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Original Research

Assessing the Impact of Big Data on Green Innovation Resilience in Manufacturing Enterprises: Evidence from China's National Big Data Comprehensive Pilot Zone

Meiling Wang*, Zhiyuan Han, Yuhang Zhao, Ping Yao

School of Economics and Management, Nanjing Forestry University, Nanjing 210037, China

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Abstract

Given the tightening constraints on environmental resources and rising external uncertainties, it is crucial for the manufacturing industry to build resilience against external disruptions and enhance its green innovation resilience (GIR). Big data, as a transformative force for green and low-carbon development in the new era, presents a valuable opportunity to boost GIR in manufacturing enterprises. Understanding how to leverage big data to strengthen GIR is essential for achieving sustainable development. This study uses China's national big data comprehensive pilot zone (NBDCPZ) policy as a natural experiment, applying difference-in-differences and mediation effect models to examine the policy's impact on manufacturing GIR and its underlying mechanisms. The results indicate that big data significantly enhances the GIR of manufacturing enterprises, with more pronounced effects observed in non-state-owned enterprises, non-heavy polluting enterprises, and enterprises located in the eastern region of China. Mechanism analysis indicates that big data improves GIR by increasing investor attention, raising public environmental awareness, and enhancing enterprises' risk-bearing capacity. The finding suggests that expanding the scope of NBDCPZ policy pilot zones, improving big data service platforms, and tailoring policies to the specific characteristics of enterprises are essential for fully realizing the benefits of big data. This study provides valuable insights for advancing GIR in the manufacturing sector and innovating big data economic policies.

Keywords: green innovation resilience, big data, natural experiment, sustainable development

Introduction

Green innovation resilience reflects an enterprise's ability to adapt to external shocks, mitigate risks, and achieve green innovation goals. Strengthening this resilience has become a vital strategy for enterprises to manage uncertainties and pursue sustainable

*e-mail: mlwang688@hotmail.com

development. Recent years have seen increased constraints on resources and the environment [1], heightened global instability, a downturn in the global economy, and rapid transformations. Countries worldwide are facing growing uncertainties and risks, with China, in particular, undergoing a crucial phase of green transformation and development. Effectively managing external shocks to achieve high-quality development is crucial for balancing sustainable economic growth, security, and stability. For manufacturing enterprises, which are central to the green economic transformation, it is essential to advance efforts to resist external disruptions and enhance green innovation resilience.

In recent years, the rise of a new wave of technological transformation driven by big data has significantly influenced green development [2]. This shift presents new opportunities for manufacturing enterprises to address existing challenges and promote green innovation. The integration of big data into production and innovation processes is accelerating, leading to the gradual dismantling of "information silos" and "data barriers." This progress drives enterprises to continuously enhance their green innovation capabilities to remain competitive. To harness the benefits of big data fully, the State Council of China introduced the "Action Plan for Promoting Big Data Development" in 2015 and established national big data comprehensive pilot zones in 67 cities. These pilot zones are central to implementing China's big data strategy and advancing digital transformation, offering a new perspective on improving the green innovation resilience of manufacturing enterprises.

Research on the impact of big data has primarily focused on three areas: economic effects [3, 4], innovation effects [5-7], and environmental effects [8]. In terms of economic effects, studies investigated big data's impact on total factor productivity [9, 10], regional economic growth [11, 12], and corporate performance [13, 14]. For instance, Lyu et al. [15] employed a Difference-in-Differences (DID) model to investigate the impact of big data on enterprises' green total factor productivity. They found that big data enhances enterprises' green total factor productivity through technological innovation, industrial structure optimization, and resource reallocation. Similarly, Calic and Ghasemaghaei [16] surveyed 297 middle and senior managers, discovering that big data boosts corporate social performance through enhanced organizational innovation. In terms of innovation effects, scholars commonly use patent application volume and citation counts to measure innovation performance and quality, showing that big data positively influences both [17, 18]. For example, Mikalef et al. [19] employed a partial least squares structural equation model to find that big data analytics significantly enhances innovation via dynamic capabilities, while Wu et al. [20] found in case studies of four types of manufacturing firms that digitalization promotes corporate innovation by integrating resources. In terms of environmental effects, big data has been shown to improve environmental performance by reducing carbon and industrial dust emissions [21, 22]. Wei et al. [23] used a DID model to demonstrate that big data reduces carbon emissions by promoting industrial structure upgrades, enhancing energy efficiency, and improving green total factor productivity. In summary, while scholars have extensively explored the effects of big data, research on its influence on the green innovation resilience of manufacturing enterprises remains limited. From a policy perspective, some enterprises adopt strategic innovations primarily to secure government subsidies, which can result in practices such as "green washing" and "powder bleaching" [24], undermining genuine advancements in green innovation resilience. China's national big data comprehensive pilot zone (NBDCPZ) policy, as a key reform facilitating the implementation of an innovation-driven strategy, is expected to significantly impact the green innovation resilience of manufacturing enterprises. This raises important questions: Does China's NBDCPZ policy enhance the green innovation resilience of manufacturing enterprises? Is there heterogeneity in this impact, and what are the possible mechanisms behind it? Addressing these questions is a valuable research endeavor. Therefore, this study uses China's NBDCPZ policy as a quasi-natural experiment, selecting 157 manufacturing enterprises from 2013 to 2022. It employs both DID and mediation effect models to systematically assess the impact of big data on the green innovation resilience of these enterprises and to identify the mechanisms behind this impact. The findings offer valuable insights for the expansion of China's NBDCPZ policy and contribute to corporate green strategy planning.

The marginal contribution of this study is manifested in three key aspects. First, while digital transformation and green innovation have become central to corporate strategy, especially amid climate change and environmental policy pressures, the rapid development of the digital economy has made big data crucial for enhancing enterprise innovation and sustainability through information integration and resource optimization. Existing research frequently examines the economic, innovation, and environmental effects of big data, but its impact on green innovation resilience, particularly from a resilience perspective, remains underexplored. Therefore, this study employs a DID model to investigate the profound effects of big data on green innovation resilience in manufacturing enterprises, clarifying the endogenous interaction between big data and green innovation resilience and highlighting big data's deeper empowering effects. Second, existing research primarily focuses on dynamic capabilities and resource integration, often overlooking the significant role of external attention and enterprise risk-bearing capacity. This gap presents substantial opportunities for further exploration. Therefore, this study examines the impact of big data on green innovation resilience from the perspectives of public environmental awareness, investor attention, and risk-bearing capacity, providing a novel analytical framework for evaluating policy tools supported by big data. Third, existing studies have not fully addressed the policy value of big data and how enterprises consider both their internal capabilities and policy support when making decisions to enhance their green innovation resilience. This study explores the heterogeneous impact of big data on the green innovation resilience of manufacturing enterprises. Specifically, it examines this impact from the perspectives of property rights, pollution levels, and regional characteristics of manufacturing enterprises, aiming to provide more precise policy recommendations for enhancing the green innovation resilience of manufacturing enterprises.

The structure of the remainder of the article is organized as follows. The second section presents the materials and methods of the study, including research hypotheses, model specifications, variable definitions, and data sources. The third section presents the results and discussion, covering benchmark regression, heterogeneity analysis, mechanism analysis, and corresponding discussion. The final section concludes the study.

Material and Methods

Theoretical Analysis and Hypotheses

The Direct Impact of Big Data on the Green Innovation Resilience of Manufacturing Enterprises

From the perspective of dynamic capability theory, relying solely on a resource-based view is insufficient for maintaining a competitive advantage in a rapidly changing environment. New variables must be considered to better understand the relationship between resources and the competitive advantage of enterprises [25, 26]. For manufacturing enterprises, possessing a resource advantage alone does not suffice to secure a long-term edge in the changing market. Enterprises must also develop specific capabilities to continuously acquire, integrate, and utilize resources. Big data, as a dynamic capability [27], enables enterprises to perceive, integrate, establish, and reconfigure internal and external resources through data analysis, thus adapting to rapid changes. It provides manufacturing enterprises with the ability to adjust to shifts in both internal and external environments. Specifically, big data enhances the dissemination and application speed of industry information, reduces decision-making uncertainty, and improves predictive analysis capabilities, leading to more efficient resource allocation. This better equips enterprises to manage the uncertainties associated with green innovation [28]. Additionally, by maintaining existing production factors, big data technology optimizes research and development activities, improves production processes, and increases the efficiency of green innovation efforts, thereby expanding the boundaries of green innovation resilience. Therefore, based on the above analysis, this study proposes the following hypothesis.

Hypothesis 1: Big data has a direct positive impact on the improvement of green innovation resilience of manufacturing enterprises.

The Indirect Impact of Big Data on the Green Innovation Resilience of Manufacturing Enterprises

Big data can enhance the green innovation resilience of manufacturing enterprises by increasing investor attention and public environmental awareness. Stakeholder theory suggests that for enterprises to achieve their development goals, they must comprehensively address the needs of various stakeholders and secure their support and investment [29]. Big data facilitates the collection and integration of both internal and external information, thereby expanding the channels through which manufacturing enterprises can disclose information and investors can access corporate data [30]. This improves the quality and transparency of corporate information disclosure, thereby attracting greater investor attention. From a financial perspective, increased investor attention optimizes the financing environment and reduces financing costs. Consequently, it alleviates financing constraints, supporting green innovation resilience. Additionally, high investor attention increases the risk of "voting with their feet"—a concept introduced by economist Tibert, referring to the withdrawal of support when an enterprise underperforms. This heightened risk accelerates the market exit for underperforming enterprises, compelling them to intensify their green innovation efforts. Furthermore, enterprises with favorable operating conditions, having garnered significant attention, will attract additional social capital, creating a virtuous circle [31]. Furthermore, big data serves as a crucial tool for environmental management, enabling enterprises to implement intelligent environmental management strategies and advanced pollution prevention and control measures. This approach effectively addresses ecological environmental challenges. Additionally, the use of big data and other advanced methods enhances environmental information disclosure, empowering the public to engage more actively in environmental governance and raising awareness of environmental issues. Concurrently, enterprises can leverage green innovation to build public confidence in their commitment to sustainable development, thereby improving their social reputation. This, in turn, attracts greater public support for green innovation initiatives and strengthens green innovation resilience. Therefore, based on the above analysis, this study proposes the following hypothesis:

Hypothesis 2: Big data can enhance external market attention and promote the improvement of green innovation resilience of manufacturing enterprises.

Big data can enhance the risk-bearing capacity of manufacturing enterprises and strengthen their green innovation resilience. Risk management theory suggests that enterprises must identify, evaluate, and manage risks to navigate market uncertainty and improve their risk-bearing capabilities. Specifically, a higher risk-bearing capacity reflects an enterprise's willingness to undertake risks in pursuit of higher returns in a competitive market [32]. This increased willingness results in a greater tolerance for innovation risks and uncertainties, enabling enterprises to better withstand the pressures of potential innovation failures [33]. Conversely, when manufacturing enterprises face external shocks, they encounter heightened operational risks and an increased likelihood of future losses. By utilizing big data, enterprises can accurately assess external market demand, better predict future earnings, make timely adjustments to their business strategies, optimize resource allocation, and invest in research and development activities [34]. This utilization of big data mitigates the uncertainty associated with research and development activities, enhances the enterprise's risk-bearing capacity, and supports the strengthening of green innovation resilience. Therefore, based on the above analysis, this study proposes the following hypothesis:

Hypothesis 3: Big data can improve the risk-bearing capacity of manufacturing enterprises and strengthen their green innovation resilience.

Modeling Design

Basic Regression Model

The DID model evaluates the net effect of policy implementation by comparing the outcomes between treatment and control groups over time. It effectively controls for reverse causality and unobservable variables, leading to more accurate estimates. This model has gained popularity in policy effect evaluation and causal analysis, becoming a standard tool in empirical research [35, 36]. In this study, the implementation of China's NBDCPZ policy, introduced in 2016, is treated as a quasi-natural experiment. Regions implementing the NBDCPZ policy are designated as the treatment group, while other regions serve as the control group. The DID model is employed to assess the impact of big data on the green innovation resilience of manufacturing enterprises in China. The core objective is to evaluate the effectiveness of the pilot policy by comparing green innovation resilience between enterprises in regions with and without the policy. Following Beck et al. [37], this study constructs a DID model with two-way fixed effects, as specified in Equation (1), to capture both time-specific and individual-specific effects, ensuring robust analysis of the policy impact.

$$GIR_{i,t+1} = \alpha_0 + \alpha_1 NBDCPZ\_Policy_{i,t} + \alpha_n Control_{i,t} + \mu_i + \gamma_i + \varepsilon_{i,t} \tag{1}$$

Where, *GIR* represents the green innovation resilience of manufacturing enterprises. *NBDCPZ_Policy* denotes the impact of the China's NBDCPZ policy. *Control* include a set of control variables. The subscripts i and t represent individual enterprises and years, respectively. To ensure the reliability of the regression results, the following measures are implemented: First, acknowledging the potential lag effect of the policy on green innovation resilience, the model uses the green innovation resilience of manufacturing enterprises in the subsequent period as the dependent variable. Second, to account for the influence of year and individual factors, year and individual fixed effects are included in the model. Third, to address heteroscedasticity among enterprises, standard errors are clustered at the enterprise level.

Mediation Effect Model

To comprehensively understand the relationship between big data and the green innovation resilience of manufacturing enterprises, it is essential to explore the underlying mechanisms. The mediation effect model is particularly effective for this purpose [38-40], as it elucidates the pathways through which explanatory variables influence dependent variables. This study adopts the methodology of Jiang [41], selecting mediating variables that have a direct causal relationship with green innovation resilience and focusing on how the explanatory variable affects these mediators. This approach addresses endogeneity issues commonly found in traditional mediation models, resulting in more precise estimation. Therefore, based on the regression model presented in Equation (1), the mediation effect model is defined in Equation (2).

$$M_{i,t} = \beta_0 + \beta_1 \mathrm{NBDCPZ}\_Policy_{i,t} + \beta_n Control_{i.t} + \mu_i + \gamma_i + \varepsilon_{i.t} \tag{2}$$

M represents the mediating variables, including public environmental awareness, investor attention, and risk-bearing capacity. The definitions and measurement methods for the remaining variables are consistent with those used in Model (1).

Description of Variable Selection and Data Sources

Explained Variable

The explained variable is green innovation resilience (GIR). Martin and Gardiner (2019) [42] proposed a widely adopted method for measuring resilience, which was applied in studies on economic resilience [43, 44], employment resilience [45, 46], and labor market resilience [47]. This study utilizes the measurement approach of Martin and Gardiner (2019) [42], which assesses changes in the actual number of green innovation patent applications by manufacturing enterprises to gauge their green innovation resilience. Whether positive or negative, a greater absolute value indicates stronger resilience. The specific calculation steps are outlined in Equations (3), (4), and (5).

$$Resis_i^t = (\Delta Y_i - \Delta E)/|\Delta E| \tag{3}$$

$$\Delta Y_i = Y_i^t - Y_i^{t-1} \tag{4}$$

$$\Delta \mathrm{E} = ((\mathrm{Y_r^t} - \mathrm{Y_r^{t-1}})/\mathrm{Y_r^{t-1}})\mathrm{Y_i^{t-1}} \tag{5}$$

Resis represents the green innovation resilience of manufacturing enterprises.ΔY represents the change in green patent applications of manufacturing enterprises, measured by the difference between the green patent applications of the current year and those of the previous year. ΔE represents the predicted green patent applications of individual enterprises from year t-1 to year t, based on the green patent applications of all enterprises in the country. In addition, i, t, and r represent individual enterprises, years, and all enterprises in the country, respectively.

Explanatory Variable

The core explanatory variable is the NBDCPZ policy (NBDCPZ_Policy). In this study, the NBDCPZ policy is treated as a quasi-natural experiment. To capture the policy effect of the NBDCPZ policy, an interaction term is utilized, combining the policy dummy variable with the year dummy variable (Treat*Post). Specifically, "Treat" is the policy dummy variable. It is assigned a value of 1 if an enterprise is registered within the NBDCPZ policy area and 0 if registered outside this area. "Post" is the year dummy variable and is assigned a value of 0 before the policy implementation and 1 afterward.

Control Variables

Given the potential influence of corporate financial characteristics and governance variables on the green innovation resilience of manufacturing enterprises, the following control variables are considered. Enterprise performance (Roa) is measured as the ratio of net profit to total profit [48]. Higher performance indicates a stronger capacity for resource allocation, supporting green innovation activities. Enterprise growth (Growth) is measured by the change in operating revenue [49]. Greater growth enhances resilience to external shocks and improves green innovation resilience. Enterprise debt (Debt) is measured as the logarithm of total debt. Excessive indebtedness can hinder investment in green innovation and negatively affect resilience. Enterprise age (Age) is measured as the logarithm of the enterprise's age [50]. Older enterprises generally possess more green innovation experience and can better manage external risks. Social wealth creation ability (Q) is measured as the ratio of market value to capital replacement cost [51]. A higher social wealth creation ability indicates a greater ability to raise capital for green innovation, thus enhancing resilience. Financing constraints (KZ) are measured using the KZ index [52]. Higher financing constraints are detrimental to green innovation resilience. Institutional investor ownership (Inst) is measured as the ratio of institutional investor shares to total shares. Higher ownership indicates greater external investor confidence, positively impacting green innovation resilience. Dual is set to 1 if the chairman of the board is also the chief executive officer and 0 otherwise. Holding dual roles can

Table 1. Descriptive statistics of variables.

	N	Mean	St. Dev	Min.	Max.
GIR	1570	6.171	14.62	0.005	294.0
NBDCPZ_Policy	1570	0.339	0.473	0	1
Roa	1570	0.035	0.0590	-0.627	0.246
Growth	1570	0.140	0.339	-0.561	6.937
Debt	1570	22.78	1.556	18.43	27.21
Age	1570	2.500	0.586	0	3.401
Q	1570	1.733	1.006	0.706	12.15
KZ	1570	1.282	1.841	-7.659	7.618
Inst	1570	0.221	0.002	0.002	1.011
Dual	1570	0.222	0.416	0	1

expedite decision-making processes and enhance green innovation resilience.

Data Sources and Descriptive Statistics

In this study, manufacturing enterprises listed on the Shanghai and Shenzhen A-shares from 2013 to 2022 were selected as research samples, resulting in an initial dataset of 22,897 observations. The dataset was refined by excluding samples from ST and ST* manufacturing enterprises, removing those with missing data, and eliminating observations with abnormal data. After these adjustments, the final dataset includes 1,570 observations from 157 manufacturing enterprises. Financial data used in this study were sourced from the Chinese Research Data Services (CNRDS) platform and the China Stock Market & Accounting Research (CSMAR) database. Table 1 presents the statistical results for the main variables, revealing that the mean green innovation resilience value is 6.171 with a standard deviation of 14.62, indicating substantial variation in the number of green patent applications among the sampled enterprises.

Results and Discussion

Regression to Benchmark

Table 2 presents the estimated results of the impact of big data on the green innovation resilience of manufacturing enterprises. Column (1) reports the results without control variables and fixed effects. Column (2) incorporates fixed effects for enterprises and years. Columns (3) and (4) include additional control variables. The results consistently show a significantly positive regression coefficient for big data across all specifications, indicating that big data substantially enhances the green innovation resilience of manufacturing enterprises. Thus, Hypothesis 1 is supported. This positive effect may be attributed to big data's ability to reduce decision-making uncertainty and optimize resource allocation, which helps enterprises better manage risks associated with green innovation. Additionally, big data enhances green R&D activities and improves their efficiency, thereby strengthening green innovation resilience.

Testing the Parallel Trend Hypothesis

When using the DID model to assess the policy impact of the big data comprehensive pilot zone, it is crucial that the parallel trend hypothesis holds before policy implementation. This means that the green innovation resilience of the treatment and control groups should follow the same trend prior to the policy's introduction. To test this hypothesis, this study constructs a parallel trend test model, as shown in Equation (6).

$$GIR_{i,t+1} = \beta_0 + \sum_{t=-3,t\neq-3}^{t=4} \beta_t Post_t + \beta_n Control_{i,t} + \mu_i + \gamma_i + \varepsilon_{i,t} \quad (6)$$

Where, $Post_{-3}$, $Post_{-2}$, $Post_{-1}$, $Post_0$, $Post_1$, $Post_2$, $Post_3$, and $Post_4$ represent the three years preceding and the four years following the implementation of the NBDCPZ policy, respectively. Following the methodology outlined by Fajgelbaum [53], the earliest year, $Post_{-3}$, is designated as the base year, and Equation (6) is used for the analysis.

Theoretically, if the parallel trend hypothesis is satisfied, the regression coefficient of the NBDCPZ policy should be non-significant before the policy implementation. The regression results presented in Table 3 show that the coefficients for $Post_{-2}$ and $Post_{-1}$ are not statistically significant, indicating no substantial difference in green innovation resilience between the treatment and control groups prior to the policy implementation, thus confirming the parallel trend hypothesis. Additionally, the NBDCPZ policy exhibits a short-term positive effect in the two years following its implementation, though this effect lacks stability.

Table 2. Benchmark regression results.

Variable	(1)	(2)	(3)	(4)
	GIR	GIR	GIR	GIR
NBDCPZ_Policy	2.1420*** (2.58)	2.7851** (2.23)	2.301*** (2.74)	3.077** (2.44)
Control_Var	No	No	Yes	Yes
Fixed effect	No	Yes	No	Yes
Obs.	1413	1413	1413	1413
R^2	0.006	0.150	0.010	0.156

Note: The values in brackets represent the robust errors of clustering at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The following tables adhere to the same format.

Table 3. Parallel trend test results.

Variable	GIR	T-value
$Post_{-3}$	-1.447	(-0.57)
$Post_{-2}$	1.385	(1.51)
$Post_{0}$	-0.659	(-0.35)
$Post_{1}$	3.324**	(2.05)
$Post_{2}$	3.877*	(1.75)
$Post_{3}$	1.142	(0.14)
$Post_{4}$	5.899*	(2.07)
Constant	24.487	(1.48)
Control_Var	Yes	
Fixed effect	Yes	
Obs.	1413	
R^2	0.162	

However, three years after the implementation, the impact coefficient of the NBDCPZ policy becomes significantly positive, suggesting that the policy can effectively enhance the green innovation resilience of manufacturing enterprises, albeit with a delay.

Based on the results of the parallel trend test (See Fig. 1.), there was no significant difference in the green innovation resilience between the treatment and control groups before the implementation of the NBDCPZ policy, thereby satisfying the parallel trend criteria. After the implementation of the NBDCPZ policy, the green innovation resilience of manufacturing enterprises in the treatment group remained significantly higher than that of the control group over several years.

Robustness Analyses

To further test the robustness of the research conclusions, this study employs several methods, including propensity score matching and difference-in-differences model, exclusion of other policy effects, sample tail reduction, and placebo tests. These methods are used to assess the stability and reliability of the regression results.

Propensity Score Matching and Difference-in-Differences (PSM-DID) Model Test

To control for the impact of systematic differences between the experimental and control groups on the conclusions, this study further tested the robustness of the PSM-DID model. First, control variables were included as covariates. Second, two datasets were created using Mahalanobis distance matching and kernel matching to identify an optimal control group that met the common support conditions for all cities in the NBDCPZ policy. Data from cities outside this common support area were excluded to form a new dataset. Third, the balance test for the two sets of matching data was performed, and the matching effect was evaluated. Compared to the pre-matching stage, the standard errors of covariates post-matching were significantly smaller, reducing by more than 10%. The DID method was then used to re-estimate the impact of big data on the green innovation resilience of manufacturing enterprises. Columns (1) and (2) in Table 4 show the PSM-DID regression results for both methods. The results indicate that the coefficients for big data remain significantly positive at the 5% level, with no deviation from the benchmark regression results. This suggests that, to a certain extent, big data enhances the green innovation

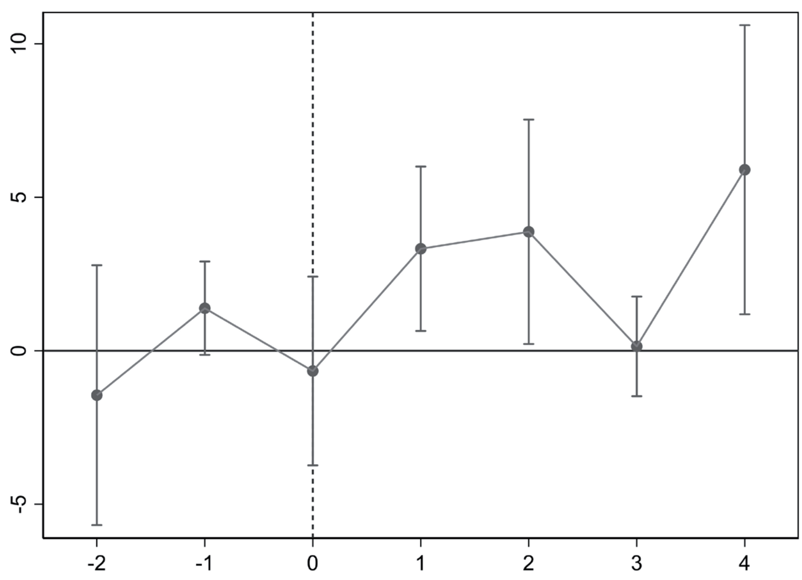

Fig. 1. Parallel trend test diagram.

Table 4. Robustness test results.

Variable	(1) Mahalobis distance matching	(2) Nuclear matching	(3) Other policies 1	(4) Other policies 2	(5) Tail reduction 1%
NBDCPZ_Policy	3.589** (2.04)	3.053** (2.42)	3.141** (2.48)	3.007** (2.32)	1.548* (1.85)
BCP_Policy	-	-	0.744 (0.82)	-	-
GreenFin_Policy	-	-	-	0.703 (0.47)	-
Control_Var	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes
Obs.	776	1408	1413	1413	1413
R^2	0.157	0.156	0.156	0.156	0.233

resilience of manufacturing enterprises after accounting for sample bias.

Exclusion of Other Policy Effects

During the study period, the pilot policies of broadband China, implemented in phases since 2014, and the green finance reform and innovation pilot zone, introduced in 2017, are pertinent to this study. To account for the potential influence of these policies, virtual variables representing their implementation—broadband China pilot and green finance reform and innovation pilot zone—were incorporated into the benchmark regression model. This adjustment aimed to control for their effects on the estimated results, as shown in columns (3) and (4) of Table 4. The results indicate that, even after accounting for these two policies, the coefficient for big data remains significantly positive at the 5% level. This finding reinforces the robustness of the conclusion.

Sample Tail Reduction

To examine the impact of outliers on the estimation results, this study applied bilateral tail truncation at the 1% level for all variables. The regression results, presented in Table 4 (5), show that the coefficient for big data remains significantly positive, affirming the robustness of the conclusion.

Placebo Test

To further address the impact of other unobservable factors on the results, and following the method proposed by Liu and Lu [54], cities with the same number of actual pilot cities were randomly selected from the sample to create a treatment group. In this study, a

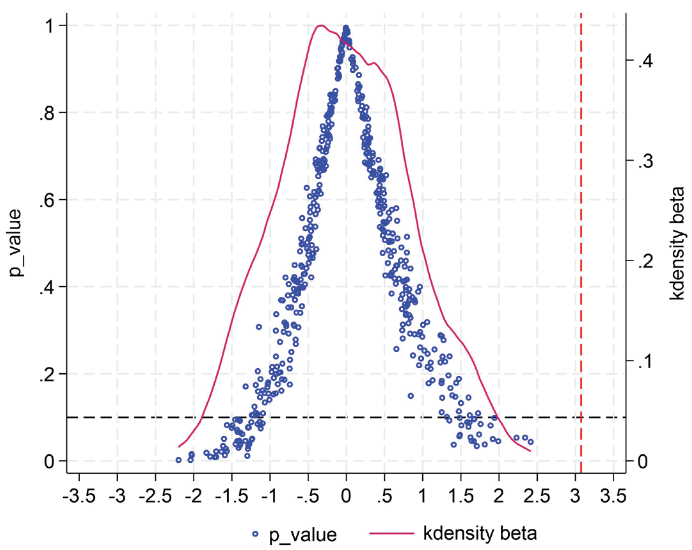

Fig. 2. Placebo test diagram of 500 random samples.

Table 5. Heterogeneity analysis results.

Variable	Nature of enterprise		Enterprise pollution degree		Enterprise region	
	State-owned	Non-state-owned	Heavy pollution	Non-heavy pollution	East region	Midwest region
	(1)	(2)	(3)	(4)	(5)	(6)
NBDCPZ_Policy	2.205* (1.66)	4.644* (1.80)	0.853 (0.39)	3.695** (2.53)	3.211** (2.04)	5.336* (1.99)
Control_Var	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	814	599	316	1097	961	452
R^2	0.184	0.152	0.248	0.141	0.142	0.218

random value was assigned to the big data variable, and regression analyses were performed based on Equation (1). This process was repeated 500 times. Fig. 2. reveals that the regression coefficients from the stochastic simulations cluster around zero, with most scatter points not being statistically significant at the 10% level. This is in stark contrast to the coefficient reported in column 4 of the benchmark regression. These results suggest that big data significantly enhances the green innovation resilience of manufacturing enterprises, with random factors having minimal impact on the findings.

Heterogeneity Test

This study's heterogeneity test examines whether big data has varying effects on the green innovation resilience of manufacturing enterprises based on property rights, pollution levels, and regional differences.

Based on the heterogeneity of property rights, the sample is divided into state-owned enterprises and non-state-owned enterprises. The regression results are presented in columns (1) and (2) of Table 5. In both samples, the coefficients of big data are significantly positive at the 10% level. However, the coefficient for non-state-owned enterprises is higher than that for state-owned enterprises, indicating that big data has a slightly more substantial impact on promoting the green innovation resilience of non-state-owned enterprises. State-owned enterprises generally have strong connections with local governments, access to more favorable financing channels, and align closely with national development strategies, which supports their green innovation efforts. In contrast, non-state-owned enterprises benefit from greater operational flexibility, faster response to market signals, and higher risk tolerance. Additionally, the digital financial model introduced by big data mitigates capital constraints, thereby enhancing non-state-owned enterprises' capacity to manage and leverage big data effectively, which further strengthens their resilience in green innovation [55].

Considering the heterogeneity in pollution levels, this study divides the sample into two groups: heavy-polluting enterprises and non-heavy-polluting enterprises. The regression results, presented in columns (3) and (4) of Table 5, show that the coefficient of big data is not statistically significant for heavy-polluting enterprises, while it is significantly positive at the 5% level for non-heavy-polluting enterprises. This suggests that big data's impact on enhancing green innovation resilience is constrained for heavily polluting enterprises but remains significant for non-heavy polluting ones. This disparity may be due to heavy polluting enterprises being under stringent supervision by national environmental protection agencies, leading to less impact from the NBDCPZ policy. Conversely, non-heavy polluting enterprises, possibly receiving heightened public and media attention post-policy, may be more motivated to engage in green innovation to meet environmental standards, thus improving their green innovation resilience.

From the perspective of regional heterogeneity, this study divides the research samples into two groups: enterprises in eastern China and enterprises in central and western China. The regression results are shown in columns (5) and (6) of Table 5. For manufacturing enterprises in eastern China, the coefficient of big data is significantly positive at the 5% level. In contrast, for enterprises in central and western China, the coefficient is significantly positive at the 10% level. This indicates that big data promotes green innovation resilience across all regions, though its impact is more pronounced in eastern China. This disparity may be attributed to the higher economic development in eastern China, which results in lower financing constraints and uncertainties for enterprises. Consequently, the digital technologies introduced by policies further expand financing channels, providing ample resources for continuous green innovation. In central and western China, while digital infrastructure has improved recently, the enabling effect of big data is less pronounced compared to eastern China. However, these regions benefit from an existing base of talent, technology, and capital. The policy's implementation will integrate

Table 6. Mechanism test results.

Variable	(1)	(2)	(3)
	Public environmental awareness	Investor attention	Risk-bearing capacity
NBDCPZ_Policy	3.912*** (3.32)	3.029** (2.17)	0.006* (1.67)
Control_Var	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes
Obs.	1570	1570	1570
R^2	0.797	0.669	0.050

current digital infrastructure and resources, enhancing the manufacturing industry's performance and green innovation resilience [56].

Mechanism Test

For the external environment concern mechanism, this study adopts the measurement methods proposed by Drake et al. [57] and El et al. [58]. To assess market attention, this study utilizes China's Baidu Search Index with the keyword "environment" to measure public environmental awareness. Additionally, investor attention is measured by the search volume for information about listed companies, reflecting investor attention in either the company or its stock. This study gauges investor interest using this search volume metric. The results presented in columns (1) and (2) of Table 6 reveal significantly positive regression coefficients of big data on both public environmental awareness and investor attention. These findings suggest that big data has a substantial positive impact on external market attention. Therefore, Hypothesis 2 is verified. Specifically, big data enhances market attention, which supports ongoing green innovation in manufacturing enterprises and strengthens their green innovation resilience. This can be attributed to two main factors. First, big data enhances the quality of corporate information disclosure and transparency, which increases investor attention. Greater investor attention can improve the financing environment for enterprises, reduce financing costs, and alleviate financial constraints. Second, enterprises utilize big data and other advanced technologies to better disclose environmental information. This encourages greater public involvement in environmental governance, raises public concern for the environment, and allows enterprises to demonstrate their commitment to green development. Consequently, this leads to increased public support for green innovation activities and strengthens the green innovation resilience of manufacturing enterprises.

To assess the risk-bearing capacity mechanism, this study employs a three-year rolling method to calculate the standard deviation of an enterprise's net cash flow, which measures the capacity of risk-bearing. A higher standard deviation indicates increased cash flow volatility and a greater risk-bearing capacity. The mediation effect test results, shown in column (3) of Table 6, show a significantly positive regression coefficient of big data on the risk-bearing capacity. This indicates that big data significantly enhances the risk-bearing capacity of manufacturing enterprises. Therefore, Hypothesis 3 is tested. Specifically, the policy improves enterprises' ability to manage external shocks, thereby strengthening their green innovation resilience. This effect is likely because enterprises use big data to better gauge external market demand, adjust business strategies promptly, allocate more resources to R&D, and mitigate uncertainties in R&D activities. A higher risk-bearing capacity allows enterprises to endure innovation risks and uncertainties, enabling them to persist with green innovation activities even in the face of external shocks.

Discussion

First, the empirical analysis in this study indicates that big data significantly enhances the green innovation resilience of manufacturing enterprises. Big data provides dynamic capabilities for enterprises to adapt to internal and external uncertainties, enabling continuous acquisition and utilization of resources and thereby improving green innovation resilience. This finding is similar to the conclusions of He et al. [59], who argue that digital transformation significantly promotes green innovation by strengthening resource and knowledge bases. The results of this study further support this view, demonstrating that big data, as a key element of digital transformation, enhances core competencies in green innovation through improved resource acquisition and utilization, thereby reinforcing the green innovation resilience of manufacturing enterprises.

Next, to investigate the mechanisms through which big data affects the green innovation resilience of manufacturing enterprises, this study specifically examined the mediating roles of external attention and enterprise risk-bearing capacity. The research findings indicate that big data enhances the green innovation resilience of manufacturing enterprises by increasing external attention and enterprise risk-bearing capacity. Specifically, increased public and investor attention reduces the cost of financing and alleviates financing constraints. This finding is similar to He et al. [60], who suggest that heightened investor attention improves the financing environment for enterprises, thereby reducing difficulties in securing funding. This study found that public and investor attention contributes to social capital and market opportunities for enterprises, reducing financing difficulties. This not only strengthens the financial foundation for enhancing green innovation resilience but also enhances market competitiveness. Moreover, this study posits that enterprises with greater risk-bearing capacity are better equipped to withstand the pressure of failed green innovation initiatives and are more inclined to invest in long-term and high-risk green innovation projects. This is consistent with Jiang and Liu [61], who found that strong risk-bearing capacity enables enterprises to explore and experiment despite uncertainties in green innovation. Furthermore, the study reveals that enterprises with robust risk-bearing capacity are more likely to engage in forward-looking and breakthrough green innovations, enhancing overall green innovation resilience. In addition, compared to existing literature [62, 63], this study constructs an explanatory framework detailing how big data enhances green innovation resilience from both internal and external perspectives. This framework highlights the crucial role of mediating effects of external attention and enterprise risk-bearing capacity in implementing big data policy, underscoring their importance in enhancing the green innovation resilience of manufacturing enterprises.

Another interesting finding of this study is the heterogeneity in the impact of big data on the green innovation resilience of manufacturing enterprises. Specifically, the policy has a more pronounced positive effect on green innovation resilience for non-state-owned enterprises and non-heavy polluting enterprises. This finding contrasts with Xu et al. [64] and Li et al. [65], who argue that digitalization has a more significant promoting effect on green innovation for state-owned enterprises and heavy-polluting enterprises. One possible reason is that non-state-owned enterprises face more severe financing issues compared to state-owned enterprises. The establishment of digital financial models through the NBDCPZ policy alleviates financing constraints for non-state-owned enterprises and strengthens their ability to withstand risks. Additionally, non-heavy polluting enterprises may receive increased public attention due to policy implementation, which pressures them to increase green innovation activities, thereby enhancing their green innovation resilience. Furthermore, the study finds that big data has a more significant promotion effect on the green innovation resilience of manufacturing enterprises in eastern China, consistent with the conclusions of Hao et al. [66]. This reflects the relative advantages of eastern China in terms of digital infrastructure, policy support, and market environment, making these enterprises more likely to benefit from big data policy. These findings provide new insights into understanding the differential effects of policies across different types of enterprises and regions.

Conclusions and Recommendations

Conclusions

The comprehensive analysis of big data's role in promoting green innovation resilience and development in manufacturing enterprises is crucial for advancing sustainable manufacturing. This study utilizes quasi-natural experiments related to the NBDCPZ policy to develop a theoretical framework for enhancing the green innovation resilience of manufacturing enterprises and systematically evaluates its impacts and mechanisms. The findings indicate that big data significantly enhance the green innovation resilience of manufacturing enterprises, as supported by a series of robustness tests. Heterogeneity analysis reveals that the effect of big data on green innovation resilience varies with property rights, pollution levels, and regional differences. Specifically, big data have a more pronounced effect on green innovation resilience among non-state-owned enterprises and those with lower pollution levels. Regional analysis shows that big data exert a more significant impact on green innovation resilience in eastern China compared to central and western China. Mechanism analysis further demonstrates that big data enhances green innovation resilience not only by increasing public and investor attention through external market mechanisms but also by strengthening the enterprise's risk-bearing capacity.

Managerial Implications

The study's findings provide important managerial insights for enhancing the green innovation resilience of manufacturing enterprises and accelerating the application of big data. First, manufacturing enterprises should capitalize on policy support for big data by conducting comprehensive data analyses to refine green innovation strategies, mitigate operational risks, and strengthen resilience. Specifically, enterprises can utilize big data to analyze market demands, evaluate the potential of innovation projects, and anticipate challenges, thereby developing more precise green innovation strategies. Second, enterprises should actively seek and use government funds and subsidies to ensure the effective implementation and sustainable development of green innovation projects. Leveraging these policy supports can alleviate financial pressures and accelerate technological upgrades and innovation processes. Third, manufacturing enterprises should implement a comprehensive real-time monitoring and evaluation system. This system should continuously track green performance using big data tools, identify and address potential issues, and support ongoing improvements in green innovation. It involves regular analysis of environmental data, assessment of innovation effectiveness, and strategy adjustments based on data feedback. Additionally, enterprises should establish an information disclosure platform to improve business transparency and bolster societal trust in their green innovation efforts. By analyzing data to understand public concerns, enterprises can refine their communication strategies, enhance transparency, and increase public engagement, thereby strengthening their corporate social responsibility image. These measures will enable manufacturing enterprises to better leverage big data in the digital economy, thereby enhancing their green innovation resilience.

Social Implications

Based on the research findings, the social implications are as follows: First, it is crucial to fully utilize the NBDCPZ policy to drive innovation and enhance green innovation resilience. This policy, aligned with digital economy trends, introduces advanced digital technologies to enterprises, significantly boosting their green innovation capacity. Continuous optimization of this policy should focus on fostering technology clusters, increasing investment in innovation, and incentivizing talent to further strengthen green innovation resilience. Second, the government should tailor the NBDCPZ policy to accommodate enterprises with varying property rights, geographical conditions, and pollution levels. Implementing uniform standards may hinder some enterprises' progress in green innovation. Addressing the “Matthew effect,” where enterprises in different regions or with varying pollution levels experience uneven impacts, requires context-specific and targeted policy planning. Enhancing the effectiveness of the NBDDCPZ policy involves designing policies that consider local conditions and specific enterprise needs, with particular emphasis on supporting regions with high pollution and underdeveloped digital infrastructure. Lastly, improving the transmission mechanism of the NBDCPZ policy is essential. This involves guiding the integration of digital technology into business models, reducing information asymmetry, and strengthening corporate risk management to better handle external shocks. Establishing an online platform for regular updates on policy implementation will enhance transparency, improve corporate information disclosure, and engage the public and investors, thereby promoting green innovation and supporting sustainable industrial development.

Limitations and Future Research

This study theoretically analyzes and quantitatively evaluates the impact of big data on the green innovation resilience of manufacturing enterprises. It offers valuable insights for implementing and optimizing NBDCPZ policy strategies and provides theoretical guidance for enhancing green innovation resilience. However, the study still has room for further improvement. First, compared to environmental benefits, enterprises place greater emphasis on economic gains. While this study focuses on enhancing green innovation resilience and examines the role of big data in promoting this resilience, it does not assess the potential economic effects of big data on green innovation resilience. Future research should therefore investigate how big data impacts enterprise growth and performance improvement. Ongoing research into the role of big data in shaping the green innovation resilience of manufacturing firms is a significant avenue for exploration. Second, due to data limitations, this study samples only listed manufacturing enterprises in China, which somewhat restricts the generalizability of the research findings. Subsequent studies should expand the scope to explore the impact of big data on green innovation resilience across different industries. Third, the influence of big data on green innovation resilience is not instantaneous but closely related to the development stage of enterprises. The impact of big data on green innovation resilience may vary across different stages of development. Therefore, future research should examine the dynamic effects of big data on green innovation resilience at various developmental stages, providing a more comprehensive basis for improving and optimizing policies.

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Conflict of Interest

The authors declare no conflict of interest.

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