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The Impact of Computing Infrastructure on Corporate Green Technological Innovation: A Quasi-Natural Experiment Based on the Construction of National Supercomputing Centers

Zhen Tian * and Jie Liu

School of Economics and Management, Zhengzhou University of Light Industry, Zhengzhou 450001, China; 332406060655@zzuli.edu.cn
* Correspondence: tianzhen@zzuli.edu.cn

Abstract

Using data on Chinese A-share listed companies from 2009 to 2024, this paper treats the construction of National Supercomputing Centers as a quasi-natural experiment and systematically examines the impact of large-scale computing infrastructure on corporate green technological innovation. Green technological innovation here refers to firms' R&D and application activities aimed at energy conservation, emission reduction, resource recycling, and mitigating environmental damage. We find that the operation of National Supercomputing Centers significantly improves corporate green technological innovation, and this effect is notably stronger among state-owned enterprises and high-tech firms. Mechanism tests show that the construction of supercomputing centers does not rely solely on computing power input; rather, it promotes green technological innovation through three significant mediating channels—promoting firms' application of artificial intelligence technology, enhancing new quality productive forces, and reducing industry-adjusted tax burdens—thereby generating a synergistic effect between digital and intelligent technology empowerment and improved innovation cost conditions. Based on the resource-based view and the perspective of digital infrastructure empowerment, this study elucidates the underlying mechanisms through which computing power infrastructure drives corporate green technological innovation. It provides systematic micro-level evidence for understanding the causal relationship between computing power and corporate green technological innovation, and offers policy implications for aligning the national computing power strategy with the green innovation system.

Keywords: computing power infrastructure; corporate green technology innovation; national supercomputing centers

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1. Introduction

At present, the breakthrough development of digital technologies such as big data, the Internet of Things, and cloud computing is driving systemic economic and social changes with unprecedented breadth and depth, propelling the world into a new phase of digital and intelligent development. This process not only reshapes industrial forms and business models but also becomes a critical force influencing national competitiveness and future growth trajectories [1]. In this context, computing power, as the foundational capability for processing data, running algorithms, and supporting intelligent applications, has evolved into an indispensable new productive force in the digital economy era, a key pillar driving industrial transformation and technological innovation [2]. Among these developments, the

construction and advancement of National Supercomputing Centers stand as a significant symbol of the modernization of the computing power system. Since the establishment and operation of the first National Supercomputing Center in 2009, by the end of 2025, China had built and commissioned 14 National Supercomputing Centers. These centers possess world-leading high-performance computing capabilities and large-scale data storage resources, serving as the core computing power that supports cutting-edge scientific research, major engineering simulations, and breakthroughs in key industrial technologies. As digitalization increasingly integrates with sustainable development goals, China's vigorous development of computing infrastructure provides crucial support for overcoming core bottlenecks that have long plagued corporate green technology innovation, such as high computational complexity, high research and development (R&D) costs, and high risks. This reality closely intertwines the development path of corporate green technology innovation with the layout of computing infrastructure.

The green technology innovation discussed in this paper refers specifically to environmentally oriented technology research, development, and application activities undertaken by enterprises to reduce energy consumption, lower emissions, and promote resource recycling. This is both a strategic choice for enterprises to respond to environmental regulations and an important pathway for building sustainable competitive advantages [3]. With increasingly stringent environmental regulations and continuously rising green consumption awareness, the endogenous motivation for enterprises to improve resource efficiency and reduce environmental risks through green technology innovation is constantly strengthening. Related technological achievements are increasingly becoming an important cornerstone supporting the long-term development of enterprises. However, green technology innovation is characterized by high costs, long cycles, and high risks. Hence, an urgent issue is how to effectively help enterprises overcome these practical difficulties through policy measures.

Although existing research has recognized the promoting effect of digital technologies on green technology innovation, it has mostly focused on general-purpose digital infrastructure such as broadband networks and smart cities [4,5], or the enabling role of artificial intelligence in specific process links [6]. It often treats computing power as a homogeneous background factor, failing to fully reveal the irreplaceable role of dedicated high-performance computing facilities in overcoming bottlenecks in green technology R&D. Furthermore, the existing literature's attention to computing infrastructure has primarily concentrated on its impact on corporate digital transformation [7], total factor productivity improvement [8], or regional knowledge innovation [9]. The field of environmental innovation shows a notable lack of systematic exploration of computing power's green enabling function. Although some studies have noted the promoting effects of data assets and progress in digital technology on green technology innovation [10], the literature has paid limited attention to the specific role of computing infrastructure and its mechanisms. In summary, existing research has not yet clearly answered the question: can China's leading supercomputing centers effectively help enterprises overcome the difficulties they face in green technology innovation by providing dedicated computing resources? What are their transmission pathways and applicable conditions? These research gaps limit our in-depth understanding of how policy, markets, and enterprises can effectively collaborate on green technology innovation and constrain the precise formulation and practical implementation of policies related to computing infrastructure.

Addressing these deficiencies, this study shifts the focus from "general-purpose digital technologies" to "computing infrastructure". Taking the physical infrastructure "National Supercomputing Centers", which provide specialized, large-scale, high-performance computing resources, as the core research object, it systematically investigates how they

drive corporate green technology innovation through targeted computing power supply. Compared to comprehensive policies such as smart city initiatives, the uniqueness of supercomputing centers lies in their technological specificity and service orientation. They do not indirectly incentivize green technology innovation by optimizing the business environment; instead, they directly target and solve the high-complexity computing bottlenecks in green technology R&D. In terms of the service model, while undertaking national strategic scientific research tasks, supercomputing centers rely on open-sharing mechanisms. Through specific arrangements, such as establishing corporate service departments and building contractual software resource-sharing systems, they construct a precise channel connecting national research platforms with enterprise R&D needs. This provides a realistic basis for studying their market-oriented transmission mechanisms.

Based on this, this study treats the construction of National Supercomputing Centers as a quasi-natural experiment and employs firm-level data to identify the effect of computing infrastructure on corporate green technology innovation. The paper makes three contributions. First, it moves from general-purpose digital technologies to a single class of specialized facility and exploits the staggered opening of the centers, which lets the effect be identified within cities that differ in the timing of access. Second, it goes beyond the single-step association between treatment and potential mediators that characterises much of the existing evidence. The mediators are required to predict green patenting and to attenuate the treatment coefficient, and three channels survive that test: AI patent applications, new-quality productive capacity, and the industry-adjusted tax burden. Third, the heterogeneity results locate the effect. It is estimated among state-owned enterprises and among high-technology firms, the groups with the resources to absorb computing capacity, and the policy discussion follows that pattern.

2. Theoretical Analysis and Research Hypotheses

2.1. The Impact of Computing Infrastructure on Corporate Green Technology Innovation

Computing power can be categorized into three types based on core hardware and application characteristics: general-purpose computing power, intelligent computing power, and supercomputing power [11]. Supercomputing power, centered on high-performance computing clusters or supercomputers, can significantly advance the transformation of green technologies from theoretical exploration to industrial application by providing exceptional computing resources and massive data processing support [12]. Concurrently, the extensive deployment of computing infrastructure facilitates the transformation of industrial structures towards service-oriented and knowledge-intensive models, fostering a more efficient industrial ecosystem with lower carbon emissions and thereby creating favorable conditions for corporate green technology innovation [13]. From a systemic synergy perspective, computing infrastructure integrates with digital infrastructures such as broadband networks and artificial intelligence, collectively forming a networked platform that promotes the agglomeration and coordination of green innovation factors. This integration helps reduce transaction costs associated with green technology innovation and enhances the efficiency of knowledge spillovers. Furthermore, the emergence of machine learning is profoundly altering the evolutionary framework of corporate decision-making. The digital–intelligent transformation of enterprises significantly enhances their green innovation capacity, a process inseparable from the support of underlying infrastructure, such as computing power [14]. Computing infrastructure not only directly enables green R&D from a technical standpoint but also serves as a systemic driver of corporate green technology innovation across multiple dimensions, including structural transformation, systemic integration, and the construction of innovation ecosystems.

However, existing research largely treats computing infrastructure as a homogeneous resource and provides limited differentiation among supercomputing centers, intelligent computing centers, cloud platforms, and conventional data centers. In practice, supercomputing centers differ substantially in both technological features and service models. Technologically, supercomputing centers are optimized for coordinated execution of large-scale computational tasks, intelligent computing centers for efficient AI model training, and cloud platforms for flexible resource allocation across multiple users. In terms of service provision, supercomputing centers, as major national research infrastructures, offer high-performance computing resources on an open-access basis, whereas cloud computing typically operates as a market-oriented commercial service with pay-as-you-go pricing. These distinctions shift the analytical focus from the mere availability of computing power to its specific type, highlighting the unique role of supercomputing in addressing the high-precision, computationally intensive challenges of corporate green technology innovation.

Understanding this deeper impact requires a deep analysis of the knowledge-production process underlying innovation. Knowledge recombination theory views innovation as the search for and recombination of existing knowledge components to generate new functions. Green technology innovation typically involves cross-disciplinary integration, broader search spaces, greater recombination complexity, and higher experimentation costs. Supercomputing can transform this knowledge-production process in several ways. First, large-scale data processing and deep learning enable firms to systematically analyze the scientific literature and patent data, shifting the search for innovation from experience-based exploration to data-driven retrieval. Second, supercomputing constructs knowledge graphs that convert dispersed knowledge into computable structured data, enabling firms to discover high-value combinations across boundary areas that are imperceptible to human cognition, thereby transforming recombination from reliance on serendipitous inspiration to systematic exploration. Third, supercomputing enables firms to conduct large-scale parallel experimentation at extremely low marginal costs through virtual simulation and digital twin technologies, shifting the R&D process from "experiment first, observe later" to "compute first, validate later", fundamentally altering the risk-return structure of innovation. Finally, supercomputing supports full-lifecycle environmental impact assessment, converting carbon reduction and resource conservation performance into auditable, traceable data assets, transforming green value from qualitative description to verifiable quantitative returns, and forming a virtuous cycle from quantitative measurement to value validation to innovation incentives. In summary, the enabling role of supercomputing infrastructure runs through the entire chain of green technology innovation, providing capabilities at every critical stage—from front-end technology opportunity identification, to mid-stream knowledge integration and solution design, to back-end feasibility validation and value realization—that traditional R&D models cannot match. Based on the above analysis, this paper proposes:

Hypothesis 1. *Computing infrastructure can significantly enhance corporate green technology innovation.*

2.2. The Mediating Role of Digital and Intelligent Technology Empowerment

The construction of supercomputing centers enhances the technological capabilities of local firms mainly through two interrelated but distinct dimensions: first, the application of artificial intelligence (AI) technology; second, the upgrading of production capacity, represented by improvements in new quality productive forces. The former concerns the technologies that firms develop and apply, whereas the latter concerns the efficiency with which firms convert inputs into outputs.

With respect to AI, supercomputing centers provide the computing power foundation necessary for adopting this technology. According to innovation diffusion theory, firms' willingness to adopt a new technology and the depth of its diffusion depend on adoption costs and technological complexity. Public high-performance computing lowers the capital threshold for using computing power and reduces the marginal costs and trial-and-error risks of training large models and deploying complex algorithms [11,15]. The adoption of AI enhances firms' green technological innovation capabilities [16,17], improves innovation efficiency through resource reallocation [18], and AI capability itself constitutes a foundation of organizational creativity [19]. After these cost reductions, firms are able to process the large-scale, multi-source, and heterogeneous data required for green R&D and to optimize resource allocation in production [20]. Evidence from Chinese listed companies shows that AI application promotes green technological innovation by improving R&D efficiency and knowledge integration [3,21], and by screening out low-quality patents [22]; meanwhile, AI adoption increases labor productivity [23], thereby leaving more internal resources for green R&D.

The second dimension is the upgrading of production capacity, which this paper characterizes using firms' new quality productive forces index. New quality productive forces refer to improvements in the production system brought about by digital technology, data, and intangible capital rather than by additional physical inputs. The economic content of AI lies in the decline in prediction costs [24], which in turn improves firm productivity [25]. The computing power required for large-scale simulation, model training, and process optimization is difficult for individual firms to maintain economically, whereas National Supercomputing Centers provide it in the form of shared assets. According to the resource-based view, such facilities constitute complementary assets that enable firms to reconfigure existing resources [26]; when the marginal cost of computing declines, firms can test more design options, shorten the interval from prototype to production, and embed data analysis into daily operations. The link between digital transformation and green innovation has been verified in manufacturing firms and listed companies [14,27], and digital infrastructure also improves total factor productivity by improving resource allocation [8,28]. The combination of AI and data further improves productivity and innovation efficiency [23,29].

Both changes are important for green technological innovation, but for different reasons: AI application reduces the costs of searching for environmental information and screening green design options; the upgrading of production capacity enables firms to shift from incremental process adjustments to the redesign of production systems, thereby directly generating green technological innovation outputs such as energy conservation, emission reduction, and resource recycling. Accordingly, we propose Hypotheses 2 and 3.

Hypothesis 2. *The construction of supercomputing centers promotes green technology innovation by enhancing the level of enterprise AI technology application.*

Hypothesis 3. *The construction of supercomputing centers promotes green technology innovation by raising enterprise new-quality productive capacity.*

2.3. The Mediating Role of Innovation Cost Conditions

The third channel concerns the costs and uncertainty of innovation rather than the technology itself. Green R&D is long-cycle, highly uncertain, and difficult to collateralize; therefore, firms facing a higher effective tax burden have fewer internal funds available for such R&D. Existing studies show that tax incentives and government subsidies can promote firms' digital and intelligent transformation and green technological innovation [30,31], while green credit also enhances green innovation by alleviating financing constraints [32].

For this paper, the key question is whether supercomputing centers can reduce firms' tax burdens. The association between access to center resources and lower local tax burdens may arise from three aspects: first, local governments competing for compute-intensive investment may attract relevant firms with tax incentives and administrative convenience; second, firms that use center resources to obtain high-tech enterprise qualifications may become eligible for corresponding preferential treatment; third, center resources make firms' R&D activities more verifiable, thereby reducing the compliance costs of claiming R&D-related tax incentives. If these mechanisms hold, firms with access to center resources will face a lighter tax burden relative to their industry peers, and the reduction in tax burden will in turn translate into more green patents through two channels—financing and incentives. On the one hand, retained earnings are the lowest-cost source of R&D funding for Chinese listed companies; a decline in the effective tax rate increases the internal funds available for projects with uncertain and delayed returns, which is precisely the characteristic of green technologies. On the other hand, a lower tax burden raises the after-tax returns to green R&D [33]. Accordingly, we propose Hypothesis 4.

Hypothesis 4. *The construction of supercomputing centers promotes green technology innovation by reducing the enterprise's industry-adjusted tax burden.*

2.4. Theoretical Analysis of Heterogeneous Effects

Unlike general digital infrastructure such as broadband networks and smart cities, National Supercomputing Centers are specialized, large-scale, high-performance computing facilities that provide open-access computing resources to firms and directly address high-complexity computing bottlenecks in green technology R&D. Therefore, the green innovation effect of supercomputing centers is not homogeneous across all firms; it depends on firms' absorptive capacity for high-performance computing and institutional resource support.

First, ownership heterogeneity: Institutional theory holds that firm behavior is embedded in a specific institutional environment, and that strategic choices and resource acquisition capabilities are deeply shaped by institutional arrangements and legitimacy mechanisms. In the Chinese context, state-owned enterprises (SOEs) are not only market participants but also bearers of policy implementation and strategic missions. They therefore have stronger willingness and capacity to respond to the national computing strategy and the green development strategy. When a National Supercomputing Center is established in a city, SOEs tend to identify policy signals earlier, access public computing platforms more quickly, and incorporate them into their green technology R&D planning. The resource-based view further argues that sustained competitive advantage stems from resources that are valuable, rare, difficult to imitate, and non-substitutable. SOEs have comparative advantages in financial strength, government–business relations, data resources, talent reserves, and risk-bearing capacity, which can provide more abundant complementary resources for the absorption, transformation, and application of high-performance computing. Dynamic capabilities theory emphasizes that a firm's ability to sense environmental changes, absorb external knowledge, and reconfigure internal resources is key to converting external technological opportunities into innovation outputs. SOEs are relatively stronger in R&D continuity, organizational slack, and long-term orientation, enabling them to undertake the high-investment, long-cycle, and high-risk activities required for green technology innovation, and thus to translate computing resources more effectively into green patents and green process improvements. Therefore, we propose:

Hypothesis 5. *The promoting effect of supercomputing center construction on green technology innovation is stronger for state-owned enterprises than for non-state-owned enterprises.*

Second, industry technological attribute heterogeneity: Absorptive capacity theory holds that a firm's ability to identify, digest, transform, and utilize external knowledge depends on its existing knowledge stock and R&D foundation. High-tech firms generally have denser R&D personnel, more advanced data analysis capabilities, richer algorithmic experience, and stronger experimental development capabilities, and thus possess stronger absorptive capacity for high-performance computing resources. The capabilities provided by supercomputing centers—such as large-scale data processing, complex system simulation, and digital twins—can complement the existing R&D systems of high-tech firms, enabling them to conduct green material screening, low-carbon process simulation, and full-lifecycle environmental assessment more efficiently. The resource-based view further suggests that external resources can be more fully converted into innovation performance only when firms possess complementary assets that match those external computing resources. High-tech firms have stronger complementary assets in experimental equipment, technological accumulation, data assets, and innovation networks, making them more likely to embed supercomputing resources into green technology R&D processes. Dynamic capabilities theory also indicates that high-tech firms typically have stronger resource reconfiguration and rapid iteration capabilities, allowing them to adjust R&D directions and organizational processes in response to changes in computing supply, thereby amplifying the promoting effect of supercomputing centers on green technology innovation. Therefore, we propose:

Hypothesis 6. *The promoting effect of supercomputing center construction on green technology innovation is stronger for high-tech firms than for traditional firms.*

Based on the above theoretical discussions and hypotheses, Figure 1 constructs a conceptual framework.

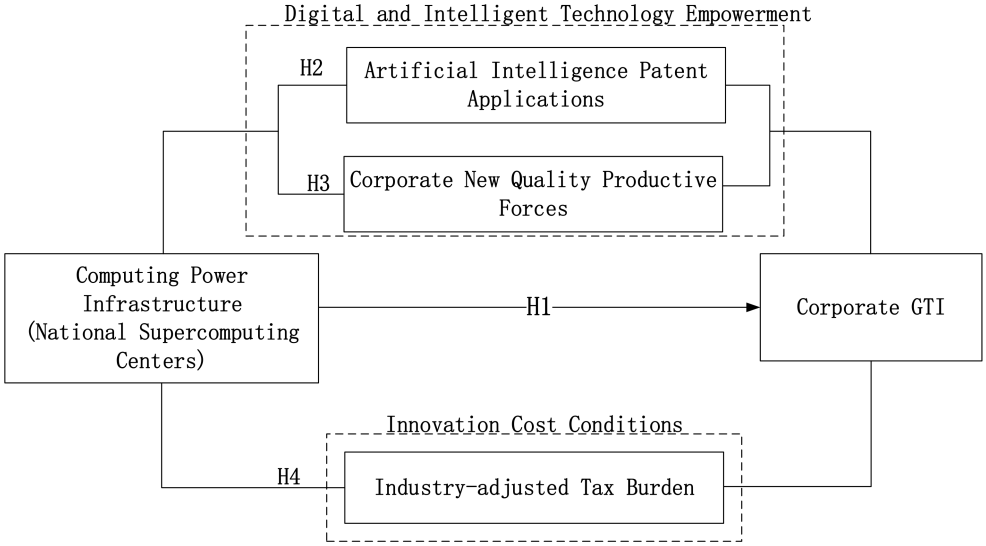


Figure 1. Conceptual framework.

3. Research Methods

3.1. Data Sources

This study is based on unbalanced panel data for Chinese A-share listed companies from 2009 to 2024. The sample excludes financial firms and ST firms, ultimately covering 4942 entity firms with a total of 43,330 firm-year observations. To mitigate the influence of extreme values on the regression results, all continuous variables are Winsorized at the 1st and 99th percentiles. The baseline regression excludes observations with missing values in

control variables using listwise deletion, resulting in a final regression sample of 43,245 firm-year observations. The study treats the construction of 14 National Supercomputing Centers in China as a quasi-natural experiment and employs a staggered difference-in-differences (DID) model to identify the causal effects of computing infrastructure on corporate green innovation. The data in this study come from three sources: first, corporate green technology innovation data are obtained from the WinGo Financial Text Data Platform's "Green Patent Database"; second, information on the locations and operation start dates of the 14 supercomputing centers is manually collected from publicly available sources; third, control variable data are sourced from the CSMAR database and the Wind database. The time span of the data fully covers the critical period of China's sustained green development strategy and the large-scale layout of new computing infrastructure, providing an ideal empirical setting for identifying the causal effects of the exogenous policy shock of supercomputing center construction on corporate green technology innovation.

3.2. Variable Definitions

Independent variable: The independent variable is the construction of National Supercomputing Centers, captured by a DID indicator. We use the establishment of these centers to characterize city-level computing infrastructure and determine each firm's treatment status and timing from the official start date of the corresponding center. One rule is applied throughout. If a center commenced operations in the first half of a year, treatment begins in that year; if it commenced operations in the second half, treatment begins in the following year. Matched to prefecture-level cities, the estimation sample contains treated firms in twelve cities. Table 1 reports, for each center, the operation date, the year in which treatment begins, and the number of treated firm-year observations; these counts sum to 7840. A further 42 treated observations are scattered across fifteen cities with no supercomputing center, at most eleven in any one city, and are recorded as unmatched city codes rather than assigned to a center. Wenchang and Tongxiang have no observations in the sample. Because the panel starts in 2009 and the Tianjin center began operating in May 2009, the Tianjin cohort has no pre-treatment year; Section 4.2 reports the baseline re-estimated without it.

Dependent variable: The dependent variable is the level of corporate green technology innovation. Referring to the research methodology of Wang and Wang [32], this paper measures the level of corporate green technology innovation using corporate green patent application data. The number of green invention patents and green utility model patents independently applied for by listed companies in a given year is selected. The measurement is calculated by taking the natural logarithm of 1 plus the patent counts, thereby constructing the core indicator of corporate green technology innovation.

Control variables: To control for other potential confounding factors, this paper introduces a series of firm-level control variables, including firm size (Size), leverage ratio (Lev), return on equity (ROE), total asset turnover (ATO), and cash flow ratio (Cashflow). In terms of corporate governance, we include a dummy variable for CEO duality (Dual) and an indicator for large shareholder expropriation measured by other receivables over total assets (Occupy). In addition, we control for audit quality (Big4), operating expense ratio (AgC1), and administrative expense ratio (Mfee). AgC1 is measured as "(selling expenses + administrative expenses)/operating revenue", reflecting the firm's overall operating expense level, while Mfee is measured as "administrative expenses/operating revenue", capturing agency costs at the governance level. These two variables capture different dimensions of firms' cost structures. All control variable data are obtained from the CSMAR and Wind databases.

Table 1. Basic Information of National Supercomputing Centers.

Supercomputing Center Name	Location	Approval Year	Approval Month	Operation Year	Operation Month	Number of Treated Firm-Years
Tianjin National Supercomputing Center	Tianjin	2009	May	2009	May	637
Shenzhen National Supercomputing Center	Shenzhen	2010	May	2011	November	2995
Changsha National Supercomputing Center	Changsha	2010	October	2014	November	549
Jinan National Supercomputing Center	Jinan	2011	March	2011	October	300
Guangzhou National Supercomputing Center	Guangzhou	2011	November	2014	April	1034
Wuxi National Supercomputing Center	Wuxi	2006	June	2016	June	684
Zhengzhou National Supercomputing Center	Zhengzhou	—	—	2020	November	114
Zhengzhou National Supercomputing Center (Suzhou)	Suzhou	—	—	2020	November	720
Chengdu National Supercomputing Center	Chengdu	2020	September	2021	June	385
Xi'an National Supercomputing Center	Xi'an	2020	August	2021	August	154
Taiyuan National Supercomputing Center	Taiyuan	2021	March	2022	April	41
Wenchang Space Supercomputing Center	Wenchang	2020	March	2023	June	0
China-Singapore (Chongqing) International Supercomputing Center	Chongqing	2019	February	2021	March	227
Zhejiang (Yangtze River Delta) Intelligent Supercomputing Center	Tongxiang	2020	November	2021	September	0
Total						7840

Note: Treated firm-years count listed firms located in the city hosting a center after the policy shock has occurred (DID = 1). Wenchang and Tongxiang have no observations in the sample. Twelve of the fourteen locations contain treated firms; the remaining treated observations in the estimation sample lie in cities without a center and are not counted here.

Mediating variables: The mediators reported in the text are the three variables that pass a three-step test with city-clustered standard errors and whose indirect effects have bootstrap confidence intervals excluding zero. AI patent applications (Lnpatents) equal the natural logarithm of one plus the number of AI patent applications a firm files in the year, taken from patent records rather than from annual-report wording; the measure follows Yao et al. [23] but substitutes patent output for word frequency. New-quality productive capacity (Npro) follows Li et al. [34]: the index takes the share of R&D personnel, the share of highly educated employees, executive green cognition, the overseas background of management, environmental performance, the fixed-asset share, capital accumulation, innovation level, digital transformation, the intangible-asset share, green technology level and the green-patent share as inputs, standardizes them and weights them by the entropy method. The industry-adjusted tax burden (Tax2) is the taxes a firm pays net of the industry-year mean. All continuous variables are Winsorized at the 1st and 99th percentiles.

Table 2 presents the definitions and measurement details of all key variables employed in our empirical analysis.

Table 2. Definition of variables.

Variable Type	Variable Symbol	Variable Definition
Explanatory variable	DID	The treatment group is assigned a value of 1 and the control group is assigned a value of 0
Explained variable	ginnov	ln(1 + number of independently filed green invention patents + number of independently filed green utility model patents)
Control variable	AgC1	(Selling Expenses + Administrative Expenses)/Operating Revenue
	Occupy	Other Receivables/Total Assets
	TobinQ	(Total Market Value + Total Liabilities)/Total Assets
	Mfee	Administrative Expenses/Operating Revenue
	Dual	=1 if the Chairman and General Manager are the same person, =0 otherwise
	Cashflow	Net Cash Flow from Operating Activities/Total Assets
	ATO	Operating Revenue/Average Total Assets
	Big4	=1 if audited by PwC, Deloitte, KPMG, or EY, =0 otherwise
	Size	ln(1 + Total Assets)
	Lev	Total Liabilities/Total Assets
	ROE	Net Profit/Shareholders' equity
Mechanism Variable	Lnpatents	ln(1 + Number of artificial intelligence patents applied for in the current year)
	Npro	Corporate New Quality Productive Forces Index, constructed from environmental performance, degree of digital transformation, proportion of intangible assets, proportion of R&D personnel, level of green technology, proportion of green patents, proportion of employees with a master's degree or above, proportion of fixed assets, overseas backgrounds of directors, supervisors, and senior executives, capital accumulation rate, and executives' green awareness and innovation level
	Tax2	Total taxes and fees paid by the firm minus the industry-year average

3.3. Research Model

To scientifically assess the causal impact of National Supercomputing Center (NSC) construction on enterprise green technology innovation, this paper establishes a quasi-natural experiment framework and employs a staggered difference-in-differences (DID) approach for empirical inspection. Given the characteristics of the multi-period policy shock, the following two-way fixed effects model is specified:

$$ginnov_{it} = \alpha + \beta DID_{it} + \lambda Control_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (1)$$

$ginnov_{it}$ represents the level of green technology innovation for firm i in year t and serves as the core dependent variable. DID_{it} is the key explanatory variable, constructed as follows: $Treat_i \times Post_t$: $Treat_i = 1$ if the city where firm i is located has an NSC, and 0 otherwise. For firms in the treatment group, $Post_t = 1$ starting from the year the NSC in their city officially commences operation (including that year), and 0 before that. The coefficient β is the core estimated parameter of interest in this study. Its significance and direction directly reflect the effect of NSC construction on enterprise green technology innovation. $Control_{it}$ represents a series of control variables; μ_i and η_t denote firm fixed effects and year fixed effects; and ε_{it} is the random error term.

3.4. Pre-Treatment Balance Test

To verify the comparability of the treatment and control groups prior to policy implementation, this paper uses 2009 as the baseline year, when the first National Supercomputing Center became operational. It classifies firms into treatment and control groups based on whether their cities host a National Supercomputing Center, and uses t-tests to compare the mean differences in covariates between the two groups. Table 3 reports the pre-treatment balance test results. Of the 11 covariates, 9 are statistically insignificant at the 10% level in most firm characteristics. Tobin's Q ($p = 0.022$) and CEO duality ($p = 0.099$) exhibit marginal differences, consistent with the tendency of supercomputing centers to be located in cities with higher levels of innovation and marketization. Overall, the treatment and control groups are reasonably comparable in the baseline year, supporting the validity of the subsequent DID estimation.

Table 3. Pre-treatment Balance Test (Year 2009).

Variables	Mean (Treated)	Mean (Control)	Diff. (T-C)	*p*-Value
AgC1	0.275	0.302	−0.027	0.577
Occupy	0.018	0.018	0.000	0.652
TobinQ	2.312	2.160	0.151 **	0.022
Mfee	0.214	0.236	−0.022	0.631
Dual	0.157	0.192	−0.036 *	0.099
Cashflow	0.067	0.070	−0.003	0.561
ATO	0.724	0.727	−0.002	0.941
Big4	0.047	0.066	−0.019	0.143
Size	21.655	21.750	−0.096	0.158
Lev	0.482	0.465	0.016	0.160
ROE	0.080	0.088	−0.008	0.295
N	896	456	/	/

Note: The table reports mean differences between treatment and control groups for each covariate in the pre-treatment year (2009). ** $p < 0.05$, * $p < 0.1$. The treatment (control) group contains 896 (456) firm-year observations.

4. Results

4.1. Descriptive Statistics

Table 4 presents the descriptive statistics for the main variables. The full sample comprises 43,330 observations. The dependent variable, corporate green technology innovation, has a mean of 0.237 and a standard deviation of 0.554, with a minimum of 0 and a maximum of 6.246, indicating substantial variation in green innovation levels across firms. Notably, its median is 0, implying that over half of the sample firms generated no green patents during the observation period, aligning with the stylized fact that innovation activities tend to concentrate among a minority of firms. The core explanatory variable, DID, has a mean of 0.182, indicating that the treatment group accounts for approximately 18.2% of the full sample, a proportion that satisfies the applicability conditions for the DID model.

Table 4. Results of Descriptive Statistics.

Variables	N	Mean	SD	Min	Median	Max
ginnov	43,330	0.237	0.554	0.000	0.000	6.246
DID	43,330	0.182	0.386	0.000	0.000	1.000
AgC1	43,330	0.284	1.394	0.009	0.124	39.165
Occupy	43,330	0.013	0.022	0.000	0.006	0.202
TobinQ	43,330	2.029	1.290	0.789	1.628	16.647
Mfee	43,330	0.239	1.604	0.006	0.071	39.165
Dual	43,330	0.305	0.460	0.000	0.000	1.000
Cashflow	43,330	0.046	0.069	−0.226	0.045	0.283
ATO	43,330	0.636	0.426	0.054	0.542	2.907
Big4	43,330	0.050	0.218	0.000	0.000	1.000
Size	43,330	22.096	1.227	19.415	21.907	26.452
Lev	43,330	0.407	0.208	0.027	0.395	0.935
ROE	43,330	0.055	0.142	−1.005	0.069	0.421

Among the control variables, the operating expense ratio exhibits a pronounced right-skewed distribution, revealing significant differences in agency costs across firms. The level of fund occupation by major shareholders is generally low. Financial indicators such as firm size, leverage ratio, profitability, cash flow, and operational efficiency are all within reasonable ranges. Furthermore, the mean Tobin's Q suggests positive market expectations regarding the growth prospects of the sample firms. Approximately 30.5% of the firms have CEO–Chairman duality, and 5.0% are audited by a Big Four firm. The distributions of all variables are reasonable.

4.2. Baseline Regression

Table 5 reports the baseline estimation results. The dependent variable is corporate green technological innovation, measured by ln(1 + green patent applications), which reflects the intensity with which firms transform green R&D activities into verifiable green technological outputs. Column (1) includes only firm and year fixed effects, while Column (2) further adds firm-level control variables. Because supercomputing centers are established at the city level, standard errors are clustered at the city level in all regressions. The estimation results show that after the establishment of supercomputing centers, treated firms' green technological innovation, measured by green patent applications, increases significantly relative to the control group: the DID coefficient is 0.052 and is significant at the 1% level. Economically, this means that the operation of supercomputing centers increases firms' green technological outputs by about 5.2% on average. Given that more than three-quarters of firm-year observations have no green patent applications, and that green technological innovation is itself a low-frequency, high-threshold activity, this increase

reflects a substantive change in which firms begin to generate or strengthen verifiable green technological outputs, rather than mechanical fluctuation. There are 12 cities containing treated firms. Under city clustering, the 95% confidence interval of the DID coefficient is [0.014, 0.089], which excludes zero. Because green patent applications are highly sparse, the within R-squared is small; this paper therefore does not use goodness of fit as a basis for interpretation, but instead judges economic significance based on the magnitude of the coefficient and its confidence interval.

Table 5. Benchmark regression results.

Variables	**(1)** **FE1**	**(2)** **FE2**
DID	0.054 *** (2.717)	0.052 *** (2.602)
AgC1		0.003 ** (2.478)
Occupy		−0.142 (−1.315)
TobinQ		0.002 (0.966)
Mfee		−0.003 *** (−2.828)
Dual		−0.003 (−0.435)
Cashflow		−0.066 * (−1.864)
ATO		0.007 (0.579)
Big4		−0.008 (−0.306)
Size		0.031 *** (3.814)
Lev		0.012 (0.516)
ROE		0.031 * (1.662)
_cons	0.225 *** (61.647)	−0.477 *** (−2.634)
Year FE Firm FE	Yes Yes	Yes Yes
N R^2	43,245 0.591	43,245 0.591

Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3. Parallel Trend Test

The results of the parallel trend test are shown in Figure 2. In the periods preceding the policy, the coefficients on the leads are 0.026, 0.039, 0.018 and 0.020, and their 95 percent confidence intervals all contain zero. The joint test that the four leads are zero gives $F(4, 413) = 1.21$ ($p = 0.305$). The lead at t = −4 is significant at the 10 percent level but not at 5 percent. After the policy takes effect the coefficients are positive and the path is

not monotonic: 0.042 in the current period, 0.087 and 0.082 in the first two post periods, 0.049 in the third, and 0.113 and 0.112 in the fourth and fifth. Four of the five post-period coefficients are significant at the 5 percent level.

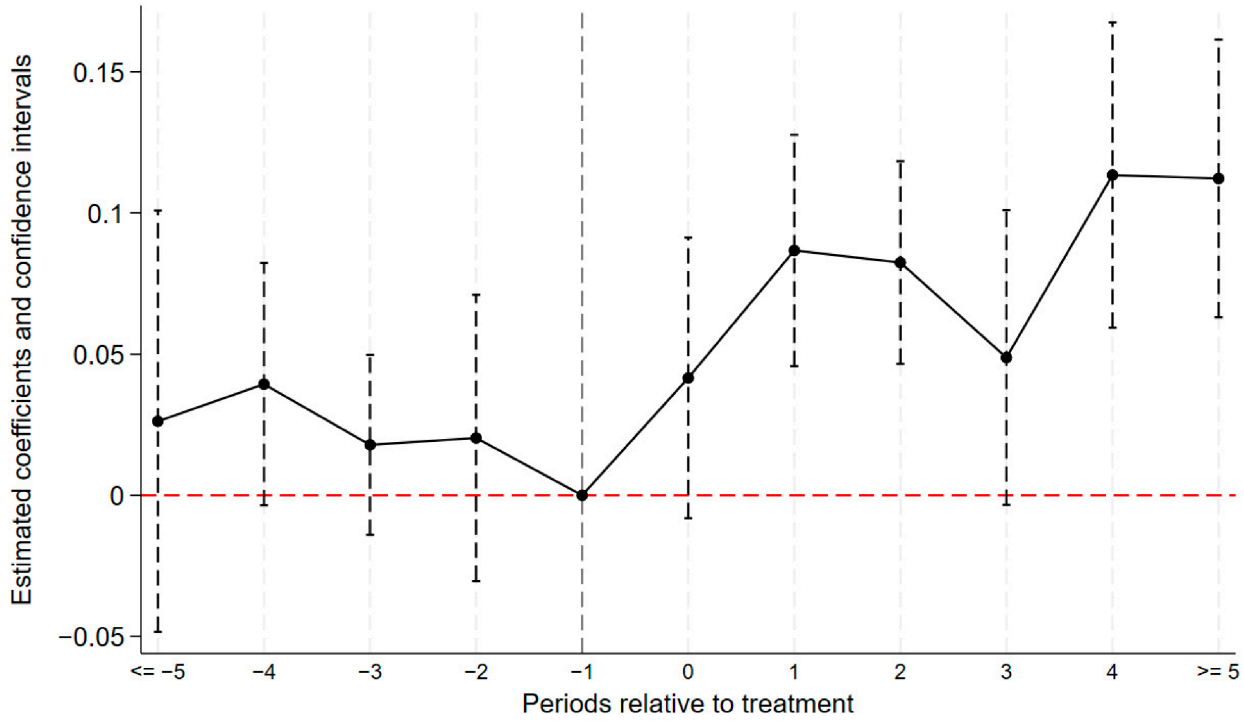


Figure 2. Parallel trend test. Note: This figure plots the estimated dynamic effects of the policy. The dots represent the point estimates, and the vertical dashed bars denote the 95% confidence intervals. The horizontal red dashed line represents the zero value (y = 0), indicating no treatment effect. The vertical grey dashed line indicates the treatment period (or baseline period).

4.4. Robustness Tests

4.4.1. Placebo Test

To further verify the robustness of the baseline regression results and rule out interference from unobservable factors and temporal randomness, this study conducts a restricted mixed placebo test for the multi-period difference-in-differences (DID) design. This test simulates the distribution of estimated coefficients under a hypothetical policy scenario by randomly reassigning the treatment timing. Figure 3 shows that the placebo effect coefficients obtained from randomization are tightly clustered around zero, with their kernel density curve approximating a normal distribution. The vast majority of the estimates fall within the interval $(-0.02, 0.02)$. The actual treatment effect coefficient from the baseline regression ($\beta = 0.052$) significantly deviates from the center of this distribution, lying at the far right tail. The corresponding empirical *p*-value is less than 0.01. This indicates that the promoting effect of supercomputing center construction on green technology innovation does not stem from time trends or random factors, thereby strengthening the causal reliability of the benchmark regression results and providing further support for the validity of research hypothesis H1.

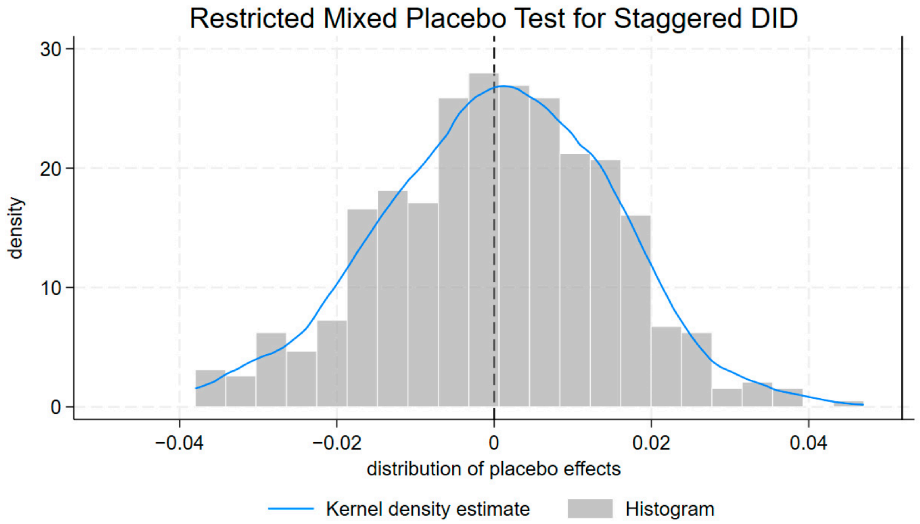


Figure 3. Restricted mixed placebo test. Note: The histogram and the blue curve represent the distribution and kernel density of the placebo estimates, respectively. The black vertical dashed line indicates the zero value (x = 0), representing the center of the placebo distribution.

4.4.2. PSM-DID

Table 6 reports the robustness results of propensity score matching difference-in-differences (PSM-DID). To ensure comparability between the treatment and control groups in terms of observable characteristics, this paper constructs balanced samples using three methods—one-to-one nearest-neighbor matching, one-to-three nearest-neighbor matching, and kernel matching—and re-estimates the DID model on the matched samples. The results show that the estimated coefficient of supercomputing centers ranges from 0.047 to 0.052, all significant at the 5% level, highly consistent with the baseline regression; the signs and significance of the control variables also remain largely unchanged.

Table 6. PSM-DID.

Variables	(1) Neighbor (1:1)	(2) Neighbor (1:3)	(3) Kernel
DID	0.055 ***	0.050 **	0.052 ***
	(2.662)	(2.517)	(2.600)
AgC1	0.003	0.001	0.003 **
	(1.408)	(0.816)	(2.467)
Occupy	−0.093	−0.100	−0.144
	(−0.476)	(−0.733)	(−1.324)
TobinQ	0.010 **	0.002	0.002
	(2.159)	(0.772)	(0.949)
Mfee	−0.003	−0.002	−0.003 ***
	(−1.264)	(−1.241)	(−2.851)
Dual	−0.004	−0.004	−0.003
	(−0.265)	(−0.428)	(−0.438)
Cashflow	−0.110 *	−0.064	−0.065 *
	(−1.726)	(−1.457)	(−1.858)
ATO	0.017	0.005	0.007
	(0.774)	(0.322)	(0.586)

Table 6. *Cont.*

Variables	(1) Neighbor (1:1)	(2) Neighbor (1:3)	(3) Kernel
Big4	−0.004 (−0.069)	−0.032 (−0.901)	−0.008 (−0.314)
Size	0.048 *** (3.308)	0.036 *** (3.465)	0.031 *** (3.809)
Lev	0.058 (1.347)	0.023 (0.742)	0.012 (0.506)
ROE	0.035 (1.046)	0.040 * (1.742)	0.031 * (1.666)
_cons	−0.871 *** (−2.859)	−0.625 *** (−2.822)	−0.528 *** (−3.042)
Year FE Firm FE	Yes Yes	Yes Yes	Yes Yes
N R^2	18,393 0.031	31,376 0.024	43,315 0.020

Note: t-statistics clustered at the city level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4.3. Heterogeneous Treatment Effects Test

Because treatment timing differs across cities, this paper re-estimates dynamic effects using heterogeneity-robust estimators. The two-way fixed effects event study is presented in Section 4.3. As shown in Figure 4, the imputation estimator of Borusyak et al. [35] constructs counterfactuals using never-treated or not-yet-treated units; its pre-treatment coefficients range from −0.018 to −0.004 and are all insignificant (p ranges from 0.381 to 0.888), while the coefficients for post-treatment periods 0 to 5 are 0.053, 0.088, 0.080, 0.017, 0.167, and 0.129, respectively. Figure 5 reports the estimator from Callaway and Sant'Anna [36], which yields an average pre-treatment coefficient of −0.000 ($p = 0.997$) and an average post-treatment coefficient of 0.101 (t = 3.50).

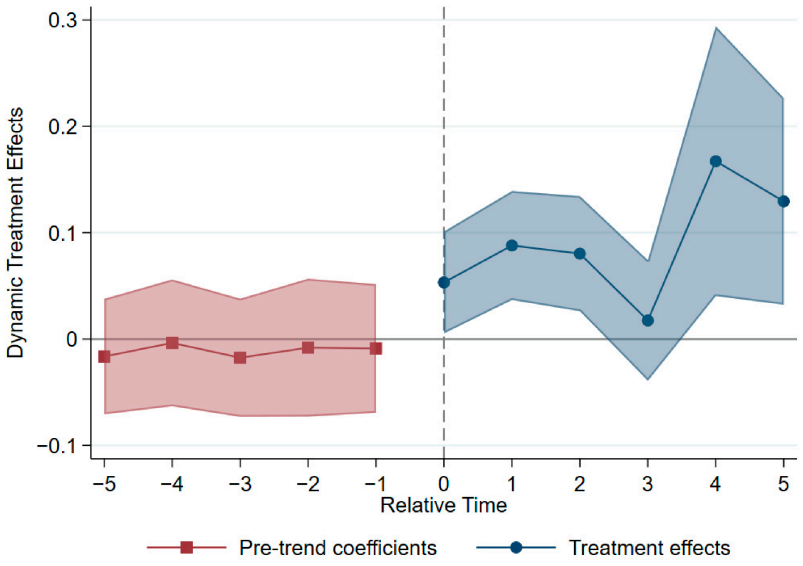


Figure 4. Borusyak.

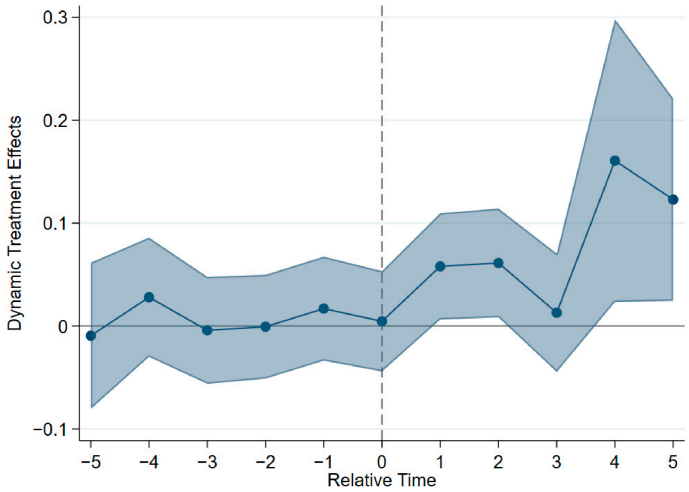


Figure 5. Callaway & Sant' Anna.

4.4.4. Excluding the Impacts of Other Policies

To isolate the potential confounding effects of other major concurrent policies, we sequentially controlled for the Business Environment Innovation Pilot (BEIP), the Smart City Pilot program (SCP), the Green Finance Reform and Innovation Pilot Zone (GFRIP), the National AI Innovative Application Pilot Zone (AIIP), and the Broadband China strategy (BC) in our baseline model. The results presented in Table 7 show that after incorporating any of these policy variables, the estimated coefficient for the national supercomputing center consistently ranges from 0.049 to 0.055, and its statistical significance remains unaffected. Concurrently, the signs and significance levels of the firm-level control variables exhibit a high degree of stability. This indicates that the green innovation effect of computing power infrastructure identified in this study is independent and robust, and is not merely a byproduct of other related policies.

Table 7. Excluding the interference of other policies.

Variables	(1)	(2)	(3)	(4)	(5)
DID	0.052 **	0.049 **	0.055 ***	0.052 **	0.050 **
	(2.580)	(2.336)	(2.679)	(2.511)	(2.321)
BEIP	−0.001				
	(−0.040)				
SCP		−0.022 *			
		(−1.763)			
GFRIP			0.001		
			(0.034)		
AIIP				0.011	
				(0.686)	
BC					−0.012
					(−0.860)
Constant	−0.474	−0.473	−0.478	−0.475	−0.505
	(−1.441)	(−1.433)	(−1.422)	(−1.441)	(−1.467)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
N	43,218	42,683	42,412	43,218	41,391
R^2	0.591	0.592	0.594	0.591	0.597

Note: Values in parentheses are t-statistics based on city-level clustering. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4.5. Controlling for Confounding Factors

This section systematically tests the robustness of the baseline results by replacing variables, adjusting model specifications, controlling for multi-dimensional fixed effects, addressing selection bias, and excluding samples from special periods, to ensure that the conclusions remain reliable under different identification conditions. Table 8 reports the full set of robustness test outcomes.

Table 8. Controlling for Confounding Factors.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Replacement of Dependent Variable	Province-Year Fixed Effects	Industry-Year Fixed Effects	Controlling for City-Specific Linear Trends	Entropy Balancing	PPML
	ginnov2	ginnov				Patent Count
DID	0.054 ***	0.053 ***	0.052 ***	0.061 ***	0.046 **	0.513 ***
	(3.040)	(2.650)	(2.600)	(2.905)	(2.348)	(3.036)
AgC1	0.000	0.003 **	0.003 **	0.003 **	0.002	0.044
	(0.403)	(3.000)	(3.000)	(3.000)	(1.147)	(1.048)
Occupy	−0.190 **	−0.139	−0.129	−0.128	−0.108	3.329 *
	(−2.280)	(−1.287)	(−1.194)	(−1.185)	(−0.729)	(1.706)
TobinQ	0.003 *	0.002	0.003	0.003	0.007 **	0.052 **
	(1.797)	(1.000)	(1.500)	(1.500)	(2.055)	(2.261)
Mfee	−0.001	−0.003 ***	−0.003 ***	−0.003 ***	−0.001	−0.045
	(−1.270)	(−3.000)	(−3.000)	(−3.000)	(−1.196)	(−1.552)
Dual	0.001	−0.003	−0.002	−0.001	−0.003	−0.003
	(0.154)	(−0.429)	(−0.286)	(−0.143)	(−0.273)	(−0.040)
Cashflow	−0.042	−0.064 *	−0.049	−0.065 *	−0.089 *	−0.533 *
	(−1.579)	(−1.829)	(−1.400)	(−1.806)	(−1.862)	(−1.910)
ATO	0.010	0.008	0.008	0.015	0.014	0.326
	(1.009)	(0.667)	(0.667)	(1.154)	(0.733)	(1.140)
Big4	0.005	−0.008	−0.008	−0.011	−0.002	−0.120
	(0.227)	(−0.296)	(−0.296)	(−0.407)	(−0.040)	(−0.333)
Size	0.028 ***	0.032 ***	0.035 ***	0.035 ***	0.044 ***	0.311 **
	(4.305)	(4.000)	(4.375)	(3.889)	(3.505)	(2.145)
Lev	0.009	0.012	0.012	0.022	0.039	−0.200
	(0.455)	(0.500)	(0.480)	(0.880)	(1.111)	(−0.917)
ROE	0.006	0.031	0.029	0.017	0.031	−0.144
	(0.450)	(1.632)	(1.526)	(0.895)	(1.202)	(−0.595)
Constant	−0.482 ***	−0.484 ***	−0.566 ***	−0.574 ***	−0.740 ***	−5.774 *
	(−3.418)	(−2.659)	(−3.127)	(−2.974)	(−2.652)	(−1.699)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-year FE	No	Yes	No	No	No	No
Industry-year FE	No	No	Yes	No	No	No
N	43,245	43,245	42,025	43,217	43,245	23,875
R^2	0.568	0.592	0.589	0.597	0.643	0.645

Note: Robust t-statistics clustered at the city level are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The first alteration replaces the dependent variable. We move from ginnov, which counts green invention and utility-model applications together, to ginnov2, which counts invention applications only. The DID coefficient is 0.054 (t = 3.82), so the centers raise innovation with higher technological content as well as its quantity, and the result does not depend on how the outcome is aggregated.

The second alteration lags the treatment indicator by one year, which allows for a delay between the opening of a center and its use. The coefficient is 0.054 (t = 3.71), essentially identical to the contemporaneous estimate.

The third and fourth alterations add province-by-year and industry-by-year fixed effects, absorbing shocks that operate at those levels within a year. The DID coefficients are 0.042 (t = 1.96) and 0.046 (t = 2.31).

The fifth alteration applies entropy balancing, which reweights the control group so that the covariate moments match those of the treated group. The DID coefficient under the entropy-balanced weights is 0.046 (t = 2.39), close to the baseline, so selection on observable characteristics does not drive the result.

The sixth alteration drops the years 2019 to 2021, when the pandemic disrupted both research activity and the comparability of firms. The coefficient is 0.047 (t = 2.11). A Poisson pseudo-maximum-likelihood specification on the raw patent count, which accommodates the large number of zeros, is reported in Table 8 as a further check.

Across these specifications the coefficient lies between 0.042 and 0.054 and remains significant at the 5 percent level, so the baseline conclusion does not depend on the particular perturbation.

5. Further Analysis

5.1. Mechanism Analysis

To identify the channels through which computing infrastructure affects green technology innovation, we follow the stepwise framework of Baron and Kenny [37] and estimate two further equations alongside the baseline:

$$M_{it} = \eta_0 + \eta_1 DID_{it} + \eta_j X_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (2)$$

$$ginnov_{it} = \lambda_0 + \lambda_1 DID_{it} + \lambda_2 M_{it} + \lambda_j X_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (3)$$

M is the mediator, X is the same set of firm-level controls as in the baseline, and μ and η are firm and year fixed effects. The stepwise test has three parts. The first is the baseline, which gives the total effect β. The second estimates Equation (2) and asks whether treatment moves the mediator, that is, whether η_1 is significant. The third estimates Equation (3) and asks whether the mediator predicts green patenting and whether the DID coefficient falls from β to λ_1. A channel is accepted when η_1 and λ_2 are both significant and λ_1 is smaller than β. Because the sampling distribution of the product $\eta_1\lambda_2$ need not be symmetric, we also resample cities 500 times and report a 95 percent percentile interval for the product, and the channel is accepted only when that interval excludes zero.

The mediators are measured as follows. AI patent applications (Lnpatents) are the logarithm of one plus the number of AI patent applications filed in the year, taken from patent records rather than annual-report wording; the measure follows the approach of Yao et al. [23] to firm AI application but substitutes patent output for word frequency. New-quality productive capacity (Npro) is a composite index aggregating environmental performance, digital transformation, intangible assets, the share of R&D personnel, the level of green technology, the share of green patents, the share of employees with postgraduate degrees, the share of fixed assets, the overseas background of directors and executives, capital accumulation, executive green cognition and innovation. Higher values indicate

a greater substitution of knowledge, data and human capital for traditional factors. The industry-adjusted tax burden (Tax2) is the taxes a firm pays net of the industry-year mean, which removes differences in tax levels that are common to an industry.

Table 9 reports the results. Column (1) is the baseline, with a DID coefficient of 0.052 (t = 2.72), which is the total effect β. Columns (2) and (3) correspond to the AI channel. In column (2) the dependent variable is Lnpatents and the DID coefficient is 0.037 (t = 2.10), so the centers raise AI patent applications. In column (3) Lnpatents enters the baseline with a coefficient of 0.183 (t = 7.88), and the DID coefficient falls from 0.052 to 0.045 (t = 2.59). The three steps satisfy the Baron–Kenny conditions: the indirect effect is 0.037 × 0.183 = 0.0067, about 13 percent of the total, and the city-clustered bootstrap interval is [0.0003, 0.0149], which excludes zero. Because the measure counts patent applications, it records technology the firm actually develops rather than wording in its annual report.

Table 9. Analysis of effect mechanisms.

Variable	**(1)** **ginnov**	**(2)** **Lnpatents**	**(3)** **ginnov**	**(4)** **Npro**	**(5)** **ginnov**	**(6)** **Tax2**	**(7)** **ginnov**
DID	0.052 ***	0.037 **	0.045 **	0.767 ***	0.050 **	−0.018 **	0.051 ***
	(2.725)	(2.095)	(2.587)	(2.646)	(2.089)	(−2.566)	(2.677)
Lnpatents			0.183 ***				
			(7.879)				
Npro					0.011 ***		
					(10.06)		
Tax2							−0.060 ***
							(−3.49)
Indirect effect			0.0067		0.0084		0.0011
95% bootstrap interval			[0.0003, 0.0149]		[0.0029, 0.0154]		[0.0002, 0.0026]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	43,245	42,829	42,829	30,887	30,887	43,245	43,245

Note: Columns (2), (4) and (6) report the second step, with the mediator as the dependent variable. Columns (3), (5) and (7) report the third step, with the mediator added to the baseline. Values in parentheses are t-statistics based on standard errors clustered by city. The indirect effect is the product of the second- and third-step coefficients, and the interval is the 95 percent percentile interval from 500 resamples of cities. *** $p < 0.01$, ** $p < 0.05$.

Columns (4) and (5) correspond to the productive-capacity channel. In column (4) the DID coefficient on Npro is 0.767 (t = 2.65), so the centers raise new-quality productive capacity; in column (5) the mediator enters with a coefficient of 0.011 (t = 10.06) and the DID coefficient falls to 0.050 (t = 2.09). The indirect effect is 0.0084, about 16 percent of the total, with an interval of [0.0029, 0.0154]. This regression uses 30,887 observations against 43,245 in the baseline because the index is missing for part of the sample. A rise in productive capacity means that knowledge, data and human capital account for a larger share of the firm's production function, which changes the organizational basis of green R&D and matches the argument in Section 2.

Columns (6) and (7) correspond to the tax channel. In column (6) the DID coefficient on Tax2 is −0.018 (t = −2.57), so the centers are associated with a lower tax burden; in column (7) the mediator enters with a coefficient of −0.060 (t = −3.49) and the DID coefficient is 0.051 (t = 2.68), a small reduction from the baseline. The indirect effect is 0.0011, about 2 percent of the total, with an interval of [0.0002, 0.0026], which excludes zero. The signs are as expected: a lower tax burden is associated with more green patenting.

The three indirect effects together account for about 31 percent of the total effect, with the remainder carried by factors the design does not observe. The AI and productive-capacity channels are substantially larger than the tax channel, which indicates that the centers operate mainly through the technology firms develop and the way production is organized, and only marginally through the fiscal environment. This ordering matches the roles assigned to the three channels in Section 2.

5.2. Heterogeneity Analysis

Based on Hypotheses 5 and 6, this paper further examines the heterogeneity of the effect across firm ownership types and industry technological attributes. The results in Table 10 show that the promoting effect of supercomputing centers on green technological innovation is not evenly distributed across all firms, but is notably concentrated in state-owned enterprises (SOEs) and high-tech firms.

Table 10. Heterogeneity analysis of ownership and technology endowment.

Variables	**(1) SOEs**	**(2) Non-SOEs**	**(3) High-Tech**	**(4) Non-High-Tech**
DID	0.088 * (1.961)	0.029 (1.186)	0.056 *** (2.742)	0.032 (1.111)
Constant	0.179 (0.461)	−0.873 ** (−2.025)	−0.600 (−1.150)	−0.595 ** (−2.221)
N	13,433	29,531	26,543	16,651
R^2	0.585	0.603	0.602	0.538
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Cluster	City	City	City	City

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

This disparity aligns with the economic characteristics of green innovation and the reality of firms' resource endowments. Green technological innovation typically involves large investments, long cycles, high uncertainty, and strong technological spillovers. Consequently, firms often lack sufficient incentives and funds to undertake such high-risk investments. With policy support and relatively abundant cash flows, SOEs have stronger risk-bearing capacity and are better able to transform public computing power into long-cycle green R&D. In contrast, non-SOEs face tighter financing constraints and higher demands for short-term returns, making them more cautious about allocating computing power to high-risk green innovation.

Similarly, as a general-purpose factor of production, the effectiveness of computing power depends heavily on firms' existing technological foundations. High-tech firms possess stronger R&D teams, technological accumulation, and data resources, enabling them to more smoothly utilize supercomputing centers for large-scale simulations and algorithm training, thereby achieving complementarity between computing power and their own business operations. By contrast, firms in traditional industries have relatively weaker technological

foundations and lack the talent and data support needed to convert computing power into substantive green patents, thus facing greater constraints.

In summary, the green innovation effect of supercomputing centers relies on firms' own financial strength and absorptive capacity. This also indicates that the empowering role of computing infrastructure is not unconditionally universal. Only when combined with firms' existing resource endowments can it effectively overcome the market failure of green innovation and translate into substantive green technological output.

6. Discussion

Although existing studies have explored the effects of traditional, communication, and digital infrastructure on enterprise innovation, micro-level evidence on how computing infrastructure influences corporate green technological innovation remains scarce. This paper uses the construction of national supercomputing centers as a quasi-natural experiment to systematically investigate the impact of computing infrastructure on corporate green technological innovation, thereby addressing this gap. The findings show that computing infrastructure significantly enhances the level of corporate green technological innovation, which aligns with the existing literature emphasizing the role of digital infrastructure in empowering corporate green transformation. Tang and Zhao [38] point out that computing power deployment can significantly promote corporate source control green innovation; our findings further support this view and highlight the unique value of computing infrastructure compared to traditional infrastructure. Traditional views often emphasize the incentive effect of fiscal and tax subsidies on green innovation. However, the mechanism decomposition in this paper shows that the driving role of computing infrastructure is far greater than that of simple fiscal and tax cost mitigation. The "technology empowerment" channels (AI technology application and the enhancement of new quality productive forces) account for approximately 29% of the total effect, while the "cost mitigation" tax burden channel contributes only about 2%. This discrepancy highlights the mechanism of computing infrastructure: when facing highly complex and uncertain green R&D, computing facilities fundamentally alter firms' knowledge production processes by reducing the marginal cost of algorithm training and trial-and-error risks. Furthermore, unlike Jia et al. [14], who mainly rely on annual report text mining to measure digitalization and green innovation, this paper measures the AI channel using patent applications, providing evidence closer to substantive technological output and effectively correcting the strategic exaggeration bias that may arise from text-disclosure-based measurement.

Heterogeneity analysis further characterizes the boundary conditions for the role of computing power. Unlike universal infrastructure such as broadband networks, supercomputing centers have extremely high technical thresholds, which means that the computing power dividend is not unconditionally inclusive. This result corroborates and expands the applicability of the resource-based view and absorptive capacity theory in the digital economy era. Notably, this paper finds that state-owned enterprises (SOEs) and high-tech enterprises can more efficiently transform public computing power into long-cycle green R&D outcomes, whereas Li and Xu [39], based on a manufacturing sample, found that computing infrastructure has a more significant innovation-promoting effect on non-state-owned enterprises. This discrepancy precisely highlights the boundary conditions of different infrastructure types: the high-threshold characteristics of supercomputing centers determine that the release of their dividends relies more on firms' resource endowments, technological accumulation, and data assets, while non-state-owned and traditional enterprises face the dual constraints of financing constraints and technological gaps. This suggests that in the layout of computing infrastructure, high vigilance is needed against the "green digital divide" arising from differences in firms' resource endowments. The city-

level study by Tian et al. [40] also indicates that the green innovation effect of computing infrastructure is non-equilibrium and highly dependent on local absorptive capacity and digital foundations, which echoes well with the micro-level findings of this paper.

Compared with comprehensive policy studies such as broadband and smart cities, this paper focuses on a single type of facility with a clear opening date—the supercomputing center—thereby substantially reducing the interference of anticipation effects in staggered DID. However, this study still has certain limitations that may affect the generalizability of the conclusions. Constrained by the city-level infrastructure assessment paradigm, this paper captures the geographic availability of computing facilities in the cities where firms are located, but cannot directly observe firms' actual use of supercomputing services and their access methods. Tian et al. [40] also pointed out the limitation of using geographic deployment proxy variables rather than actual computing power consumption. In addition, this paper focuses on evaluating the innovation benefits of computing infrastructure, without incorporating its inherent high energy consumption characteristics into the cost–benefit analysis framework, so its net environmental effect remains unclear. Based on this, future research can attempt to obtain firm-level computing power procurement data and, referring to the approach of Tang and Zhao (2026) in constructing instrumental variables using exogenous geographic variables, focus on energy-intensive industries to comprehensively evaluate the long-term and nonlinear impacts of computing infrastructure [38].

7. Conclusions

This study takes the construction of China's National Supercomputing Centers as a quasi-natural experiment to examine the impact of computing infrastructure on corporate green technological innovation. The findings show that National Supercomputing Centers significantly improve corporate green technological innovation. Mechanism tests indicate that this promoting effect mainly depends on the application of artificial intelligence (AI) technology and the enhancement of new quality productive forces, rather than merely on the reduction in corporate tax burdens. In addition, the effect is highly concentrated in state-owned enterprises (SOEs) and high-tech enterprises, suggesting that firms' absorptive capacity is a key prerequisite for converting computing power into green output.

This study extends the theoretical framework of computing infrastructure driving corporate green transformation and provides micro-level evidence for understanding the causal relationship between computing power supply and green technological innovation. Constrained by data and identification strategy, this study captures the effect of the geographic availability of computing facilities in firms' cities on corporate green technological innovation, rather than the actual intensity of firms' use of supercomputing services. Moreover, this study evaluates the innovation benefits of computing infrastructure and does not incorporate energy consumption costs into the analysis of net environmental effects. Therefore, the conclusions mainly apply to the sample context and identification framework examined in this study, and caution should be exercised when extrapolating them to other types of digital infrastructure, actual use intensity, and assessments of net environmental effects.

This study has the following limitations. First, constrained by the city-level paradigm for assessing infrastructure, this study cannot directly observe firm-level computing power procurement, actual use, or access modes, and thus the mechanism interpretation remains indirect. Second, this study does not incorporate the energy consumption characteristics of National Supercomputing Centers into a cost–benefit analysis, leaving the net environmental benefits unclear. Third, the conclusions are mainly based on the context of China's National Supercomputing Center construction, and caution is needed when extrapolating them to other types of digital infrastructure or institutional environments. Future research could

further incorporate firm-level actual use data, track the long-term dynamic and nonlinear effects of computing facilities on green innovation, and focus on energy-intensive industries by incorporating energy consumption into the evaluation system to comprehensively assess the net environmental benefits of computing infrastructure. Meanwhile, future research could also examine the constraint mechanisms faced by non-SOEs and traditional firms in computing power access and conversion, thereby providing more direct policy evidence for narrowing the "green digital divide."

8. Policy Recommendations

To promote effective synergy between computing power infrastructure and corporate green technological innovation, this paper proposes the following policy recommendations:

First, continuously optimize the layout of computing infrastructure to enhance the accessibility of public computing power. Given that supercomputing centers have significantly driven corporate green innovation overall, the construction and expansion of national computing power hub nodes should continue to be steadily advanced. On the one hand, it is necessary to accelerate the building of a nationally integrated computing network, break down "computing power silos" among data centers across different regions and levels, and promote the convenient cross-regional scheduling of computing resources. On the other hand, the entry barriers for using public computing platforms should be further lowered, and the administrative approval processes for enterprises to apply for high-performance computing resources should be streamlined. By providing "one-stop" computing access services, a wide range of enterprises—especially real-economy firms located in non-core cities—can rely on public computing power to conduct environmental technology R&D at a lower threshold, fully unleashing the overall green spillover effects of computing facilities across society.

Second, guide computing resources toward core technology breakthroughs and strengthen the technology empowerment orientation. Given that computing power primarily functions by promoting AI applications and the upgrading of production methods, policies should guide enterprises to utilize computing power where it matters most. It is recommended to establish a "dedicated computing power pool" for green technology R&D within national supercomputing centers and widely implement a "green computing voucher" system. In practice, enterprises conducting substantive technological research—such as the development of new energy-saving and carbon-reducing materials, training of environmental protection large models, and low-carbon process simulation testing—should be granted targeted computing power fee reductions or subsidies. Meanwhile, supercomputing centers should be encouraged to collaborate with industry-leading enterprises to customize and develop dedicated algorithm models and simulation software in frontier fields such as new energy storage and Carbon Capture, Utilization, and Storage (CCUS). This will help enterprises overcome the obstacle of "purchasing hardware without knowing how to build models," effectively transforming computing power advantages into high-quality green technological innovation outcomes.

Third, improve fiscal, tax, and financial supporting policies to reduce enterprises' costs of using computing power. While strengthening technological empowerment, it is necessary to further alleviate the financial pressure on enterprises utilizing computing power for innovation. Regarding fiscal and tax policies, it is recommended that expenses incurred by enterprises in purchasing services from national supercomputing centers be explicitly treated as R&D inputs and included in the additional tax deduction for R&D expenses, directly reducing their trial-and-error costs. Regarding financial support, banks and other financial institutions should be guided to take the scale of investment and actual effectiveness of enterprises using public computing power for green R&D as important reference

indicators when approving green credit and issuing green bonds. Local governments with the necessary conditions are encouraged to establish special "computing power + green" guiding funds, forming a policy synergy of "computing support + tax relief + financial assistance" to effectively hedge against the financial pressure brought by the long cycles and high risks of green R&D.

Fourth, implement categorized policies and public technical assistance to bridge the endowment gap in enterprises' computing power application. Given that the green innovation effect of supercomputing centers is highly dependent on enterprises' financial strength and technological absorptive capacity, the benefits of computing power tend to concentrate in state-owned enterprises (SOEs) and high-tech firms. Policy design should respect this objective law and avoid a "one-size-fits-all" approach to blind universal provision. On the one hand, for SOEs and high-tech firms with abundant funds and solid technological foundations, they should be encouraged to play a "leading goose" role. They should be supported in using public computing power to conduct frontier and highly complex green technology research, and to establish open-source sharing mechanisms to radiate and drive the upstream and downstream of the industrial chain. On the other hand, targeting the bottlenecks of tight financing constraints and weak technological foundations faced by non-SOEs and traditional enterprises, the government should strengthen "capacity building" while providing computing power subsidies. It is recommended to establish supporting public technical service stations at supercomputing centers. By collaborating with universities and research institutes, these stations can provide "hands-on" technical services and talent training—such as computing power adaptation, data cleaning, and model fine-tuning—for technologically disadvantaged enterprises. This will effectively enhance their absorptive capacity to transform computing power into green patents and gradually narrow the "green digital divide" among enterprises with different endowments.

Fifth, promote the coordinated development of computing facilities and green energy to achieve the dual carbon goals. When advancing the layout of major projects such as the "Eastern Data, Western Computing" initiative, it is imperative to balance both the economic benefits and environmental costs of computing power. Priority should be given to guiding large data centers and supercomputing centers to cluster in western regions rich in renewable energy such as wind and solar power, and green energy-saving standards such as Power Usage Effectiveness (PUE) should be strictly enforced during project approval. Computing enterprises are encouraged to increase the proportion of clean energy use through direct green power purchases and the construction of distributed photovoltaic systems. At the same time, circular economy models such as the recovery and utilization of waste heat from data centers should be explored. By reducing the energy consumption and carbon emissions of computing facilities themselves, a true synergy and win-win situation between digital economy infrastructure construction and environmental protection can be achieved.

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