economy to influence environmental sustainability in nuanced ways.

While a substantial body of research has attested to the beneficial role of the digital economy in enhancing environmental quality, it is crucial to acknowledge and examine the potential negative impacts of the digital economy on environmental pollution. The digital economy exerts a multifaceted influence on environmental outcomes: on one hand, it bolsters the efficiency of environmental governance through the deployment of information technology; on the other hand, it may amplify the emission of pollutants due to the scale expansion and the consequent energy rebound effect. Wang and Cao (2019) discovered a non-linear association between the advancement of the digital economy and total factor productivity (TFP). Moreover, they observed that the energy rebound effect precipitated by the digital economy's growth can lead to an escalation in carbon emissions. This finding underscores the intricate relationship between the digital economy and environmental sustainability, suggesting that while the digital economy holds promise for environmental improvement, its development must be carefully managed to mitigate adverse environmental consequences.

A comprehensive review of the literature indicates that the majority of studies have explored the interplay among the digital economy, environmental quality, and carbon emissions. Initially, it is observed that due to disparate research timeframes and subjects, the conclusions drawn have lacked uniformity. Additionally, the methodologies for quantifying the digital economy are still in evolution; the use of diverse measurement techniques can yield substantially divergent results, thereby influencing the research findings. Moreover, the employment of proxy variables in empirical analyses frequently grapples with issues of endogeneity and estimation biases (Cheng *et al.* 2019; Qiu *et al.* 2021). In light of these challenges, the present study endeavors to ascertain whether the establishment of the NBDZ has significantly bolstered carbon emission efficiency. Leveraging the initiation of the NBDZ as a quasi-natural experimental setting, this paper applies the DID model to scrutinize the policy's impact on carbon emission efficiency and the mechanisms through which these effects are transmitted. The ultimate goal is to furnish empirical evidence to inform policies aimed at realizing the "dual carbon" targets, which refer to achieving peak carbon dioxide emissions and carbon neutrality.

2.2. Hypotheses development

The digital economy represents a novel economic paradigm that is propelled by digital resources as pivotal components, with modern information networks serving as the primary conduits, and the convergence and utilization of information and communication technologies alongside the digitization of all elements. Within the amalgamation and evolution of the digital and traditional economies, the deployment of digital technology accelerates the swift circulation of various production factors, thereby significantly elevating the degree of societal productivity. This enhancement, in turn, effectively fosters the enhancement of carbon emission efficiency (Xu *et al.* 2022). On one hand, the implementation of the NBDZ ensures the ongoing integration of digital technologies, epitomized by big data and artificial intelligence, with conventional industries. This integration not only facilitates a gradual shift towards industrial digitization, intelligence, and green sectors (Ma *et al.* 2022), but also contributes to the reduction of energy consumption and carbon emissions while concurrently augmenting industrial added value (Qin and Cheng 2017). On the other hand, NBDZ enhance production coordination through digital management, enabling efficient and precise connectivity and integration of all stages of production, avoiding excessive consumption of production factors, and thereby improving urban carbon emission efficiency (Thompson *et al.* 2013).

From a geographical economics perspective, it is argued that there are no independent observations in reality, and ignoring the spatial dependence between subjects of study can lead to distortions in empirical results (Anselin 1988). Undoubtedly, the establishment of NBDZ has significantly mitigated the economic interaction impediments stemming from geographical distances. The spatial externalities they engender not only influence local carbon emission efficiency but also exert an impact on the carbon emission efficiency of adjacent regions (Zhu *et al.* 2022). For instance, Liu (2021) conducted an analysis of carbon emissions across Chinese cities, revealing that carbon emissions display distinct spatial clustering characteristics. Xu *et al.* (2022) demonstrated that the development of ICT capital not only augments urban carbon emission efficiency within the region but also generates a significant spatial spillover effect on surrounding areas. This leads to the first hypothesis H1 proposed in this paper.

H1: NBDZ not only actively promote the improvement of urban carbon emission efficiency but also exhibit a significant spatial spillover effect.

Firstly, the establishment of NBDZ is accompanied by a digital transformation that shifts the focus from resource-intensive and labor-intensive industries to technology-intensive sectors, thereby optimizing the industrial structure (Zhong *et al.* 2022). Secondly, the extensive adoption of digital technologies has catalyzed the growth of emerging industries, including the big data sector, cloud computing, and artificial intelligence. Furthermore, the integration of digital elements into traditional production domains enhances the operational efficiency of these industries, thereby accelerating their transformation and upgrading processes. The optimization and upgrading of the industrial structure is characterized by an increased proportion of the tertiary sector, which is predominantly composed of technology-intensive industries. These industries are notably efficient and are low-emission, clean industries, which contribute to a reduction in carbon emissions during the production process (Li *et al.* 2018). This shift towards a more service-oriented and technology-driven economy is essential for achieving sustainable development goals, including the reduction of carbon emissions.

The efficient information transmission channels facilitated by NBDZ has enhanced the dissemination of knowledge, thereby promoting the concentration of high-tech talent and research and development capital. This concentration, in turn, has led to a comprehensive enhancement in the level of technological innovation. In the realm of digital industries, the advancement of digital industrialization has bolstered the sharing of information and knowledge among enterprises, thereby improving their innovation capacity and output. This has also mitigated information asymmetry, which is crucial for fostering a more equitable and efficient market environment (Li *et al.* 2020). Tang *et al.* (2021) posit that the implementation of digital policies has spurred green technological innovation within enterprises. The accumulation of digital technology capital has not only facilitated the development of a variety of low-carbon technologies but also enabled technological spillovers. These spillovers have significantly reduced production redundancies and improved environmental impacts, thereby enhancing urban carbon emission efficiency (Lange *et al.* 2020). Anderson (2001) further underscores the positive role of technological innovation in mitigating environmental pollution, highlighting its importance in achieving sustainable development objectives.

The establishment of NBDZ has expanded information dissemination channels, thereby accelerating the speed of information acquisition and intensifying regional knowledge spillovers. These zones have also contributed to the acceleration of human capital accumulation and the enhancement of its quality, providing intellectual support that is crucial for improving carbon emission efficiency (Haini 2021). As the level of human capital gradually increases, it aligns high-tech material capital with high-level labor, which in turn promotes productivity improvements and enhances carbon emission efficiency. In essence, the sustained growth in both the quantity and quality of human capital stimulates a new cycle of information and communication technology development, creating a virtuous cycle that ultimately leads to improved carbon emission efficiency (Ilmakunnas and Miyakoshi 2013). This interplay between human capital development and technological advancement underscores the importance of educational and skill-enhancing initiatives within the context of sustainable economic growth. The synergistic relationship between human capital and technological progress is a key driver in the transition towards a more efficient and environmentally conscious economy. Based on this, this paper proposes the hypothesis H2、H3 and H4.

H2: NBDZ can promote the improvement of urban carbon emission efficiency by optimizing the industrial structure.

H3: NBDZ can promote improvements in urban carbon emission efficiency through technological innovation.

H4: NBDZ can promote improvements in urban carbon emission efficiency by accelerating the accumulation of human capital.

3. Research design

3.1. Methods of measuring urban carbon emission efficiency

Chambers (1996) initially introduced the application of directional distance functions for the measurement of efficiency. Fukuyama and Weber (2009) posited that, despite the widespread adoption of traditional radial directional distance functions as a metric for efficiency, these methods may overestimate efficiency values in scenarios where there is non-zero slack. Conversely, non-radial approaches incorporate slack variables, permitting proportional adjustments in inputs and outputs, rendering them more appropriate for assessing energy and environmental efficiency. Building upon this body of research, the present study employs the MNDDF model to quantify energy efficiency (Fang *et al.* 2024; Hu *et al.* 2020; Wang and Shao 2022). In this analysis, each city is considered a Decision-Making Unit (DMU) for constructing the production frontier. Each DMU utilizes capital (K), labor (L), and energy (E) as input indicators, with the city's Gross Domestic Product (GDP) (Y) serving as the desired output, and carbon dioxide emissions (CO2) as the undesired output. Consequently, the technology production set that encompasses non-desired outputs can be articulated as follows:

$$T=\{(K,L,E,Y,CO2):\sum_{n=1}^{N}\gamma_n K_n\le K;\sum_{n=1}^{N}\gamma_n L_n\le L;\sum_{n=1}^{N}\gamma_n E_n\le E;\sum_{n=1}^{N}\gamma_n Y_n\le Y;\sum_{n=1}^{N}\gamma_n CO2_n\le CO2, n=1,2,\cdots,N\} \quad (1)$$

Expressed in Eq. 1, γ_n is the weight of each cross-section. If $\gamma_n\ge 0,\sum_{n=1}^{N}\gamma_n=1$, it means that the variable scale return (VRS), otherwise constant scale return. In order to measure the carbon emission efficiency of each DMU, a non-radial distance function is constructed based on the practice of Zhang *et al.* (2013).

$$\vec{D}\begin{pmatrix}K,L,E,Y\\,CO2;g\end{pmatrix}=sup\left\{w^T\beta:\begin{bmatrix}(K,L,E,Y,CO2)\\+g*diag(\beta)\end{bmatrix}\in T\right\} \quad (2)$$

In Eq. 2, $w^T=(w_K,w_L,w_E,w_Y,w_{CO2})$ represents the standardized weight vector. As there are three input variables, one desirable output, and one undesirable output, we set $w^T=\left(\frac{1}{9},\frac{1}{9},\frac{1}{9},\frac{1}{3},\frac{1}{3}\right)$. $g=(-g_K,-g_L,-g_{E,}-g_{Y,}-g_{CO2})$ represents the direction vector, which is set as g=(-K, -L, -E, -Y, -CO2). $\beta=(\beta_K,\beta_L,\beta_E,\beta_Y,\beta_{CO2})\ge 0$ indicates the relaxation vector, which needs to be obtained by solving the following linear program:

$$\vec{D}(K,L,E,Y,CO2;g)=\max\frac{\beta_K}{9}+\frac{\beta_L}{9}+\frac{\beta_E}{9}+\frac{\beta_Y}{3}+\frac{\beta_{CO2}}{3} \quad (3)$$

$$s.t.\ \begin{cases}\sum_{n=1}^{N}\gamma_n K_n\le(1-\beta_K)K\\ \sum_{n=1}^{N}\gamma_n L_n\le(1-\beta_L)L\\ \sum_{n=1}^{N}\gamma_n E_n\le(1-\beta_E)E\\ \sum_{n=1}^{N}\gamma_n Y_n\le(1-\beta_Y)Y\\ \sum_{n=1}^{N}\gamma_n CO2_n\le(1-\beta_{CO2})CO2\\ \gamma_n\ge 0, n=1,2,\cdots,N\\ \beta_Y\ge 0, 0\le\beta_K,\beta_L,\beta_E,\beta_{CO2}\le 1\end{cases}$$

According to the researches of Cheng *et al.* (2018), the urban carbon emission efficiency (CEE) can be expressed as:

$$CEE=\frac{CO2-\dfrac{\beta_{CO2}CO2}{Y+\beta_Y Y}}{\dfrac{CO2}{Y}}=\frac{(1-\beta_{CO2})}{(1+\beta_Y)} \quad (4)$$

3.2. Empirical model

To ascertain whether a data-centric digital policy can enhance carbon emission efficiency, this paper employs the establishment of NBDZ as a quasi-natural experiment. The study sample encompasses 268 prefectural-level cities and above in China. Cities under the jurisdictions of the provinces of Guizhou, Hebei, Guangdong, Henan, and Inner Mongolia, as well as the municipalities of Beijing, Shanghai, Tianjin, Chongqing, and Shenyang, totaling 66 cities, are designated as the treatment group. The remaining cities constitute the control group. The year 2016 is chosen as the policy implementation time point for the pilot zones, primarily because, although the State Council's "Action Outline for Promoting the Development of Big Data," issued in August 2015, explicitly proposed regional pilot initiatives and the advancement of big data pilot zones in Guizhou, it was not until February 2016 that the National Development and Reform Commission, the Ministry of Industry and Information Technology, and the Cyberspace Administration of China formally approved the establishment of Guizhou's pilot zone. Subsequently, the second batch of pilot zones was approved in October of the same year. Consequently, this paper uniformly designates the policy time point as 2016 to align with the formal commencement of the pilot zones.

The DID model offers a robust approach for evaluating policy impacts by accounting for influences other than the policy intervention. It captures the relative differences between the treatment and control groups before and after policy changes, thereby controlling for pre-existing trends and other confounding factors (Feng *et al.* 2023; Li *et al.* 2018; Qiu *et al.* 2021). The application of this method is predicated on certain assumptions, most notably the parallel trends assumption. This assumption requires that the control and treatment groups exhibit consistent development trajectories prior to the policy intervention. Should there be inherent disparities in development between the two groups, the policy evaluation outcomes may be compromised. Consequently, this study conducts parallel trend tests to ensure the validity of the DID approach, as detailed in subsequent sections. In this vein, to empirically examine the impact of the NBDZ on urban carbon emission efficiency, this paper draws upon existing literature to construct the following benchmark model (Gao *et al.* 2024b; Wang and Shao 2024; Xu 2022). This model serves as a foundational analytical framework to assess the efficacy of the NBDZ policy in enhancing carbon emission efficiency, while also accounting for potential biases due to pre-existing differences between the treatment and control groups.

$$CEE_{it}=\beta_0+\beta_1 NBDZ_{it}+\sum\beta_j\times X_{it}+\gamma_i+\mu_t+\varepsilon_{it} \quad (5)$$

Here, i and t represent the city and year, respectively; CEE denotes the carbon emission efficiency; $NBDZ_{it} = Treat_i \times Time_t$, where $Treat_i$ indicates whether it is a NBDZ, with a value of 1 indicating that it is a national big data pilot zones and a value of 0 indicating that it is not; $Time_t$ is a time dummy variable, with a value of 1 indicating that the policy of NBDZ was implemented in that year for the treatment group cities, and a value of 0 indicating that the NBDZ has not yet been implemented; X represents a set of control variables; γ_i and μ_t represent individual fixed effects and time effects, respectively; ε_{it} is a random error term.

It should be noted that the above econometric model primarily examines the impact of the NBDZ on the conditional expectations of carbon emission efficiency, inherently being a mean regression, thus susceptible to outliers. However, in certain cases, for the unconditional distribution, the mean does not fully reflect the overall situation of the conditional distribution. The traditional approach involves grouping the overall sample based on specific statistical measures and examining it through grouped mean regression. While dividing the sample can provide information on the distribution's tails, such truncated regression inevitably leads to selection bias and sample loss. The quantile regression model can overcome the shortcomings of mean regression by avoiding subjective grouping of samples and instead using the entire sample dataset to model different quantiles separately, thus fully capturing the overall characteristics of the distribution. Therefore, to accurately depict the complete statistical characteristics of the conditional distribution and effectively capture the impact of the NBDZ in the extreme areas of urban carbon emission efficiency, illustrating the dynamic evolution of the marginal effects in the process of enhancing carbon emission efficiency, this paper further constructs the following quantile regression model based on Wang and Shao (2023).

$$CEE_{it}(\tau) = \alpha_0(\tau) + \alpha_1(\tau) NBDZ_{it} + \sum \beta_j X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (6)$$

Herein, τ (0<τ<1) represents different quantiles of the conditional distribution, the core coefficient $\alpha_1(\tau)$ reveals the marginal impact of the NBDZ on urban carbon emission efficiency at different quantile points.

Tobler's first law of geography posits that everything is related to everything else, but nearer things are more closely connected than distant ones (Tobler 1969). Additionally, the traditional DID method is suited for estimating policy impacts in the absence of spillover effects. However, due to the presence of spatial economic connections, the impact of the NBDZ may have some degree of spillover effect. Therefore, considering that the influence of the NBDZ on urban carbon emission efficiency might exhibit spatial effects, this paper employs SDM-DID analysis to further examine the emission reduction effects of the NBDZ (Peng and Gao 2025). The econometric model is as follows:

$$CEE_{it} = \alpha_0 + \rho_1 \sum W_{ij} CEI_{it} + \alpha_1 NBDZ_{it} + \rho_2 \sum W_{ij} NBDZ_{it} + \sum \alpha_\omega \times X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (7)$$

Where, W is the spatial weight matrix. In this paper, the geographic distance spatial weight matrix is used in benchmark regression, which measures the relationship between more distant spatial units. The specific calculation is as follows:

$$W_{ij}^{d} = e^{-ad_{ij}} \quad (8)$$

$$W_{ij}^{'d} = \begin{cases} \dfrac{W_{ij}^{d}}{\sum_j W_{ij}^{d}}, & i \neq j \\ 0, & i = j \end{cases} \quad (9)$$

Where, W_{ij} is the matrix element of the ith row and column j; d_{ij} is the geographic distance between spatial unit i and spatial unit j, and $W_{ij}^{'d}$ represents the normalized spatial weight. At the same time, the economic distance spatial weight matrix is used to test the robustness, which is calculated as follows:

$$W_{ij}^{e} = W^{ij} diag\left(\frac{\overline{Y_1}}{\overline{Y}}, \frac{\overline{Y_2}}{\overline{Y}}, \cdots, \frac{\overline{Y_n}}{\overline{Y}}\right) \quad (10)$$

$$W_{ij}^{'e} = \begin{cases} \dfrac{W_{ij}^{e}}{\sum_j W_{ij}^{e}}, & i \neq j \\ 0, & i = j \end{cases} \quad (11)$$

Where, W_{ij}^{e} is the spatial weight matrix of economic distance, $\overline{Y_i}$ is the average of the per capita GDP of the ith region in the sample period, and $\overline{Y}$ is the average of the per capita GDP in the sample period. ρ is the spatial spillover coefficient; the meaning of the rest of the variables are the same as Eq. 5.

To further investigate the mechanisms through which the NBDZ affect urban carbon emission efficiency, we have established the following model, drawing on existing research (Li and Du 2021):

$$ME_{it} = \alpha_0 + \alpha_1 NBDZ_{it} + \sum \alpha_j \times X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (12)$$

Among them, ME_{it} represents the mechanism variable, and the meanings of other variables are the same as Eq. 5.

3.3. Data and variable definition

3.3.1. Data source

Considering the availability of data, this paper compiles panel data for prefecture-level cities in China from 2006 to 2019, deliberately excluding data post-2019 to mitigate the confounding effects of the COVID-19 pandemic. The analysis is confined to 268 prefecture-level cities, excluding those that have been newly established, experienced boundary adjustments, or have incomplete data. The dataset is primarily derived from the China City Statistical Yearbook, complemented by various provincial and municipal statistical yearbooks, as well as the EPS database. For the minor gaps in the dataset, missing values were interpolated using trend fitting techniques. Moreover, given the potential for heteroscedasticity in the data, the majority of the data processing was conducted using the ratio method. This approach helps to normalize the data, reducing the impact of scale differences and facilitating a more accurate analysis of the relationships under investigation.

3.3.2. Variable and definition

Input and output variables: According to existing research, the input factors for measuring carbon emission efficiency mainly include capital, labor, and energy, while the outputs comprise both desired and undesired outputs (Haider and Mishra 2021; Wang and Shao 2022). For capital inputs, this paper selects the capital stock as a representation. Since no official survey data on the capital stock in China are currently available, we use the perpetual inventory method to estimate the capital stock of cities (Li and Ma 2021; Lin and Tan 2016); labour input is represented by the number of employees at the end of the year in cities (Guo *et al.* 2018); as major energy consumption data such as coal and oil are not recorded in city-level data in China, we follow the approach of Fu *et al.* (2021) and use city electricity consumption as a proxy for energy input. Desired output is selected as the gross domestic product of cities to reflect economic growth. Undesired output in this paper is measured by the CO_2 emissions of the cities.

Empirical variables: The dependent variable in this paper is urban carbon emission efficiency, abbreviated as CEE. The study uses the implementation of the NBDZ starting in 2016 as a quasi-natural experiment. The dummy variable $Treat_i$ indicates whether a city is part of the experimental group, and the dummy variable $Time_t$ denotes whether the experimental group city implemented the National Big Data Pilot Zones in that year. Hence, the interaction term $Treat_i \times Time_t$ is the core explanatory variable of this paper. To minimise the impact of omitted variables on the model estimation, based on existing research, this paper includes the following control variables: city economic development level (PGDP), marketization level (MR), government intervention (GI), financial development (FI), urbanization level (UR), and population density (DP) (Hu *et al.* 2020; Wang and Shao 2022; Zhu *et al.* 2022). Among these, the level of urban economic development is measured using the natural logarithm of the city's per capita GDP (Murshed *et al.* 2022); the level of marketization is directly represented by the marketization index published in the "Report on the Marketization Index by Provinces in China (2021)" (Fan *et al.* 2011); government intervention is represented by the ratio of fiscal expenditure to GDP (Li and Lin 2017); financial development is assessed based on the ratio of city deposits and loan balances to city GDP, following existing literature (Rasoulinezhad and Taghizadeh-Hesary 2022); the level of urbanization is represented by the proportion of the urban population to the total population (Chai *et al.* 2023; Wang *et al.* 2024); population density is measured using the natural logarithm of the number of people per unit land area in cities (Zhang *et al.* 2023).

To further analyze the mechanisms through which the NBDZ influence urban carbon emission efficiency, the paper tests industrial structure upgrading (ST), technological innovation (TI), and human capital (HC) as mechanistic variables. Industrial structure transformation is measured by an industrial upgrading index, denoted as: S=r1*1+r2*2+r3*3, where S represents the industrial structure upgrading index, and r1, r2, r3 respectively represent the shares of primary, secondary, and tertiary industry outputs in the city's GDP (Wang and Shao 2022). Patent data, reflecting regional research personnel, research funding, and research capabilities, serve as an output indicator of regional innovation inputs and can directly measure regional innovation capabilities. Thus, this paper adopts the practice of using the number of green invention patent applications per 10,000 people as a proxy for the level of technological innovation (Gao *et al.* 2022; Lin and Ma 2022). Human capital is represented by the ratio of the number of regular university students to the total population (Xue *et al.* 2021).

4. Results

4.1. Benchmark model regression

This article utilizes the DID approach to evaluate the policy effects of the NBDZ on urban carbon emission efficiency. To bolster the robustness of the baseline regression analysis, control variables are incrementally incorporated (Gao *et al.* 2024c; Shao *et al.* 2019). **Table 1** presents the detailed regression outcomes. In Model 1, the NBDZ is employed as the sole explanatory variable, with the coefficient being significantly positive at the 1% significance level. These results suggest that the policy has significantly contributed to the enhancement of urban carbon emission efficiency, aligning with the findings of Zhang *et al.* (2022) and thus validating Hypothesis 1. This finding implies that, on one hand, the implementation of the NBDZ has expedited the integration of digital technologies, including big data and artificial intelligence, with traditional industries. This integration has facilitated a gradual transformation of these industries towards digitalization, intelligence, and more environmentally sustainable sectors (Ma *et al.* 2022; Wang and Shao 2024). On the other hand, the policy's implementation, through digitalized management practices, has enhanced production coordination, curbed the excessive consumption of production factors, and consequently improved urban carbon emission efficiency (Thompson *et al.* 2013). These insights underscore the pivotal role of data-centric digital policies in fostering sustainable development and environmental efficiency.

4.2. Parallel trend test

The foundational assumption underlying the use of the DID model for policy effect analysis is the parallel trends assumption (Tan *et al.* 2024). This assumption posits that the treatment and control groups must exhibit identical developmental trajectories prior to the policy's implementation; otherwise, the policy evaluation results derived from the DID model may be compromised (Song *et al.* 2020; Qiu *et al.* 2020). Consequently, this study necessitates a rigorous test of the parallel trends within the research sample. The standard approach for testing parallel trends typically involves incorporating dummy variables for each time period relative to the policy event and interaction terms between these dummies and the policy dummy variable into the regression model. The significance of the coefficients for these interaction terms is then scrutinized. If the interaction term's regression coefficient is non-significant before the policy's implementation and becomes significant thereafter, it suggests that the treatment and control groups adhere to the parallel trends assumption, thereby satisfying a key precondition for the application of the DID model. Consequently, the potential for selection bias to skew the policy evaluation effects is mitigated, enhancing the reliability of the study's conclusions (Roth 2022). This rigorous approach ensures that any observed policy effects are more likely to be attributable to the intervention itself rather than to pre-existing differences between the groups. To ensure the accuracy of the research results, this paper constructs the following model to test the parallel trends:

$$CEE_{it} = \alpha_0 + \sum_{n=-10}^{3} \alpha_n \left(I_{i,t}^{t-setyear_i=n} \times NBDZ_{it} \right) + \sum \beta_j X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{13}$$

In Eq. 13, the value of $I_{i,t}^{t-setyear_i=n}$ is determined as follows: it takes a value of 1 when $t - setyear_i = n$, and 0 otherwise. Here, t represents the year, and $setyear_i$ indicates the year in which city i became a pilot city for the NBDZ. The other variables are consistent with those in Eq. 5.

The results of the parallel trends test are shown in **Figure 3**. Before the implementation of the NBDZ, there were no significant differences in the energy transition development between the treatment group and the control group. However, after the implementation of this pilot policy, the NBDZ significantly promoted urban carbon emission efficiency. This indicates that before the implementation of the NBDZ, the treatment and control groups essentially met the prerequisite of parallel trends, justifying the use of the DID model for empirical testing in this article.

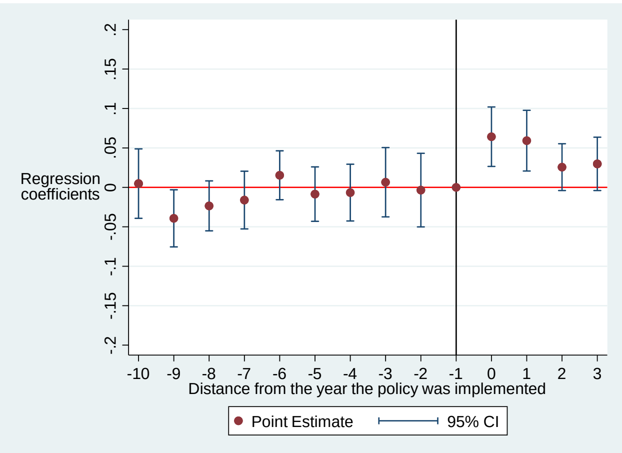


Figure 3. Parallel trend test **Note:** The small dots in the graph represent point estimates, and the upper and lower bounds of the vertical lines represent the 95% confidence interval.

4.3. Placebo test

The comparability between the control and treatment groups is a prerequisite for employing the DID method in this study to analyze the impact of the NBDZ policy on urban carbon emission efficiency. The assumption is that, in the absence of the NBDZ policy, the trend in urban carbon emission efficiency levels between the treatment and control groups would remain consistent over time. Therefore, adhering to the methodology of Yang *et al.* (2020), this article performs 1,000 random samplings across all 268 prefecture-level cities. In each iteration, 66 cities are randomly designated as the pseudo treatment group, with the remaining cities acting as the control group. The modified policy variables are introduced into the original model for regression analysis, and the outcomes are compared to ascertain the policy's effects. As depicted in **Figure 4**, the absolute value of the t-statistic for the majority of the sampling estimation coefficients falls within the range of 2, and the corresponding p-values exceed 0.1. This suggests that environmental information disclosure does not exert a significant influence in these 1,000 random samplings. Consequently, the placebo test is passed, indicating that there is no spurious causal relationship between urban carbon emission efficiency and other unobserved factors. This rigorous placebo test strengthens the credibility of the study's findings by ruling out the influence of confounding variables that could potentially bias the policy evaluation.

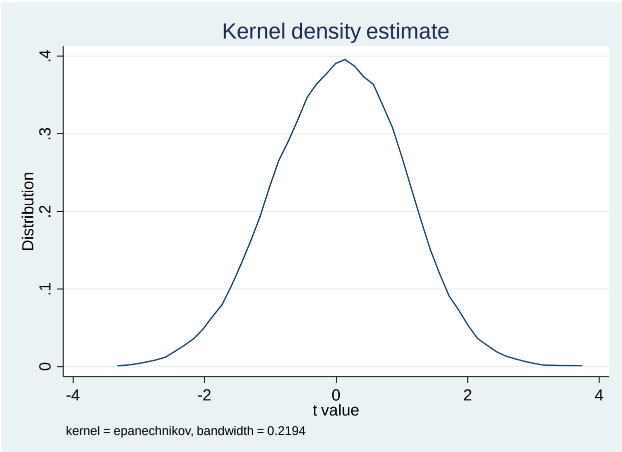


Figure 4. Kernel density distribution

4.4. Robustness test based on PSM-DID method

Another prerequisite for using the DID method is that the selection of the treatment and control groups must be random. Although logically, the implementation of NBDZ seems unaffected by local carbon emission efficiency, it is necessary to conduct a robustness test based on empirical results. Therefore, this paper uses control variables and mechanism variables as covariates and employs the one-to-one nearest neighbor matching method to match the samples of the treatment and control groups, thereby mitigating the issue of selection bias (Wang and Shao 2024). The effectiveness of the propensity score matching method relies on the assumption of balance, meaning there should be no significant differences in the matched characteristic variables between the treatment and control groups. Thus, the following text will test whether the propensity score matching has balanced the distribution of variables between the treatment and control groups. According to the test results in **Table 2**, after matching, there are no significant differences in the means of the covariates between the experimental and control groups. Additionally, as can be visually observed from **Figure 5**, the standardized biases of most variables are reduced after matching. This indicates that the use of the propensity score matching method effectively reduces potential endogeneity and selection biases. According to the regression results in **Table 3**, the sign of the core explanatory variable is consistent with the findings of the baseline regression. In summary, even taking selection bias into account, the implementation of the NBDZ still significantly contributes to urban carbon emission efficiency, highlighting the robustness of the empirical results of this study.

Table 1 Benchmark regression results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NBDZ	0.049^{***}	0.054^{***}	0.056^{***}	0.057^{***}	0.056^{***}	0.054^{***}	0.054^{***}
	(4.55)	(5.06)	(5.26)	(5.30)	(5.22)	(5.12)	(5.06)
PDG		0.088^{***}	0.088^{***}	0.078^{***}	0.067^{***}	0.071^{***}	0.072^{***}
		(7.69)	(7.67)	(6.53)	(5.19)	(5.53)	(5.54)
MR			0.015^{***}	0.016^{***}	0.016^{***}	0.016^{***}	0.016^{***}
			(3.26)	(3.31)	(3.35)	(3.35)	(3.37)
GI				-0.170^{***}	-0.144^{**}	-0.159^{***}	-0.158^{***}
				(-3.00)	(-2.49)	(-2.76)	(-2.74)
FI					-0.010^{**}	-0.009^{**}	-0.009^{**}
					(-2.25)	(-2.14)	(-2.14)
UR						-0.189^{***}	-0.189^{***}
						(-4.27)	(-4.26)
DP							0.161
							(0.91)
City-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3752	3752	3752	3752	3752	3752	3752
R^2	0.3791	0.3895	0.3914	0.3930	0.3939	0.3970	0.3972

*Note: ***p<0.01, **p<0.05, *p<0.1.*

Table 2. Common support test of PSM-DID method

Variables	Sample	Mean		Reduct		T-test	
		Treatment	Control	bias (%)	|bias| (%)	T value	P>|T|
PGDP	Unmatched	10.744	10.344	44.9	81.2	7.65	0.000
	Matched	10.726	10.650	8.5		0.94	0.346
MR	Unmatched	12.807	10.222	112.3	87.1	15.53	0.000
	Matched	12.812	13.144	-14.4		-1.85	0.065
GI	Unmatched	0.189	0.172	22.7	78.3	3.21	0.001
	Matched	0.189	0.194	-4.9		-0.45	0.653
FI	Unmatched	2.862	2.221	51.4	87.8	8.53	0.000
	Matched	2.846	2.768	6.3		0.68	0.495
UR	Unmatched	0.604	0.509	57.7	83.2	9.10	0.000
	Matched	0.5951	0.6028	-5.2		1.20	0.231
DP	Unmatched	0.065	0.043	51.2	59.9	9.76	0.000
	Matched	0.064	0.055	20.6		2.25	0.025
TI	Unmatched	1.669	0.440	43.5	65.7	13.26	0.000
	Matched	1.491	1.069	14.9		1.84	0.067
HC	Unmatched	0.022	0.017	18.4	61.1	3.16	0.002
	Matched	0.022	0.020	7.2		0.82	0.414
ST	Unmatched	2.396	2.263	94.0	92.5	14.25	0.000
	Matched	2.395	2.385	7.1		0.85	0.396

4.5. Other robustness tests

To ensure the robustness of the empirical findings, this article conducts additional robustness checks through the following methodologies: (1) Acknowledging the distinctive characteristics of the four municipalities—Beijing, Tianjin, Shanghai, and Chongqing—these cities were excluded from the comprehensive sample. Subsequently, the reduced sample size was reintroduced into the model for regression analysis to verify the stability of the results (Li *et al.* 2022b). This exclusion is justified by the unique administrative and economic status of these municipalities, which may influence the generalizability of the findings to other prefecture-level cities in China. By conducting sensitivity analyses with and without these municipalities, the study aims to provide a more nuanced understanding of the policy effects across different urban contexts.

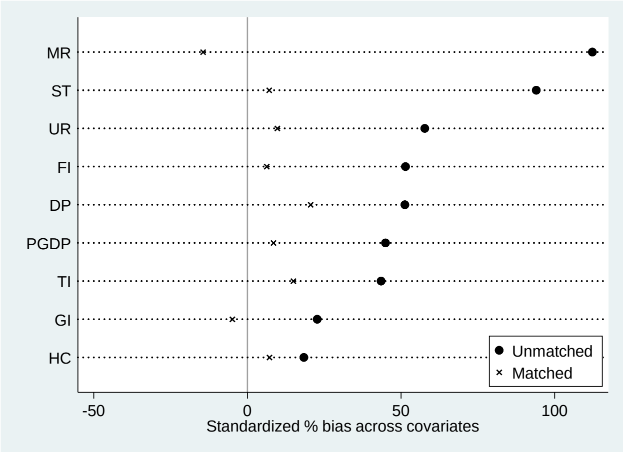


Figure 5. Standardized deviation diagram of each variable

Table 3 PSM-DID regression results

Variables	(1)	(2)
NBDZ	0.081*	0.078
	(1.74)	(1.62)
Control variables	No	Yes
City-FE	Yes	Yes
Time-FE	Yes	Yes
Observations	447	447
R^2	0.4741	0.4973

*Note: ***p<0.01, **p<0.05, *p<0.1.*

(2) To mitigate the influence of extreme values, the top and bottom 1% of all continuous variables were subjected to winsorization, a statistical technique that involves capping extreme values at a specified percentile. Following this procedure, the baseline model was re-estimated to ensure that the results are not unduly influenced by outliers, thereby enhancing the reliability of the findings (Guo *et al.* 2023). This methodological approach is crucial for maintaining the integrity of the regression analysis by reducing the potential distortion caused by data points that deviate significantly from the rest of the distribution.

(3) To achieve more robust empirical results, this paper further considers that other policies on urban development during the sample period might interfere with the causal identification of the study. Therefore, based on documents issued by the National Development and Reform Commission and the Ministry of Housing and Urban-Rural Development, two overlapping policies with the research sample were collected and organized: the "Broadband China" strategy (BCS) and the Low-Carbon City Pilot (LCCP). Accordingly, the paper incorporates dummy variables representing the aforementioned policies into the control variables and re-estimates the baseline model (Wang and Wang 2023).

The outcomes of the aforementioned robustness tests, as delineated in **Table 4**, reveal that the directional signs of the core explanatory remain invariant, thereby underscoring the robustness of the baseline regression findings presented in this study. These consistent results across various methodological checks provide compelling evidence of the stability and reliability of the estimated effects.

Table 4 Other robustness test results

Variables	(1)	(2)	(3)	(4)	(5)
NBDZ	0.040***	0.050***	0.054***	0.054***	0.054***
	(3.58)	(4.74)	(5.05)	(5.06)	(5.03)
BCS			Yes	No	Yes
LCCP			No	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
City-FE	Yes	Yes	Yes	Yes	Yes
Time-FE	Yes	Yes	Yes	Yes	Yes
Observations	3696	3752	3752	3752	3752
R^2	0.3904	0.3990	0.3940	0.3942	0.3949

*Note: ***p<0.01, **p<0.05, *p<0.1.*

Table 5 Quantile regression results

	(1)	(2)	(3)
Variables	Q10	Q25	Q50
NBDZ	0.159***	0.081***	0.005**
	(7.42)	(4.61)	(2.11)
_cons	1.067***	1.211***	1.027***
	(5.91)	(17.80)	(83.21)
Control variables	Yes	Yes	Yes
Observations	3752	3752	3752
R^2	0.0884	0.0767	0.0015

*Note: ***p<0.01, **p<0.05, *p<0.1.*

4.6. Nonlinear analysis

In previous research, the main focus was on examining the impact of the explanatory variable x on the conditional expectation E (y | x) of the response variable y, i.e., mean regression. In actual studies, the real interest lies in the effect of the explanatory variable on the entire conditional distribution y | x. However, the conditional expectation E (y | x) only characterizes one aspect of the central tendency of the conditional distribution y | x. If the conditional distribution y | x is not symmetrical, then the conditional expectation E (y | x) will struggle to reflect the entire scope of the conditional distribution. Therefore, Koenker and Bassett (1978) introduced the quantile regression method, which uses the weighted average of the absolute values of the residuals as the objective function to minimize. This method is less affected by outliers, making the regression results more robust.

In order to accurately depict the asymmetric impact of the NBDZ on urban carbon emission efficiency and effectively capture the tail characteristics of the distribution between NBDZ and urban carbon emission efficiency, this chapter next utilizes quantile regression. It estimates the quantile equations affected by NBDZ at the 0.1, 0.25, and 0.5 quantiles respectively. As indicated by the regression results in **Table 5**, the absolute value of the quantile regression coefficients for the new energy demonstration city policy decreases as the quantiles increase. That is, at different developmental stages of urban carbon emission efficiency, the marginal effects of the NBDZ are dynamically changing and show a decreasing trend. This suggests that the NBDZ have a more pronounced effect on enhancing urban carbon emission efficiency at lower levels, thus providing cities still at lower levels of urban carbon emission efficiency with opportunities to catch up, which is beneficial in narrowing regional disparities.

Table 6 Heterogeneity analysis results

Variables	Eastern	Central and Western	Non-resource-based	Resource-based	Small and medium	Large
NBDZ	0.068^{***}	0.021	0.059^{***}	0.027	0.033^{**}	0.061^{***}
	(5.07)	(1.43)	(4.74)	(1.55)	(2.35)	(4.32)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
City-FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3752	3752	3752	3752	3752	3752
R^2	0.3972	0.3931	0.3966	0.3931	0.3937	0.3960

*Note: ***p<0.01, **p<0.05, *p<0.1.*

Table 7 SDMDID model suitability test

Test type	Statistical value	P value
Wald_ spatial_ lag	47.74	0.0000
LR_ spatial_ lag	47.52	0.0000
Wald_ spatial_ error	38.02	0.000
LR_ spatial_ error	50.58	0.0000
Hausman Test	101.64	0.0000

Table 8 SDMDID regression results

Variables	Geographical matrix	Economic matrix
NBDZ	0.058^{***}	0.060^{***}
	(5.56)	(5.76)
ΣW_{ij}NBDZ	0.146^{***}	0.038
	(2.81)	(1.51)
Control Variables	Yes	Yes
Spatial-rho	0.278^{***}	0.093^{***}
	(3.78)	(3.26)
sigma2-e	0.015^{***}	0.016^{***}
	(42.91)	(42.89)
Direct effect	0.059^{***}	0.061^{***}
	(5.58)	(5.81)
Indirect effect	0.198^{***}	0.041^{*}
	(3.62)	(1.83)
Total effect	0.257^{***}	0.102^{***}
	(4.64)	(4.24)
City-FE	Yes	Yes
Time-FE	Yes	Yes
Observations	3682	3682
R^2	0.0649	0.0524

*Note: ***p<0.01, **p<0.05, *p<0.1.*

4.7. Heterogeneity analysis

The analysis presented above indicates that, overall, the NBDZ have exerted a significant influence on enhancing carbon emission efficiency. On one hand, as a pivotal catalyst in the new technological revolution, the NBDZ profoundly shape the economic development paradigm of cities, with this impact exhibiting distinct heterogeneity across different entities. On the other hand, given China's extensive geographical expanse and intricate social characteristics, there are pronounced disparities among cities in terms of natural geography, economic development, and resource endowment (Ma and Lin 2023). Consequently, examining the diverse effects of the NBDZ on carbon emission efficiency has emerged as a critical area of focus for comprehending this heterogeneity. Building on this foundation, this paper further dissects the heterogeneous impacts of the NBDZ on carbon emission efficiency across three dimensions: urban location, urban attributes, and city size. By adopting a multifaceted approach, the study aims to provide a more nuanced understanding of how the NBDZ policy influences carbon emission efficiency in different urban contexts. This granular analysis is essential for tailoring policy interventions to the specific needs and characteristics of each city, thereby maximizing the policy's effectiveness in promoting sustainable development and environmental efficiency.

The regression results from **Table 6** show that, firstly, the coefficients for the Eastern region are significantly positive at the 1% level and above, while in the Central and Western regions, the coefficients are also positive but not significant. This may be because cities in the Eastern region have clear advantages in infrastructure, labor quality, transportation, and innovation (Zhang *et al.* 2023), providing a solid material basis for the national-level big data comprehensive pilot zones, thereby stimulating policy effects. In contrast, the Central and Western regions face many challenges due to uneven terrain, sparse populations, and underdeveloped economic conditions, which hinder the construction of national-level big data comprehensive pilot zones. Additionally, the industries in these regions are more dispersed and lack scalability (Dong *et al.* 2018), thus limiting the policy effects of the NBDZ. Secondly, the regression coefficients for non-resource-based cities are significantly positive, whereas for resource-based cities, the coefficients are not significant. The likely reason is that cities based on resources are more dependent on energy-intensive and highly polluting industries related to traditional resources, making it difficult to adjust the industrial structure. They also compete for capital and talent with other emerging industries, exacerbating the "resource curse," thus inhibiting the ability of the NBDZ to enhance urban carbon emission efficiency. Lastly, regardless of whether they are small or large cities, the core explanatory variable's coefficients are significantly positive at the 5% level and above. However, for large cities, the absolute values of the coefficients are greater than those for small and medium-sized cities, indicating that the NBDZ have a higher impact on enhancing carbon emission efficiency in large cities than in smaller ones.

4.8. Spatial spillover effect test

Previous research has shown that the implementation of NBDZ has a significant promoting effect on enhancing carbon emission efficiency. However, an implicit assumption of the DID model is that no individual will be affected by the treatment status of others, hence neglecting the spatial interdependence among study units could lead to biased estimation results. Based on this, this paper utilizes the SDM-DID model to examine the impact of the implementation of NBDZ on local and neighboring carbon emission efficiency.

In order to investigate whether the SDM-DID model degenerates into the Spatial Autoregressive DID (SAR-DID) and Spatial Error Model DID (SEM-DID) models, the simplification test for spatial econometric models is carried out following the testing approach by Elhorst (2014). **Table 7** reports the specific test results, with both the Wald test and the LR test rejecting the null hypothesis, indicating that the use of the SDM-DID model is appropriate. In conjunction with the Hausman test results, this paper uses a model with time and spatial fixed effects for estimation. Considering that the spatial autoregressive model has some endogeneity issues, if OLS estimation is used, it would result in some bias in the estimation results. Therefore, this paper opts to estimate the SDM-DID model using the maximum likelihood method. **Table 8** displays the regression results of the SDM-DID model, showing that the implementation of the NBDZ has a positive effect on enhancing carbon emission efficiency, further validating Hypothesis 1.

Additionally, the coefficient of the spatial lag term of the NBDZ, denoted as, $\sum W_{ij} NBD$, is 0.146 and significant at the 1% level, indicating that the implementation of the NBDZ affects not only the local urban carbon emission efficiency but also has a significant spatial spillover effect. The conclusions obtained from the regression using the economic distance matrix are similar, demonstrating that the model's regression results possess a certain degree of robustness.

Since the regression coefficients of the SDM-DID model do not reflect the magnitude of the spatial spillover effects, to further measure the direct effects and spatial spillover effects of the implementation of the NBDZ on carbon emission efficiency, this paper employs the partial differential approach as proposed by Pace and LeSage (2009). The specific calculation results are shown in **Table 8**. Both the direct and indirect effects' coefficients are significantly positive, indicating that the NBDZ have a significant positive spillover effect. They not only enhance the carbon emission efficiency of the pilot cities but also drive improvements in the neighboring cities. The findings suggest that the implementation of the NBDZ does not lead to predatory behavior by pilot cities towards neighboring cities. Instead, by establishing a normalized knowledge feedback mechanism and an information-sharing platform, pilot cities strengthen inter-city collaborative cooperation. This, on one hand, accelerates the cross-regional transfer and flow of knowledge and information technology, and on the other hand, optimizes the spatial allocation of information and innovative resource elements. This facilitates the spillover and diffusion of knowledge and technology, thereby impacting the enhancement of urban carbon emission efficiency in neighboring cities and playing a positive role in promoting "demonstration-led collaborative development."

4.9. Mechanism analysis

The empirical analysis and robustness checks delineated previously demonstrate that the implementation of NBDZ can significantly enhance urban carbon emission efficiency. However, the specific policy mechanisms underlying this effect remain to be established. To gain a more profound comprehension of the nexus between the implementation of NBDZ and urban carbon emission efficiency, this paper delves into the potential mechanisms through which the NBDZ policy exerts its influence on urban carbon emission efficiency. This exploration is crucial for elucidating the pathways through which the NBDZ policy contributes to environmental efficiency improvements. By identifying the key mechanisms, policymakers can design more targeted and effective interventions to harness the full potential of big data in promoting sustainable development. Furthermore, this analysis can provide valuable insights into the conditions under which the NBDZ policy is most likely to succeed, thereby informing the strategic allocation of resources and the prioritization of policy efforts.

According to the regression results shown in **Table 9**, column (1) indicates that NBDZ have a significant positive impact on technological innovation. The implementation of these zones reduces the cost of technological innovation and enhances the innovative vitality of industries and enterprises, thereby facilitating an increase in carbon emission efficiency, thus validating Hypothesis 3. Column (2) shows that the NBDZ have a positive effect on enhancing human capital. Their implementation speeds up information acquisition, strengthens regional knowledge spillover, accelerates the accumulation of human capital, and improves the quality of human capital. Column (3) reveals that the NBDZ have not significantly promoted the upgrading of industrial structures. The likely reason is that industrial upgrading emphasizes the optimization of existing industrial efficiency and productivity, which is a lengthy process. Thus, to date, the impact of NBDZ on promoting industrial structure upgrades remains unclear.

Table 9 Mechanism test

Variables	TI	HC	ST
NBDZ	0.485^{***}	0.001^{***}	-0.005
	(6.57)	(2.64)	(-1.47)
Control variables	Yes	Yes	Yes
City-FE	Yes	Yes	Yes
Time-FE	Yes	Yes	Yes
Observations	3752	3752	3752
R^2	0.6798	0.9608	0.9271

*Note: ***p<0.01, **p<0.05, *p<0.1.*

5. Conclusions and policy implications

In light of the recent degradation of environmental conditions and the ensuing heightened public concern for health, the shift in developmental paradigms and the reduction of pollution emissions have become pivotal for achieving sustainable development in both the present and the future. The burgeoning digital economy is at the forefront of this transformation, driving innovations in production technologies and industrial activities. This digital revolution provides a novel impetus for the reduction of urban carbon emissions and the advancement of sustainability initiatives. The integration of digital technologies into traditional sectors not only enhances operational efficiencies but also facilitates more sustainable practices. By optimizing resource allocation and enabling real-time monitoring and management, the digital economy can significantly contribute to the mitigation of environmental impacts. Therefore, this paper views the implementation of NBDZ as a quasi-natural experiment, empirically examining the impact of data-centric digital policies on urban carbon emission efficiency. The research findings indicate: (1) NBDZ significantly promote urban carbon emission efficiency. This conclusion remains valid after undergoing placebo tests and excluding other policy interferences. (2) Nonlinear regression results demonstrate that the marginal effect of NBDZ on urban carbon emission efficiency varies dynamically at different levels, showing a continuous declining trend. (3) Heterogeneity tests reveal that NBDZ can significantly promote energy transition development in eastern regions, non-resource-based cities, and large cities, but their impact on central and western regions and resource-based cities is not significant. (4) Spatial effects tests find that the implementation of NBDZ does not lead to predatory behavior of pilot cities towards adjacent cities. On the contrary, this pilot policy promotes the spatial diffusion of technological innovation in pilot cities to a certain extent, playing a positive role in "demonstration to promote coordinated development." (5) The mechanism analysis suggests that NBDZ can affect energy transition development by enhancing levels of human capital and technological innovation.

Drawing from the research findings presented herein, this paper consequently centers on formulating targeted recommendations for the refinement of digital policy action mechanisms and for fostering the augmentation of urban carbon emission efficiency. The aim is to provide actionable insights that can guide policymakers in enhancing the efficacy of digital policies, thereby contributing to more sustainable environmental outcomes. Firstly, it is necessary to further expand the scope of NBDZ to facilitate the rapid development of the digital economy. The research in this paper indicates that data-centric digital policies not only contribute to economic growth but also help achieve the goal of low-carbon transformation and development. Therefore, the scope of NBDZ should be expanded to allow their successful experiences to generate positive policy effects over a wider range. Accelerating the depth and breadth of integration between data elements and traditional industries will spur the emergence of new industries and development models, continually enhancing industrial and value chains.

Secondly, it is important to reasonably promote the process of NBDZ, tailoring the approach to local conditions and guiding the process according to the situation to enhance its flexibility and inclusiveness. Based on the geographical location, resource endowment, and economic development of each city, targeted development plans for NBDZ should be formulated, and efforts should be made to ensure alignment with other plans. Furthermore, it is essential to strengthen cross-regional cooperation in the digital economy and expand channels for inter-regional dialogue and collaboration. As regions continuously promote the deep integration of the digital economy with the traditional economy, they should also enhance cross-regional cooperation and assistance. Leveraging the advantages of the digital economy in information dissemination and resource allocation, promoting the cross-regional flow of production factors within the digital economy, and effectively harnessing spatial spillover effects are crucial.

Lastly, exploring multidimensional pathways for NBDZ to enhance carbon emission efficiency. On one hand, efforts should focus on promoting interregional green innovation cooperation to improve the efficiency of transforming new green innovation achievements. On the other hand, enhancing relevant supporting systems and measures to create a conducive environment for accelerating the development of human capital. Additionally, expediting the elimination of outdated production capacity, facilitating the low-carbon transformation of traditional "three-high" industries, guiding the aggregation of high-tech industries to form smart industry clusters, optimizing urban industrial layout, and driving industrial structural upgrading are essential.

However, this study still has some limitations. Concerning variable selection, although an attempt was made to cover some key variables for measuring digital policy and the urban carbon emission efficiency, some potentially important influencing factors may still have been omitted. In terms of data, the study may have utilised data from a specific time period or region only, which could limit the generalisability of the findings. Therefore, future research could explore the following directions. In terms of data refinement, integrating multi-source data could enable the construction of richer and more precise datasets, thereby providing robust support for in-depth studies. In the realm of variable expansion, further exploration could involve incorporating additional variables that may influence the relationship between digital policy and urban carbon emission efficiency.

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Declaration of Competing Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Author statement

Lianghu Wang conceived and designed the research question. Lianghu Wang constructed the models and analyzed the optimal solutions. Lianghu Wang wrote the paper. Jun Shao reviewed and edited the manuscript. All authors have read and agreed to the published version of the manuscript.

Author Biography

Dr. Wang has published more than 20 papers in journals such as Socio-Economic Planning Sciences, Journal of the Knowledge Economy, Energy, Energy & Environment, Environment Development and Sustainability. Dr. Wang has participated in 2 Major programs of National Social Science Foundation of

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Professor Shao has published 80 papers in journals such as Economic Research Journal, Technological Forecasting and Social Change, Energy Policy, China & World Economy, Journal of Cleaner Production, Journal of the Knowledge Economy, Energy, Energy & Environment, Environment Development and Sustainability. Dr. Shao has presided over many national and provincial scientific research projects, such as Major programs of National Social Science Foundation of China, the National Natural Science Foundation project of China, and some of his research outcomes have been adopted by government departments.

Appendix

Abbreviations	Full name
NBDZ	National Big Data Comprehensive Pilot Zone
MFNDDF	Meta-frontier Non-radial Directional Distance Function
DID	Difference-in-Differences
ICT	Information and Communication Technologies
SDM	Spatial Durbin Model
SBM	Slacks-Based Measure
DEA	Data Envelopment Analysis
SFA	Stochastic Frontier Analysis
GVC	Global Value Chain
TFP	Total Factor Productivity
DMU	Decision-Making Unit
GDP	Gross Domestic Product
VRS	Variable Scale Return
PSM	Propensity Score Matching
BCS	Broadband China Strategy
LCCP	Low-Carbon City Pilot
SAR	Spatial Autoregressive
SEM	Spatial Error Model

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