

## Article

# How Green Data Center Establishment Drives Carbon Emission Reduction: Double-Edged Sword or Equilibrium Effect?

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## Abstract

As inevitable outcomes of the digital economy's low-carbon development, green data centers play a crucial role in environmental impact and underlying mechanisms. This study focuses on green data center establishment as a representative practice, utilizing Chinese A-share listed companies and urban data from 2009 to 2023 to construct a multi-period difference-in-differences model. From a supply chain perspective, we investigate the impact of green data centers on corporate carbon emissions and their mechanisms. The results demonstrate that regional establishment of green data centers significantly promotes corporate carbon emission reduction, with conclusions remaining robust after a series of comprehensive robustness and endogeneity tests. This process primarily operates through two channels: green total factor energy efficiency and green attention. Green data center establishment significantly enhances green total factor energy efficiency and corporate green attention. The more developed the regional digital infrastructure and the higher the computing power development levels, the stronger the incentive effect on corporate carbon reduction. Heterogeneity analysis reveals that green data centers have more significant promoting effects on carbon emission reduction in state-owned enterprises and high-tech enterprises. This research contributes to a deeper understanding of the effects, mechanisms, and regional variations related to green data centers in facilitating corporate carbon emission reduction.

**Keywords:** green data centers; enterprise carbon emissions; multi-period difference-in-differences analysis



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## 1. Introduction

In recent years, as the digital economy has entered a phase of rapid development, data centers have continuously expanded in scale as critical infrastructure for digital economic growth. According to relevant information from the Information and Communication Development Department of China's Ministry of Industry and Information Technology, based on the standard rack metric of 2.5 kW, China's data center rack scale reached 2.26 million in 2018 and expanded to 6.8 million by 2023. This represents a compound annual growth rate exceeding 40% over the past six years. The total computing power output reached 230 EFlops, accounting for approximately 31% globally, with growth rates exceeding 50% for two consecutive years, higher than the global average. Alongside this rapid expansion of data centers, their high energy consumption and carbon emissions have emerged as significant concerns. Statistics indicate that in 2023, China's data centers consumed 150 billion kilowatt-hours of electricity, representing 1.6% of the nation's total electricity consumption,

with carbon dioxide emissions of approximately 84 million tons. By 2030, total energy consumption is projected to exceed 400 billion kilowatt-hours; without increased utilization of renewable energy, carbon emissions could surpass 200 million tons. In response to this challenge and to achieve high-quality green development of data centers while supporting China's dual carbon goals, the National Development and Reform Commission and three other departments issued the "Special Action Plan for Green and Low-Carbon Development of Data Centers" in 2024, with 246 green data centers already established nationwide. Consequently, the impact and effects of green data centers on carbon emissions have become widely discussed among government officials and society in recent years.

Based on the aforementioned data, the construction of digital infrastructure inevitably entails substantial resource consumption and generates significant carbon dioxide emissions. Digital infrastructure primarily comprises hardware and software technology systems. Bashroush et al. [1] proposed that during the construction process of digital infrastructure, IT equipment, particularly servers, accounts for a considerable portion of the entire facility's energy consumption and environmental impact, requiring substantial energy inputs and exerting negative environmental effects. Furthermore, as a representative of information technology development, Cai et al. [2] proposed that digital infrastructure increases internet usage duration during operation, thereby elevating energy consumption. Tang et al. [3] concluded that digital infrastructure significantly increases total carbon emissions, per capita carbon emissions, and carbon intensity in Chinese cities. Lee et al. [4] even suggested that similar information technology developments may trigger energy security concerns. Unlike conventional data centers, green data centers must balance computational power provision with the policy objective of "end-of-pipe treatment". This study argues that green data centers inevitably exhibit a double-edged sword effect, simultaneously increasing carbon emissions while reducing them due to their policy objectives. According to the data presented in the first paragraph and the research findings of the aforementioned scholars, green data centers, as a category of data centers, inherently possess the objective reality of increasing carbon emissions. Therefore, this study primarily aims to verify their carbon reduction dimension namely, the carbon mitigation effect of green data centers.

To address global climate change and promote high-quality, sustainable economic development, China proposed its "dual carbon" commitment in 2020. Domestic and international scholars have conducted extensive research on this topic, recognizing that enterprises, as the backbone of the economy, play a crucial role in reducing carbon emissions [5,6]. Previous research has explained carbon emission influencing factors from multiple perspectives, primarily in three directions: first, from a technological perspective, including digital technology transformation [7] and artificial intelligence [8]; second, from a financial perspective, including green investment [9,10], green finance [11], and inclusive finance [12]; third, from external drivers, including policy regulations [13,14] and consumer preferences [15]. Overall, with the development of digital and green transformation, an increasing number of studies are examining these issues through dynamic data analysis.

Meanwhile, with the continuous innovation of network information technology, the digital economy, with its high penetrability, scale effects, and network effects, has become a direct response to significant changes in both internal endowments and external environments within the new economic development framework, attracting widespread scholarly attention. Green data centers are an inevitable product of low-carbon development in the digital economy, essentially functioning as energy-saving, low-carbon digital infrastructure. Domestic and international scholars have conducted extensive research on this topic, primarily focusing on various effects of digital infrastructure, including economic effects of digital economy development [16], technological innovation effects [17], industrial transformation and upgrading [18], and employment effects [19]. Among these studies, Li et al. [16]

found that green data center digital infrastructure has a significant positive impact on urban digital economic development; Lee and Wang [17] proposed that digital infrastructure can promote innovation ecosystem development; Hong et al. [18] argued that the “Broadband China” strategy can significantly promote industrial structure rationalization. Closely related to this paper are studies focusing on the environmental effects of digital infrastructure. For example, Liao and Liu [20] discovered that digital infrastructure primarily influences urban carbon emissions by driving enterprises, individuals, and governments toward digitalization. Although previous research has explored carbon emission determinants and various effects of digital infrastructure from multiple perspectives, empirical studies that rigorously assess the impact of green data centers on corporate carbon reduction remain limited, presenting an opportunity for this study to contribute to the literature.

The original purpose of establishing green data centers was to balance computing power development with carbon emission benefits. Although green data centers have been incorporated into the energy-saving and carbon reduction system of new infrastructure at the policy level, systematic verification of their carbon reduction impact and mechanisms at the micro level remains lacking. Do green data centers’ carbon reduction effects exhibit heterogeneity across regions due to differences in computing power and digital infrastructure levels? In light of this, based on data from Chinese A-share listed companies and cities from 2009 to 2023, this paper employs multiple methods, including multi-period difference-in-differences, to empirically test the impact of green data centers on enterprise carbon reduction and their operating mechanisms. Research results show that the establishment of green data centers significantly reduced enterprise carbon emission levels. This conclusion remains valid after utilizing Heckman models, IV estimation, and a series of robustness tests. Promoting green total-factor energy efficiency and increasing green attention are important ways green data centers influence carbon emissions. Simultaneously, a region’s computing power level and digital infrastructure level have positive moderating effects on carbon emission reduction, with these results becoming more pronounced when grouping data by high-tech enterprises and heavily polluting enterprises. Theoretically, this research breaks through the traditional environmental economics framework for verifying the Porter hypothesis, revealing how green data centers function as “digital leverage” to mobilize enterprise-wide value chain carbon emission management, providing new explanations for understanding digitally driven enterprise environmental strategies. At the policy level, the research conclusions provide micro-level evidence for the “East Data, West Computing” project and new infrastructure energy-saving and carbon reduction policies, offering methodological support for enterprises to formulate carbon neutrality roadmaps, helping China secure a low-carbon technology advantage in global digital economy competition.

The potential marginal contributions of this paper exist in three aspects: First, distinct from previous studies that mainly focused on the environmental and economic effects of digital infrastructure, this paper investigates from the perspective of China’s green data center construction practice, demonstrating the carbon reduction effects of new green digital infrastructure, which serves as an important supplement to previous research. Second, this study manually collected evidence of green data center deployment at the city level. By examining the “National Green Data Center Pilot Work Program” and subsequent series of policy documents, we incorporated the three batches of green data center pilots from 2018, 2020, and 2021 into the assessment scope. We compiled statistics on whether cities established green data center pilots, using the deployment of green data centers in the city where enterprises are located as the core explanatory variable to explore its impact on corporate carbon reduction. Third, in addressing endogeneity issues, this study employed two methods. One was the Heckman test, where we calculated the proportion of enterprises in the same industry that disclose environmental information as an instrumental variable,

adding the disclosure probability of enterprises disclosing environmental information estimated by Probit regression to the control variables for regression. The other was IV estimation, which does not require instrumental variables and uses the singular least squares method, which does not rely on instrumental variables to analytically correct the bias of OLS estimation across the range of endogeneity assumptions. This study also excluded other contemporaneous policies that might affect carbon emissions, such as low-carbon city pilots, the Air Pollution Prevention and Control Action Plan (Air Ten Measures), and green finance reform and innovation pilot zones, significantly enhancing the robustness of the paper's conclusions.

## 2. Theoretical Analysis and Research Hypotheses

### 2.1. Direct Impact of Green Data Centers on Corporate Carbon Emissions

According to the "Evaluation for green data center" jointly issued by the State Administration for Market Regulation and the Standardization Administration of China, a green data center refers to a data center that, throughout its entire lifecycle, maximizes energy and resource conservation while minimizing negative environmental impacts, under the condition of ensuring personnel safety and the secure, stable, and reliable operation of information systems and their supporting equipment. As stated in the first paragraph of this paper's introduction, data indicate that data centers' high energy consumption problem can no longer be ignored. Therefore, in response to the dual carbon targets, China established three batches of green data center pilot programs in 2018, 2020, and 2021. As a new type of digital infrastructure, the direct impact of green data centers on corporate carbon emissions can be discussed from three perspectives: environmental regulation, resource endowment, and operational development.

The Porter hypothesis suggests that genuine environmental regulation not only does not increase corporate costs but promotes corporate technological innovation, thereby achieving a win-win situation for both the environment and the economy [21]. Establishing green data centers originates from government policies introduced to strengthen ecological and environmental protection, which involves a more stringent environmental regulatory system. Meanwhile, institutional theory [22,23] posits that the institutional pressure formed by green data centers can promote the institutionalization of corporate carbon reduction behaviors through three dimensions: regulative, normative, and cognitive. Specifically, urban green data center policies first drive corporate compliance through regulative institutional pressure via regulatory requirements and policy incentives, then guide proactive corporate action through normative institutional pressure via industry standards and social responsibility expectations, and finally promote corporate managers' internalization of green development concepts through cognitive institutional pressure, transforming carbon reduction from passive response to proactive strategy.

From the perspective of resource endowment [24], the original intention and primary task of green data centers is to enhance computing power while balancing "end-of-pipe treatment" and efficiency improvement, compensating for the high energy consumption drawbacks of traditional data centers through the utilization of renewable energy electricity and efficient cooling technologies. Resource-based theory suggests that urban strategic resources can support corporate carbon reduction through infrastructure sharing, technology spillover, and information services, thereby reducing emission reduction costs and improving emission reduction efficiency. Specifically, the construction of green data centers accelerates urban digitalization processes, facilitating comprehensive innovation, penetration, and application of information technology; breaking down barriers to knowledge, technology, and information dissemination; and improving the speed and efficiency of knowledge, technology, and information transmission within and between regions. This

enables enterprises to update their existing knowledge and technology repositories by incorporating advanced knowledge and technology from other regions, promoting the development and diffusion of technological innovation, and helping enterprises in industries that are major sources of carbon emissions achieve clean and intelligent production, thereby improving carbon emission efficiency through strengthened end-of-pipe treatment.

The operation and development of green data centers themselves have both positive and negative impacts on energy consumption intensity: on one hand, there is the substitution effect, where network information technology replaces traditional production and lifestyle methods [25], such as paperless offices, remote conferencing, online payment systems, and intelligent transportation systems, achieving energy conservation and emission reduction by decreasing timber consumption and reducing transportation; on the other hand, there is the creation effect, where the construction of green data centers involves the rapid development of the telecommunications industry it catalyzes, stimulating new energy consumption demands and energy inputs [3] and thereby increasing social energy consumption. Secondly, the development of green data centers promotes computing power advancement, accelerates digitalization processes, and triggers network dissemination effects, such as internet search volume data regarding global warming and non-environmental regulations generated by online low-carbon public opinion [26]. Non-environmental regulations often play roles that many environmental regulations cannot, by raising public awareness of low-carbon environmental protection and advocating for all citizens to practice green and low-carbon lifestyles in aspects of clothing, food, housing, and transportation.

Overall, the construction of green data centers has positive and negative effects on corporate carbon emissions, but the benefits generally outweigh the drawbacks. This paper proposes the first hypothesis based on the above analysis for ease of verification in subsequent sections.

**H1.** *The establishment of green data centers in cities promotes corporate carbon reduction.*

## 2.2. Green Data Centers, Green Total Factor Energy Efficiency, and Corporate Carbon Reduction

Green total factor energy efficiency (GTFEE) is a comprehensive evaluation indicator of energy efficiency that considers environmental constraints, assessing the comprehensive effectiveness of energy utilization by measuring the ratio of economic output to multiple input factors [27,28]. The construction of green data centers is the cornerstone of digital technology development. Promoting the advancement of digital technologies penetrates corporate production processes. On one hand, the application of digital technologies improves the efficiency and dematerialization level of production inputs, thereby mitigating the continuous upward trend of energy consumption [29]; on the other hand, through internet-controlled operation platforms, it achieves orderly configuration, interconnection, and coordinated dispatching of multiple energy systems [30]. Simultaneously, coupled with the green development concept of green data centers, it enhances the overall efficiency of energy systems [31], promotes corporate green total factor energy efficiency, and consequently facilitates corporate carbon reduction. Therefore, this paper proposes the second hypothesis.

**H2.** *The establishment of green data centers in cities promotes corporate carbon reduction by enhancing green total factor energy efficiency.*

### 2.3. Green Data Centers, Green Attention, and Corporate Carbon Reduction

Currently, the academic community has no clear definition of green attention, with only a broad consensus on “attention”. Yang et al. [32] studied government green attention, considering green attention as the government’s degree of emphasis on environmental issues and environmental governance, which influences local environmental decision making. In this paper, green attention refers to the degree of corporate executives’ attention to green issues such as carbon emissions and energy, thereby influencing corporate green development reforms or employee governance and exerting governance effects [33].

This paper argues that green digital infrastructure can promote the influx of digital talent and stimulate digital entrepreneurship vitality, thereby driving the vigorous development of urban green innovation activities. Specifically, green data center pilot regions enjoy the natural advantage of policy priority, which can better solve problems related to household registration, housing, and funding for high-level digital talents, leveraging the agglomeration effect of digital talents [34]. The introduction of green digital technology talents will change the human capital structure of enterprises, resulting in an overall increase in corporate green attention. When corporate green perspectives increase, enterprises are more likely to invest in high-quality green R&D and reduce carbon emissions [35]. Therefore, this paper proposes the third hypothesis.

**H3.** *The establishment of green data centers in cities promotes corporate carbon reduction through the pathway of enhancing green attention.*

### 2.4. Green Data Centers, Computing Power, and Corporate Carbon Reduction

Computing power refers to computational capacity, which is the efficiency of information processing [36]. Computing power, as the core productivity of the digital economy, has an intrinsic essence of data processing capability and an external manifestation as the measurement standard for the continuous development of industrial digitalization and digital industrialization technologies [37]. In regions with high levels of computing power development, its regulatory effect can be analyzed from two perspectives: policy objectives and scale effects. First, high levels of computing power development often indicate larger data center scale in the region, with greater electricity consumption and carbon emissions from these data centers. Green data centers aim to compensate for traditional data centers’ high energy consumption drawbacks through renewable energy power and efficient cooling technologies [38]; therefore, policy intensity for green data center construction in such regions will also be strengthened. Second, with large-scale adoption of green methods such as cloud computing, artificial intelligence, and system operations, additional computing power can achieve the objectives of the lowest cost per bit and optimal energy efficiency ratio of chips, hardware architecture, and applications through low-energy, high-performance concurrent processing capabilities [39]. Based on the above, this paper proposes the fourth hypothesis.

**H4.** *The higher the regional computing power level, the stronger the promotional effect of urban green data center construction on corporate carbon reduction.*

### 2.5. Green Data Centers, Digital Infrastructure Level, and Corporate Carbon Reduction

Digital infrastructure is a new system that includes telecommunications and network infrastructure, computing and data infrastructure, and digitally integrated infrastructure [40]. The core production factor of digital technology is data. As the carrier of data, digital infrastructure has a development level that is key to driving digital technology advancement and has made enormous contributions to enterprise transformation and upgrading [41]. In the current era where the breadth and depth of integration between

the digital economy and various fields of economy and society continue to expand [42], the green, ecological, and low-carbon thinking concepts generated by green data centers will also permeate the economic and social development process, creating a social environment conducive to green development and low-carbon development in the region as a whole. Therefore, digital infrastructure exhibits strong spatial spillover effects [43]. In places with high levels of digital infrastructure, the penetration effect of green data centers on enterprises tends to be more intense. Based on the above, this paper proposes the fifth hypothesis.

**H5.** *The higher the regional digital infrastructure level, the stronger the promotional effect of urban green data center construction on corporate carbon reduction.*

### 3. Research Design

#### 3.1. Data Sources and Processing

This study examines whether green data center construction can effectively incentivize corporate carbon emission reduction and the underlying mechanisms involved. Our research sample consists of Chinese A-share listed companies on the Shanghai and Shenzhen Stock Exchanges from 2009 to 2023. The year 2009 was selected as the starting point because China implemented new enterprise accounting standards in 2006 and essentially completed the capital market's split-share structure reform in 2007. These reforms may have influenced corporate accounting practices and financing policies, potentially affecting the research conclusions. Additionally, considering the impact of the 2008 financial crisis, this study utilized data from 2009 onwards as the research sample.

Furthermore, carbon emission reduction data were collected from corporate social responsibility reports, sustainability reports, and environmental reports. Financial data were obtained from the CSMAR and Wind database, with missing variables supplemented by annual reports and sustainability reports of listed companies. Data processing followed these logical steps: (1) companies with ST and \*ST designations were excluded; (2) companies undergoing delisting arrangements, suspended trading, or terminated listing status during the year were removed; (3) companies with obvious anomalous values were eliminated; (4) financial institution samples were excluded; (5) listed companies with missing key financial indicators were removed. Supply chain data were sourced from the China Research Data Service Platform, which records information such as the names of the top five domestic suppliers and customers. Additionally, digital infrastructure-related data were obtained from the Peking University Law Database website. After removing erroneous values, the final sample comprised 3432 A-share manufacturing listed companies, totaling 29,359 observations. To mitigate the influence of extreme values on research conclusions, all continuous variables underwent winsorization at the 1% level on both tails.

#### 3.2. Variable Definition

##### 3.2.1. Dependent Variable: Corporate Carbon Emissions (*co2*)

This study measures corporate carbon emissions using enterprises' total annual carbon emissions. According to the international standards established by the Greenhouse Gas Protocol, corporate carbon emissions encompass three major scopes: first, direct carbon emissions from sources owned or controlled by the enterprise; second, indirect carbon emissions resulting from the consumption of purchased electricity and heat; and third, other scattered indirect emissions that result from company activities. The total corporate carbon emissions represent the sum of these direct and indirect emissions. Following this framework, this study considers that carbon emissions primarily consist of four components: emissions from combustion and energy fuels; emissions from production processes;

emissions from solid waste incineration and wastewater treatment; and emissions from land use change.

### 3.2.2. Core Explanatory Variable: Establishment of Green Data Centers

This study collected pilot policy documents related to green data centers from the official websites of all city-level local governments, systematically reviewing the specific regions and implementation timelines of three batches of green data center pilots. A difference-in-differences (DID) variable was constructed, where the value is 1 for cities implementing green data center pilots in the current year and thereafter and 0 otherwise.

### 3.2.3. Control Variables

To exclude other variables that might influence enterprises carbon reduction, this study selected the following enterprise-level variables: firm age (*age*), asset/liability ratio (*tl*), asset structure (*tang*), intangible assets ratio (*itang*), financial leverage (*finlev*), cash flow (*cflow*), return on assets (*roa*), return on equity (*roe*), and firm size (*size*), among other control variables. Detailed variable definitions are presented in Table 1.

**Table 1.** Variable definitions.

| Variable Type and Name    | Variable      | Variable Definition                                                                           |
|---------------------------|---------------|-----------------------------------------------------------------------------------------------|
| Explained variable        |               |                                                                                               |
| Carbon emission           | <i>co2</i>    | Enterprise carbon dioxide emissions                                                           |
| Core explanatory variable |               |                                                                                               |
| Green data center         | <i>did</i>    | Takes value 1 if belonging to a pilot region and time is after the pilot year and 0 otherwise |
| Control variables         |               |                                                                                               |
| Enterprise age            | <i>age</i>    | Natural logarithm of enterprise establishment years plus 1                                    |
| Asset/liability ratio     | <i>tl</i>     | Total liabilities/Total assets                                                                |
| Asset structure           | <i>tang</i>   | (Net fixed assets + Net inventory)/Total assets                                               |
| Intangible asset ratio    | <i>itang</i>  | Net intangible assets/Total assets                                                            |
| Financial leverage        | <i>finlev</i> | Financial liabilities/Total assets                                                            |
| Cash flow                 | <i>cflow</i>  | Net cash flow from operating activities/Total assets                                          |
| Return on assets          | <i>roa</i>    | Net profit/Average total assets                                                               |
| Return on equity          | <i>roe</i>    | Net profit/Average net assets                                                                 |
| Enterprise size           | <i>size</i>   | Logarithm of total assets                                                                     |

## 3.3. Model Construction

### 3.3.1. Baseline Regression Model

To examine whether the establishment of green data centers affects enterprise carbon reduction, this paper establishes a multi-period difference-in-differences model for testing:

$$co2_{i,c,t} = \gamma_0 + \gamma_1 did_{c,t} + \sum \lambda X_{i,c,t} + \mu_i + \mu_t + \varepsilon_{i,c,t} \quad (1)$$

where the subscripts *i* and *t* represent the enterprise and year, respectively; *c* represents the city where the enterprise is located; *co2<sub>i,c,t</sub>* is the explained variable in this paper, namely enterprise carbon emissions. *did<sub>i,t</sub>* is the core explanatory variable, representing the establishment of green data centers. *X<sub>i,t</sub>* represents the set of control variables in enterprises that affect carbon reduction and vary with individuals and time. *μ<sub>i</sub>* represents individual fixed effects, which absorb individual-level characteristics that do not change over time.

$\mu_t$  represents time fixed effects, which absorb time-level characteristics.  $\varepsilon$  represents the random error term.

Table 2 presents the descriptive statistics of the variables in this study. As shown in the table, the mean value of *co2* is 9.1611, with a standard deviation of 4.7918, a minimum value of 0, and a maximum value of 17.6938. This indicates considerable disparity in carbon emissions across the sample, with an overall right-skewed distribution, suggesting significant growth potential for enterprise carbon reduction and an urgent need to identify carbon reduction drivers. Since the sample data in this study only include listed companies and do not consider relevant data from non-listed companies, it is necessary to analyze sample carbon differences from the perspective of industry data. According to CSMAR data, carbon emissions in each industry are composed of eight elements: coal carbon dioxide emissions, coke carbon dioxide emissions, crude oil carbon dioxide emissions, gasoline carbon dioxide emissions, kerosene carbon dioxide emissions, diesel carbon dioxide emissions, fuel oil carbon dioxide emissions, and natural gas carbon dioxide emissions. Among these, the total carbon dioxide emissions of the ferrous metal smelting and rolling processing industry in 2022 were 1.73 billion tons, while the specialized equipment manufacturing industry only emitted 4.53 million tons. This demonstrates that cross-industry differences in carbon emission baselines significantly increase overall dispersion. The mean value of *did* is 0.3059, indicating that 30.59% of enterprises in the sample are in green data center pilot regions. The descriptive statistics for other variables also fall within reasonable ranges and are not elaborated further here.

**Table 2.** Descriptive statistics.

| Variable Name | Sample Size | Mean    | Standard Deviation | Minimum  | Maximum  |
|---------------|-------------|---------|--------------------|----------|----------|
| <i>co2</i>    | 29,359      | 9.1611  | 4.7918             | 0.0000   | 17.6938  |
| <i>did</i>    | 29,359      | 0.3059  | 0.4608             | 0.0000   | 1.0000   |
| <i>gtfpe1</i> | 29,359      | 0.4660  | 0.2167             | 0.1026   | 1.1928   |
| <i>sgc</i>    | 29,359      | 7.9074  | 25.7659            | 0.0000   | 414.0000 |
| <i>din2</i>   | 29,359      | 0.0018  | 0.0016             | 0.0000   | 0.0138   |
| <i>comp2</i>  | 29,359      | 0.4730  | 0.4993             | 0.0000   | 1.0000   |
| <i>age</i>    | 29,359      | 1.9150  | 0.9504             | 0.0000   | 3.5264   |
| <i>tl</i>     | 29,359      | 0.3933  | 0.2002             | 0.0071   | 0.9994   |
| <i>tang</i>   | 29,359      | 0.3585  | 0.1535             | 0.0000   | 0.9552   |
| <i>itang</i>  | 29,359      | 0.0431  | 0.0391             | 0.0000   | 0.6773   |
| <i>finlev</i> | 29,359      | 0.3929  | 0.2461             | 0.0000   | 1.1458   |
| <i>cflow</i>  | 29,359      | 0.0479  | 0.0778             | −1.9377  | 2.2216   |
| <i>roa</i>    | 29,359      | 0.0397  | 0.1768             | −3.9944  | 22.0051  |
| <i>roe</i>    | 29,359      | 0.0526  | 4.7849             | −76.7641 | 713.2036 |
| <i>size</i>   | 29,359      | 21.9838 | 1.2016             | 17.3882  | 27.6377  |

### 3.3.2. Mediation Effect Model

To examine whether green data center construction affects corporate carbon reduction, this paper establishes the following regression equations for testing:

$$gtfpe1_{c,t} = \theta_0 + \theta_1 did_{c,t} + \sum \lambda X_{c,t} + \mu_i + \mu_t + \varepsilon_{c,t} \quad (2)$$

$$sgc_{i,c,t} = \beta_0 + \beta_1 did_{c,t} + \sum \lambda X_{i,c,t} + \mu_i + \mu_t + \varepsilon_{i,c,t} \quad (3)$$

where *gtfpe1*<sub>*c,t*</sub> and *sgc*<sub>*i,c,t*</sub> represent mediating variables, namely green total factor energy efficiency and green attention;  $\beta_1$  and  $\beta_2$  represent the coefficient estimates of the core explanatory variable on the mediating variables. In the previous theoretical analysis, we already proved that mediating variables affect corporate carbon emissions. Therefore, we

only need to prove that  $\beta_1$  and  $\beta_2$  are significant, i.e., that green data centers can influence green total factor energy efficiency and green attention, to demonstrate that the mediation effect is established.

### 3.3.3. Moderating Effect Model

To examine whether green data center construction affects corporate carbon reduction, this paper establishes the following regression equations for testing:

$$co2_{i,c,t} = \alpha_0 + \alpha_1 did_{c,t} + \alpha_2 din2_{c,t} + \alpha_3 din2\_did_{c,t} + \sum \lambda X_{i,c,t} + \mu_i + \mu_t + \varepsilon_{i,c,t} \quad (4)$$

$$co2_{i,c,t} = \delta_0 + \delta_1 did_{c,t} + \delta_2 comp2_{c,t} + \delta_3 comp2\_did_{c,t} + \sum \lambda X_{i,c,t} + \mu_i + \mu_t + \varepsilon_{i,c,t} \quad (5)$$

In the above equations,  $din2_{c,t}$  and  $comp2_{c,t}$ , respectively, represent moderating variables. Taking Equation (4) as an example,  $\beta_1$  represents the main effect, and  $\beta_2$  represents the moderating effect. If the main effect is positive and the moderating effect positive, it indicates that the moderating variable enhances the positive effect of the main effect; if the main effect is positive and the moderating effect negative, it indicates that the moderating variable weakens the positive effect of the main effect; if the main effect is negative and the moderating effect positive, it indicates that the moderating variable weakens the negative effect of the main effect; if the main effect is negative and the moderating effect negative, it indicates that the moderating variable enhances the negative effect of the main effect.

## 4. Empirical Analysis

### 4.1. Parallel Trend Test

This paper aims to construct a multi-period difference-in-differences model to verify the impact of green data center construction on enterprises' carbon reduction. Before conducting the analysis, it is necessary to ensure that the treatment and control groups exhibit the same pre-treatment trends in carbon reduction. This paper employs the event study method to decompose and analyze the dynamic economic effects of the policy, initially requiring a centralization of policy time—that is, subtracting the implementation time of respective policies from each period. The following model is established for testing:

$$co2_{i,c,t} = \alpha_0 + \sum_{\kappa=-m}^N \beta_{\kappa} d_{i,c,t-\kappa} \gamma X_{i,c,t} + \mu_i + \mu_t + \varepsilon_{i,c,t} \quad (6)$$

In the equation above,  $d$  represents a dummy variable that takes the value of 1 if entity  $i$  experienced a policy shock in year  $t - k$  and 0 otherwise.  $m$  represents the number of periods before the policy implementation point, and  $N$  represents the number of periods after. As shown in the Figure 1,  $d\_2$ – $d\_4$  represent policy dummy variables for 2–4 years before policy implementation, while  $d1$ – $d4$  represent policy dummy variables for 1–4 years after implementation. The dotted line represents the period before the policy shock (this paper selects  $d\_1$  as the base period). According to Figure 1, it is evident that before the policy implementation point, the 95% confidence intervals of the estimated coefficients for each period all contain the value 0, indicating no significant differences between the treatment and control groups before policy implementation. Therefore, the parallel trend test is satisfied, meaning that before enterprises were affected by green data center shocks, the carbon reduction of enterprises corresponding to treatment group enterprises and control group enterprises was essentially similar. Consequently, if significant differentiated results between the two groups can be obtained, such results can be attributed to the impact of green data center shocks on enterprises. In conclusion, the policy effects estimated using the DID method are neither biased nor impure.

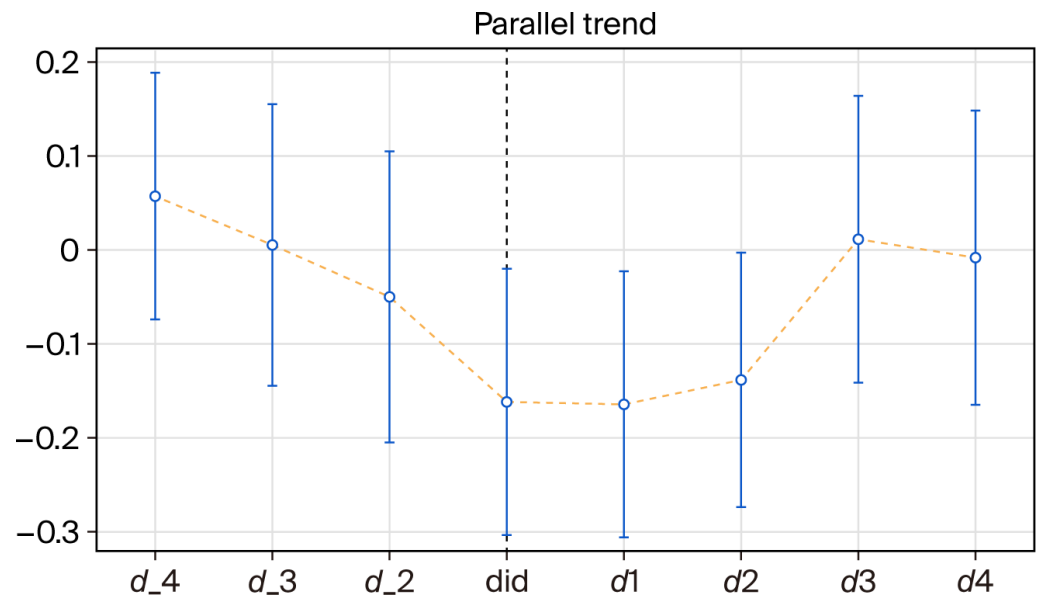


**Figure 1.** Parallel trend test. The horizontal axis represents time, the vertical axis represents confidence intervals, the solid vertical lines represent the confidence intervals of the core explanatory variable coefficients, and the middle dashed vertical line represents the period when the policy was implemented.

#### 4.2. Baseline Regression

Table 3 reports the regression results of the multi-period DID model. To further exclude the influence of multicollinearity, this paper successively reports results controlling for other control variables, individual fixed effects, and year fixed effects. Specifically, regardless of whether other variables or fixed effects are controlled for, the coefficient estimates of the core explanatory variable in all regressions are significantly negative at the 1% significance level. This indicates that the construction of green data centers can significantly promote carbon reduction in enterprises. Therefore, Hypothesis 1 is supported.

**Table 3.** Green data centers and enterprises carbon reduction.

|        | (1)                     | (2)                     | (3)                     | (4)                     |
|--------|-------------------------|-------------------------|-------------------------|-------------------------|
|        | co2                     | co2                     | co2                     | co2                     |
| did    | −2.5969 ***<br>(0.0588) | −2.6527 ***<br>(0.0574) | −0.2502 ***<br>(0.0450) | −0.2463 ***<br>(0.0446) |
| age    |                         | 0.2920 ***<br>(0.0316)  |                         | −0.2188 ***<br>(0.0379) |
| tl     |                         | −0.3165 *<br>(0.1660)   |                         | 0.6338 ***<br>(0.1254)  |
| tang   |                         | 1.7258 ***<br>(0.1862)  |                         | 0.3789 ***<br>(0.1374)  |
| itang  |                         | 0.8951<br>(0.6734)      |                         | −0.1039<br>(0.4404)     |
| finlev |                         | −1.0403 ***<br>(0.1205) |                         | −0.4754 ***<br>(0.0890) |
| cflow  |                         | 3.4482 ***<br>(0.3530)  |                         | 0.6565 ***<br>(0.1800)  |

Table 3. Cont.

|                             | (1)                    | (2)                      | (3)                    | (4)                     |
|-----------------------------|------------------------|--------------------------|------------------------|-------------------------|
|                             | co2                    | co2                      | co2                    | co2                     |
| roa                         |                        | 2.2695 ***<br>(0.2427)   |                        | 0.5934 ***<br>(0.1121)  |
| roe                         |                        | −0.0402 ***<br>(0.0088)  |                        | −0.0127 ***<br>(0.0040) |
| size                        |                        | 0.9651 ***<br>(0.0257)   |                        | 0.6159 ***<br>(0.0295)  |
| _cons                       | 9.9554 ***<br>(0.0325) | −12.1810 ***<br>(0.5313) | 9.2726 ***<br>(0.0176) | −4.0996 ***<br>(0.6355) |
| Individual<br>Fixed Effects | Not Controlled         | Not Controlled           | Controlled             | Controlled              |
| Year Fixed<br>Effects       | Not Controlled         | Not Controlled           | Controlled             | Controlled              |
| N                           | 29,359                 | 29,359                   | 29,245                 | 29,245                  |
| r2                          | 0.0624                 | 0.1466                   | 0.8613                 | 0.8644                  |
| r2_a                        | 0.0623                 | 0.1463                   | 0.8435                 | 0.8469                  |

Note: Standard errors in parentheses; \*\*\*, \* represent significance at 1%, 10% levels, respectively.

#### 4.3. Robustness Tests

To gain a deeper understanding of the impact of green data center construction on enterprises carbon reduction, this paper conducts a series of robustness tests to ensure the reliability and validity of the research conclusions. The specific steps are as follows:

##### 4.3.1. Sample Self-Selection Problem

Previous research has verified the impact of green data center construction on enterprise carbon reduction. However, an important premise relies on the randomness of sample selection and the “one-way” influence between variables. For enterprises corresponding to companies with green data centers, if their carbon reduction levels were already high, or if the growth rate of enterprise carbon reduction was already high, then the increase in enterprise carbon reduction might be attributed to the enterprise’s internal factors rather than the impact of green data center construction. This could lead to sample self-selection issues in the results, meaning that enterprises of companies with high green data center levels may have differences in baseline characteristics. In light of this, this paper uses PSM (propensity score matching) tests to mitigate this problem. Specifically, this paper first groups based on treatment and control groups, then uses the k-nearest neighbor caliper radius matching method to estimate the average treatment effect. This paper continues to use the control variables from the aforementioned research as covariates to estimate the propensity matching scores of treatment and control group enterprises. Through matching, treatment and control groups that are almost completely similar except for participation in green data centers are derived. After eliminating enterprises that do not fall within the common value range, the remaining samples are used for regression. The results are shown in regression (1) of Table 4, where the coefficient estimate of *did* remains significantly negative, maintaining the robustness of the conclusion.

**Table 4.** Robustness tests.

|                          | (1)                     | (2)                     | (3)                     |
|--------------------------|-------------------------|-------------------------|-------------------------|
|                          | <i>co2</i>              | <i>co2</i>              | <i>co2</i>              |
| did                      | −0.2474 ***<br>(0.0446) | −0.2774 ***<br>(0.0456) | −0.1722 ***<br>(0.0452) |
| age                      | −0.2205 ***<br>(0.0379) | −0.2483 ***<br>(0.0387) | 0.0385<br>(0.0392)      |
| tl                       | 0.7196 ***<br>(0.1274)  | 0.5868 ***<br>(0.1273)  | 0.8151 ***<br>(0.1325)  |
| tang                     | 0.3787 ***<br>(0.1378)  | 0.3641 ***<br>(0.1390)  | 0.4132 ***<br>(0.1402)  |
| itang                    | −0.0095<br>(0.4411)     | −0.0500<br>(0.4450)     | 0.1073<br>(0.4501)      |
| finlev                   | −0.4790 ***<br>(0.0893) | −0.4561 ***<br>(0.0898) | −0.3481 ***<br>(0.0909) |
| cflow                    | 0.6301 ***<br>(0.1805)  | 0.6958 ***<br>(0.1822)  | 0.3391 *<br>(0.1817)    |
| roa                      | 0.7298 ***<br>(0.1394)  | 0.5780 ***<br>(0.1136)  | 0.7952 ***<br>(0.1294)  |
| roe                      | 0.0179<br>(0.0125)      | −0.0126 ***<br>(0.0040) | −0.0201 **<br>(0.0091)  |
| size                     | 0.6078 ***<br>(0.0296)  | 0.6157 ***<br>(0.0301)  | 0.3631 ***<br>(0.0307)  |
| _cons                    | −3.9599 ***<br>(0.6375) | −4.0155 ***<br>(0.6471) | 0.9363<br>(0.6599)      |
| Individual Fixed Effects | Controlled              | Controlled              | Controlled              |
| Year Fixed Effects       | Controlled              | Controlled              | Not Controlled          |
| N                        | 29,233                  | 29,245                  | 25,528                  |
| r2                       | 0.8644                  | 0.8679                  | 0.8789                  |
| r2_a                     | 0.8469                  | 0.8486                  | 0.8626                  |

Note: Standard errors in parentheses; \*\*\*, \*\*, and \* represent significance at 1%, 5%, and 10% levels, respectively.

#### 4.3.2. Omitted Variable Problem

Although previous sections controlled for multiple control variables as well as enterprise and year-level fixed effects, eliminating the influence of unobservable factors specific to enterprises but invariant over time as well as unobservable factors specific to time, each industry has its unique operating model, market environment, policy orientation, technological progress speed, and complex internal interactions. These factors collectively shape the industry's overall development trend and enterprises' micro-behavior and are often difficult to fully capture and quantify. To uniformly consider and control for these unobservable factors that may interfere with enterprise carbon reduction, this paper further incorporates industry-by-year interaction fixed effects while simultaneously controlling for individual fixed effects. Regression (2) of Table 4 reports these results. The coefficient of *did* remains significantly negative, maintaining the robustness of the conclusion.

#### 4.3.3. Lagged Dependent Variable

Considering that carbon dioxide emissions are end-of-pipe emission outcomes for enterprises, which are often dependent on the influence of internal factors from the current or previous year, this paper lags *co2* emissions by one period. Regression (3) of Table 4 reports these results. As can be seen, the coefficient estimate of the core explanatory variable remains significantly negative, indicating that the previous conclusions are robust.

#### 4.3.4. Placebo Test

This paper conducts placebo tests to enhance the credibility of the baseline regression results. When performing empirical analysis using multi-year data for difference-in-differences, there may be standard error bias problems caused by serial correlation, which could lead to over-rejection of the null hypothesis in regression tests. This paper uniformly sets the policy shock time as 2017 and randomly samples the sample, each time selecting 70 enterprises as the treatment group and the remaining enterprises as the control group. This process is repeated 500 times, obtaining 500 DID regression coefficient estimates from virtual treatment groups and virtual policy time interactions. Figure 2 reports the results of the placebo test, where the horizontal axis of each scatter point represents the coefficient estimate of *did* in 500 regressions, and the vertical axis represents the *p*-value of *did* in 500 regressions. In the 500 sampling regressions, most coefficient estimate scatter points are distributed almost normally around the value 0, and most *p*-values are greater than 0.1. This indicates that after setting different treatment groups and treatment times, the core explanatory variables' coefficient estimates are insignificant. This indirectly confirms that the previous conclusions are only valid under the current settings, thus maintaining the robustness of the conclusions.

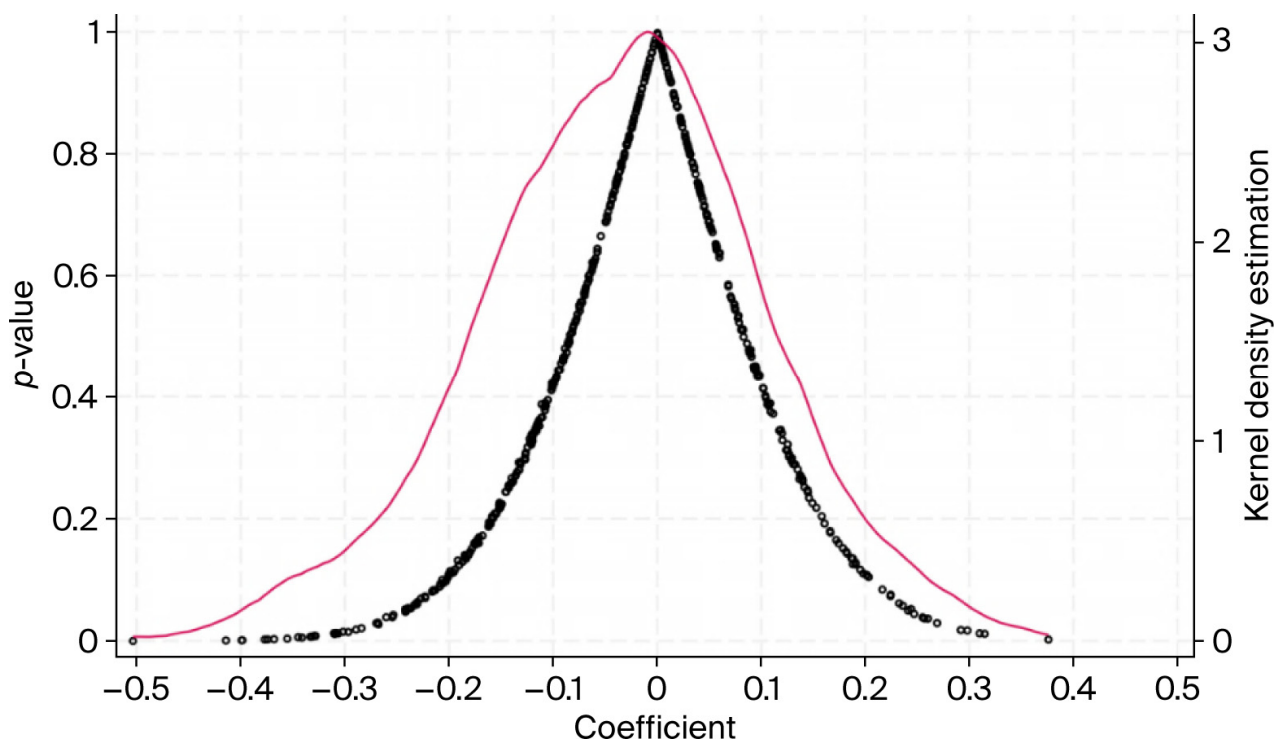


**Figure 2.** Placebo test. The horizontal axis represents the Coefficient of core variables, and the vertical axis represents *p*-value; the red solid line in the figure represents the distribution-fitted normal curve, and the scatter plot represents the distribution of (Coefficient, *p*-value).

#### 4.3.5. Excluding Contemporary Policy Interference

During the period of green data center construction, the Chinese government simultaneously issued other policies. To exclude interference from these contemporary policies, this study further identified and eliminated such samples from the regression analysis (1) Low-carbon City Pilot Policy: This policy promotes low-carbon urban development and builds a resource-conserving and environmentally friendly society. Implemented since 2010, it has designated dozens of cities and regions as pilots in multiple batches, requiring these cities to incorporate climate change response into regional development planning, formulate low-carbon development plans, adopt measures to reduce carbon emission in-

tensity, explore low-carbon green development models, and provide demonstrations for nationwide low-carbon development. (2) Air Pollution Prevention and Control Action Plan (Ten Measures for Air): This policy is a systematic and comprehensive air pollution prevention and control policy formulated and implemented by the Chinese government in 2013 to address increasingly severe air pollution problems. It proposed ten specific measures, including reducing pollutant emissions, strictly controlling new capacity in high-energy-consuming and high-polluting industries, and vigorously promoting clean production. (3) Green Finance Reform and Innovation Pilot Zone Policy: This policy, aimed at advancing green finance development and promoting green low-carbon economic and social transformation, was officially launched in June 2017. Pilot areas include parts of five provinces (regions): Zhejiang, Jiangxi, Guangdong, Guizhou, and Xinjiang, with subsequent additions including Lanzhou New Area in Gansu and Chongqing, covering multiple provinces and cities in eastern, central, and western China. (4) Dual Control Policy: Proposed in 2015 and gradually implemented nationwide, this policy aims to guide local governments to transform development concepts and promote ecological civilization construction by setting energy consumption increment and intensity control targets for supervision and assessment at all local government levels. (5) Provincial Capital Regions: Compared to other areas, provincial capitals typically have higher levels of technological innovation and more developed natural resource endowments. (6) Special Economic Zones: These zones often have more supportive policies for innovation and a higher concentration of innovative enterprises. Based on the above, this study eliminated all enterprises covered by these policies and all enterprises in some of the aforementioned regions. Using the remaining samples for regression, the results are shown in regressions (1)–(6) of Table 5. The coefficient estimates of the core explanatory variable remain significantly negative, thus maintaining the robustness of the conclusions.

**Table 5.** Excluding contemporary policy interference.

|        | (1)                        | (2)                        | (3)                        | (4)                        | (5)                        | (6)                        |
|--------|----------------------------|----------------------------|----------------------------|----------------------------|----------------------------|----------------------------|
|        | <i>co2</i>                 | <i>co2</i>                 | <i>co2</i>                 | <i>co2</i>                 | <i>co2</i>                 | <i>co2</i>                 |
| did    | −0.2950<br>***<br>(0.0754) | −0.2934<br>***<br>(0.0694) | −0.2398<br>***<br>(0.0449) | −0.2695<br>***<br>(0.0467) | −0.2518<br>***<br>(0.0511) | −0.2049<br>***<br>(0.0469) |
| age    | −0.4791<br>***<br>(0.0550) | −0.4955<br>***<br>(0.0542) | −0.2360<br>***<br>(0.0380) | −0.2187<br>***<br>(0.0396) | −0.3061<br>***<br>(0.0434) | −0.2847<br>***<br>(0.0399) |
| tl     | 0.6454 ***<br>(0.1780)     | 0.5568 ***<br>(0.1707)     | 0.6376 ***<br>(0.1255)     | 0.5721 ***<br>(0.1310)     | 0.7682 ***<br>(0.1454)     | 0.7180 ***<br>(0.1326)     |
| tang   | 0.4856 **<br>(0.1910)      | 0.6915 ***<br>(0.1865)     | 0.3729 ***<br>(0.1374)     | 0.3786 ***<br>(0.1425)     | 0.3651 **<br>(0.1593)      | 0.4549 ***<br>(0.1432)     |
| itang  | 0.0300<br>(0.6222)         | 0.3034<br>(0.6085)         | 0.2186<br>(0.4534)         | 0.1901<br>(0.4626)         | 0.5425<br>(0.5355)         | −0.0346<br>(0.4624)        |
| finlev | −0.3426<br>***<br>(0.1262) | −0.3943<br>***<br>(0.1237) | −0.4346<br>***<br>(0.0893) | −0.4268<br>***<br>(0.0929) | −0.3957<br>***<br>(0.1015) | −0.4663<br>***<br>(0.0938) |
| cflow  | 0.8181 ***<br>(0.2471)     | 0.7648 ***<br>(0.2449)     | 0.7380 ***<br>(0.1801)     | 0.6717 ***<br>(0.1865)     | 0.6592 ***<br>(0.2039)     | 0.7317 ***<br>(0.1923)     |
| roa    | 0.4533 ***<br>(0.1730)     | 0.3721 ***<br>(0.1389)     | 0.6308 ***<br>(0.1114)     | 0.4901 ***<br>(0.1180)     | 0.7798 ***<br>(0.1296)     | 0.7876 ***<br>(0.1308)     |

Table 5. Cont.

|            | (1)                        | (2)                        | (3)                        | (4)                        | (5)                        | (6)                        |
|------------|----------------------------|----------------------------|----------------------------|----------------------------|----------------------------|----------------------------|
|            | co2                        | co2                        | co2                        | co2                        | co2                        | co2                        |
| roe        | 0.0114<br>(0.0133)         | −0.0074<br>(0.0046)        | −0.0137<br>***<br>(0.0039) | −0.0103<br>**<br>(0.0041)  | −0.0071<br>(0.0055)        | −0.0001<br>(0.0058)        |
| size       | 0.5819 ***<br>(0.0414)     | 0.6001 ***<br>(0.0398)     | 0.6301 ***<br>(0.0295)     | 0.6235 ***<br>(0.0311)     | 0.6095 ***<br>(0.0340)     | 0.6302 ***<br>(0.0312)     |
| _cons      | −3.4452<br>***<br>(0.8933) | −3.8302<br>***<br>(0.8606) | −4.3944<br>***<br>(0.6344) | −4.2745<br>***<br>(0.6696) | −3.9416<br>***<br>(0.7305) | −4.3941<br>***<br>(0.6728) |
| Individual |                            |                            |                            |                            |                            |                            |
| Fixed      | Controlled                 | Controlled                 | Controlled                 | Controlled                 | Controlled                 | Controlled                 |
| Effects    |                            |                            |                            |                            |                            |                            |
| Year       |                            |                            |                            |                            |                            |                            |
| Fixed      | Controlled                 | Controlled                 | Controlled                 | Controlled                 | Not Con-<br>trolled        | Not Con-<br>trolled        |
| Effects    |                            |                            |                            |                            |                            |                            |
| N          | 18,761                     | 18,971                     | 28,565                     | 27,034                     | 22,246                     | 26,157                     |
| r2         | 0.8635                     | 0.8631                     | 0.8664                     | 0.8637                     | 0.8664                     | 0.8651                     |
| r2_a       | 0.8373                     | 0.8376                     | 0.8491                     | 0.8460                     | 0.8489                     | 0.8477                     |

Note: Standard errors in parentheses; \*\*\*, \*\* represent significance at 1%, 5% levels, respectively.

#### 4.4. Endogeneity Tests

##### 4.4.1. Heckman Test

Notably, enterprises that voluntarily disclose environmental information or regions with enterprises that have more comprehensive environmental information disclosure are often more likely to establish green data centers. This may lead to significant sample selection bias in this paper's conclusions. Given this, this paper references the research of Wang et al. [44], using an environmental information disclosure index to define the variable *disclosed*. Specifically, if an enterprise discloses any of 25 indicators, such as social responsibility reports, environmental reports, wastewater discharge volume, COD emissions, SO<sub>2</sub> emissions, etc., then *disclosed* = 1; otherwise, *disclosed* = 0, indicating very poor enterprise environmental information disclosure. Therefore, it is possible that some enterprises have high carbon reduction levels but have not established green data centers due to poor environmental information disclosure. Conversely, some enterprises with low carbon reduction levels might more easily establish green data centers simply due to high levels of environmental information disclosure. This selection behavior leads to non-randomness in the sample, meaning enterprises are not random representatives of all enterprises in the population. This paper employs the Heckman model for testing to mitigate this endogeneity problem caused by sample selection bias. The Heckman model resolves sample selection bias problems through two steps. First, it uses a selection equation to estimate factors that influence selection behavior and calculates selection probability, identifying which factors affect whether enterprises choose to disclose environmental information. Then, when estimating the relationship between green data centers, the selection probability is added as a control variable to the regression model, thereby correcting bias caused by non-random sample selection. Specifically, this paper first uses Probit regression to estimate the probability of enterprises disclosing environmental information, as shown in regression (1) of Table 6. The paper calculates the proportion of enterprises in the same industry that disclose environmental information as an instrumental variable (*z1*). Then, it adds the inverse Mills ratio *lambda* obtained from the first-stage regression to the control variables for re-regression analysis. The specific results are shown in regression (2) of Table 6. At this point, the coefficient estimate of the core explanatory variable on carbon

emissions remains significantly negative, consistent with expectations. It should be noted that the independent variable in this study is a dummy variable, and the error terms of its selection equation and outcome equation are prone to exhibiting non-normal distributions. In this case, the generation process of the inverse Mills ratio (IMR) may produce certain estimation biases due to the distortion of error term distribution, and the results are for reference only.

**Table 6.** Endogeneity tests.

|                          | (1)                     | (2)                     | (3)                      |
|--------------------------|-------------------------|-------------------------|--------------------------|
|                          | disclosed               | co2                     | co2                      |
| did                      |                         | −0.2482 ***<br>(0.0445) | −2.6527 ***<br>(0.0574)  |
| z1                       | 3.8257 ***<br>(0.0437)  |                         |                          |
| age                      | 0.1612 ***<br>(0.0131)  | −0.2340 ***<br>(0.0379) | 0.2920 ***<br>(0.0316)   |
| tl                       | −0.3164 ***<br>(0.0704) | 0.6018 ***<br>(0.1253)  | −0.3165 *<br>(0.1660)    |
| tang                     | 0.3923 ***<br>(0.0788)  | 0.4157 ***<br>(0.1373)  | 1.7258 ***<br>(0.1862)   |
| itang                    | −1.1357 ***<br>(0.2638) | −0.1578<br>(0.4399)     | 0.8951<br>(0.6734)       |
| finlev                   | 0.0243<br>(0.0507)      | −0.4557 ***<br>(0.0890) | −1.0403 ***<br>(0.1205)  |
| cflow                    | 1.0095 ***<br>(0.1469)  | 1.0208 ***<br>(0.1855)  | 3.4482 ***<br>(0.3530)   |
| roa                      | 0.1218<br>(0.0871)      | 0.6017 ***<br>(0.1119)  | 2.2695 ***<br>(0.2427)   |
| roe                      | −0.0043<br>(0.0031)     | −0.0129 ***<br>(0.0040) | −0.0402 ***<br>(0.0088)  |
| size                     | 0.1954 ***<br>(0.0115)  | 0.6342 ***<br>(0.0296)  | 0.9651 ***<br>(0.0257)   |
| imr                      |                         | −0.0015 ***<br>(0.0002) |                          |
| _cons                    | −6.5381 ***<br>(0.2475) | −4.4542 ***<br>(0.6363) | −12.1810 ***<br>(0.5313) |
| Individual Fixed Effects | Controlled              | Controlled              | Controlled               |
| Year Fixed Effects       | Controlled              | Controlled              | Controlled               |
| N                        | 29,359                  | 29,245                  | 29,359                   |
| r2_p                     | 0.5922                  |                         |                          |
| r2                       |                         | 0.8472                  |                          |

Note: Standard errors in parentheses; \*\*\*, \* represent significance at 1%, 10% levels, respectively.

#### 4.4.2. IV Estimation Without Instrumental Variables

This paper aims to study the correlation between green data centers and enterprise carbon reduction, but enterprise carbon reduction may in turn affect green data centers. When governments consider establishing green data centers, they comprehensively evaluate regional resource endowments, especially innovation levels and market development degrees. Typically, regions with high innovation levels and market development are more likely to be selected by the government as demonstration enterprises for green supply chain management due to their technological innovation and market adaptation advantages. As the main entities of regional economic activities, enterprises' technological innovation activities are important in regional innovation levels. Therefore, enterprises in these pilot

regions often already possess a certain foundation in carbon reduction. Consequently, the model may face serious bidirectional causality issues; hence, this paper employs instrumental variable methods for testing. However, selecting a completely exogenous instrumental variable is extremely difficult. This paper references a new method recently developed by Fang et al. [45] and Kiviet [46], namely the internal instrumental variable method, no-instrument method, or simply the kinky least squares (KLS) method. Unlike 2SLS, which relies entirely on instruments, the KLS method does not depend on instrumental variables, with the advantage of analytically correcting bias in the endogeneity assumption range of OLS estimates.

Furthermore, when using weak instruments, the confidence intervals produced by the KLS method are often narrower than those of 2SLS [47]. Regression (3) of Table 6 reports the regression results after using the *kinkyreg* command. It can be observed that after considering endogeneity issues, the coefficient estimate of *did* remains significantly negative, thus maintaining the robustness of the conclusion.

#### 4.5. Mediating Effect Tests

##### 4.5.1. Testing the Mediating Effect of Green Total-Factor Energy Efficiency

The preceding analysis verifies the impact of green data center construction on supplier carbon reduction. This study further validates the roles of green total factor energy efficiency and green attention. For the former, this study uses production factor inputs such as labor and capital as input variables, where labor is the logarithm of the number of employed persons in the region, and capital is the logarithm of total fixed asset investment. Regional GDP is the desirable output, while the three industrial wastes are undesirable. Subsequently, the SBM–Malmquist–Luenberger index method is employed to calculate and measure regional green total factor energy efficiency. Relevant data are primarily sourced from the China City Statistical Yearbook and China Energy Statistical Yearbook. Regressions (1) and (2) in Table 7 report the impact of green data center construction on enterprises' green total-factor energy efficiency, where *gtfpe1* represents enterprises' green total-factor energy efficiency. It can be observed that the coefficient estimate of *did* remains significantly positive at the 5% significance level, indicating that green data center construction can significantly promote the green total-factor energy efficiency level of enterprises. Theoretically, green total-factor energy efficiency can inhibit enterprise carbon emissions; thus, green data center construction can reduce enterprise carbon emissions by promoting green total-factor energy efficiency. The possible reasons are that green data center construction significantly improves energy use efficiency by adopting high-performance servers, storage devices, and network equipment as well as advanced cooling technologies and energy management systems. These measures reduce data center energy consumption and decrease carbon emissions produced during energy conversion and transmission processes. Meanwhile, green data centers guide enterprises to actively utilize renewable energy sources such as solar and wind power, further reducing dependence on fossil fuels and decreasing carbon emissions. Additionally, regions with green data center construction often pay more attention to enhancing the intelligence level of overall operational management, achieving precise energy dispatch and management through data analysis and prediction, effectively improving energy use efficiency, reducing operational costs, and providing strong support for enterprises to achieve low-carbon operations.

**Table 7.** Mediation effect test.

|               | (1)                    | (2)                    | (3)                    | (4)                    |
|---------------|------------------------|------------------------|------------------------|------------------------|
|               | gtfpe1                 | gtfpe1                 | sgc                    | sgc                    |
| did           | 0.0788 ***<br>(0.0023) | 0.0786 ***<br>(0.0023) | 0.9851 ***<br>(0.1878) | 0.9872 ***<br>(0.1881) |
| age           |                        | −0.0031<br>(0.0020)    |                        | −0.1392<br>(0.1598)    |
| tl            |                        | 0.0082<br>(0.0065)     |                        | 0.6550<br>(0.5288)     |
| tang          |                        | 0.0328 ***<br>(0.0071) |                        | 1.5735 ***<br>(0.5794) |
| itang         |                        | 0.0619 ***<br>(0.0229) |                        | −0.0815<br>(1.8575)    |
| finlev        |                        | −0.0011<br>(0.0046)    |                        | −0.3055<br>(0.3755)    |
| cflow         |                        | 0.0088<br>(0.0094)     |                        | 0.8883<br>(0.7595)     |
| roa           |                        | −0.0137 **<br>(0.0058) |                        | 0.5700<br>(0.4726)     |
| roe           |                        | 0.0004 *<br>(0.0002)   |                        | −0.0103<br>(0.0168)    |
| size          |                        | 0.0047 ***<br>(0.0015) |                        | 0.2569 **<br>(0.1245)  |
| _cons         | 0.4417 ***<br>(0.0009) | 0.3279 ***<br>(0.0331) | 7.4213 ***<br>(0.0734) | 1.2765<br>(2.6807)     |
| Individual    | Controlled             | Controlled             | Controlled             | Controlled             |
| Fixed Effects |                        |                        |                        |                        |
| Year Fixed    | Controlled             | Controlled             | Controlled             | Controlled             |
| Effects       |                        |                        |                        |                        |
| N             | 29,245                 | 29,245                 | 29,245                 | 29,245                 |
| r2            | 0.8216                 | 0.8219                 | 0.9141                 | 0.9142                 |
| r2_a          | 0.7986                 | 0.7990                 | 0.9031                 | 0.9031                 |

Note: Standard errors in parentheses; \*\*\*, \*\*, and \* represent significance at 1%, 5%, and 10% levels, respectively.

#### 4.5.2. Testing the Mediating Effect of Green Attention

The measurement of corporate green attention is divided into two steps: First, this study constructs a keyword list covering three dimensions—green competitive advantage awareness, corporate social responsibility awareness, and external environmental pressure cognition—including energy conservation and emission reduction, environmental protection strategy, environmental protection concept, environmental management organization, environmental protection education, environmental protection training, environmental technology development, environmental audit, energy conservation and environmental protection, environmental protection policy, environmental protection department, environmental protection inspection, low-carbon environmental protection, environmental protection work, environmental protection governance, environmental protection and environmental governance, environmental protection facilities, environmental protection-related laws and regulations, and environmental protection and pollution control.

Second, based on the listed companies' annual reports, this study uses text analysis methods to count the frequency of the aforementioned keywords appearing in corporate annual reports. The logarithm of this frequency plus one is calculated to measure corporate managers' attention to environmental management, namely green attention (*sgc*). Generally, the larger this value, the higher the corporate managers' attention to environmental management and thus the higher the green attention.

Regressions (3) and (4) in Table 7 report these results, where *sgc* represents enterprise green attention. The coefficient estimate of *did* is significantly positive at the 1% significance level, indicating that green data center construction can promote enterprise green attention. The possible reason is that establishing city data centers is a high recognition of enterprises' practices in environmental protection, sustainable development, and green supply chain management. This honor enhances the enterprise's green image within the industry and signals to the market its commitment to environmental protection and efficient resource utilization. This positive demonstration effect serves as a powerful incentive and guidance for enterprises. Enterprises often actively improve their green management levels to meet environmental requirements and market demands; thus, Hypothesis 3 is supported.

#### 4.6. Moderating Effect Tests

##### 4.6.1. Testing the Moderating Effect of Digital Infrastructure

To further verify the role of digital infrastructure, this paper constructs interaction terms for testing. *din2* represents the digital infrastructure of enterprises, measured by the ratio of enterprise R&D expenditure to operating revenue. Specifically, Regressions (1) and (2) in Table 8 report the results of the moderating effect tests. The coefficient estimate of *did* is significantly negative: at least the 1% significance level. *din2\_did* represents the interaction term between green data center construction and enterprise digital infrastructure, with its coefficient estimate significantly negative: at least the 1% significance level. Therefore, enterprise digital infrastructure can negatively moderate the inhibitory effect of green data center construction on enterprise carbon emissions. This means that the stronger the digital infrastructure, the stronger the promoting effect of green data center construction on enterprise carbon reduction. The possible reasons are that as urban digital infrastructure continues to improve, the connection between green data centers and enterprises becomes increasingly close. Enterprises can conveniently access various services green data centers provide through high-speed networks, such as data storage, processing, and analysis. This deep integration enables enterprises to more efficiently utilize the resources provided by green data centers, reducing their own energy consumption and carbon emissions. Additionally, urban digital infrastructure optimizes resource allocation and improves overall energy utilization efficiency. Through smart grid and microgrid technologies, green data centers can achieve precise dispatch and management of electricity, reducing energy loss, and through Internet of Things technology, green data centers can conduct real-time monitoring and early warning of equipment status, promptly discovering and resolving potential energy waste problems.

**Table 8.** Moderation effect test.

|                  | (1)                     | (2)                     | (3)                     | (4)                     |
|------------------|-------------------------|-------------------------|-------------------------|-------------------------|
|                  | <i>co2</i>              | <i>co2</i>              | <i>co2</i>              | <i>co2</i>              |
| <i>did</i>       | −0.2003 ***<br>(0.0580) | −0.2198 ***<br>(0.0576) | −0.1201 *<br>(0.0669)   | −0.1316 **<br>(0.0663)  |
| <i>din2</i>      | −2.7847 ***<br>(0.1321) | −2.5498 ***<br>(0.1315) |                         |                         |
| <i>din2_did</i>  | −0.5413 ***<br>(0.1808) | −0.3997 **<br>(0.1796)  |                         |                         |
| <i>comp2</i>     |                         |                         | −0.2786 ***<br>(0.0449) | −0.2595 ***<br>(0.0444) |
| <i>comp2_did</i> |                         |                         | −0.1581 **<br>(0.0707)  | −0.1399 **<br>(0.0703)  |

Table 8. Cont.

|                             | (1)                    | (2)                     | (3)                    | (4)                     |
|-----------------------------|------------------------|-------------------------|------------------------|-------------------------|
|                             | <i>co2</i>             | <i>co2</i>              | <i>co2</i>             | <i>co2</i>              |
| age                         |                        | −0.1873 ***<br>(0.0376) |                        | −0.1984 ***<br>(0.0380) |
| tl                          |                        | 0.6254 ***<br>(0.1241)  |                        | 0.6285 ***<br>(0.1252)  |
| tang                        |                        | 0.3420 **<br>(0.1361)   |                        | 0.3614 ***<br>(0.1373)  |
| itang                       |                        | −0.2292<br>(0.4361)     |                        | −0.1905<br>(0.4400)     |
| finlev                      |                        | −0.4478 ***<br>(0.0882) |                        | −0.4587 ***<br>(0.0890) |
| cflow                       |                        | 0.6523 ***<br>(0.1783)  |                        | 0.6665 ***<br>(0.1799)  |
| roa                         |                        | 0.5797 ***<br>(0.1109)  |                        | 0.5965 ***<br>(0.1119)  |
| roe                         |                        | −0.0126 ***<br>(0.0039) |                        | −0.0129 ***<br>(0.0040) |
| size                        |                        | 0.5372 ***<br>(0.0294)  |                        | 0.6091 ***<br>(0.0295)  |
| _cons                       | 9.7824 ***<br>(0.0298) | −1.9506 ***<br>(0.6363) | 9.4027 ***<br>(0.0264) | −3.8611 ***<br>(0.6357) |
| Individual<br>Fixed Effects | Controlled             | Controlled              | Controlled             | Controlled              |
| Year Fixed<br>Effects       | Controlled             | Controlled              | Controlled             | Controlled              |
| N                           | 29,245                 | 29,245                  | 29,245                 | 29,245                  |
| r2                          | 0.8646                 | 0.8670                  | 0.8617                 | 0.8647                  |
| r2_a                        | 0.8472                 | 0.8499                  | 0.8439                 | 0.8472                  |

Note: Standard errors in parentheses; \*\*\*, \*\*, and \* represent significance at 1%, 5%, and 10% levels, respectively.

#### 4.6.2. Testing the Moderating Effect of Computing Power

This paper further examines whether urban computing power development amplifies the effects of green data center construction. Specifically, computing power is measured by the scale of regional graphics card imports, with higher values indicating higher computing power levels in the region. Regressions (3) and (4) in Table 8 report the results of the moderating effect tests for computing power. The coefficient estimate of *did* remains significantly negative, *comp2* represents computing power, and *comp2\_did* represents the interaction term between computing power and green data center construction, with its coefficient estimate also significantly negative at the 5% significance level. Therefore, computing power can negatively moderate the inhibitory effect of green data centers on enterprises' carbon emissions, meaning that the higher the regional computing power development level, the stronger the inhibitory effect of green data center construction on carbon emissions. The possible reason is that the development level of computing power is an important indicator for measuring a region's information technology strength and data processing capability. With the continuous growth of computing power demand, data centers, as key infrastructure supporting computing power services, expand accordingly in scale. In regions with higher computing power development levels, data centers are often larger in number and scale, with stronger data processing capabilities and correspondingly increased energy consumption. Therefore, these regions have more urgent demands for green data center construction to address the growing pressure of energy consumption and carbon emissions. Thus, Hypothesis 5 is supported.

#### 4.7. Heterogeneity Tests

##### 4.7.1. Testing Heterogeneity by Ownership Type

Previous sections have verified the impact of green data center construction on enterprise carbon reduction. To further verify the heterogeneous effects of this result among enterprises with different ownership types, this paper divides the sample into state-owned and non-state enterprises. Table 9 reports these results, showing that the promoting effect of green data center construction on carbon reduction is more significant for state-owned enterprises. The possible reason is that state-owned enterprises often bear more social responsibilities as pillars of the national economy. Regarding environmental protection and sustainable development, state-owned enterprises typically have stronger awareness and higher standards. As an important measure to promote energy conservation, emission reduction, and environmental protection, green data center construction is more likely to receive a positive response and implementation in state-owned enterprises.

**Table 9.** Ownership structure test.

|                          | (1)                     | (2)                     |
|--------------------------|-------------------------|-------------------------|
|                          | <i>co2</i>              | <i>co2</i>              |
| did                      | −0.3792 ***<br>(0.0750) | −0.1818 ***<br>(0.0548) |
| age                      | −0.0750<br>(0.0926)     | −0.4401 ***<br>(0.0468) |
| tl                       | −0.3831 *<br>(0.2072)   | 0.8995 ***<br>(0.1594)  |
| tang                     | 0.7816 ***<br>(0.2209)  | 0.3989 **<br>(0.1734)   |
| itang                    | 0.0301<br>(0.7706)      | 0.1231<br>(0.5404)      |
| finlev                   | −0.3439 **<br>(0.1606)  | −0.5279 ***<br>(0.1073) |
| cflow                    | 0.7732 **<br>(0.3116)   | 0.5742 ***<br>(0.2181)  |
| roa                      | 0.4178 **<br>(0.1831)   | 0.7744 ***<br>(0.1735)  |
| roe                      | −0.0037<br>(0.0055)     | −0.0161<br>(0.0109)     |
| size                     | 0.7822 ***<br>(0.0473)  | 0.5989 ***<br>(0.0381)  |
| _cons                    | −6.7430 ***<br>(1.0504) | −3.8955 ***<br>(0.8134) |
| Individual Fixed Effects | Controlled              | Controlled              |
| Year Fixed Effects       | Controlled              | Controlled              |
| N                        | 7767                    | 21,416                  |
| r2                       | 0.8778                  | 0.8614                  |
| r2_a                     | 0.8643                  | 0.8406                  |

Note: Standard errors in parentheses; \*\*\*, \*\*, and \* represent significance at 1%, 5%, and 10% levels, respectively.

##### 4.7.2. Testing Heterogeneity by High-Tech Enterprise Status

Previous sections have verified the impact of green data center construction on enterprise carbon reduction. To further verify the heterogeneous effects of this result among different high-tech enterprises, this paper divides the sample into high-tech enterprises and non-high-tech enterprises. Table 10 reports these results, showing that the promoting effect of green data center construction on carbon reduction is more significant for high-tech enterprises. The possible reason is that high-tech enterprises typically possess stronger

technological innovation capabilities and higher receptivity to advanced technologies. Green data center construction involves numerous advanced energy-saving technologies and environmentally friendly materials, such as liquid cooling technology, intelligent temperature control systems, and renewable energy utilization. These technologies are more easily promoted and applied in high-tech enterprises, highly compatible with their business characteristics and technological requirements. Therefore, high-tech enterprises have greater potential for carbon reduction.

**Table 10.** High-tech enterprise test.

|                          | (1)                     | (2)                     |
|--------------------------|-------------------------|-------------------------|
|                          | <i>co2</i>              | <i>co2</i>              |
| did                      | −0.2389 ***<br>(0.0449) | −0.1501<br>(0.2212)     |
| age                      | −0.1282 ***<br>(0.0383) | −1.5009 ***<br>(0.1911) |
| tl                       | 0.7112 ***<br>(0.1292)  | −0.4732<br>(0.4796)     |
| tang                     | 0.2500 *<br>(0.1429)    | 1.4775 ***<br>(0.4725)  |
| itang                    | −0.2906<br>(0.4491)     | 2.9651<br>(1.8151)      |
| finlev                   | −0.5387 ***<br>(0.0907) | 0.1829<br>(0.3715)      |
| cflow                    | 0.4978 ***<br>(0.1924)  | 1.7289 ***<br>(0.5744)  |
| roa                      | 0.6478 ***<br>(0.1254)  | 0.7592 ***<br>(0.2904)  |
| roe                      | −0.0146 ***<br>(0.0043) | −0.0065<br>(0.0245)     |
| size                     | 0.6218 ***<br>(0.0302)  | 0.4356 ***<br>(0.1344)  |
| _cons                    | −4.2152 ***<br>(0.6513) | 0.1753<br>(2.8777)      |
| Individual Fixed Effects | Controlled              | Controlled              |
| Year Fixed Effects       | Controlled              | Controlled              |
| N                        | 27,305                  | 1910                    |
| r2                       | 0.8631                  | 0.8921                  |
| r2_a                     | 0.8458                  | 0.8717                  |

Note: Standard errors in parentheses; \*\*\*, \* represent significance at 1%, 10% levels, respectively.

## 5. Discussion

This paper empirically investigates the impact of green data centers on enterprise carbon reduction using multi-period difference-in-differences models based on data from Chinese A-share listed companies and cities from 2009 to 2023.

Previous research has primarily focused on various effects of digital infrastructure, with the most relevant to this paper being studies on the impact of “Broadband China” on carbon emissions. For example, Zhang and Bai [48] found that Broadband China can produce synergistic emission reduction effects with environmental regulation, primarily by increasing green factors in the input–output stage and improving production efficiency. Xiao and Liu [49] discovered that the Broadband China policy has heterogeneous effects on regional carbon emissions and achieves this effect through industrial upgrading and green technological innovation. Studies directly focusing on the environmental effects of green data centers have mainly examined the energy consumption and emissions generated by

them. From a global perspective, Li et al. [50], based on China's policies promoting the green development of data centers over the years and their effects, proposed optimization paths for green low-carbon technology systems in areas including IT equipment, cooling systems, power supply and distribution systems, lighting, and intelligent operation and maintenance. From a more detailed perspective, Shuja et al. [51] proposed that utilizing thermal stratification can provide natural cooling water to cooling systems, helping green data centers achieve continuous decarbonization, enabling data centers to consume less energy and generate fewer greenhouse gas emissions. Building on this, Zhang et al. [52], using the large-scale pumped storage power station (PSPS) at Jinshuitan Reservoir in a green data center in southeastern China as an example, further explored solutions to enhance the climate resilience of this energy-saving and emission reduction method under extreme climate scenarios through simulating different climate scenarios.

Unlike previous research, this study demonstrates the direct effects of green data centers on carbon emissions. It explores the mediating effects of green total factor energy efficiency and green attention from two perspectives: energy efficiency at the city level and corporate attention at the enterprise level. This significantly compensates for the cross-level causal inference defects caused by explanatory and explained variables belonging to different dimensions in this study. Related research was also validated, proving that the mediating effects of both are positive. Additionally, this study identified the positive moderating roles of computing power level and digital infrastructure level in this relationship.

Through enterprise grouping analysis, this study found that these effects are more pronounced in state-owned and high-tech enterprises. The construction of green data centers demonstrates a more substantial promotional effect on carbon emission reduction for state-owned enterprises, which is manifested in two aspects: the inherent nature and responsibilities of state-owned enterprises and the integration of national policies. State-owned enterprises consistently play an important, even leading role in promoting social stability and adhering to national policies [53]. Compared to private enterprises, state-owned enterprises are more likely to comply with national policies to achieve environmental performance targets [54]. State-owned enterprises face stronger negative market reactions to carbon neutrality commitments [55]; therefore, state-owned enterprises will take more actions than private enterprises to align with green data center construction and reduce carbon emissions. Furthermore, the party-building development model of Chinese state-owned enterprises is relatively mature, with many enterprises achieving a "party-building + green" development model. Party organizations promote corporate fulfillment of social responsibilities and carbon emission reduction by strengthening enterprise supervision to ensure alignment with national environmental goals [56,57]. The stronger inhibitory effect of green data centers on the carbon emissions of high-tech enterprises can be verified from both internal and external perspectives. First, it is undeniable that the internal carbon management, green technology talent, and related advanced equipment and technologies of high-tech enterprises enable them to have a stronger response speed and absorption capacity in developing green data centers, allowing for rapid application. On the other hand, as consumer environmental awareness strengthens, high-tech enterprises face greater pressure, which further drives enterprises to invest in green production [58] and actively rely on green data centers to achieve carbon emission reduction.

The paper reveals the mechanism of action between green data centers and enterprise carbon emissions, enriching both the theoretical and empirical research on the environmental effects of green data centers at the micro level. This contributes to promoting integrating and developing new digital infrastructure construction with the green economy.

However, this research also has certain limitations. First, the research data only apply to China as an emerging economy, and their applicability to other developing countries cannot be confirmed, limiting the findings' universality. However, Trinh et al. [59], based on an international survey of 56 countries, verified the relationship between green growth, technological innovation, and infrastructure investment trends, demonstrating that increased green infrastructure will promote carbon reduction, which is particularly important for emerging economies and polluting economies with high climate risk exposure. Second, due to constraints in corporate information disclosure, this study focused exclusively on Chinese listed companies, resulting in incomplete measurement of carbon emissions for non-listed enterprises. While using listed company samples limits the representativeness of our findings, the most comprehensive dataset currently available for small and medium-sized enterprises in China is the China Industrial Enterprise Database. However, this database only provides data through 2015, making it inadequate for capturing the full timeline of green data center deployment. Consequently, it is challenging to satisfy both currency and comprehensiveness requirements simultaneously. Third, this paper only explores the impact of green data centers on enterprise carbon reduction from an overall perspective. For future research, the relationship could be further explored from two perspectives: digital industrialization and industrial digitalization.

## 6. Conclusions and Policy Recommendations

Global priorities are promoting energy conservation and emission reduction, accelerating green transformation, and achieving net-zero carbon emissions. Against the backdrop of integrated development between digital and green economies, green data centers play a crucial role in global carbon reduction. Based on data from Chinese A-share listed companies from 2009 to 2023, this paper constructs multi-period difference-in-differences models to investigate the impact of green data centers as green digital infrastructure on enterprise carbon emissions and their operating mechanisms. The main conclusions are as follows: First, the establishment of green data centers has significantly promoted corporate carbon emission reduction and has become an important force for corporate green and high-quality development in the new era. Combined with the Porter hypothesis, resource-based theory, and institutional theory, it was found that green data centers primarily function through three dimensions: environmental regulation, resource endowment, and operational development, achieving the regulatory function of macro policies on micro entities and thereby attaining carbon emission reduction effects. This conclusion remained valid after conducting endogeneity tests through the construction of Heckman models and IV estimation without instrumental variables and performing a series of robustness checks, including the exclusion of competitive effects. Second, improving corporate green total factor energy efficiency and green attention is an important mechanism through which green data centers promote corporate carbon emission reduction. Enhancing green total factor energy efficiency and attention will promote corporate investment in green production and reduce energy consumption. Additionally, regional computing power levels and digital infrastructure levels significantly and positively moderate the impact of green data centers on corporate carbon emission reduction. Improving computing power levels and constructing and enhancing digital infrastructure will vigorously promote regional "hard power" and "soft power" in addressing carbon emissions, driving technological advancement while strengthening regional green concepts. Third, through enterprise grouping analysis, it was found that in heavily polluting and high-tech enterprises, the promotional effect of green data centers on corporate carbon emission reduction is more pronounced compared to other enterprises. This is closely related to the distinctive political, structural, and cultural

characteristics of state-owned enterprises and the technological capabilities, equipment reserves, and employee competencies of high-tech enterprises.

The findings of this paper have the following policy implications:

First, government policy guidance and economic support are crucial for green data center development. As digital infrastructure, green data centers require strategic deployment support from national or local governments. Although China's green data centers have progressed from the pilot period to rapid development, improvements are still needed in areas such as geographic coverage and energy supply from a policy perspective. Significant regional contradictions exist between China's energy and computing power resources, particularly concerning regional energy supply imbalances. The "East Data, West Computing" strategy has partially alleviated geographical energy supply–demand contradictions, but data security and energy loss issues persist. Therefore, under the "East Data, West Computing" strategic framework, the government should accelerate green data center construction in western regions, fully leveraging western energy advantages and improving computing power levels to better harness the positive moderating effects of computing power and digital infrastructure on green data centers' promotion of enterprise carbon reduction. The government should also expedite the standardization of green data centers, improve legal requirements, and strengthen low-carbon oversight of green data centers to enhance standardization while adapting to local conditions, strengthening inter-regional infrastructure connections, and establishing reasonable cross-provincial collaboration mechanisms.

Second, local enterprises should be encouraged to fully utilize green data centers, strengthening their linkage while accelerating technological innovation in green data centers. As green data centers continue to be built, the market environment for transactions between enterprises and green data centers should be further optimized, improving collaborative mechanisms between both parties. Through enhanced fiscal subsidies and green finance policies, enterprises can be motivated to voluntarily participate in green data center construction and actively invest in research and development, accelerating solutions to challenges such as energy consumption and insufficient computing power in green data centers. While further promoting data centers' breakthroughs in overcoming technological barriers, enterprises' carbon reduction capabilities should be strengthened. Policies can reinforce the connection between enterprise participation in green data centers, contribution to their construction, and carbon emission trading rights, encouraging and promoting enterprise green transformation, especially for heavily polluting enterprises. Additionally, the "point-to-area" effect can be effectively leveraged, fully utilizing the technological dividends that some enterprises gain from green data centers, expanding the coverage of these effects, and motivating more enterprises to engage in green data center cooperation and construction.

Third, the strategic position of "dual carbon" policies within enterprises should be strengthened, promoting the construction of corporate green environmental protection culture. The green attention of executives in enterprises can reduce carbon emissions; therefore, when recruiting management and technical personnel, enterprises can appropriately include environmental awareness as an assessment indicator. They can also strengthen employee training, enhance corporate staff's green consciousness, and shape a positive corporate green culture. Enterprises should adopt green sustainable development philosophy, actively pursue technological innovation, and improve energy utilization efficiency. Simultaneously, low-carbon strategic awareness can accelerate enterprise digital intelligent transformation, reducing carbon reduction costs in supply chain tracking. Additionally, enterprises should actively fulfill their social responsibilities and standardize their disclosures.

Fourth, the evaluation system for data centers requires substantial improvement, and relevant standards and specifications need further clarification. Establishing and refining comprehensive standards for green data centers that encompass planning, construction, management, and feedback evaluation is essential to ensure a closed-loop system. This approach will promote green data center development and enhance the effectiveness of carbon emission reduction. For instance, an energy efficiency monitoring and optimization system should be developed based on green total factor energy efficiency (GTFEE) indicators. First, the key monitoring components of GTFEE must be identified, including infrastructure construction, associated energy inputs, projected computing capacity, data storage volumes, and potential carbon emissions. While conducting comprehensive monitoring and evaluation, efforts should focus on mitigating the negative aspects of the complex effects that green data centers may have on carbon emissions. This involves optimizing performance from an “efficiency maximization and waste minimization” perspective regarding inputs and outputs. Such optimization will encourage further green data center development and maximize their positive environmental impacts. Governments should regularly conduct energy efficiency assessments and rankings, implement effective feedback evaluations, and monitor energy efficiency trends across different data centers by establishing a GTFEE database. This database can also incentivize enterprises to incorporate relevant indicators into their evaluation systems, driving concrete actions toward corporate carbon emission reduction.

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