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Quantity Reduction and Quality Improvement: Assessing the Carbon Effects of China's National Big Data Comprehensive Pilot Zone Policy for Sustainable Development

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Abstract

Promoting low-carbon and sustainable development has become an important policy objective in the context of digital transformation. Using China's National Big Data Comprehensive Pilot Zone (NBDCPZ) policy as a quasi-natural experiment, this study employs a staggered difference-in-differences approach to examine the policy's effects on carbon emission quantity and carbon emission quality. The results show that the NBDCPZ reduces carbon emission quantity by 12.3% and improves carbon emission quality by 2.6%. These effects are more pronounced in the central and eastern regions and in areas with stronger government support. The analysis suggests that the NBDCPZ may affect carbon outcomes through green technological innovation and energy structure adjustment.

Keywords: National Big Data Comprehensive Pilot Zone; sustainable development; carbon performance; green technological innovation; energy structure

1. Introduction

Energy conservation and emission reduction pose a major challenge to sustainable development worldwide [1]. As global climate change intensifies and increasingly affects both ecosystems and socioeconomic systems, governments and international organizations have introduced a wide range of policies to curb greenhouse gas emissions and promote environmental sustainability [2,3]. Although various policy instruments can generate short-term effects, sustained emission reduction and long-run sustainability may depend more fundamentally on technological progress, particularly in digital technologies [4]. In this context, the digital economy is reshaping traditional modes of economic operation and driving broad economic and social transformation [5]. By fostering new business models, new industries, and new organizational forms, the digital economy promotes industrial upgrading and structural transformation [6]. These changes generate not only economic gains but also new opportunities for environmental protection, low-carbon transition, and sustainable development. By supporting green development and the circular economy, the digital economy is expected to play an important role in addressing environmental challenges and advancing sustainability [6].

Existing studies suggest that the digital economy affects carbon emissions through multiple channels, including industrial upgrading, economic growth, and energy use [7,8].

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Empirical research in this area has adopted different approaches. One strand of the literature incorporates digital economy indicators into econometric models to evaluate carbon outcomes and provides important evidence on their environmental implications [9,10]. Another strand focuses on policy-driven effects and shows that digital-economy-related initiatives can also reduce emissions [11,12]. Overall, the existing literature provides valuable insights into the determinants of CO_2 emissions, their relationship with digital economy development, and the sustainability implications of digital transformation.

Despite this progress, two limitations remain. First, much of the existing literature relies on indicator-based measures of regional digital economy development, which may raise endogeneity concerns, while causal evidence based on policy shocks remains relatively limited. Second, existing studies have focused mainly on a single dimension of carbon outcomes and have rarely examined carbon emission quantity and carbon emission quality simultaneously. Therefore, evidence on the effects of a digital economy policy on both dimensions remains scarce.

Against this background, China offers an appropriate setting for further analysis. In recent years, China has placed increasing emphasis on digital transformation as a means of promoting broader economic and social development through big data and related technological innovation. In this context, the Chinese government launched the NBDCPZ as a policy initiative to promote the application of big data, stimulate innovation in related technologies, and facilitate the integration of these technologies across industries and sectors [13,14]. A growing body of research has examined the NBDCPZ from different perspectives, including city-level carbon emissions [15], corporate low-carbon innovation [16], city eco-efficiency [17–20], and firm-level outcomes such as ESG performance and manufacturing resilience [21,22]. These studies provide an important foundation for understanding the economic and environmental consequences of the NBDCPZ, but evidence on its sustainability effects through simultaneous changes in carbon emission quantity and carbon emission quality remains limited.

Accordingly, this study aims to examine whether and how the NBDCPZ affects CO_2 emissions in terms of carbon emission quantity and carbon emission quality. To strengthen causal inference, the analysis considers potential reverse causality and omitted-variable bias. In addition, the 1984 level of total urban postal and telecommunication services serves as an instrumental variable (IV) to mitigate endogeneity concerns. We also conduct a series of diagnostic and robustness checks, including event-study analysis, sensitivity analysis of the parallel trends assumption, Bacon decomposition, PSM-DID estimation, placebo tests, and additional specification checks, to examine whether the results hold under alternative settings.

This study makes three contributions. First, this study provides a more comprehensive assessment of the environmental effects of the NBDCPZ by jointly examining carbon emission quantity and carbon emission quality. Existing studies have explored related issues from different perspectives. For example, some studies discuss the broader economic and innovation implications of digital development [23], the joint relationship among digital development, energy structure, and carbon emissions [24], and the effect of big data pilot policies on corporate sustainability [25]. Other studies focus more directly on environmental performance, such as carbon emission efficiency [26,27] and green total factor productivity [28]. However, these studies generally focus on a single outcome dimension. By jointly considering carbon emission quantity and carbon emission quality, this study extends the literature by providing a broader assessment of the carbon effects of the NBDCPZ.

Second, existing literature often relies on composite indices [29], value-added or accounting-based measures [30], and text-based proxies to capture the digital economy.

While these approaches provide useful information on the level or characteristics of digital development, they may also be subject to limitations such as subjective index construction, dependence on accounting assumptions, or measurement error in text-based proxies. By contrast, this study identifies the carbon effects of the NBDCPZ from the perspective of a policy shock. By exploiting the staggered implementation of the NBDCPZ as a quasi-natural experiment, this study is able to more directly examine the causal effects of the policy on carbon emission quantity and carbon emission quality, thereby alleviating concerns related to measurement error and endogeneity in proxy-based approaches.

Third, this study examines the mechanisms through which the NBDCPZ may affect CO_2 emissions, with a focus on energy structure optimization and green technological innovation. By clarifying these mechanisms, the paper deepens understanding of the environmental effects of the NBDCPZ and provides policy implications for governments and enterprises seeking to promote low-carbon development.

2. Policy Background and Theoretical Analysis

2.1. Policy Background

The Chinese government launched the NBDCPZ policy to promote big data innovation and related technological applications. In September 2015, the State Council issued the Outline of Action for Promoting the Development of Big Data, which explicitly called for the development of comprehensive big data pilot zones in regions such as Guizhou. In February 2016, Guizhou Province was approved to establish the first NBDCPZ. Later that year, the second batch of pilot zones was announced, including Beijing, Tianjin, Hebei, Inner Mongolia, Shenyang, Henan, Shanghai, Chongqing, and Guangdong. These pilot zones covered several categories, including cross-regional pilots, regional demonstration pilots, and pilots for the integrated development of big data infrastructure. Although the specific roles of these pilot zones differ, they share a common objective, namely, to promote big data innovation and application through a set of policy measures. This policy therefore provides a useful setting for examining the effects of the NBDCPZ on carbon emission quantity and carbon emission quality.

2.2. Direct Effect of NBDCPZ on Carbon Mitigation Performance

The establishment of the NBDCPZ may promote carbon mitigation by accelerating digital technology adoption. As a policy initiative centered on the application of big data and digital transformation, the NBDCPZ promotes the use of big data and related digital technologies in production, resource allocation, and industrial upgrading [29,30]. These changes can improve production efficiency, reduce unnecessary energy consumption, and support the low-carbon transformation of traditional industries [31]. In addition, the NBDCPZ may foster new business models and innovation, thereby improving resource utilization and reducing production costs. Through better information processing, data sharing, and digital coordination, firms and local economies may optimize production decisions and energy use, thereby reducing carbon emissions and improving low-carbon performance [32,33]. Accordingly, we propose the following hypothesis:

Hypothesis 1: *The establishment of the NBDCPZ reduces carbon emission quantity and improves carbon emission quality.*

2.3. The Role of Green Technological Innovation

New growth theory emphasizes the importance of knowledge accumulation in technological innovation. With the rapid development of big data technologies and more efficient information transmission, the efficiency of knowledge production, diffusion, and

application can improve, thereby increasing the overall stock of knowledge in society. The improvement in knowledge production, diffusion, and application helps attract innovation factors and enhance regional technological capability. At the firm level, digital technologies can accelerate knowledge diffusion and reduce the cost of information acquisition, storage, and use, making it easier for firms to transform knowledge into innovative outcomes [34]. As a result, both the external innovation environment and firms' internal knowledge accumulation may improve, thereby promoting green technological innovation. In addition, digital technologies help reduce barriers to information exchange and mitigate the geographical constraints faced by green innovation actors. Digital technologies can strengthen communication among firms, universities, and research institutions, accelerate knowledge spillovers, and promote information sharing, thereby enhancing innovation capability across different actors. This process contributes to the development of cleaner and less polluting technologies and products, which help reduce carbon emissions during production [35]. Based on the above arguments, we propose the following hypothesis:

Hypothesis 2: *The establishment of the NBDCPZ reduces carbon emission quantity and improves carbon emission quality through the promotion of green technological innovation.*

2.4. The Role of Energy Structure

The NBDCPZ may also affect carbon outcomes through adjustments in the energy structure. By promoting the application of big data and related digital technologies, the NBDCPZ may improve the collection, monitoring, and analysis of information on energy production, consumption, and distribution, thereby helping identify patterns and trends in energy use. This, in turn, may enhance the ability of local governments, firms, and energy systems to forecast demand, optimize energy allocation, and make more efficient decisions regarding energy use, which can facilitate adjustments in the energy structure [36].

At the same time, the NBDCPZ may foster the development of technology- and knowledge-intensive sectors and promote the digital upgrading of energy-intensive production processes. In heat-intensive industries, digital technologies can improve process monitoring, advanced process control, and real-time optimization, thereby reducing fuel consumption and improving thermal efficiency. For example, research on cement kilns shows that advanced process control, especially model predictive control, can improve process stability and energy performance in one of the most energy-intensive thermal processes in manufacturing [37]. Case evidence from rotary kiln operations further shows that economic model predictive control can optimize coal consumption and improve carbon-related performance in high-temperature industrial production [38]. Similar digital-twin-based approaches have also been applied in steelmaking to improve process monitoring, shorten refining time, and enhance production efficiency [39]. These examples suggest that digital technologies may reduce dependence on coal-intensive energy use not by directly replacing thermal processes, but by improving the control, coordination, and efficiency of such processes.

Moreover, pilot areas are often located in cities or urban agglomerations where the application of big data technologies can support smart-city development. By integrating information from energy, transportation, buildings, and other urban sectors, smart-city development may improve resource allocation and urban governance, enhance energy efficiency, and create more favorable conditions for the low-carbon transition. Taken together, these channels suggest that energy structure adjustment may represent an important mechanism through which the NBDCPZ affects carbon outcomes. Based on the above arguments, we propose the following hypothesis:

Hypothesis 3: *The establishment of the NBDCPZ reduces carbon emission quantity and improves carbon emission quality through the optimization of the energy structure.*

3. Methodology

3.1. Empirical Strategy

Because the NBDCPZ was implemented at different points in time across pilot regions, this study adopts a staggered DID design to identify its policy effects. Specifically, the DID framework compares changes in carbon outcomes between pilot cities and non-pilot cities before and after policy implementation, while exploiting variation in treatment timing across cities. This design helps isolate the effect of the NBDCPZ from time-invariant city characteristics and common shocks affecting all cities in a given year. Our sample consists of 279 Chinese cities, including 67 pilot cities and 212 non-pilot cities. The 67 pilot cities are identified based on the list of pilot regions announced in the Outline of Action for Promoting the Development of Big Data issued by the State Council. Specifically, when a pilot region is designated at the provincial or cross-regional level, the prefecture-level cities covered by that pilot region are coded as treated cities in the city-level panel. The control group consists of the remaining prefecture-level cities in the cleaned sample. In coding the treatment timing, we follow the actual onset of substantive policy implementation rather than formal approval alone. Since Guizhou began pilot zone construction in September 2015, earlier than the other pilot regions, we code 2015 as the policy year for Guizhou and 2016 for the other pilot regions. Based on this staggered implementation schedule, the empirical model is specified as follows:

$$lnCO_{2it} = \alpha_1 + \alpha_2 DID_{it} + \alpha_3 X_{it} + \delta_i + \gamma_t + \varepsilon_{it} \quad (1)$$

$$lnCTFP_{it} = \beta_1 + \beta_2 DID_{it} + \beta_3 X_{it} + \varphi_i + \rho_t + u_{it} \quad (2)$$

where $lnCO_{2it}$ and $lnCTFP_{it}$ represent carbon emission quantity and carbon emission quality, respectively; DID_{it} is the policy dummy variable; and X_{it} is a vector of control variables, defined below. δ_i and φ_i denote city fixed effects, while γ_t and ρ_t denote time fixed effects. ε_{it} and u_{it} are the error terms, and α_1 and β_1 are the constant terms. The coefficients of interest are α_2 and β_2, which reflect the policy effects. If $\alpha_2 < 0$, the establishment of the NBDCPZ reduces carbon emission quantity; if $\beta_2 > 0$, the establishment of the NBDCPZ improves carbon emission quality.

3.2. Data and Variables

3.2.1. Data

The data mainly come from the annual editions of the China City Statistical Yearbook (2011–2024), corresponding to city-level observations for 2010–2023. Cities with substantial missing values were excluded to ensure data quality and the reliability of the empirical analysis.

The data were processed as follows. First, to reduce the influence of outliers, all continuous variables were winsorized at the 1st and 99th percentiles. Second, to adjust for inflation, all price-related variables were deflated to constant 2010 prices. Third, for continuous variables with a small number of missing observations, this study imputes the missing values using linear interpolation between adjacent years within the same city. Specifically, when a variable is missing only for a short period in an intermediate year, and observations are available for both the preceding and following years, the missing value is estimated based on the linear trend implied by the two adjacent observations. In a few cases where this approach is not applicable, moving-average interpolation is used as a supplementary method. The main reason for adopting linear interpolation is that this

study uses annual city-level panel data, in which most variables exhibit a certain degree of temporal continuity, while the proportion of missing values is low and the missing intervals are short. Compared with more complex imputation methods, linear interpolation allows us to make transparent use of available information without introducing strong additional modeling assumptions.

3.2.2. Dependent Variables

1. Carbon emission quantity: We measure carbon emission quantity as the logarithm of CO_2 emissions. The estimation follows the IPCC guidelines:

$$CO_2 = C_n + C_p + C_e = kE_n + \varsigma E_p + \vartheta(\eta \times E_e) \quad (3)$$

where E_n, E_p, and E_e denote the city-level consumption of natural gas, liquefied petroleum gas, and electricity, respectively. In the empirical calculation, the CO_2 emission coefficients for natural gas, liquefied petroleum gas, and electricity-related emissions are set to 2.1622 kg CO_2/m^3, 3.1013 kg CO_2/kg, and 1.3023 kg CO_2/kWh, respectively. Here, η denotes the share of coal-fired power generation in total power generation. Following the IPCC methodology, these emission coefficients are treated as fixed parameters. By contrast, η is not assumed to be constant, but is measured using year-specific dynamic data so as to reflect changes in the regional energy structure over the sample period.

2. Carbon emission quality: In this study, carbon emission quality is measured by carbon total factor productivity (CTFP). Unlike a simple indicator such as emissions per unit of GDP, CTFP captures how efficiently a city generates economic output while treating carbon emissions as an undesirable by-product. Conceptually, it reflects not only whether a city emits more or less carbon, but also whether it achieves economic development in a cleaner and more resource-efficient way. A higher CTFP indicates that a city can produce the same level of desirable output with fewer resource inputs and/or lower carbon emissions, or generate more output without a proportional increase in resource use and emissions. Thus, this index reflects not simply lower emissions, but a better overall balance among economic growth, resource conservation, and climate protection. In addition, because it jointly considers inputs, desirable output, and undesirable output, it provides a multidimensional assessment of carbon-related performance rather than relying on a single input or emission indicator. The metafrontier framework allows comparisons across cities with different technologies and development conditions, while the Malmquist–Luenberger (ML) productivity index captures whether such performance improves over time. Therefore, CTFP can be understood as an indicator of the quality of low-carbon development. In the presence of undesirable outputs, CTFP is measured within a metafrontier framework using the Malmquist–Luenberger (ML) productivity index and the super-efficiency DEA method. This study takes 2010 as the base period and normalizes CTFP to 1. The CTFP for 2011 is calculated by multiplying the base-period value by the 2011 GML index, and the same procedure is applied to subsequent years. The logarithm of the final GML index is then used to measure carbon emission quality ($lnCTFP$).

3.2.3. Variable of Interest

The key independent variable is the policy treatment dummy. If city i is included in the NBDCPZ policy in year t, then $DID_{it} = 1$ for year t and all subsequent years; otherwise, $DID_{it} = 0$.

3.2.4. Control Variables

Based on the STIRPAT framework, we include a set of control variables [40]. Specifically, *POPD* is measured as the logarithm of population density; GDP is measured as the logarithm of GDP per capita; *SCIT* is measured as the logarithm of government expenditure on science and technology; *IS* is measured as the share of value added of the secondary sector in GDP; *OPEN* is measured as the share of FDI in GDP; and *EDU* is measured as the share of education expenditure in total fiscal expenditure.

3.2.5. Mechanism Variables

To explore the potential mechanisms through which the NBDCPZ affects carbon outcomes, we further consider two mechanism variables. Green technological innovation (*Green*) is measured by the number of green patents per 10,000 people, which captures the intensity of region-specific green innovation activity. Energy structure (*Es*) is measured as the ratio of coal consumption to total energy consumption. This indicator captures the extent to which local energy consumption relies on coal-intensive sources and is therefore used to characterize the local energy consumption structure. Given that coal remains the most carbon-intensive primary energy source in China's energy system, a higher value of Es indicates a more carbon-intensive local energy structure, whereas a lower value indicates a relatively cleaner local energy mix. It should be noted, however, that this measure primarily reflects the composition of local energy consumption and does not fully capture broader issues such as interregional electricity trade or potential upstream emission displacement. Table 1 reports the descriptive statistics for these variables.

Table 1. Descriptive statistics.

Variable	Definitions	Observations	Mean	Standard Deviation	Minimum	Maximum
$lnCO_2$	Logarithm of CO_2 emissions	3906	6.882	1.106	3.946	9.421
lnCTFP	Logarithm of carbon total factor productivity	3906	−0.023	0.082	−0.386	0.142
DID	Policy dummy, NBDCPZ = 1	3906	0.138	0.345	0.000	1.000
POPD	Logarithm of population density	3906	5.755	0.877	2.895	7.273
GDP	Logarithm of GDP per capita	3906	16.523	0.929	14.590	19.096
SCIT	Logarithm of government expenditure on science and technology	3906	11.355	1.315	7.074	14.981
IS	Share of value added of the secondary sector in GDP	3906	44.851	10.923	17.480	71.260
OPEN	Share of FDI in GDP	3906	1.648	1.701	0.016	8.850
EDU	Share of education expenditure in total fiscal expenditure	3906	8.211	7.771	0.119	23.964
Green	Number of green patents per 10,000 people	3906	0.817	1.475	0	24.411
Es	Ratio of coal consumption to total energy consumption	3906	56.161	9.355	4.236	77.296

4. Results

4.1. Baseline Results

Table 2 reports the baseline regression results. Columns (1) and (3) present the specifications without control variables, while columns (2) and (4) include the full set of controls. Across all specifications, the coefficients on DID remain statistically significant at the

1% level, indicating that the NBDCPZ is associated with both lower carbon emission quantity and higher carbon emission quality.

Table 2. Baseline regression results.

Variable	$lnCO_2$		$lnCTFP$	
	(1)	(2)	(3)	(4)
DID	−0.072 ***	−0.123 ***	0.014 ***	0.026 ***
	(0.027)	(0.028)	(0.004)	(0.004)
Control Variables	N	Y	N	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	3906	3906	3906	3906
Adjusted R^2	0.906	0.913	0.668	0.690

Heteroskedasticity-robust standard errors are reported in parentheses. *** $p < 0.01$.

In columns (2) and (4), where control variables are included, the coefficient estimates show that the NBDCPZ reduces carbon emission quantity by 12.3% and improves carbon emission quality by 2.6%. Moreover, the signs and significance of the DID coefficients remain stable after adding control variables. In standardized terms, the estimated effects on carbon emission quantity and carbon emission quality are −0.033 and 0.087, respectively. Overall, the results provide baseline evidence in support of Hypothesis 1.

4.2. Parallel Trend Test and Sensitivity Analysis

Models (1) and (2) rely on the parallel trends assumption, under which the treatment and control groups would have followed similar trends in the absence of the policy. Following a standard event-study approach [41], we estimate the following models:

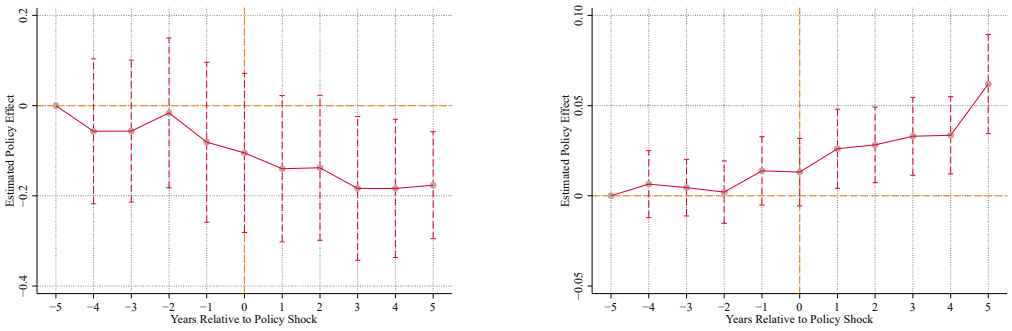
$$lnCO_{2it} = \alpha_1 + \sum_{k=-4}^{5} \theta_k DID_{it}{}^k + \alpha_3 X_{it} + \delta_i + \gamma_t + \varepsilon_{it} \quad (4)$$

$$lnCTFP_{it} = \beta_1 + \sum_{k=-4}^{5} \psi_k DID_{it}{}^k + \beta_3 X_{it} + \varphi_i + \rho_t + u_{it} \quad (5)$$

where DID_{it}^k denotes event-time dummy variables. When $k > 0$, $DID_{it}^k = 1$ if city i is in the k-th year after policy implementation in year t, and equals 0 otherwise. When $k < 0$, $DID_{it}^k = 1$ if city i is in the $\mid k \mid$-th year before policy implementation in year t, and equals 0 otherwise. The fifth year prior to policy implementation is omitted as the reference period. Meanwhile, we collapse the event-time indicators at both tails of the sample window. Specifically, observations from five or more years before policy implementation are grouped into period −5, while observations from five or more years after policy implementation are grouped into period 5.

Figure 1 presents the event-study estimates for carbon emission quantity and carbon emission quality. The lead coefficients are generally close to zero and do not display a clear systematic pre-treatment pattern, suggesting that pilot and non-pilot cities followed broadly similar trends prior to policy implementation. By contrast, the post-treatment coefficients move in the expected direction, consistent with the emergence of policy effects after the implementation of the NBDCPZ. To complement the graphical evidence, Table 3 reports the estimated pre-treatment coefficients and the joint significance tests for the lead terms. Most of the pre-treatment coefficients are statistically insignificant. Although the coefficient on Pre_1 for carbon emission quality is marginally significant at the 10% level, the joint tests fail to reject the null hypothesis that the pre-treatment coefficients are jointly

equal to zero for either outcome variable ($lnCO_2$: F = 0.510, p = 0.725; $lnCTFP$: F = 0.970, p = 0.420). Taken together, these results support the parallel trends assumption.



(**a**) Carbon emission quantity (**b**) Carbon emission quality

Figure 1. Parallel trends test.

Table 3. Pre-treatment coefficients and joint tests of parallel trends.

Variable	$lnCO_2$ (1)	$lnCTFP$ (2)
*Pre*_5	-	-
*Pre*_4	−0.057	0.006
	(0.062)	(0.007)
*Pre*_3	−0.056	0.005
	(0.061)	(0.006)
*Pre*_2	−0.016	0.002
	(0.064)	(0.007)
*Pre*_1	−0.081	0.014 *
	(0.069)	(0.007)
Joint test of pre-treatment coefficients = 0		
F-statistic	0.510	0.970
p-value	0.725	0.420

*Pre*_5 is omitted as the reference period. * $p < 0.1$.

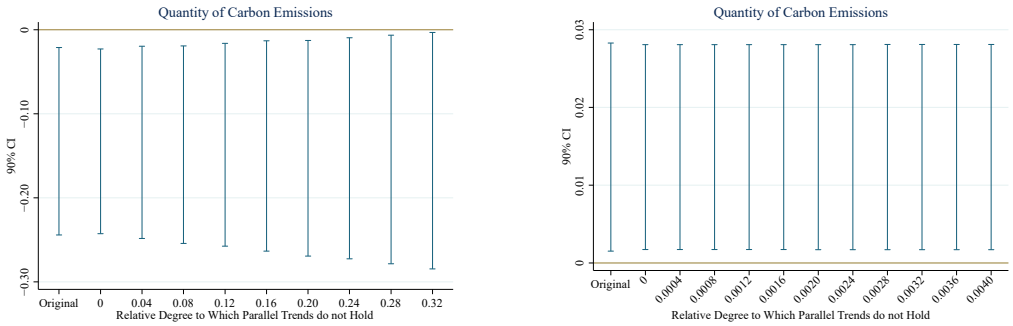
This figure presents the event-study estimates of the effects of the NBDCPZ on carbon emission quantity and carbon emission quality. The horizontal axis shows event time relative to policy implementation (in years), while the vertical axis reports the estimated regression coefficients. The error bars indicate 95% confidence intervals. The treatment timing is defined according to the actual onset of policy implementation: Guizhou is assigned to 2015, while the other pilot regions are assigned to 2016. The fifth year prior to policy implementation is omitted as the reference period.

However, the parallel trends test is neither sufficient nor necessary for DID models. Traditional dynamic-effects tests may fail to correctly identify pre-treatment parallel trends and may even lead to biased or distorted estimates [42]. Accordingly, we conduct a parallel-trends sensitivity analysis [43]:

$$\Delta^{RM}(\overline{M}) = \left\{ \beta : \forall t \geq 0, |\beta_{t+1} - \beta_t| \leq \overline{M} \cdot \underbrace{\max}_{s<0} |\beta_{s+1} - \beta_s| \right\} \quad (6)$$

where $\Delta^{RM}(\overline{M})$ denotes a set of admissible deviations in which, after imposing the relative-magnitude restriction, the change in adjacent post-treatment periods is allowed to be no greater than $\overline{M}$ times the maximum change observed across adjacent pre-treatment periods.

Figure 2 presents the results of the sensitivity analysis for the parallel trends assumption. The estimated effects remain robust when moderate deviations from the baseline assumption are allowed, suggesting that the main findings are not sensitive to modest violations of parallel trends. This provides additional support for the credibility of the baseline DID estimates.



(**a**) Carbon emission quantity (**b**) Carbon emission quality

Figure 2. Sensitivity analysis of parallel trends.

4.3. Bacon Decomposition

The DID estimator may be biased when treatment effects are heterogeneous across groups or over time. To assess this issue, we conduct a Bacon decomposition of the DID estimator [44]. As shown in Table 4, the comparison between treated and untreated groups accounts for 95.4% of the total weight, whereas the component related to treatment heterogeneity accounts for only 4.6%. This suggests that bias arising from negative weighting is unlikely to drive the baseline results.

Table 4. Bacon decomposition results.

	(1) $lnCO_2$	(2) *lnCTFP*	Weight
Treated vs. Untreated Group	−0.074	0.015	0.954
Presence of Treatment Heterogeneity Group	−0.052	0.012	0.046

Columns (1) and (2) report the Bacon decomposition results for $lnCO_2$ and *lnCTFP*, respectively.

4.4. Endogeneity Analysis

To address potential endogeneity, this study uses the total postal and telecommunications business volume of each city in 1984 as an instrumental variable (*IV*). This variable captures a city's early communications infrastructure and information transmission capacity. Cities with stronger historical communications foundations were more likely to develop first-mover advantages in information networks, administrative coordination, and factor agglomeration. Such advantages may persist over time, translate into stronger digital development capacity in later periods, and thereby further increase the likelihood that a city would be selected into the NBDCPZ policy, thereby supporting the relevance condition.

Regarding exogeneity, the 1984 postal and telecommunications business volume was determined in a very different technological and institutional context, long before the emergence of modern digital transformation policies and the carbon outcomes examined in this study. It mainly reflects historical communication demand and infrastructure conditions rather than contemporary low-carbon development strategies. After controlling for city fixed effects, year fixed effects, and a range of time-varying city characteristics, it is unlikely to affect current carbon emission quantity or carbon emission quality through channels other than subsequent digital development capacity and the probability of policy inclusion. Therefore, this IV plausibly satisfies the exclusion restriction [45,46].

Table 5 reports the IV estimation results. The first-stage coefficient on the instrument is significant at the 1% level, and the coefficient on DID remains significant in the second stage. In addition, the LM statistic is significant, rejecting the null of underidentification. The Cragg–Donald Wald F-statistic is 59.461, which is well above the relevant weak-instrument critical value, indicating that the null of weak instruments is rejected. Nevertheless, because the exclusion restriction cannot be tested directly, the IV results should be interpreted as supportive evidence on endogeneity mitigation rather than as definitive proof of exogeneity.

Table 5. IV estimation results.

Variable	First Stage	Second Stage	
	(1) *DID*	(2) $lnCO_2$	(3) *lnCTFP*
DID		−2.057 ***	0.240 ***
		(0.252)	(0.032)
IV	0.001 ***		
	(0.000)		
Observations	3094	3094	3094
Adjusted R^2	0.615	0.781	0.232
LM statistic		25.025	
C-D Wald F statistic		59.461	

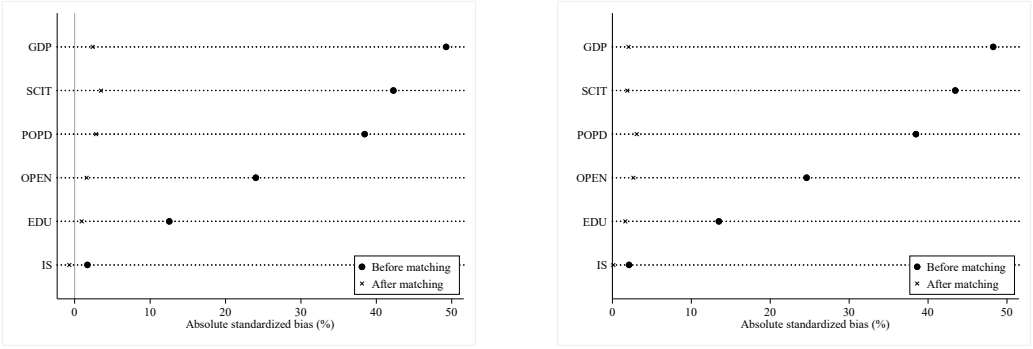
Control variables and city and year fixed effects are included in all models. *** $p < 0.01$.

4.5. Robustness Checks

4.5.1. PSM-DID

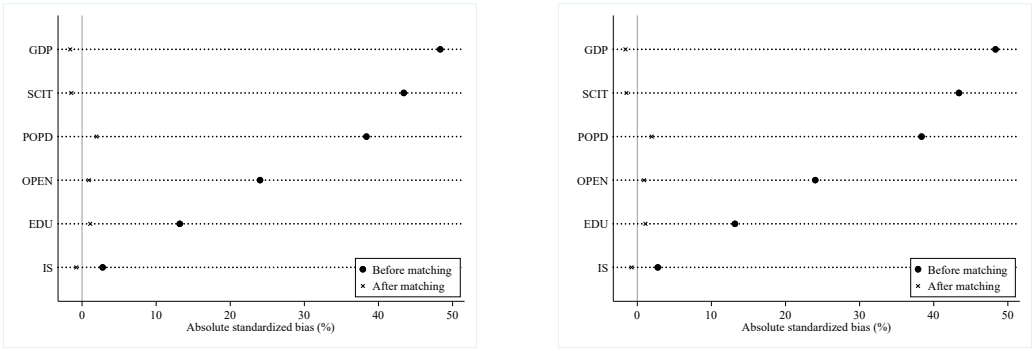
Combining DID with PSM can help mitigate potential sample selection bias by improving the comparability between the treatment and control groups on observable characteristics. In the PSM-DID framework, matching can be implemented using mixed matching or year-by-year matching. Mixed matching typically pools observations from different years into a single dataset before matching, which may overlook time trends and period-specific effects. By contrast, year-by-year matching performs matching separately in each year, but it may reduce the sample size over time when some observations fail to find suitable matches. Given the potential limitations of both approaches, this study employs both matching strategies. Specifically, we use mixed caliper matching and year-by-year 1:3 nearest-neighbor matching.

The balance tests show that covariate imbalances are substantially reduced after matching, indicating that the matching quality is acceptable (see Figures 3 and 4). Table 6 reports the PSM-DID results. The estimated coefficients are broadly consistent with the baseline regressions, suggesting that the main findings remain robust after accounting for potential sample selection bias.



(**a**) Carbon emission quantity (**b**) Carbon emission quality

Figure 3. Covariate balance after mixed caliper matching.



(**a**) Carbon emission quantity (**b**) Carbon emission quality

Figure 4. Covariate balance after year-by-year nearest-neighbor matching.

Table 6. PSM-DID.

Variable	Mixed Caliper Matching		Year-By-Year Nearest-Neighbor Matching	
	(1) $lnCO_2$	(2) *lnCTFP*	(3) $lnCO_2$	(4) *lnCTFP*
DID	−0.068 **	0.021 ***	−0.056 *	0.015 ***
	(0.032)	(0.004)	(0.030)	(0.004)
Observations	2960	3815	2571	2571
Adjusted R^2	0.900	0.669	0.908	0.663

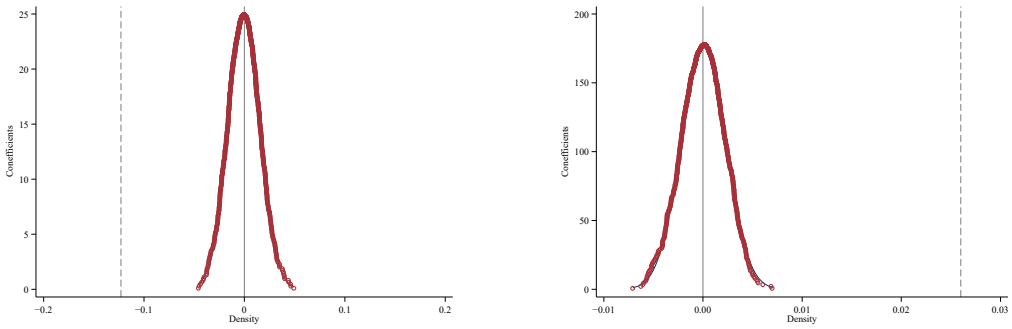
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The horizontal axis reports the absolute standardized bias (%) for each covariate before and after matching. Smaller values indicate better balance.

4.5.2. Placebo Test

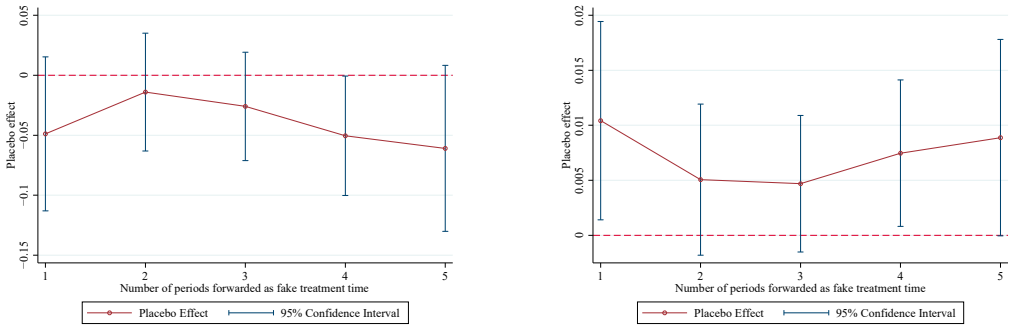
To rule out the possibility that unobservable factors or spurious policy timing drive the estimated effects, we conduct both spatial and temporal placebo tests [47,48]. In the spatial placebo test, placebo treatment status is randomly assigned to cities and the baseline regressions are repeated 1000 times. In the temporal placebo test, placebo policy years are randomly assigned and the regressions are re-estimated accordingly.

As shown in Figures 5 and 6, the coefficients from the spatial placebo test are concentrated around zero and clearly separated from the benchmark estimates, while those from the temporal placebo test are also largely insignificant. These findings suggest that the estimated effects of the NBDCPZ on carbon emission quantity and carbon emission quality are unlikely to be driven by omitted variables, random assignment, or spurious policy timing, supporting the robustness of the baseline results.



(**a**) Carbon emission quantity (**b**) Carbon emission quality

Figure 5. Spatial placebo test.



(**a**) Carbon emission quantity (**b**) Carbon emission quality

Figure 6. Temporal placebo test.

4.5.3. Analysis of Non-Random Selection of Pilot Cities

Identifying the policy effects of the NBDCPZ requires the treatment variable DID_{it} to be as good as exogenous. In an ideal setting, pilot cities would be selected randomly. In practice, however, NBDCPZ cities are selected according to policy criteria such as big data infrastructure planning, public data openness, and support for macro-governance, suggesting that pilot-city selection is non-random. Instead, pilot-city selection may be correlated with pre-existing city characteristics, including geographic location, economic development, population density, environmental constraints, and openness. These characteristics may generate differential trends across cities and thus bias the estimation of the policy effects on carbon emission quantity and carbon emission quality. To address this concern, we gradually add interactions between pre-determined city characteristics and polynomial time trends to the baseline model [49]. The specifications are as follows:

$$lnCO_2 = \alpha_1 + \alpha_2 DID_{it} + \mathrm{T}rend \times f(t)^i \alpha_3 X_{it} + \delta_i{}^p + \gamma_t{}^p + \varepsilon_{it}{}^p \quad (7)$$

$$lnCTFP = \beta_1 + \beta_2 DID_{it} + Trend \times f(t)^i \beta_3 X_{it} + \delta_i{}^p + \gamma_t{}^p + \varepsilon_{it}{}^p \quad (8)$$

where $f(t)^i$ denotes polynomial time-trend terms, including $f(t)^1$, $f(t)^2$, and $f(t)^3$. *Trend* denotes a set of pre-determined city characteristics, including whether a city is a municipality directly under the central government, a sub-provincial city, or a provincial capital, as well as its energy consumption, number of broadband subscribers, and environmental regulation intensity in 2010. The interaction term $Trend \times f(t)^i$ controls for the effects of these pre-existing city characteristics through differential trends. Table 7 shows that the main findings remain robust after controlling for such time trends.

Table 7. Analysis of non-random selection of pilot cities.

Variable	$lnCO_2$			$lnCTFP$		
	(1)	(2)	(3)	(4)	(5)	(6)
DID	−0.113 ***	−0.068 **	−0.106 ***	0.024 ***	0.024 ***	0.023 ***
	(0.028)	(0.029)	(0.028)	(0.004)	(0.004)	(0.004)
$Trend \times f(t)^1$	Y	Y	Y	Y	Y	Y
$Trend \times f(t)^2$	N	Y	Y	N	Y	Y
$Trend \times f(t)^3$	N	N	Y	N	N	Y
Observations	3906	3906	3906	3906	3906	3906
Adjusted R^2	0.915	0.926	0.916	0.695	0.697	0.698

*** $p < 0.01$, ** $p < 0.05$.

4.5.4. Controlling for Contemporaneous Environmental Regulatory Policies

To rule out potential confounding effects from contemporaneous environmental regulatory policies, we further control for three major policies implemented during the sample period (2010–2023): the Green Finance Reform and Innovation Pilot Zone (GFPZ), the Carbon Emissions Trading Policy (CETP), and the Ecological Civilization Advance Demonstration Zone Policy (ECADZ) [50–52]. Specifically, we include three policy dummy variables, $Policy_{it}^{q}$, which equal 1 if city i is subject to policy q in year t, and 0 otherwise. Table 8 shows that the baseline findings remain robust after controlling for these contemporaneous policies.

Table 8. Controlling for contemporaneous environmental regulatory policies.

Variable	GFPZ Controlled		CETP Controlled		ECADZ Controlled	
	(1) $lnCO_2$	(2) *lnCTFP*	(3) $lnCO_2$	(4) *lnCTFP*	(5) $lnCO_2$	(6) *lnCTFP*
DID	−0.119 ***	0.025 ***	−0.097 ***	0.023 ***	−0.093 ***	0.022 ***
	(0.028)	(0.004)	(0.029)	(0.004)	(0.029)	(0.004)
Control Variables	Y	Y	Y	Y	Y	Y
Observations	3906	3906	3906	3906	3906	3906
Adjusted R^2	0.914	0.693	0.914	0.691	0.914	0.694

*** $p < 0.01$.

4.5.5. Alternative Dependent Variables

To further examine robustness, we replace the dependent variables with alternative measures. Specifically, carbon emission quantity is measured by the logarithm of carbon intensity, while carbon emission quality is measured by the two-period Malmquist–Luenberger productivity index [53]. The results in columns (1) and (2) of Table 9 show that the main findings remain unchanged, supporting the robustness of the baseline conclusions to alternative dependent variables.

Table 9. Alternative dependent variables and additional weather controls.

Variable	(1) Carbon Intensity	(2) Two-Period ML Index	(3) $lnCO_2$	(4) *lnCTFP*
DID	−0.143 ***	0.031 ***	−0.111 ***	0.024 ***
	(0.029)	(0.007)	(0.028)	(0.004)
Weather-controlled Variables	N	N	Y	Y
Observations	3906	3906	3906	3906
Adjusted R^2	0.792	0.720	0.914	0.691

*** $p < 0.01$.

4.5.6. Additional Weather Controls

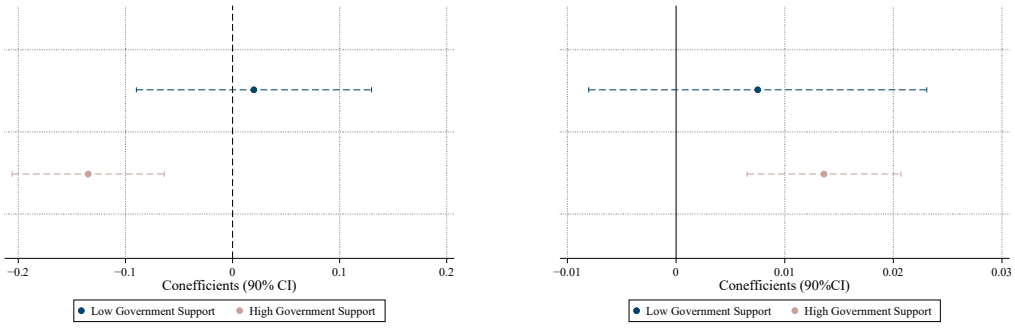
The benchmark regressions control for a range of city-level characteristics, but they do not explicitly account for weather conditions. Since weather factors may affect the estimation results [47], we further include average annual temperature, rainfall, and wind speed as city-year weather controls. The results in columns (3) and (4) of Table 9 are consistent with the baseline estimates, supporting the robustness of the main findings.

4.6. Heterogeneity Analysis

4.6.1. Heterogeneity Across Levels of Government Support

Given that the level of government support may shape low-carbon development and environmental governance, this study examines whether the policy effects vary by government support intensity. The sample is divided into high- and low-government-support groups based on the ratio of government expenditure to regional GDP, using the 50th percentile as the cutoff. Subsample regressions are then conducted.

Figure 7 reports the estimated coefficients for cities with different levels of government support. The estimated effects on carbon emission quantity and carbon emission quality are significant in cities with high-government support, but not in cities with low-government support. One possible explanation is that stronger government support may facilitate technological R&D, infrastructure development, and enterprise upgrading related to low-carbon development. Regions with greater support may receive more funding for carbon reduction projects, thereby improving policy effectiveness. In addition, regions with stronger government support may be more likely to develop collaborative mechanisms involving governments, firms, universities, and social organizations. Such cooperation may promote the implementation of low-carbon policies. Governments may also devote more resources to public awareness and education related to emission reduction, thereby encouraging broader participation by the public and enterprises in low-carbon actions.



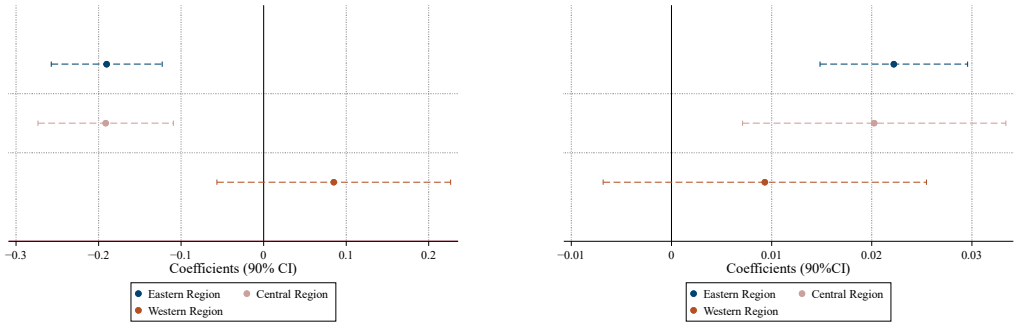
(**a**) Carbon emission quantity (**b**) Carbon emission quality

Figure 7. Heterogeneity across levels of government support.

4.6.2. Heterogeneity Across Geographic Regions

Differences in resource endowments and development stages may lead to regional heterogeneity in the carbon effects of the NBDCPZ. Accordingly, the sample is divided into eastern, central, and western China for subgroup regressions.

Figure 8 presents the estimated coefficients by region. The NBDCPZ significantly reduces carbon emission quantity and improves carbon emission quality in the eastern and central regions, but shows no significant effect in the western region. One possible explanation is that the eastern and central regions benefit more from factor agglomeration, knowledge spillovers, and economies of scale, together with higher urban density, stronger specialization, and greater innovation capacity. By contrast, infrastructure in the western region, especially in transportation and energy, remains relatively underdeveloped. Limited facilities and weaker technical support may constrain carbon reduction efforts. In addition, western cities often face stronger development pressure and may place greater emphasis on economic growth than on environmental goals, which may weaken the policy effect.



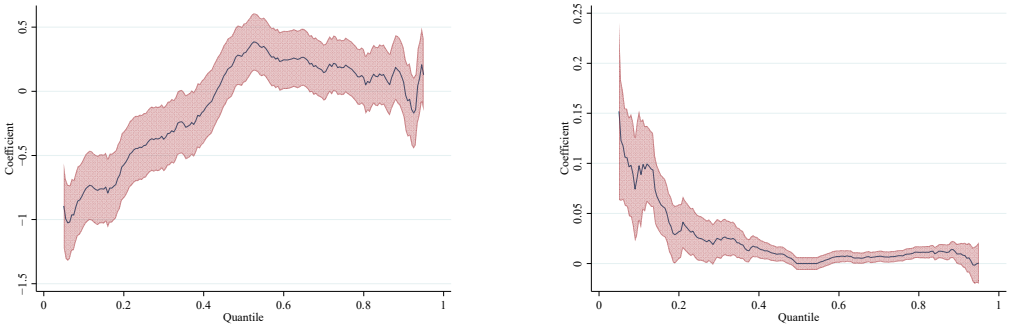
(**a**) Carbon emission quantity (**b**) Carbon emission quality

Figure 8. Heterogeneity across geographic regions.

4.6.3. Heterogeneity Across Quantiles

To further examine heterogeneity in the effects of the NBDCPZ, this study uses quantile regression to assess whether the effects vary across the distribution of carbon emission quantity and carbon emission quality. Quantile regression requires fewer distributional assumptions and is better suited to non-normality and heteroskedasticity in the dependent variables, thus complementing mean regression.

Figure 9 shows that the estimated effects on carbon emission quantity are significant up to the 0.4 quantile, but become insignificant at higher quantiles. In contrast, the estimated effects on carbon emission quality are significant up to the 0.5 quantile and also appear to be significant again around the 0.8 quantile. Overall, the policy effect is more pronounced among cities in the lower part of the outcome distribution, where there may be greater scope for improvements in resource allocation, production efficiency, and low-carbon transition. For cities in the upper part of the distribution, the policy effect is generally more limited.



(**a**) Carbon emission quantity (**b**) Carbon emission quality

Figure 9. Heterogeneity across quantiles.

5. Mechanisms

The baseline results show that the NBDCPZ significantly affects carbon emission quantity and carbon emission quality. We next examine the potential mechanisms underlying these effects. Given the identification challenges involved in formally decomposing mediation effects in observational studies, this study adopts a more cautious mechanism-analysis approach. Specifically, after establishing the theoretical links between the NBDCPZ and the proposed mechanism variables, we estimate whether the policy significantly affects these variables. The empirical specification is as follows:

$$M_{it} = \vartheta_1 + \vartheta_2 DID_{it} + \vartheta_3 X_{it} + \delta_i + \gamma_t + \varepsilon_{it}, \quad (9)$$

where M_{it} denotes the mechanism variable, and the other variables are defined as in the baseline models. A statistically significant coefficient on DID_{it} indicates that the NBDCPZ has a meaningful effect on the corresponding mechanism variable, thereby providing evidence on the mechanism through which the policy may affect carbon outcomes.

5.1. Green Technological Innovation

Following the establishment of the NBDCPZ, the application of digital technologies and more efficient information transmission may improve knowledge production and diffusion, expand the knowledge base, and promote the agglomeration of innovation factors, thereby enhancing urban green technological innovation. In addition, digital technologies and more efficient information transmission can shift many traditional activities, such as document exchange, meetings, and shopping, online, thereby reducing transport demand, energy use, and resource consumption. These changes may contribute to lower carbon emission quantity and higher carbon emission quality.

To examine the mechanism of green technological innovation, we estimate the effect of the NBDCPZ on the corresponding mechanism variable. The results are reported in Table 10. Column (1) shows that the coefficient on DID is significantly positive, indicating that the NBDCPZ significantly promotes green technological innovation. This result is consistent with the theoretical expectation that the policy may improve carbon outcomes by strengthening green technological progress. These findings suggest that green technological innovation is a plausible mechanism through which the NBDCPZ may affect carbon emission quantity and carbon emission quality.

Table 10. Mechanisms.

Variable	(1) Green	(2) Es
DID	0.293 ***	−0.021 ***
	(0.084)	(0.004)
Observations	3906	3906
Adjusted R^2	0.914	0.798

*** $p < 0.01$.

5.2. Energy Structure

The establishment of the NBDCPZ may contribute to energy structure adjustment by improving information processing, energy monitoring, and the allocation of energy use. In addition, the integration of digital technologies with traditional industries may accelerate the green and low-carbon transition, thereby reducing reliance on coal-intensive production.

To examine the mechanism of energy structure adjustment, we estimate the effect of the NBDCPZ on the corresponding mechanism variable. The results are reported in Table 10. Column (2) shows that the coefficient on DID is significantly negative, indicating that the NBDCPZ reduces the share of coal in total energy consumption and thus improves the energy structure. This finding suggests that the policy may improve carbon outcomes by promoting a cleaner local energy mix and reducing dependence on coal-intensive energy use. These findings suggest that energy structure adjustment is a plausible mechanism through which the NBDCPZ may affect carbon emission quantity and carbon emission quality.

6. Discussion, Further Research and Limitations, Conclusions and Policy Implications

6.1. Discussion

The baseline results of this study are broadly consistent with earlier research on the NBDCPZ and related digital policies, but they also extend this literature in an important way. At the city level, existing studies show that the NBDCPZ can reduce air pollution and carbon emissions [13,15,18]. Other city-level studies find that the policy improves eco-efficiency [17] and green total factor productivity [28]. At the firm level, related evidence suggests that the policy promotes corporate low-carbon innovation [16] and enhances enterprises' green total factor productivity [19]. Relative to this literature, the contribution of the present study is not simply to provide additional evidence that the NBDCPZ generates environmental benefits. More importantly, because the NBDCPZ is implemented as a city- and region-based policy, evaluating its effects within a unified city-level framework is particularly important for understanding its aggregate environmental consequences. By jointly examining carbon emission quantity and carbon emission quality, this study shows that the NBDCPZ is associated with both lower carbon emission quantity and higher carbon emission quality. In this sense, the present study complements earlier work that often focuses on a single outcome indicator or a different level of analysis, and provides a more integrated assessment of the environmental consequences of the NBDCPZ.

6.2. Further Research and Limitations

While our findings suggest that the NBDCPZ is associated with improved carbon outcomes at the city level, this evidence primarily reflects the policy's average net effects rather than a direct physical accounting of all energy-use processes related to digital infrastructure expansion. The energy structure measure used in this study mainly captures local energy consumption patterns and therefore cannot fully reflect interregional electricity trade or potential upstream emission displacement. Accordingly, our results cannot rule out the possibility that part of the observed reduction in local carbon emissions reflects displacement to electricity-supplying regions. The estimated policy effects in this study are therefore better understood as net effects at the city level. Due to data limitations, the present analysis cannot further quantify localized electricity demand from data centers, cooling-related efficiency, or power usage effectiveness, nor can it fully identify whether part of the observed reduction in local emissions is associated with the spatial redistribution of electricity-related emissions across regions. At the same time, although the mechanism analysis is consistent with the roles of green technological innovation and energy structure adjustment, these findings should be understood as evidence on plausible mechanisms rather than as a strict identification of the full physical processes through which digital transformation affects carbon outcomes. These limitations constitute the main shortcomings of this study. Constrained by data availability and identification conditions, the present analysis is unable to examine in greater detail the underlying physical mechanisms related to energy flows, interregional emission displacement, and the operation of digital infrastructure. Future research could build on more granular and higher frequency data on energy use, digital infrastructure, and industrial production processes to provide a deeper and more precise analysis of these mechanisms.

6.3. Conclusions

Using panel data for China's prefecture-level cities from 2010 to 2023, this study takes the NBDCPZ as a quasi-natural experiment and applies a staggered DID approach to examine its effects on carbon emission quantity and carbon emission quality. The results show that the NBDCPZ significantly reduces carbon emission quantity and improves carbon

emission quality, as reflected in a 12.3% decrease in CO_2 emissions and a 2.6% increase in carbon total factor productivity in pilot cities. Moreover, the policy effect varies with government support intensity and geographic location, indicating substantial heterogeneity. Specifically, the NBDCPZ has stronger effects in cities with higher government support, especially in the eastern and central regions, whereas the effects are weaker in cities with lower government support, particularly in the western region. Overall, the mechanism analysis suggests that green technological innovation and energy structure adjustment are plausible mechanisms through which the NBDCPZ may contribute to lower carbon emission quantity and higher carbon emission quality.

6.4. Policy Implications

Drawing on the above findings, we propose policy recommendations for the central government, local governments, and enterprises. First, the central government should formulate region-specific implementation strategies for the NBDCPZ by taking local conditions into account and strengthening policy coordination. Our results suggest that the carbon effects of the NBDCPZ vary across regions and across levels of government support because of differences in local characteristics. Accordingly, the design and implementation of NBDCPZ-related policies should better reflect local development conditions, resource endowments, and institutional capacity. This would help improve the flexibility and effectiveness of policy implementation and avoid the simple replication of development models from other regions.

Second, local governments should strengthen policy support for technological innovation. Our findings suggest that green technological innovation is a plausible mechanism through which the NBDCPZ may affect carbon outcomes. Governments can provide research and development funding, subsidies, and other incentives to support enterprises and research institutions developing low-carbon technologies. They can also strengthen intellectual property protection to provide a more secure institutional environment for innovation, thereby encouraging greater investment in green technological progress.

Third, enterprises should strengthen green innovation and further optimize their energy use structure. Our results suggest that energy structure adjustment is a plausible mechanism through which the NBDCPZ may contribute to lower carbon emission quantity. Enterprises can adopt cleaner materials and production methods, increase the use of renewable energy where feasible, and work with supply-chain partners to promote low-carbon production practices. These efforts would help reduce dependence on fossil-energy-intensive production and support low-carbon development.

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