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The Impact of National Big Data Pilot Zones on the Persistence of Green Innovation: A Moderating Perspective Based on Green Finance

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Abstract: Enhancing the persistence of corporate green innovation is crucial for promoting sustainable societal development. As big data technologies and related policies advance, digitalization emerges as an effective enabler of green innovation in enterprises. This study, grounded in resource-based theory and corporate ecology theory, examines the impact of national-level big data pilot zone reforms on the persistence of corporate green innovation, utilizing data from China's A-share-listed companies from 2011 to 2021. It also explores the moderating effect of green finance development. Empirical results indicate that (1) the implementation of national-level big data pilot zones positively influences the persistence of green innovation, with robustness and endogeneity tests confirming these findings. (2) The development of regional green finance positively moderates this relationship. (3) A mediation analysis reveals that national-level big data policies enhance innovation persistence by alleviating financing constraints, promoting talent aggregation, and facilitating industrial upgrading. (4) The heterogeneity analysis shows that the positive impact of these reforms is more pronounced in non-state-owned, non-heavy polluting firms, those receiving high subsidies, and in regions with stringent environmental regulations. This study offers a novel theoretical perspective on and empirical evidence for digital transformation from the angle of national policy, supporting societal green development and contributing to policy enhancement aimed at achieving sustainable growth.

Keywords: national big data pilot zones; persistence of green innovation; green finance; policy effects

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1. Introduction

Rapid economic development has exerted immense pressure on the environment. In 2010, China's total carbon emissions reached approximately 8.122 billion tons, accounting for nearly one third of total global carbon emissions [1]. In response, the Chinese government has proposed the dual carbon strategy goals of peaking carbon emissions by 2030 and achieving carbon neutrality by 2060 [2]. Additionally, the government actively promotes corporate clean energy policies [3]. For enterprises, persistent green innovation aimed at energy conservation and emission reduction is becoming increasingly crucial.

According to the stakeholder theory and the triple bottom line theory, economic benefits should not come at the expense of the environment [4]. An increasing number of stakeholders are demanding stronger environmental protection measures [5]. Green innovation serves as a vital approach to effective environmental management [6–9], helping to reconcile the tension between ecological stability and economic development [10,11]. Green technological innovation can conserve the energy consumption of enterprises [12,13], reduce pollution, and promote waste recycling [14–19]. It also decreases resource consumption and potential penalty costs for companies. Persistent green technological innovation

enhances the supply of environmental products and services for enterprises [16,20], providing them with a competitive edge in the green market [21]. Strategically, implementing green innovation helps embed green concepts into the organizational culture [5,22]. It enhances adaptability to external environmental regulations [23,24], mitigates environmental risks, fosters broader environmental practices [14], and ultimately promotes the green reputation of companies and thus, in turn, attracts external resources [25]. However, due to the high risks and uncertainties associated with innovation activities, the persistence of innovation becomes the driving mechanism for improving the efficiency of green innovation. Continuous technological innovation shapes the long-term competitive advantage of companies through knowledge accumulation [26] and path dependence [27], based on the resource-based theory and dynamic capability theory [28]. Persistent innovation safeguards the market share and monopolistic position of companies. Intensive innovation investment helps companies build entry barriers and exit barriers [29], generating a "lock-in" effect [30]. This effect continuously provides the resources needed for innovation, resulting in the company gaining the ability to be dynamic. Previous studies have indicated that sustained investment in R&D helps companies build a dynamic competitive advantage [31]. It reduces short-term investment myopia, continuously increases innovation output [32], and helps companies achieve long-term excess profits [33] and a good competitive performance [34]. Considering the characteristics of green technological innovation, research has shown that persistent investment in innovation is even more important in the process of green innovation [35].

The continuous advancement of digital technologies, such as big data and artificial intelligence, has significantly propelled enterprise innovation. For example, big data analytics enhances companies' sensitivity to customer demands [36] and improves knowledge search capabilities [37]. Generative AI utilizes machine learning and deep learning algorithms to replace certain aspects of labor productivity [38], overcoming cognitive limitations and facilitating more informed decision-making [39]. By integrating into business management processes [40], digital technologies enhance internal control efficiency, improve risk management, optimize internal resource allocation, and bolster the acquisition of external financial resources [41]. They also increase the efficiency of transferring information from market data to the technology innovation process [42], providing more space and resources for innovation [43,44].

Numerous studies have explored whether digital transformation can enhance green innovation, and they have yielded positive conclusions. From an information transfer perspective, digitalization increases media attention on companies, enabling analysts to easily track innovation progress [45,46] and enhancing the transparency of sustainable development information, such as corporate social responsibility [47–53]. This reduces information asymmetry between resource holders and firms. Considering the effects of resource acquisition and allocation, green innovation requires increased quality innovation resources. Digital transformation significantly alleviates financing constraints, improves firms' financing capabilities [48,54–56], reduces tax burdens, increases government subsidies [57,58], and enhances resource allocation efficiency [59], thereby improving green investment efficacy. In terms of human resources, green innovation increasingly relies on skilled talent [60]. The ongoing development of digitalization accelerates the flow of highly compatible talent and fosters the aggregation of green innovation professionals [61–63]. Regarding corporate governance and management, digitalization embedded in governance frameworks reduces green agency costs [64], ensuring the effective implementation of green innovation processes.

Given the important role of green innovation in sustainable development, there is a focus on exploring mechanisms to enhance the level of green innovation in enterprises. Green innovation exhibits a dual externality resulting from innovation spillovers and external environmental costs [65], which leads to an insufficient willingness of enterprises to invest in green innovation. From an environmental economics perspective, policy tools become an effective means to promote green innovation behavior in companies. Based on

Porter's hypothesis [66], the implementation of environmental regulations stimulates the optimization of the innovation environment in a country, resulting in increased innovation investment and efficiency. Jaffe proposed three variants of Porter's hypothesis [67], with the strongest version suggesting that well-designed environmental regulations strengthen a company's profitability and competitive advantage, offsetting the costs of environmental protection. Therefore, moderate policy interventions can significantly improve the imbalance in innovation resource allocation under inadequate market mechanisms [68]. Existing research partially validates this conclusion. Market-based policies provide more resources for companies to reduce pollution [69]. Demand-side and supply-side driving policies are the existing policy tools [70]. Supply-side driving policies incentivize companies to create markets and increase market demand for green innovation through taxation, subsidies, carbon emission trading schemes, and support for public procurement [71–74]. On the other hand, supply-side driving policies primarily promote technological progress, facilitating the provision of knowledge, technology, and talent for green innovation [75–78]. In addition, numerous studies have explored mechanisms to promote the persistence of innovation and found that, apart from internal factors such as executive technological cognition and organizational technological integration capabilities [31,79], policy tools also positively influence innovation persistence. Policy subsidies, government procurement, and implicit government guarantees significantly promote innovation persistence [31,80,81]. These findings highlight the important role of policies in green innovation and innovation persistence.

Digital transformation plays a promoting role in green innovation, but it also faces uncertainties, resource demands, and market failures. Therefore, it requires intervention with digital policy tools. However, research on the relationship between digital policies and the persistence of green innovation in enterprises remains limited. To examine the effects of digital policy tools, we choose the reform of the national comprehensive big data pilot zone in China. The aim of this reform is to enhance digital infrastructure construction and strengthen the implementation of digital technology applications. The first comprehensive big data pilot zone was initiated by Guizhou in September 2015. Since then, several other cities, including Inner Mongolia, Shanghai, Beijing–Tianjin–Hebei, Chongqing, the Pearl River Delta, Shenyang, and Henan, have been established as major big data pilot cities. This policy treats data as an emerging resource element, promoting the acceleration of digitization within the region and improving the efficient utilization and circulation of economic and environmental resources.

Moreover, persistent green innovation requires significant financial resources. In recent years, a green finance system focused on supporting green projects and innovations has emerged, encompassing green bonds, credit, and insurance [82]. This system plays a crucial role in directing capital towards green industries, facilitating the transition to a clean energy structure, and enhancing the quality of green innovation [83]. Additionally, it promotes the development of new energy systems, resulting in improved energy efficiency [84–86]. The impact of the green finance system extends beyond providing initial funding for green innovation. It also delivers ongoing support and confidence from capital markets. Therefore, investigating the role of green finance in promoting the persistence of green innovation within the context of digital policy tools is essential for advancing financial systems and enhancing corporate sustainability.

Compared to previous studies, this research makes three main innovations and contributions. Firstly, existing research mostly analyzes the impact of regulatory environmental policies on firms' green innovation behavior. However, with the increasing trend of digital transformation, the significant influence of digital technologies on firms' green innovation behavior remains unverified. Therefore, this study selects the reform of the national comprehensive big data pilot zone as the explanatory variable to examine the effects of the national policies driving digital development on the persistence of firms' green innovation behavior and the mechanisms behind these effects, thereby extending the research into Porter's hypothesis. Secondly, considering the higher requirement of financial resources for

green innovation persistence, this paper discusses the moderating role of green finance in the relationship between digital policy and green innovation persistence. Lastly, in order to further explore the paths and mechanisms through which the reform of the big data pilot zone promotes the persistence of green innovation, this paper discusses three dimensions: overall resource constraints, industrial structure upgrading, and talent agglomeration effects. By doing so, it fully identifies the mechanisms through which the policy operates. Additionally, this study conducts heterogeneity tests from four aspects: firm ownership, whether it is a heavy pollutant, government subsidy intensity, and regional environmental regulation intensity. This further helps identify the influencing factors that may lead to changes in policy implementation effects.

The remaining sections of this paper are organized as follows: In Section 2, through theoretical analysis, we establish the logical relationship and develop research hypotheses. In Section 3, we construct the research framework, describe the measurement of the variables and data sources, and develop the research model. Sections 4 and 5 are dedicated to empirical research, where we focus on the driving effects of digital policies. Specifically, we analyze the impact of the reform of the national comprehensive big data pilot zone on the persistence of firms' green innovation. To ensure the stability of the results, we perform a series of robustness checks and endogeneity tests. We also place particular emphasis on examining the promoting role of green finance development in the effects of the policy. Additionally, we test the mediating effects of three variables: resources constraints, industrial structure, and talent. Furthermore, we conduct various heterogeneity tests. Finally, based on the empirical findings, we provide insightful recommendations for both firms and government policymaking. These recommendations lay a theoretical foundation for advancing China's digital construction strategy and sustainable development strategy. Moreover, they can serve as effective guidelines for other developing countries seeking to achieve green sustainable development and digitally upgrade their socio-economic systems. Section 6 concludes the study. The research framework of this study is shown in Figure 1.

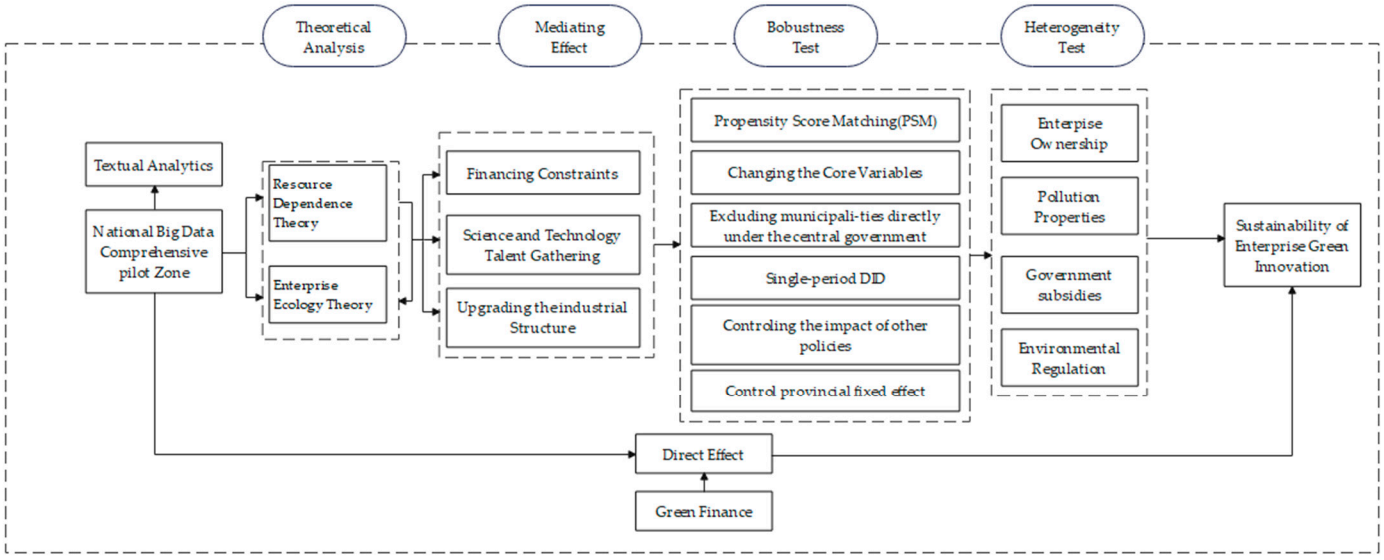


Figure 1. The framework of this study.

2. Literature and Hypothesis

2.1. National Comprehensive Big Data Pilot Zone and the Persistence of Green Innovation

Existing research has confirmed that the establishment of a national comprehensive big data pilot zone can effectively promote the quality and efficiency of digital technology innovation among enterprises in the region [87–90]. Building upon a literature review, this study investigates whether the reform policy of the national comprehensive big data

pilot zone, according to resource dependence theory and corporate ecological theory, can facilitate firms' green innovation persistence.

According to resource-based theory, the comprehensive big data pilot zone policy enhances digital platform development, enabling firms to sustainably acquire essential resources—such as data, technology, and funding—for green innovation. This is achieved by optimizing resource utilization and allocation efficiency. Firstly, the information platforms and big data technologies established by national pilot zones dismantle information silos, coordinating governmental and societal data to integrate decentralized resources into a large, environmentally friendly, low-cost, and efficient regional center. This facilitates the exchange and sharing of innovation resources among firms [91], reorganizing these resources to enhance the quality of green innovation while effectively reducing the costs of information gathering and resource acquisition [92,93]. Secondly, the big data pilot zone policy promotes local fiscal sustainability by encouraging pilot city governments to strengthen financial and technical support for green development, thereby increasing firms' commitment to green innovation. The alignment of national comprehensive pilot zones with macro digital strategies facilitates government recognition and access to additional subsidies and resources for companies [94,95]. Moreover, the proliferation of digital technologies addresses traditional regulatory gaps, introducing new methodologies for overseeing financial resource safety, thereby ensuring fair and rational allocation and reducing constraints on sustainable green innovation. Thirdly, improved digital infrastructure enhances the attractiveness of innovative talent, increasing both the quality and quantity of human capital. This fosters talent retention and local circulation, leading to the accumulation of skilled professionals in green innovation. Fourthly, digital technologies enhance resource utilization efficiency. In the digital economy, big data analytics and intelligent management enable the precise matching and efficient use of resources [96], reducing investment risks and improving financing efficiency, directing funds more accurately into green technology innovation [97]. This reduces reliance on proprietary assets [98], alleviating supply–demand conflicts, minimizing resource waste, and lowering innovation costs. Overall, the establishment of big data pilot zones offers essential resources for green innovation while optimizing resource allocation efficiency, thereby enhancing the level of green innovation.

According to corporate ecological theory, a business ecosystem is an economy grounded in the interactions between individuals and organizations, with firms as key components. The enterprises' ecological environment encompasses public services, innovation landscapes, and market conditions [99], which directly influence corporate innovation activities [87]. Existing research indicates that the establishment of national comprehensive big data pilot zones enhances urban entrepreneurship and innovation efficiency [88,89], facilitates the ecological transformation of urban industries [100], and improves urban ecological efficiency and green total factor productivity [101,102]. Further analysis reveals that the pilot zone policy promotes the transfer of key economic resources through regional industrial structure adjustments, guiding the rational allocation of green innovation resources to meet national sustainable development goals. Increased levels of industrial digitization can foster resource sharing ecosystems [103,104], optimizing firms' green innovation models. Furthermore, by accessing policy information in a timely manner, companies can effectively coordinate upstream and downstream supply chain relationships, reinforcing their momentum for sustainable green development and promoting industrial structure upgrades. This creates a favorable industrial environment for the persistence of green innovation, allowing regional system members to collectively benefit and establishing a virtuous cycle within the ecosystem, thus supporting the continuous, healthy, and green development of enterprises. Based on this discussion, we propose the following hypotheses.

Hypothesis 1. *The establishment of national comprehensive big data pilot zones enhances the persistence of corporate green innovation.*

2.2. Moderating Effect of Green Finance

Green finance is an innovative approach that provides an alternative funding pathway for individuals, corporations, and governments interested in supporting green and low-carbon initiatives [105]. Its benefits are significant: it facilitates the allocation of funds for environmental preservation [106], promotes sustainable trade and investment activities [107], offers low-risk financing options [108], and fosters the development of green investment instruments [109]. Despite its potential, green finance often lacks the necessary incentives and support for growth. Various strategies can be implemented to encourage organizations and investors to advance green finance globally. These strategies include establishing transparent policy frameworks and ensuring companies provide long-term resource commitments. Our study sheds light on the potential linkage between green finance, green innovation, and government policies.

Due to the strong dependence of corporate green innovation persistence on resources, a robust financial environment and innovative financial technology are essential [110]. In 2016, multiple Chinese government departments jointly issued the "Guiding Opinions on Building a Green Financial System", proposing measures such as developing green credit, green bonds, and green funds, alongside improving environmental rights trading markets to promote effective allocation of financial resources for sustainable development. By 2022, the balance of green loans reached 19.55 trillion yuan, with a stock of green bonds at 1.2 trillion yuan, ranking second globally, thus providing financial support for corporate green development.

The research indicates that a green financial system positively impacts industrial structure optimization, energy structure transformation, and green technology promotion [111,112]. Building on this theoretical analysis, we propose that the impact of comprehensive big data pilot zone reform policies on the persistence of green innovation is moderated by the level of green finance.

First, an optimized green financial system implies a richer pool of financial resources for green innovation, providing enhanced funding support for corporate sustainability. Green finance policies direct capital towards green innovation firms, improving their sustainable development potential, which synergizes with the comprehensive big data pilot zone reforms to create a more transparent information environment. This increases oversight, enhances the exposure of environmental violations, raises compliance requirements for firms, restricts funding for heavily polluting enterprises, and promotes capital allocation to resource-saving and environmentally friendly industries [113], alleviating the financial pressures on firms pursuing sustainable green innovation and enhancing the efficiency of green investment allocation.

Second, regions with a high level of green finance can establish effective green credit platforms and environmental information platforms that integrate the needs of governments and businesses, fostering an environment of shared and open financial information. This mitigates information asymmetry among governments, financial institutions, and R&D entities, improving the business and entrepreneurial environment for green innovation. Consequently, this supports the formation of industry structures and talent reserves conducive to green innovation. Firms can then enhance their green innovation levels and the competitiveness of their green products, gaining better reputations and more recognition from stakeholders, thereby creating a virtuous cycle that drives sustainable green innovation. Based on the above analysis, we propose the following hypothesis.

Hypothesis 2. *Regarding a better regional green finance level, the influence of big data pilot zone policy on the green innovation persistence is more pronounced.*

3. Data Selection and Model Setting

3.1. Data Sources

This research employs data from China's A-share-listed companies from 2011 to 2021. The data on green patent applications were sourced from the National Intellectual Property Administration, while corporate characteristic data were obtained from the CSMAR database. The sample data underwent the following processing: (1) Exclusion of financial sector firms from the sample. (2) Removal of samples with significant missing data for relevant variables during the 2011–2021 period. (3) Elimination of firms classified as ST (Special Treatment) or *ST. (4) Winsorization of all continuous variables at the 1% level. Additional data sources utilized in this research include the National Bureau of Statistics, environmental status bulletins, the Science and Technology Statistical Yearbook, Energy Statistical Yearbook, Financial Yearbook, Agricultural Statistical Yearbook, Industrial Statistical Yearbook, and the Tertiary Industry Statistical Yearbook.

3.2. Model Setting

Assessing whether the Explanatory Variable significantly impacts the persistence of corporate green innovation falls under the category of policy evaluation. Typically, the evaluation of policy effects employs a difference-in-differences (DIDs) model, wherein a grouping dummy variable is established based on the implementation of the policy. Individuals affected by the policy constitute the treatment group, assigned a value of 1, while those not affected serve as the control group, with a value of 0. This approach allows for the effects of the policy to be isolated by examining the differing impacts experienced by the above two groups pre and post the policy implementation. By accounting for unobserved, time-invariant factors, this methodology facilitates a robust evaluation of the policy.

To test the fundamental hypothesis of this study, we use the policy as a quasi-natural experiment. Among all the provinces and municipalities, Guizhou Province was designated as a pilot in 2015. Subsequently, in 2016, five provinces—Inner Mongolia, Hebei, Henan, Guangdong, and Liaoning—as well as four municipalities—Beijing, Shanghai, Chongqing, and Tianjin—were authorized to initiate the construction of pilot zones. Thus, these provinces and municipalities constitute the treatment group. Following the methodology outlined by Back (2001) [114], we have constructed a multi-period DIDs model as follows:

$$OIP = \beta_0 + \beta_1 Treat_{it} \times Time_{it} + Z_{it} + \sum Year + \sum Industry + \varepsilon_{it} \quad (1)$$

In this model, the dummy variable indicates whether a firm belongs to the treatment group: if a firm is located in a province authorized to establish a big data pilot zone in 2015 or 2016, the variable will be assigned the value of 1; otherwise, it is 0. Another dummy variable represents the temporal aspect of the approval for establishing the pilot zone: if a firm is in a province that received approval in $year_t$, the value is 1 from $year_t$ until 2021; otherwise, it is 0. The model also includes various financial and operational characteristics as control variables, such as number of employees, ROA, equity multiplier, leverage level, and firm age. Additionally, it incorporates corporate governance attributes, including the shareholding proportions of the top three shareholders and the dual role of positions. ∑Year denotes the fixed effects of the year, while ∑Industry denotes the fixed effects of the industry, with the error term represented as a random disturbance. The coefficients β_1 will indicate the impact of the big data policy on green innovation persistence.

3.3. Variable Setting

3.3.1. Dependent Variable

Drawing on He's [115] definition of innovation persistence, this study constructs a green innovation persistence indicator (OIP). While corporate innovation is typically measured in terms of inputs and outputs, isolating green innovation inputs from R&D activities is challenging. Therefore, this study uses the output metric of green patents,

represented as the total number of utility model patent applications and green invention (OIN). There are three types of patents: (1) invention patents, which are primarily proposed for new technical solutions related to products, methods, or improvements in products or methods, (2) utility model patents, which are primarily proposed for practical new technical solutions related to the shape, structure, or combination of products, (3) design patents, which are primarily proposed for new designs for the shape or pattern of a product. In general, the quality of patents is considered to be high to low in the order of invention patents, utility model patents, and design patents [116]. The persistence of green innovation is reflected through a comparison of OIN before and after, employing a logarithmic transformation.

$$OIP = (OIN_t + OIN_{t-1}) \times \frac{OIN_t + OIN_{t-1}}{OIN_{t-1} + OIN_{t-2}} \quad (2)$$

3.3.2. Explanatory Variable

We employed a DID approach, using a binary variable indicating whether a company is located in a pilot zone as the independent variable. The explanatory variable is constructed from the interaction of a policy dummy variable (Treat) and a time dummy variable (Time). The policy implementation year is designated as 2015 for Guizhou Province and 2016 for the other pilot zones. Within Treat, provinces in the experimental group are valued as 1, while control group are valued as 0. In Time, provinces in the experimental group are valued as 1 for the year the pilot zone was established and subsequent years and coded as 0 otherwise. Then, we created the interaction term Treat × Time, with a value of 1 for years and regions following the establishment of pilot zones, and 0 otherwise.

3.3.3. Moderating Variable

We employed regional green finance development (GreenFin) as the moderating variable. Drawing upon existing research [117], we used green investment, green credit, green bonds, green insurance, green funds, green support, and green equity to construct an indicator system to measure the level of green finance. After standardizing the data, we utilized the entropy method to compute a comprehensive evaluation index for the level of green finance development and the variation in the scores. Details of indicators are shown in Table 1.

Table 1. Evaluation System for green finance.

Layer 1 Index	Layer 2 Index	Proxy Variable
Green Finance	Green Credit	Credit for environmental projects in the province/credit in the province
	Green Investment	Investment in environmental pollution control/GDP
	Green Insurance	Income from environmental pollution liability insurance/total insurance premium income
	Green Bonds	Total issuance of green bonds/total issuance of all bonds
	Green Support	Fiscal expenditure on environmental protection/total fiscal budget expenditure
	Green Funds	Market value of green funds/market value of all funds
	Green Equity	Transactions in carbon trading, energy use rights trading, pollution rights Trading/total transactions in the equity market

3.3.4. Mediating Variable

This study investigates the potential mechanisms through which the establishment of pilot zones influences the corporate green innovation persistence. First, we propose that the advanced levels of digital infrastructure and technology within these zones create a favorable economic ecosystem for firms. This environment not only attracts high-end talent and innovative enterprises but also compels pollution-intensive firms to undergo transformation and upgrades, thereby facilitating industrial structural advancement. Furthermore, the widespread application of digital technologies effectively reduces information asymmetry between firms and stakeholders, promotes optimal resource allocation, and ensures

that capital flows toward more promising and high-quality enterprises. Additionally, it enhances financial institutions' positive assessments of these firms, making them more inclined to provide financial support to those demonstrating social responsibility and green innovation potential. This support alleviates the financing challenges that companies face in advancing green innovation, thereby contributing to the sustainability of such initiatives. Based on this discussion, we utilize the following mediating variables to verify these mechanisms:

(1) Financing constraint (WW)

In this study, we use the WW index to represent the degree of financial constraints faced by companies [118]. A higher WW index indicates a greater level of financial constraints, implying that companies face greater difficulty in obtaining financing, resulting in smaller amounts of financing. Consequently, companies have limited funds available for green innovation, which hinders the sustainable development of green innovation.

(2) Industry Structure Upgrade (UIS)

The industry structure upgrade index is a metric used to assess the overall quality improvement and structural optimization of the industries in which enterprises operate. An increase in this index reflects the extent to which traditional industries have successfully transformed and upgraded, as well as the positive changes to the economic structure driven by emerging sectors. Drawing upon the research paradigm established by scholars such as Lan Qingxin [119], this study assigns scientifically justified weights to the three sectors (i.e., primary, secondary, and tertiary industries) and employs a weighted average approach to compute the industry structure upgrade index. As a comprehensive evaluation metric, this index accurately characterizes the optimization of overall industry quality. The specific calculation formula is presented in Equation (3).

$$Structure = \sum_{n=1}^{3} S_n \times n, 1 \leq Structure \leq 3 \quad (3)$$

In Equation (3), S_n represents the output share of a certain industry.

(3) Scientific and technological talent gathering (STG)

High-quality scientific and technological talent is a crucial human resource for enterprises engaging in green innovation, with R&D personnel representing a significant category. We select R&D personnel within enterprises as a representative indicator of scientific talent, using the year-end full-time equivalents of R&D personnel to measure the scale of scientific talent. To further reflect the concentration and development level of scientific talent in a region, this study introduces the concept of 'scientific talent agglomeration' in relation to the level of talent concentration. Drawing on the findings of Rui Xueqin [120], we define the concentration of scientific talent as the ratio of the total number of scientific personnel in the region to the total population of that region at the year-end. This metric not only provides a clear representation of the agglomeration of scientific talent but also directly indicates the density of R&D personnel in the area. Specifically, the concentration of scientific talent is calculated by determining the proportion of R&D personnel's full-time equivalents to the total population of the region at year-end. A higher value signifies a greater density of R&D talent in that area. The calculation formula is detailed in Equation (4).

$$STG_j = \frac{R_j}{Q_j} \quad (4)$$

In Equation (4), STG_i denotes the concentration of scientific talent, R_j represents the total quantity of scientific personnel in the region, and Q_j signifies the total population of the region at year-end.

3.3.5. Other Control Variables

This study incorporates seven control variables that may influence green innovation persistence, including (1) employee size (Labor); (2) leverage (Lev); (3) return on assets (ROA); (4) equity multiplier (EM); and (5) firm age (Age), (6) the shareholding proportion of the top three shareholders (Top 3); and (7) Dual (dual role).

All variable definitions are shown in Table 2.

Table 2. Definitions of variables.

Classification	Variable	Symbol	Description
Dependent variable	Persistence of green innovation	OIP	Green patent applications before and after the number of contrast plus a natural logarithm
Explanatory variable	National Big Data Comprehensive Test Zone	Treat × Time	Whether the enterprise belonged to the big data pilot area in that year
Control variable	Total number of employees	Labor	The total number of labors take the natural logarithm
	Return on assets	ROA	NET profit/Average total assets
	Equity multiplier	EM	Average total assets/Average balance of owner's equity
	Asset-liability ratio	Lev	Total liabilities at year-end/Total assets at year end
	The proportion of shares held by the top three shareholders	Top 3	Number of shares held by the first three shareholders/Total number of shares
	Age of the enterprise	Age	ln(Current year—Year of listing + 1)
	The two jobs are one	Dual	The chairman and the CEO are the same person for 1, otherwise 0
	Dummy variable	Ind	Industry
	Dummy variable	Year	Year

4. Analysis of Empirical Results

4.1. Descriptive Statistics

We show a descriptive statistical analysis of the primary variables in Table 3. The findings indicate that the average persistence of green innovation (OIP) among A-share-listed companies is 0.522, with a median of 0, suggesting that the level of green innovation persistence is generally weak, as most companies fall significantly below the average. This indicates a low overall level of green innovation persistence. Overall, the descriptive statistics offer important insights for enhancing the persistence of green innovation among A-share-listed companies.

Table 3. Descriptive statistics.

Variable	Minimum Value	Maximum Value	Mean Value	Standard Deviation
OIP	0.000	4.748	0.522	1.090
Bigdata	0.000	1.000	0.271	0.444
Labor	4.605	11.130	7.619	1.253
ROA	−0.225	0.214	0.038	0.062
EM	0.000	7.892	1.940	1.234
Lev	0.051	0.886	0.415	0.206
Top 3	16.750	85.710	49.070	15.440
Age	0.000	3.332	2.010	0.953
Dual	0.000	1.000	0.293	0.455

4.2. Baseline Regression Results

Table 4 shows the baseline regression results. In Column (1) we do not control for any variable, while in Column (2) we control for all relevant variables. As the results in Column (1) show, the coefficient for the policy variable associated with the pilot zone is 0.078, with a t-value of 5.2, achieving statistical significance at the 1% level. In Column (2), the regression coefficient is 0.054, with a t-value of 3.867, also significant at the 1% level, which indicates that the establishment of the pilot zone has led to an average increase of

5.4% in the corporate green innovation persistence compared with non-pilot provinces. This indicates that, after controlling for other factors, the national big data pilot zones still contribute to a significant increase in green innovation persistence. This finding underscores the fact that the positive impact of big data pilot zones on green innovation persistence is not merely a result of other confounding factors but is an inherent benefit of these zones. These results collectively demonstrate that national big data pilot zones play a significant role in promoting the persistence of corporate green innovation. The digital policies implemented within these zones enhance the efficiency of resource allocation across society, encouraging continuous green innovation practices and the generation of effective green patents. This, in turn, supports corporate sustainable development and validates Hypothesis 1. Moreover, the comprehensive digital planning and construction at the city level within these zones significantly improve local digital infrastructure and optimize the innovation ecosystem. This environment provides substantial digital resources and data, facilitating green innovation activities in companies. The incentive policies in these zones also attract high-tech companies and talent, thereby augmenting human capital and further driving the persistence of green technological innovation. Overall, the core variable of national big data pilot zones significantly and positively impacts the persistence of corporate green innovation, both with and without the consideration of other influential factors. These findings support the hypothesis that the establishment of national-level big data pilot zones enhances the persistence of corporate green innovation (Hypothesis 1).

Table 4. Regression results.

Variables	**1**	**2**
	OIP	**OIP**
Treat × Time	0.078 *** (0.015)	0.054 *** (0.015)
Labor		0.190 *** (0.006)
ROA		0.971 *** (0.092)
EM		−0.019 *** (0.007)
Lev		0.347 *** (0.046)
Top3		−0.001 *** (0.000)
Age		0.125 *** (0.007)
Dual		−0.020 (0.012)
_cons	0.500 *** (0.007)	−1.268 *** (0.044)
Industry	Yes	Yes
Year	Yes	Yes
R-squared	0.121	0.200
N	32,383	32,383

Note: *** $p < 0.01$. The same as follows.

Control variables are also significant. For instance, employee count exhibits a positive correlation with green innovation persistence, suggesting that companies with a larger workforce are better positioned to foster sustainable green innovation. The coefficients

for financial leverage, return on assets, and equity multiplier are significantly positive, likely indicating that firms in a better financial position are more inclined to embrace social responsibility, pursuing not only innovative sustainability but also green development, which enhances green innovation persistence. Conversely, in the overall sample, the proportions of the top three shareholders and the dual-role coefficient are significantly negative, potentially reflecting that an increased ownership concentration may hinder the development of green innovation persistence by consolidating power in the hands of a few. Additionally, the coefficient for the age of the company is negative in relation to green innovation persistence, possibly due to older firms adopting a more cautious approach, being content with current developments and reluctant to take risks in innovative investments.

4.3. Robustness and Endogeneity Test Results

To ensure the reliability of the research findings, we employ seven robustness checks, including the parallel trends test, PSM-DID, placebo tests, substitution of dependent variable, exclusion of municipalities directly under the central government, single-period DID, control for other policy interferences, and introduce provincial fixed effect.

4.3.1. Parallel Trends Test Results

The application of the DIDs methodology is predicated on the assumption that the treatment and control groups exhibit similar developmental trends prior to the implementation of the policy. In the context of this study, this implies that, before the establishment of pilot zones, the trends in the green innovation persistence for both groups should align closely. As illustrated in Figure 2 and Table 5, there is no significant difference in the trends between the two groups prior to the establishment of pilot zones. However, in the following 2–3 observation periods after the establishment, the coefficients are significantly different from zero, indicating that the establishment of pilot zones has positively influenced the green innovation persistence. It is noteworthy that the policy's impact exhibits a certain degree of lag. This may be attributed to several factors: first, the implementation of the policies in these pilot zones commenced relatively late, with Guizhou initiating construction in September 2015, followed by other cities establishing their zones in October 2016, both toward the end of the year. Second, the realization of policy effects necessitates time. The government requires time to develop the necessary infrastructure, such as data governance platforms and cloud computing centers, and there is also a lag in attracting talent and high-quality enterprises. In summary, although there is a temporal lag in the impact of pilot zones on the green innovation persistence, the evidence suggests that, overall, the policy has had a significant positive effect among enterprises within the pilot zones compared to the control group.

Table 5. Parallel trend test results.

Variables	OIP
pre_4	0.032 (0.027)
pre_3	0.058 (0.041)
pre_2	0.063 (0.041)
pre_1	0.066 (0.040)
current	0.044 (0.040)

Table 5. *Cont.*

Variables	OIP
post_1	0.053 (0.038)
post_2	0.094 ** (0.039)
post_3	0.050 *** (0.019)
Labor	0.190 *** (0.006)
ROA	0.966 *** (0.092)
EM	−0.019 *** (0.007)
Lev	0.347 *** (0.046)
Top3	−0.001 *** (0.000)
Age	0.125 *** (0.007)
Dual	−0.020 (0.012)
_cons	−1.273 *** (0.044)
Industry	Yes
Year	Yes
R-squared	0.200
N	32,383

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

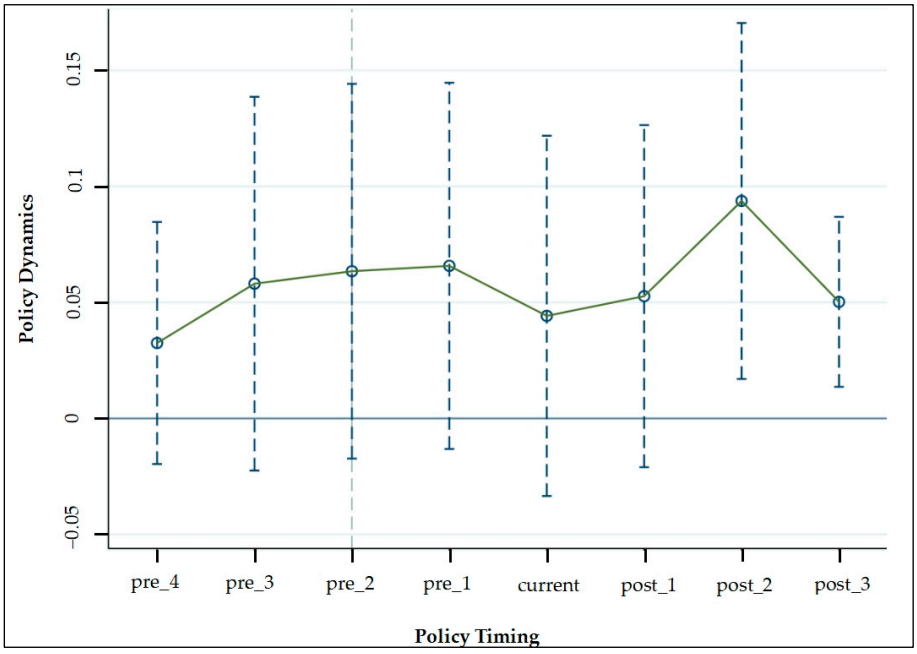


Figure 2. Parallel trends test.

4.3.2. Placebo Test Results

To effectively eliminate other potential or unobservable influencing factors, this study employed a placebo test methodology. Specifically, we randomly extracted 500 samples from the total dataset for analysis. As illustrated in Figure 3, the estimated coefficients of the 'pseudo-treatment group' variable concerning the persistence of green innovation cluster closely around zero and exhibit characteristics of a normal distribution. This result robustly supports our research conclusions by mitigating the interference of unobservable factors on the regression analysis outcomes, thereby ensuring the reliability and accuracy of the findings.

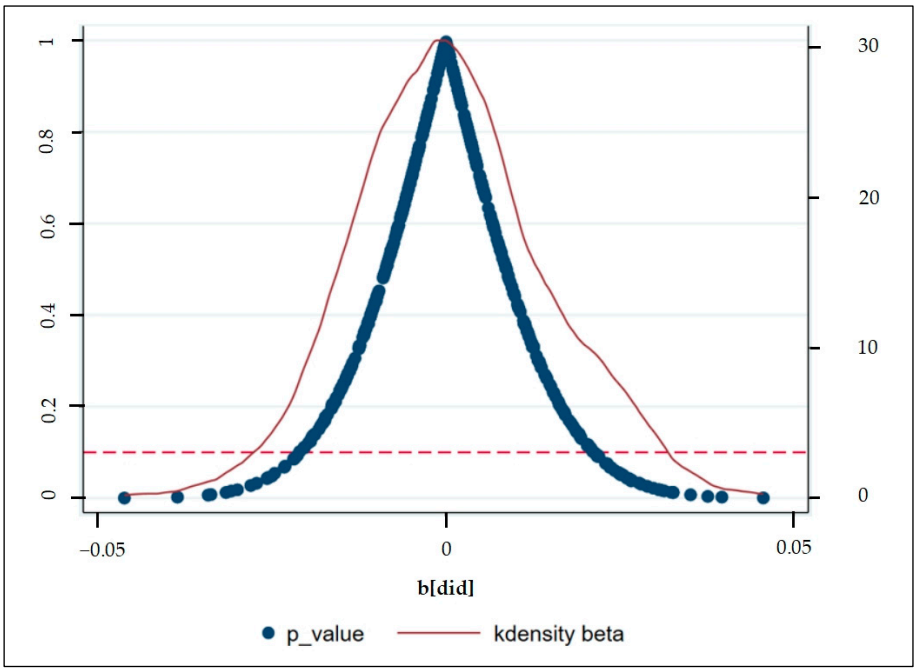


Figure 3. Placebo test.

4.3.3. PSM-DID

In our study we employed the PSM method to address endogeneity issues related to the "selection effect" from sample self-selection, using a 1:1 nearest neighbor matching approach for PSM-DID analysis. In constructing the PSM model, all previously discussed control variables were included as predictors. The balance tests indicate no significant differences between the experimental and control groups at the 10% level, suggesting effective matching. After 1:1 nearest neighbor matching, we obtained 13,917 observations and conducted a reanalysis. As shown in column (1) of Table 6, the policy effects remain significant at the 1% level.

Table 6. Robustness test results.

Variables	1	2	3	4	5	6
	PSM	Changing the Core Variables	Excluding Municipalities Directly Under the Central Government	Single-Period DID	Control the Impact of Other Policies	Control Provincial Fixed Effect
	OIP	OIP	OIP	OIP	OIP	OIP
Treat × Time	0.065 *** (0.021)	0.030 ** (0.012)	0.042 ** (0.018)	0.055 *** (0.015)	0.030 * (0.016)	0.038 ** (0.015)
didcc					−0.021 * (0.013)	
diddk					0.075 ***	
					(0.016)	

Table 6. *Cont.*

Variables	1	2	3	4	5	6
	PSM	Changing the Core Variables	Excluding Municipalities Directly Under the Central Government	Single-Period DID	Control the Impact of Other Policies	Control Provincial Fixed Effect
	OIP	OIP	OIP	OIP	OIP	OIP
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−1.259 *** (0.068)	−0.423 *** (0.058)	−1.343 *** (0.047)	−1.268 *** (0.044)	−1.274 *** (0.048)	−1.039 *** (0.077)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Province						Yes
R-squared	0.217	0.131	0.198	0.200	0.205	0.201
N	13,917	32,383	26,175	32,383	28,938	32,383

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The same as follows.

4.3.4. Replace the Dependent Variable

To address the potential impact of varying measurement methods on the core variables, we substituted the dependent variable and conducted a new regression analysis. Since green invention patents have a higher technological content and practical value compared to green utility model patents, we specifically selected patent applications as the core metric. We calculated the cumulative number of green invention patent applications from $year_{t-1}$ to $year_t$ and computed the year-on-year growth rate relative to the cumulative applications from $year_{t-2}$ to $year_{t-1}$. This growth rate was then multiplied by the total number of applications from $year_{t-1}$ to $year_t$, and the natural logarithm of this value was taken as an alternative measure of green innovation persistence. Using this new metric, we re-evaluated our research hypotheses. As shown in column (2) of Table 6, the regression coefficient for the alternative indicator of green innovation persistence remains positive at the 5% significance level. This further supports Hypothesis 1 and confirms the robustness of our research conclusions.

4.3.5. Exclude Special Samples

Municipalities often have broader economic management authority and abundant political resources, which could potentially influence research outcomes. To verify the generalizability and accuracy of the test results, we excluded samples of firms registered in municipalities and re-evaluated the model. After this adjustment, the results in column (3) of Table 6 show that, after removing these outliers, the regression coefficient for green innovation persistence (OIP) remains significantly positive at the 5% level. This further validates the robustness of our study's conclusions.

4.3.6. Single Period DID

Due to different establishment times of the pilot zones—with only Guizhou Province establishing their zone in 2015 and the others in 2016—we designated 2016 as the unified policy start date for consistency and comparability, following Qiu's methodology [121]. Based on this, we re-estimated the model. As shown in Table 6 column (4), after using the single-period DIDs method, the re-estimated results align with our benchmark results and remain significant. These results not only confirm the robustness of our research results but also further support our hypothesis.

4.3.7. Control for Other Policies

During the study period, several related digital policies were implemented, potentially promoting green innovation in enterprises. If these policies are not considered, the enabling effect of the pilot zones could be overestimated. To accurately assess the "net effect", we systematically reviewed policies implemented around 2016. We specifically analyzed the

"Broadband China" policy (didkd) and the smart city pilot policy (didcc). By incorporating these policy dummy variables into the model, we could more precisely measure the actual impact of the pilot zones policy. As shown in column (5) of Table 6, even after including the dummy variables for the two similar policies, the impact of the pilot zones on enterprise innovation remains positively significant at the 10% level. This suggests that even though the policy effect might be overestimated, the promotion of green innovation persistence by the pilot zones remains significant and robust, further validating the reliability of our study's conclusions.

4.3.8. Introducing the Provincial Fixed Effect

Following Gong [122], when analyzing the particular pilot zones' policies, it is crucial to consider provincial fixed effects, as these zones are established at the provincial level. Therefore, in addition to controlling for industry and year fixed effects, we control for provincial fixed effects to avoid potential endogeneity issues. The results in column (6) of Table 6 show that the coefficient is still significant at the 5% level, further supporting our research hypothesis.

4.4. Moderating Effect of Green Finance

This study suggests that the effectiveness of national big data pilot zones in promoting sustainable corporate green innovation relies on a robust green finance environment. Table 7 presents the results of the moderation effect. Column (1) shows that in regions with high green finance levels, the establishment of big data pilot zones significantly boosts the persistence of corporate green innovation, with a coefficient of 0.061, significant at the 1% level. In contrast, Column (2) indicates that in regions with low green finance levels, the establishment of big data pilot zones does not significantly enhance the persistence of corporate green innovation.

Table 7. Moderating effect of green finance test results.

Variables	1	2
	High Green Financial Standards	**Low Green Financial Standards**
	OIP	**OIP**
Treat × Time	0.061 ***	0.003
	(0.017)	(0.034)
Labor	0.188 ***	0.194 ***
	(0.008)	(0.008)
ROA	0.994 ***	0.975 ***
	(0.115)	(0.157)
EM2	−0.018 *	−0.016
	(0.011)	(0.010)
Lev	0.433 ***	0.266 ***
	(0.065)	(0.067)
Top3	−0.001	−0.002 ***
	(0.001)	(0.001)
Age	0.137 ***	0.107 ***
	(0.009)	(0.010)
Dual	−0.035 **	0.003
	(0.017)	(0.018)
_cons	−1.306 ***	−1.225 ***
	(0.061)	(0.065)
N	17,139	15,241
R-squared	0.206	0.202
industry	Yes	Yes
year	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The same as follows.

This finding clearly demonstrates that green finance can enhance the positive impact of national big data pilot zone policies on the persistence of corporate green innovation. This study suggests that the effectiveness of national big data pilot zones in promoting sustainable corporate green innovation relies on a robust green finance environment. Green finance improves the efficiency and precision of capital allocation within enterprises, ensuring funds are directed towards green and eco-friendly companies, thus providing a stable, long-term financial chain for green innovation. In regions with advanced green finance, financial institutions, governments, and society place greater emphasis on green development, financing, and transition. This environment supports the recognition of green innovation activities, enhancing the reputation and credibility of enterprises and leading to intangible benefits. This positive feedback mechanism encourages ongoing green innovation, creating a virtuous cycle that supports sustainability. To examine whether green finance enhances the impact of national big data pilot zones on the persistence of technological innovation, this study categorizes sample regions into high and low green finance levels based on the average regional green finance level.

4.5. Mediating Effect Test Results

The basic findings above support the principles of resource dependence theory and corporate ecology theory. The implementation of big data pilot zones has had positive impacts, such as attracting top talent and high-tech enterprises, and promoting the transformation and upgrading of traditional industries. These factors contribute to optimizing the regional business environment. Furthermore, it can reduce information asymmetry between enterprises and stakeholders, enhancing financing capability for sustainable green innovation. These findings reveal the importance of exploring the mechanisms through which data policies affect corporate green innovation.

4.5.1. Mechanism for Mitigating Financing Constraints

Columns (1) and (2) of Table 8 demonstrate the mediation effect of financing constraints. In Column (1), the coefficient for big data pilot zones is significantly negative at 0.010, indicating that enterprises within these zones face lower levels of financing constraints. In Column (2), the coefficient for big data pilot zones is significantly positive at the 1% confidence level, suggesting that financing constraints partially mediate the impact of big data pilot zones.

Green innovation activities in enterprises require substantial resources and face higher risks and longer product cycles. Challenges such as information asymmetry, lack of government policy support, and inadequate risk management by financial institutions persist. Due to the pilot zones policy, the digital infrastructure has been improved, meaning that financial institutions can more easily access companies' financial status, operational data, and credit history, reducing information asymmetry and consequently lowering risk premiums and capital costs. Additionally, these zones enhance the integration of digital technology and financing activities, fostering financial industry agglomeration and enriching financial market products and services, thus providing enterprises with more financing options. By incorporating advanced technologies like big data and artificial intelligence, financial institutions have digitized and streamlined financing processes, reducing cycles and approval times, thereby significantly enhancing financing efficiency. In summary, these measures effectively alleviate enterprises' financing constraints, providing essential financial support for green innovation activities.

Table 8. The result of mechanism Analysis.

Variables	1	2	3	4	5	6
	WW	**OIP**	**STG**	**OIP**	**UIS**	**OIP**
Treat × Time	−0.010 ** (0.005)	0.053 *** (0.015)	23.952 *** (0.468)	0.030 ** (0.015)	0.044 *** (0.006)	0.048 *** (0.015)
WW		−0.055 *** (0.017)				
STG				0.001 *** (0.000)		
UIS						0.065 *** (0.018)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−0.177 *** (0.013)	−1.278 *** (0.045)	45.838 *** (1.316)	−1.313 *** (0.046)	2.448 *** (0.015)	−1.399 *** (0.065)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.333	0.200	0.273	0.201	0.080	0.205
N	32,383	32,383	32,383	32,383	28,904	28,904

Note: *** $p < 0.01$, ** $p < 0.05$. The same as follows.

4.5.2. Mechanism for Concentrating Scientific and Technological Talent

Columns (3) and (4) of Table 8 demonstrate the mediation effect of tech talent aggregation. In Column (3), the coefficient for the big data pilot zones is significantly positive at 23.952, indicating that establishing national-level big data pilot zones can enhance the regional aggregation of tech talent. In Column (4), the coefficients for both the big data pilot zones and tech talent aggregation are significantly positive at the 1% confidence level, suggesting that tech talent aggregation partially mediates the impact of big data pilot zones on the persistence of green innovation.

Enhancing a company's green technological innovation capability and building core competitiveness rely on innovative talent. The establishment of pilot zones provides a comprehensive data exchange platform for scientific and technological talent, offering services such as policy consultation and project applications through talent service centers and startup incubators. This creates a more convenient and efficient environment, enhancing talent satisfaction within these zones. The zones offer incentives like tax reductions, financial subsidies, and allowances for talent acquisition, reducing the costs of entrepreneurship and living for scientific talent, and increasing their sense of fulfillment and belonging. Additionally, initiatives such as overseas talent recruitment plans are in place to attract high-level international scientific talent. These policies effectively draw a large influx of innovative talent, enriching the green innovation talent pool and creating an agglomeration effect. This effect provides a rich resource of talent for the persistence of corporate green innovation, promoting the continuous enhancement of green technological innovation capabilities.

4.5.3. Mechanism for Industrial Structure Upgrading

Columns (5) and (6) of Table 8 demonstrate the mediation effect of industrial upgrading. In Column (5), the coefficient for the big data pilot zones is significantly positive at 0.044, indicating that establishing national-level big data pilot zones can promote regional industrial upgrading. In Column (6), the coefficients for both the big data pilot zones and industrial upgrading are significantly positive at the 1% confidence level, suggesting that industrial upgrading partially mediates the impact of big data pilot zones on the persistence of green innovation.

From an industrial upgrading perspective, national-level industrial policies play a crucial role as drivers. The implementation of national big data pilot zones has optimized regional industrial structures and resource allocation, effectively directing resources towards sustainable green innovation. Firstly, these zones promote the deep integration of big data technology with traditional industries, enabling their transformation towards intelligence and sustainability. This accelerates the growth of emerging industries such as artificial intelligence, smart manufacturing, and cloud computing, attracting related enterprises and creating a ripple effect that promotes digital innovation and entrepreneurship. Moreover, digital policies facilitate collaboration along the industrial chain, further refining regional industrial structures. Secondly, the zones facilitate the integration and sharing of data resources among governments, enterprises, universities, and research institutions. By enabling precise data collection, efficient processing, and in-depth analysis, companies can better capture shifts in market demand, driving innovation in products and services. This reshapes industry competition, enhances product and service differentiation, and accelerates industrial restructuring. This analysis demonstrates that national big data pilot zones can support industrial upgrading and transformation, providing a more structured and favorable external environment for corporate green innovation. They optimize market competition mechanisms, offer greater support for green innovation, and improve innovation efficiency, thereby fostering a virtuous cycle and promoting sustainable green innovation in enterprises.

4.6. Heterogeneity Analysis Results

4.6.1. Group Testing of State-Owned and Non-State-Owned Enterprises

Enterprises with different ownership structures may vary in their willingness and ability to pursue green innovation, affecting the relationship between national big data pilot zones and the persistence of such innovation. State-owned enterprises (SOEs) typically focus on long-term stability, showing less demand for change and innovation. They often receive more resources and less punishment, which may reduce their intrinsic motivation for green innovation. In contrast, non-state-owned enterprises (NSOEs), especially emerging ones, face intense competition and prioritize enhancing innovation capabilities, particularly in sustained innovation, investing significant resources in this area.

The impact of big data pilot policies is more pronounced on NSOEs, allowing them to use big data technology more flexibly, respond swiftly to market changes, and allocate resources accurately, alleviating resource constraints. This enhances the quality and efficiency of their green technological innovation, suggesting that the marginal effect of big data pilot policies is higher for NSOEs. The results in Table 9 Column (1) show the SOE results, and it can be seen that the coefficient for the explanatory variable is not significant. In Column (2), the coefficient is significantly positive at 0.074. This indicates that the pilot zones policy has a positive effect on the green innovation persistence in NSOEs, aligning with expectations.

4.6.2. Group Testing of Heavy-Polluting and Non-Heavy-Polluting Enterprises

The classification of a firm as a heavy polluter can affect its motivation for green innovation. In comparison to non-heavy polluters, heavy-polluting firms face greater challenges and higher costs in technological upgrading and transformation. Therefore, more resources are needed in order to innovate and sustain green practices, which might reduce their motivation for green innovation.

As shown in Table 9 column (3), the coefficient for heavy polluters is negative but not statistically significant. In Column (4), for non-heavy polluters, the coefficient for national big data pilot zones is significantly positive at 0.080. This suggests that the pilot zones policy has a stronger impact on the green innovation persistence in non-heavy-polluting firms.

Table 9. Heterogeneity analysis results.

Variable	State-Owned Enterprise	Non-State-Owned Enterprise	Polluting Enterprises	Non-Polluting Enterprises	High-Level Government Subsidized Enterprises	Low-Level Government Subsidized Enterprises	Low-Level Environmental Regulation	High-Level Environmental Regulation
	1	2	3	4	5	6	8	7
	OIP	OIP	OIP	OIP	OIP	OIP	OIP	OIP
Treat × Time	−0.015 (0.029)	0.074 *** (0.017)	−0.013 (0.032)	0.080 *** (0.016)	0.088 *** (0.025)	0.025 (0.018)	0.025 (0.021)	0.076 *** (0.020)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−0.835 *** (0.150)	−0.824 *** (0.084)	−1.321 *** (0.153)	−0.970 *** (0.080)	−1.260 *** (0.084)	−1.257 *** (0.054)	−1.335 *** (0.059)	−1.155 *** (0.068)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.256	0.186	0.187	0.200	0.210	0.205	0.200	0.208
N	10,834	21,547	7237	25,146	10,881	21,498	18,913	13,485

Note: *** $p < 0.01$. The same as follows.

4.6.3. Group Testing of High-Level and Low-Level Government Subsidies

The level of government subsidies a company receives can have a significant impact on its persistence in green innovation. The key to enhancing this persistence lies in receiving sufficient resource support, particularly stable financial investment. Government subsidies play a crucial role in providing the necessary financial backing for green innovation activities, complementing other policies. This dual support effectively alleviates financial constraints and concerns related to insufficient funding, enabling companies to actively engage in green innovation and fulfill their social responsibilities, thereby contributing to sustainable development.

We employ a median grouping method to classify companies based on the ratio of government subsidies to revenue. Companies with ratios below the median were categorized as low-subsidy. Otherwise, it is classified as high-subsidy. The results in Table 9 column (5) reveal that for high-subsidy companies, the coefficient for national big data pilot zones is significantly positive at 0.088. In Column (6), for low-subsidy companies, the coefficient is not significant. This indicates that the pilot zones policy has a greater impact on the green innovation persistence in high-subsidy companies.

4.6.4. Group Testing of High-Level and Low-Level Environmental Regulation Enterprises

The environmental regulation level reflects the government's capacity for environmental governance and can significantly influence the persistence of corporate green innovation. Regions with robust governance typically require more precise environmental monitoring and management data. In these areas, governments can utilize digital technologies for real-time monitoring of and early warnings for pollution sources, enabling the prompt identification and resolution of environmental issues. This stringent regulation serves as a deterrent, exerting significant policy pressure on companies. Firms, under this pressure, are compelled to continuously innovate and implement green technologies to enhance their environmental performance and market competitiveness.

In this study, companies were classified using a median grouping method based on their level of environmental regulation. Companies below the median were categorized as low-regulation, while those above were categorized as high-regulation. The results in Table 9 column (7) show that, for low-regulation companies, the coefficient for national big data pilot zones is not significant. In Column (8), for high-regulation companies, the coefficient is significantly positive at 0.076. This indicates that the pilot zones policy has a greater positive impact on the green innovation persistence in high-regulation companies, which aligns with our expectations.

4.7. Additional Tests for Overall Input/Output Persistence of Innovation

Based on the results of the benchmark regression, we have shown the impact of big data experimental zone policies on the persistence of green innovation. However, green innovation is just one category of innovation. Therefore, further testing is needed to determine whether the policies have the same effect on other types of innovation or if the effect on green innovation is due to a broader impact on innovation activities. In addition, according to the definition of innovation persistence by He (2015), both input-based and output-based perspectives can be used to define innovation persistence. It is important to verify if different conclusions are reached when considering these two perspectives.

To do so, we conducted the following tests. We constructed measures of overall innovation persistence from the perspectives of R&D investment and the quantity of innovation patents and utility models. However, we found that listed companies did not disclose specific information on green innovation investment in their annual reports. Nevertheless, we were able to find information on green patents and utility models in the enterprise patent database. Therefore, we did not construct an innovation persistence measure based on green innovation investment. Due to missing values in the disclosed innovation investment data, we adjusted the sample size and analyzed the impact of big data policies on the persistence of green innovation, overall output-based innovation persistence, and input-based innovation persistence using the same sample. The empirical results in Table 10 show that the improvement in green innovation persistence due to big data policies is 4.8%, compared to 1.5% for overall innovation persistence and 1.7% for input-based innovation persistence. This demonstrates that the effect of big data policies on the persistence of green innovation is stronger than on overall innovation investment persistence, as the green attributes of innovation enhance the effectiveness of these policies. This further validates the robustness of our hypothesis.

Table 10. Additional test results for persistence of overall innovation from input/output perspective.

Variables	1	2	3
	OIP	**Overall OIP**	**Overall IIP**
Bigdata	0.048 ** (0.019)	0.015 *** (0.005)	0.017 *** (0.002)
Labor	0.259 *** (0.009)	0.143 *** (0.003)	0.082 *** (0.001)
ROA	1.034 *** (0.123)	0.451 *** (0.042)	0.262 *** (0.018)
EM	−0.072 *** (0.013)	−0.031 *** (0.004)	−0.020 *** (0.002)
Lev	0.735 *** (0.076)	0.134 *** (0.025)	0.069 *** (0.011)
Top3	−0.002 *** (0.001)	−0.000 (0.000)	−0.000 (0.000)
Age	−0.136 *** (0.014)	−0.007 (0.004)	−0.012 *** (0.002)
Dual	−0.046 *** (0.017)	0.006 (0.005)	0.002 (0.002)
_cons	−1.096 *** (0.070)	0.470 *** (0.072)	1.726 *** (0.009)
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
R-squared	0.195	0.324	0.420
N	21,794	21,794	21,794

Note: *** $p < 0.01$, ** $p < 0.05$. The same as follows.

5. Policy and Managerial Suggestions

Our research offers significant theoretical and practical implications. Theoretically, it bridges the gap between digital policies and the persistence of corporate green innovation, contributing to the field by elucidating mechanisms such as alleviating financial constraints, promoting talent aggregation, and facilitating industrial restructuring. It highlights the unique institutional context and heterogeneous environmental factors in China, thereby enriching the existing literature on persistence of green innovation.

From a policy perspective, this study provides valuable insights and empirical evidence for enhancing the persistence of green innovation. We empirically examine the relationship between national policies promoting digital development and corporate green innovation persistence, investigating the mechanisms of influence, as well as the varying impacts of ownership structure, pollution attributes, government subsidies, and environmental regulations on this relationship. Based on these findings, we offer specific recommendations for government digital policies and corporate strategies to enhance green innovation persistence.

Based on our empirical results, we propose the following suggestions for enterprises and government:

Firstly, companies should capitalize on policy benefits by employing big data technologies, attracting and cultivating talent in innovation fields, and increasing investments in green innovation. They should establish specialized teams for green innovation, create data sharing platforms with industry peers and research institutions, and jointly advance green technology innovation.

Secondly, the government should continuously optimize the policy system of national-level big data comprehensive experimental zones, promote the expansion of these zones, and emphasize the implementation effectiveness of big data policies. In pilot cities, control measures and resource allocation methods that align with the trends of digital technology development should be adopted to guide increased capital participation in digital infrastructure construction, promote regional digital technological advancements, facilitate the integration of industry, academia, and research in digital technology, and establish hubs of digital innovation. Long-term resource support should be provided for sustainable green innovation in enterprises, along with fiscal support policies to promote the transformation and upgrading of traditional industries. Incentive policies for high-level scientific and technological personnel should be improved to ensure policy support for talent mobility and development, thereby creating a favorable external environment for the development of green innovation in enterprises.

Thirdly, the government should actively coordinate the development of the social financial system, accelerate the establishment and improvement of green financial products, and expedite the development of green finance. Efforts should be made to promote the innovation of green financial instruments to alleviate financing constraints for green technological innovation, thereby mobilizing the enthusiasm of enterprises and other entities to engage in green technological innovation. This will provide more financial resources to support green innovation in enterprises, while leveraging the positive regulatory role of the financial system in promoting innovative behavior under big data policies. The synergistic development of green finance and big data can foster the continuous development of green technological innovation in enterprises.

Fourthly, based on the results of heterogeneity analysis, the government should actively adjust the policy system and work in conjunction with the development of big data experimental zones to form a joint force of policies. Specifically, mandatory requirements for the green innovation behaviors of state-owned enterprises should be increased, and the digital transformation of state-owned enterprises should be actively promoted to facilitate the acquisition of technological innovation resources and the conduct of innovation activities in the context of digital technology. Stricter punitive control measures should be introduced to enhance the willingness of heavily polluting enterprises to engage in

green innovation. Subsidies for enterprise green innovation should be increased to provide greater policy support and enhance the government's credibility and endorsement effect.

6. Conclusions

This study examines the impact of establishing national-level big data pilot zones on the persistence of corporate green technology innovation. Our empirical analyses yield several significant conclusions. We find that the establishment of a comprehensive digital infrastructure serves as a crucial driver for corporate green development. In particular, the policy significantly promotes the level of corporate green innovation. This core conclusion remains robust after conducting parallel trend tests and various other robustness checks, confirming the positive impact of these pilot zones on the persistence of corporate green innovation. Following the baseline regression, we conducted a mediation analysis, revealing that the establishment of big data pilot zones alleviates financing constraints, fosters the aggregation of technological talent, and facilitates industrial restructuring. These factors collectively promote the continuous advancement of green technology innovation. The enhanced digital technology levels in pilot cities reduce information asymmetry between financial institutions and firms, which in turn alleviates financing constraints and supports the persistence of green innovation. Additionally, the improved digital environment attracts more high-caliber talent and high-tech enterprises, catalyzing the transformation and upgrading of traditional industries and fostering a conducive external environment for the corporate green innovation persistence. Heterogeneity analyses indicate that the influence of corporate green innovation varies based on ownership structure, pollution levels, government subsidies, and the degree of environmental regulation. The pilot policies exert a stronger positive effect on the persistence of green innovation in non-state-owned enterprises, non-polluting firms, and in contexts with high levels of government subsidies and stringent environmental regulations. These findings elucidate the mechanisms through which corporate green innovation can effectively operate.

In summary, within the context of promoting green and sustainable development, these results underscore the importance of China's digitalization policies and their relation to the persistence of corporate green innovation. Such initiatives will effectively drive firms to enhance both the quantity and quality of green innovation, facilitating a transition toward greener and more sustainable practices, thereby contributing positively to ecological optimization goals.

This research has certain limitations. First, the measurement of green innovation persistence requires further investigation, as refining indicator metrics may potentially influence the current conclusions. Second, the national-level digital policy framework is extensive, encompassing various domains such as social financial resource provision, digital infrastructure improvement, and the realization of sustainable development goals. There remains room for further identification of the mechanisms influencing corporate green innovation behaviors. Lastly, this study primarily considers the effects of policies from the perspective of the external environment surrounding firms, recognizing the shaping influence of significant national policies. However, the extent to which managers accept these policies—considering factors such as executive demographic backgrounds and management team heterogeneity—can also significantly impact policy outcomes. These areas present opportunities for future research opportunities.

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