

Article

Green Technology Innovation and Enterprise Performance: An Analysis Based on Causal Machine Learning Models

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Abstract: As increasingly stringent environmental regulations are put into effect, Environmental, Social, and Governance (ESG) concepts are being seamlessly integrated into the core of corporate innovation strategies. Due to the quasi-public product perspective of green innovation, the performance of enterprises as a result of green innovation activities exhibits significant heterogeneity. This heterogeneity exists not only between corporate value and financial performance but also among individual enterprises. This paper is based on a sample of 1510 listed Chinese companies examined from 2013 to 2020 and uses machine learning algorithms and quasi-natural experiments to precisely estimate the causal relationship and mechanisms between green innovation and corporate performance. The findings elucidate several critical aspects of green innovation within the corporate sphere: Firstly, rather than attracting green incentives from financial markets, green innovation activities inadvertently stifle the enhancement of corporate value. Secondly, these activities markedly bolster corporate financial performance, primarily by diminishing operational costs, which in turn elevates the return on assets (ROA). Lastly, of all corporate characteristics examined, enterprise size and equity concentration stand out as key determinants influencing the variability in outcomes of green innovation performance. The above findings provide information on the significant implications of enhancing green technology innovation systems and green incentive mechanisms.

Keywords: green innovation; enterprise performance; causal forest; machine learning



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1. Introduction

Green development is both an important goal of economic and social development and an essential path for the further development of enterprises. The consumption of resources, the emission of pollutants, ecological deterioration, and external pressures compel enterprises to incorporate resource conservation, ecological protection, and green technology upgrades into their development strategies. This transformation positions enterprises as important actors in green governance and innovation. With the deepening of the ESG concept, enterprises have gradually become the main participants in the green technology innovation market. However, green innovation is distinguished by its quasi-public good nature [1], leading enterprises' green technological innovation endeavors to be subject to the dual externalities of knowledge and environmental spillover [2,3]. Quasi-public goods in green innovation refer to those goods or services that are neither entirely public nor completely private, possessing certain characteristics of non-exclusivity and non-competitiveness. The activities of green innovation inherently have positive externalities. Specifically, the funding channels for green activities of state-owned enterprises in China are not fully marketized, and many clean technology transformations stem from higher-level administrative orders. Furthermore, green transformation technologies are often promoted to other entities through non-market mechanisms. Consequently, the influence of corporate involvement in green technological innovation on performance markedly

diverges from traditional innovation activities, thereby introducing increased complexity and sparking significant scholarly discussion.

The distinctive nature of green innovation within Chinese enterprises is subject to the multifaceted influences of local government policies and state-owned bank loans, resulting in performance disparities between state-owned and non-state-owned enterprises. This exacerbates the inherent endogeneity challenges faced by traditional econometric models. Therefore, this paper leverages the causal forest—the latest machine learning algorithm—which overcomes the endogeneity problem of traditional empirical testing and explores the relationship between green innovation, enterprise costs, and enterprise performance from multiple dimensions. The complex relationship between green technology innovation and corporate performance is primarily reflected in the following aspects:

Firstly, green innovation can enhance enterprise performance through product competitiveness and green finance incentives. On the one hand, if a company can successfully introduce green concepts into the improvement or production of new products, the variety of its products will be greatly enriched, thereby enhancing its competitive advantage through product differentiation. For example, researchers such as Zhang [4] find that enterprises can increase profits by promoting green products to consumers through advertising. On the other hand, green innovation helps enterprises mitigate environmental risks, which is a crucial signal for future high returns, thus enabling them to obtain green incentives in the financial markets. Specifically, green innovation activities serve as a reliable signal for enterprises to respond to national environmental protection policies and their potential future excess returns. Improving environmental performance will increase the ownership of debt issuers, making them attractive to green investors [5]. Compared to non-green concept companies, the stocks of green concept listed companies have excess returns, indicating a green incentive in the securities market for these companies [6]. This not only offsets the specific risks associated with stocks of companies listed with a green concept but also mirrors investor recognition of their growth potential and the emergence of a green investment culture. The escalating concerns over climate and environmental changes have culminated in a rise in the stock prices of green enterprises [7,8]. Zhu suggests that when carbon taxes are low, companies opting for green product manufacturing as their innovation model stand to gain higher profits [9]. This reflects a strategic adaptation to environmental policies, highlighting the intricate relationship between green innovation, regulatory frameworks, and corporate profitability.

Secondly, green innovation has increased enterprise costs to some extent, hindering the improvement of enterprise performance. Green innovation, pivotal for sustainability, may adversely affect enterprise performance through elevated system and waste disposal costs, particularly in resource-limited firms, necessitating meticulous evaluation and strategic investment to alleviate these impacts [10,11]. Due to stringent environmental regulations imposed by the government, enterprises invest more resources in uncertain and high-risk green technology innovation, thereby “squeezing out” other normal R&D investments and incurring additional costs [12]. Moreover, due to the quasi-public good attributes of green innovation, governments often face information asymmetry and cannot fully understand the external costs borne by enterprises. Environmental regulations internalize environmental externalities, increasing the cost burden of enterprises [13], leading to weakened innovation capabilities and reduced production efficiency. Even though there may be “innovation compensation” benefits arising from pollution control, the additional wear and tear on environmental facilities and mismatched equipment will still cause a decrease in productivity. Amores et al. [14] contend that although green innovation contributes to environmental betterment, it could potentially reduce a company’s economic advantages. The nexus between green innovation and corporate expenses is intricately linked to the government’s staggered implementation of environmental policies [15]. Furthermore, there is an underlying assumption that adopting environmental responsibilities could detrimentally impact economic performance and competitiveness [16,17], and the economic benefits of green innovation exhibit a clear “time-lag” effect. Due to the high risk associated with

green innovation, any positive effects resulting from technological progress and product upgrades due to research and development investment take a considerable amount of time to materialize [18]. After the implementation of environmental regulations, enterprises need time to optimize their factors and upgrade their technology. Through green governance, enterprises can internalize the external costs of pollution and then reduce pollution emissions. Green innovation activities increase enterprise costs in the short term, negatively affecting the allocation of production resources in the short term, but a long-term positive impact does exist. In other words, green innovation is a relatively dynamic process, and its impact path varies between the short and long term [19]. The dynamic relationship between green innovation activities and corporate performance shows significant heterogeneity in different economies. Some examples of domestic research suggest that there is a “U”-shaped relationship between green innovation and corporate competitiveness under environmental regulations [2]. However, the empirical results by Soltmann et al. [20] reveal an inverted “U”-shaped relationship between green inventions and performance.

Due to differences in sample selection, measurement indicators, and empirical methods, the existing literature on the impact of green technology innovation on corporate performance has not yet reached a consistent conclusion. The inconsistency and even contradiction in previous research regarding whether and how companies can use green innovation to enhance corporate value stem from the fact that the impact of green innovation on corporate value is influenced by various factors. It is essential to consider the different mechanisms and effects of green innovation on enterprise value.

Starting from the implementation of the “Green Credit Guidelines” in China in 2012, this study empirically analyzed various indicators of 1510 listed companies from 2013 to 2020 using the latest machine learning causal inference method and determined the heterogeneous causal effects of green innovation on the enterprise value and financial performance of listed companies. China’s stock market is underdeveloped, and it operates within an economy dominated by bank credit financing, where the vast majority of funding for domestic green innovation activities comes from the banking system. Furthermore, much of the financing for green innovation activities is derived from policy-based green credits, whose issuance and interest rate levels are not entirely determined by the market. It is necessary to adopt approaches similar to policy evaluation to analyze green innovation.

Specifically, this study discusses several crucial issues, namely: Does green innovation contribute to an increase in corporate value and financial performance? To what extent are the causal effects significant? Is there significant individual-level heterogeneity in causal effects? Which corporate characteristics affect causal effects? How does the cost mechanism it adheres to work? The contributions of this paper lie in the following.

① The study results expand the research framework on the benefits of corporate green innovation. Research on green effects based on the theory of heterogeneous enterprises has been widely applied in areas such as economic growth, environmental policies, and market demand. However, research on the micro-level implementation, heterogeneity degree, and impact mechanisms of green innovation at the enterprise level is still limited. This article provides a detailed review of the achievements and shortcomings of enterprises’ green innovation through multidimensional heterogeneity analysis. It not only enriches the research perspective of green innovation theory but also enriches the understanding of green innovation and introduces new ideas to promote the growth of enterprise value in China.

② This study addresses the endogeneity challenges in traditional empirical research on the relationship between green innovation and corporate value and provides a more precise understanding of the inherent patterns in the performance of corporate green innovation. This paper uses causal forest inference to overcome issues such as missing variables and endogeneity arising from reciprocal causation, thereby rendering the research conclusions more objective and accurate. Regression Discontinuity Design (RDD) and Difference in Differences (DID) are econometric models. Compared to Regression Discontinuity Design

and Difference in Differences methods, causal forests are capable of assessing heterogeneity treatment effects (HTEs) throughout the entire sample, thereby providing more robust and scalable outcomes. These important research conclusions on the relationship between green innovation and corporate performance can provide new insights for both corporate decision-making and government green innovation policies.

The content of this paper is arranged as follows: the second section provides a summary of the relevant literature, the third section addresses variable selection, the fourth section describes the empirical process, and the final section contains the conclusions and policy recommendations.

2. Literature Review

Green innovation plays a significant role in steering the economy towards a sustainable development path, so enterprises can adopt proactive green innovation strategies that combine ecological protection goals with economic performance [21,22]. From the theoretical analysis of green innovation, existing research primarily focuses on the driving factors and economic effects of green innovation.

The existing literature on green innovation bifurcates into focusing on external drivers, encapsulated by the “environmental regulation-green innovation-enterprise benefits” logic derived from the Porter hypothesis. This hypothesis posits that environmental regulations, by making pollution costs internal and impacting enterprise efficiency [23], incentivize technological innovation [24], enhancing green productivity and fostering business and environmental synergy. Despite the theoretical support for effective environmental policies boosting innovation and economic performance, the scholarly consensus on the Porter hypothesis remains divided. Proponents argue that environmental regulations enhance profitability through innovation [9,11], while critics question its universality [21,25]. The debate extends to the type of environmental regulation, with suggestions that market-oriented approaches are more effective than command-and-control ones [24]. However, much of this analysis adopts a static view, neglecting the delayed effects of regulations [1], potentially underestimating their positive impact. Given the absence of a unified perspective on how green technology innovation influences corporate economic performance, there is a pressing need for analysis using medium- to long-term data to explore the sustained competitive edge through green innovation, a critical aspect of green development.

On the other hand, this study involves internal driving factors of enterprises, which means the proactive assumption of social responsibility and the disclosure of environmental information. From the perspective of social responsibility, enterprises fulfill their social responsibilities by implementing green innovations to reduce the emission of pollutants. However, the authors of existing studies have not reached a unified conclusion on the relationship between corporate social responsibility and economic performance. Petersen and Vredenburg [26] contend that enterprises that effectively fulfill their social responsibilities and adeptly manage social and environmental concerns not only enhance investor wealth but also secure a competitive edge for themselves [27]. On the contrary, David et al. [28] suggest that fulfilling corporate social responsibility affects social performance and reduces the value of institutional investors. Furthermore, research on environmental disclosure has found that substantial environmental disclosure reduces information asymmetry between enterprises and banks because disclosure quality reflects better environmental information; it can increase company value, while symbolic disclosure can increase information asymmetry. Public interest in environmental concerns impacts stock index returns [7], yet it fails to enhance the performance of publicly traded companies [3]. The revelation of illicit environmental practices by U.S. firms results in a detrimental impact on their market valuation [29]. Conversely, the reaction to disclosed environmental penalty information by companies within China’s A-share market appears to be negligible [17]. Furthermore, it has been observed that stock prices can fluctuate due to information that does not pertain to the fundamental aspects of a company, underscoring the significant influence of market attention [30,31]. Currently, there is relatively limited research that directly analyzes the

internal driving factors of green innovation and enterprise value, and most studies focus on overall economic performance.

Research on the economic effects of green innovation focuses on the impact of green innovation on enterprise profits, productivity, business performance, international competitiveness, and other aspects. Due to variations in the selection of indicators, the conclusions drawn from these studies exhibit significant differences. Debate exists within the scholarly community regarding the impact of green innovation on economic performance [32]. While certain researchers affirm its potential to boost corporate value [15,33,34], contrasting evidence from other studies indicates that green innovation may actually detract from company performance [35,36]. On the one hand, studies initially explored green management activities, finding that companies implementing environmental strategies early on can gain advantages from environmental management activities. This advantage can lower corporate debt costs [37], promote green management outputs, and consequently enhance financial performance. Research has increasingly focused on the realm of green technological innovation [3,10,24,38], highlighting how such innovation not only elevates environmental performance but also bolsters a company's competitive edge [9,20]. Through enhancing a firm's environmental reputation, green innovation serves to indirectly boost its economic outcomes, a perspective echoed by various scholars [24]. Moreover, studies have investigated the varying impacts of different green innovation strategies on corporate value, revealing the multifaceted benefits of adopting environmentally friendly technologies [10]. Studies by Wan and Wang [38] found that positive green innovation significantly increases later-stage corporate value and boosts the number of green patent applications. In contrast, Li and Zheng [39] found that invention patents significantly increase corporate value, but there was no significant relationship found between non-invention patent applications and corporate value, and it was concluded that only substantive innovation could promote the development of enterprises. Zhang [40] also supported this viewpoint in his analysis of China's manufacturing industry. Presently, research on the relationship between corporate green activities and economic performance mostly examines single dimensions, and most studies are conducted from the perspectives of financial performance, environmental performance, and so forth. There is still a lack of comprehensive and systematic analyses of the impact of green behavior on the value of listed companies in China.

3. Indicator and Variable Selection

3.1. Data Sources

This study focuses on 1510 A-share listed companies in China from 2013 to 2020, of which 585 companies have a green innovation growth rate exceeding the median. The data source mainly includes two parts: The first is the green innovation data of listed companies. The patent classification number information of all A-share listed companies was obtained from the China Research Data Service Platform (CNRDS) and matched with the green patent classification number list on the official World Intellectual Property Organization (WIPO) website in 2010 to obtain the company's green patents. The second part comprises other enterprise-level data from the CSMAR and RESSET databases.

3.2. Variable Selection and Definition

Despite the debate among scholars on the best method to quantify an enterprise's green innovation capacity, the majority of research identifies the count of green invention patents as the primary indicator of a company's green innovation efforts [38,41]. Consequently, this research utilizes the volume of green patent applications as the metric for assessing a corporation's capability in green technological innovation [34]. When conducting empirical research on the causal relationship between green technology innovation activities and the corporate value of listed companies, the change rate of corporate green innovation activities is relative between the research period and the comparison period. Specifically, the approach is to take the logarithm of the annual average number of green patent applications

for the years 2013 to 2020 (research period) subtracted from the number of green patent applications for the years 2007 to 2012 (baseline period). The reason why 2012 is regarded as an important watershed moment is that the important financial laws and regulations that encourage green innovation in the country, the “Green Credit Guidelines”, were introduced during this year [38]. This green financial regulation had a direct impact on companies’ environmental response strategies and the flow of innovation capital. If the change rate of a certain company’s green innovation variable is higher than the median in the sample, the treatment variable *W* is set to 1; otherwise, the treatment variable *W* is set to 0.

The dependent variable (outcome variable) is enterprise value (TobinQ). This study regards enterprise value (TobinQ) as the measure of a company’s economic performance, which is measured by the ratio of the company’s market value to total assets. Higher enterprise value means high investment return and performance growth. Compared to the lag of green innovation, which means it is difficult to achieve benefits in the short term, enterprise value can reflect long-term performance and future cash flow returns.

Using machine learning algorithms to “plant” causal trees on 1510 A-share listed companies, the objective was to explore the heterogeneous causal effects of green innovation on enterprise performance. The split process of the causal tree involves the various characteristics (i.e., covariates) of the sample company. For example, 15 covariates such as agency cost, operating cost, state-owned stock ownership, debt repayment capability, financial performance, and enterprise size were introduced, and a series of covariates, denoted as *X*, were introduced. Additionally, this paper also controls for covariates such as the growth ability; operating ability; shareholding of directors, supervisors, and senior executives; dual roles; and cash flow of the enterprise. The specific dependent variables and covariates are detailed in Table 1:

Table 1. Variable definition and description.

Variable Properties	Variable Indicators	Abbreviation	Description
Enterprise value	Ratio of market value to the book value of total assets	TobinQ	The higher the value, the stronger its ability to create social value [34]
Financial performance	Return on assets	ROA	Net profit/total assets $\times$ 100%
Agency costs	Ratio of management expenses to total operating revenue	agency_cost	The higher the value, the higher the actual cost of agency behavior [38]
Operating costs	Ratio of total operating costs to total revenue	cost_income	-
Shareholding situation of state-owned shares	Ratio of state-owned shares	stated_shares	The ratio of the number of state-owned shares to the total number of shares [38]
Debt-paying ability	Asset liability ratio	asset_liability	The ratio of total liabilities to total assets
Growth ability	Growth rate of total operating revenue	operat_income	(Current period – the same period adjustment of the previous year)/ABS adjustment of the same period of the previous year $\times$ 100%
	Net profit growth rate	net_profit	(Current period – the same period adjustment of the previous year)/ABS adjustment of the same period of the previous year $\times$ 100%

Table 1. Cont.

Variable Properties	Variable Indicators	Abbreviation	Description
Shareholding situation of directors, supervisors, and senior executives Equity concentration	Management shareholding ratio	manage_ownership	The proportion of management shareholding in the total number of shares of the company
	Independent director ratio	ndep_director	The proportion of independent directors to the total number of directors
Business capability Dual position situation	The shareholding ratio of the first largest shareholder	first_shareholder	-
	The sum of the shareholding ratios of the top three major shareholders	top3_shareholders	Equity concentration, considering that equity concentration can affect the degree of innovation of enterprises
Cash flow situation	Total asset turnover rate	asset_turnover	Total operating income/(total assets at the beginning of the period + total assets at the end of the period)/2
Enterprise scale	Whether to concurrently serve as chairman and CEO	concurrent_post	Do the chairman and CEO hold dual roles? 1 indicates yes; 0 indicates no
Shareholding situation of directors, supervisors, and senior executives	Operating cash flow to total operating income ratio	cash_income	-
Equity concentration	Total assets	Lnassets	Taking the natural logarithm of total assets [38]

3.3. Statistical Analysis

The descriptive statistical analysis results of the annual average of various variable indicators from 2013 to 2020 are shown in Table 2.

Table 2. Statistical description of the average values of each variable.

	Mean	Stdev	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
TobinQ	1.559	1.254	0.245	0.64	1.164	2.015	4.967
ROA	1.538	2.366	−3.483	0.286	1.447	2.862	6.291
w	0.387	0.487	0	0	0	1	1
agency_cost	0.090	0.063	0.019	0.045	0.074	0.112	0.266
cost_income	0.955	0.110	0.692	0.904	0.963	1.007	1.185
stated_shares	12.507	12.974	0.000	0.070	9.478	20.328	41.757
asset_liability	0.521	0.189	0.192	0.379	0.523	0.665	0.840
operat_income	17.342	26.151	−7.942	2.694	9.554	19.955	103.991
net_profit	5.355	185.550	−479.722	−19.180	18.948	66.712	429.482
manage_ownership	1.526	3.690	0.000	0.000	0.014	0.386	14.246
ndep_director	38.266	4.621	31.756	34.803	37.434	41.059	48.677
first_shareholder	0.337	0.134	0.138	0.226	0.320	0.432	0.599
top3_shareholders	0.458	0.134	0.241	0.351	0.450	0.557	0.713
asset_turnover	0.438	0.277	0.084	0.227	0.380	0.571	1.128
concurrent_post	0.018	0.054	0.000	0.000	0.000	0.000	0.200
cash_income	−0.006	0.216	−0.640	−0.060	0.025	0.099	0.371
Lnassets	22.719	1.274	20.631	21.787	22.584	23.554	25.436

The statistical results of the various variables in Table 2 show that the average annual values of corporate value (TobinQ) and return on assets (ROA) are 1.559 and 1.538, respectively. The standard deviations for corporate value and return on assets in the sample are 1.254 and 2.366, respectively. The larger standard deviations indicate significant heterogeneity and volatility in corporate value (TobinQ) and return on assets (ROA) across companies with different characteristics.

4. Empirical Analysis

4.1. Algorithm Model

The empirical method to be used next employs the causal forest algorithm, based on the Rubin causal model framework, to address the endogeneity problems inherent in traditional econometric models. This is the first time it has been applied to analyze the relationship between X , green innovation, and Y , enterprise value, shifting the focus from correlation to causal analysis. The limitation involves identifying appropriate control and treatment groups within observational data, which requires exogenous variations to alleviate this difficulty.

In the empirical process of this study, the outcome variable Y_i refers to the enterprise value. Taking whether green innovation activities are carried out as the treatment process, if the treatment variable $W_i = 1$, this indicates that the green innovation change rate of the company during the study period is higher than the median in the sample; otherwise, $W_i = 0$ and $Y_i(1)$ are used to represent the performance of enterprise i after high-intensity green innovation and low green innovation activities, respectively; the difference between the two is the causal effect of green innovation activities on enterprise performance changes, also known as the treatment effect (TE). According to the causal forest algorithm established by Athey et al. [42,43], the processed estimator should exhibit asymptotic normality. Therefore, before analyzing the inference of heterogeneous treatment effects (HTE), it is necessary to compare the average differences between the treatment group and the control group and obtain an estimate of the conditional average treatment effect (CATE):

$$\tau(x) = E[Y_i(1) - Y_i(0) | X_i = x] \quad (1)$$

When the conditions of no confounding effects and overlap are satisfied, the CATE can be identified and provides well-estimated results. This study employs the causal forest algorithm by ‘planting’ causal trees with data from 1510 listed companies, where the splitting process involves 15 company features (covariates x). Specifically, referring to the approach of Hu Zunguo et al. [44], this study obtains causal trees, final partition L “leaves”, and estimates of conditional average treatment effects (CATEs) for the sample. The causal forest algorithm processes the covariate space formed by the 15 features of listed companies and calculates weights $\alpha_i(x)$. Following the concepts of Athey [45] and Nie [46], this study uses the following HTE estimate $\hat{\tau}$ to analyze the heterogeneity effects of corporate green innovation activity performance. This can be seen in Equation (2):

$$\hat{\tau} = \frac{\sum_{i=1}^n \alpha_i(x) (Y_i - \hat{m}^{(-i)}(X_i)) (W_i - \hat{e}^{(-i)}(X_i))}{\sum_{i=1}^n \alpha_i(x) (W_i - \hat{e}^{(-i)}(X_i))^2} \quad (2)$$

In the equation, $e(X_i) = P[W_i = 1 | X_i]$ represents the propensity score, $m(x) = E[Y_i | X_i = x]$ represents the expected value of innovation activity effectiveness, and the symbol i represents the ‘out-of-bag’ prediction; for example, Y_i is not used in the calculation $\hat{m}^{(-i)}(X_i)$. Following the causal forest algorithm designed by Athey et al. (2018) [43], the probability distribution of the treatment assignment in Equation (2) and the heterogeneous treatment effect (HTE) results can be obtained (for information regarding the causal forest algorithm and heterogeneous treatment effects (HTEs) used in this study, please refer to the following links: <https://cloud.r-project.org/web/packages/grf/grf.pdf>; <https://github.com/grf-labs> (accessed on 14 January 2024)).

Figure 1 illustrates that the distribution of the propensity score, $e(x)$, ranges from 0 to 1. For the enterprise characteristics x it not only satisfies $\eta < e(x) < 1 - \eta$ ($\eta > 0$) but also satisfies the overlap assumption in the Neyman–Rubin framework; this implies that in the causal forest analysis of the heterogeneous effects of green innovation in this study, reasonable treatment and control groups can be identified.

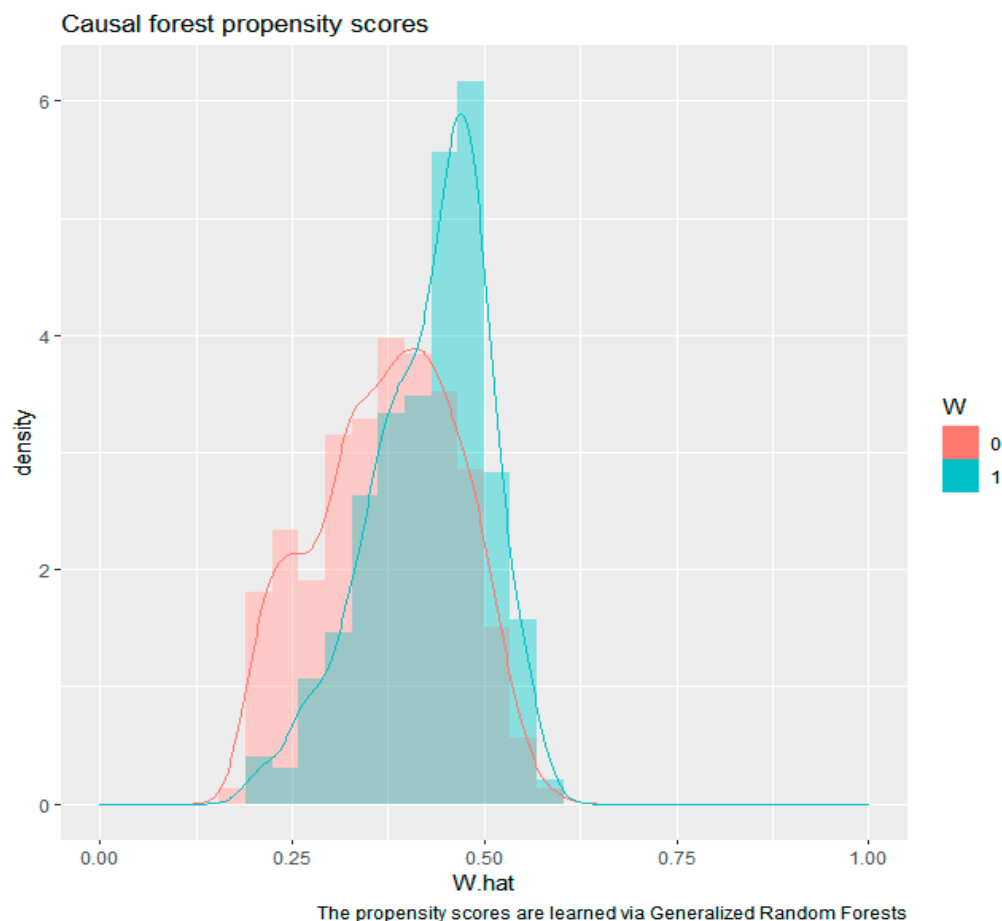


Figure 1. Distribution of propensity values. The x axis represents the overlap between the treatment and control groups in the causal forest model, as demonstrated by the propensity score values.

4.2. Average Causal Effect

The causal forest provides the causal effects (or treatment effects) of listed companies under different covariate conditions, with an honesty fraction and sample fraction both set at 50%. The average treatment effect (ATE) can be obtained by calculating the average HTE value. At the same time, this study also reports several other sub-sample average treatment effects: the average treatment effect for the treated group (ATT), the average treatment effect for the control group (ATC), and the average treatment effect for the overlap portion (ATO). Here, the ATO is similar to the ATE but assigns greater weight to the overlapping part.

Based on the ATE, ATT, ATC, and ATO results provided in Table 3, the average causal effects of implementing green innovation activities on firm value (TobinQ) and return on assets (ROA) in Chinese enterprises exhibit distinct patterns. Firstly, green innovation activities do not enhance enterprise value; instead, they generate a negative impact, with ATE of -0.358 and ATO of -0.377 . This suggests that green innovation inhibits the annual growth of firm value. Secondly, green innovation capability significantly improves the average level of return on assets (ROA), with an average annual effect of 8.009 . Both the treated group ($ATT = 3.551$) and the control group ($ATC = 11.209$) show positive average

treatment effects, indicating that upgrading green technologies leads to positive returns and a substantial improvement in financial performance (ROA).

Table 3. Results of causal forest estimation.

Outcome	Environment Settings	Causal Effect
Enterprise value (TobinQ)	ATE	-0.358 ± 0.304
	ATT	-0.408 ± 0.315
	ATC	-0.321 ± 0.564
	ATO	-0.377 ± 0.663
Return on assets (ROA)	ATE	8.009 ± 7.423
	ATT	3.551 ± 7.027
	ATC	11.209 ± 17.248
	ATO	5.321 ± 9.715

Note: Table 3 presents the treatment effects calculated for the entire sample, treated group, control group, and overlapping portion (“all”, “treated”, “control”, and “overlap”). The corresponding results include the ATE, ATT, ATC, and ATO. The numbers before ‘ $\pm$ ’ indicate the estimated values obtained through the AIPW method, while the numbers after ‘ $\pm$ ’ represent the lower limit error at a 10% significance level.

While green innovation and the enhancement of ecological efficiency stand as pivotal avenues for the sustainable development of businesses, their practical implementation may yield adverse effects, notably in scenarios where governmental policies and market frameworks lag in fully embracing the essence of green innovation. This observation echoes the insights gleaned from the research conducted by Xu, J. [47] and Rahelliamelinda, L. [48]. The detrimental consequences predominantly arise from the hefty expenses and risks entwined with green innovation endeavors, coupled with the nascent recognition of green innovation’s value within burgeoning economies. Furthermore, despite China’s policy-driven push towards greener production modalities, the prevailing reality underscores that many entities on the Chinese stock exchange are either state-owned or under state dominion, with their foray into green innovation or akin clean technologies frequently steered by governmental mandates. This situation, married with the underdevelopment of the securities market, significantly skews the valorization process of innovation within corporations, imposing a negative bearing on the fiscal health of enterprises. The manifestation of this adverse influence primarily spans escalated operational costs, misconstrued innovation risks, and the underdeveloped nature of the securities market, collectively undermining the aggregate value of the firm.

4.3. Heterogeneous Treatment Effects

The discussion above focuses on the average effects of green innovation on firm value and return on assets, and it is necessary to further test the heterogeneous effects of green innovation. HTEs in this study refer to the conditional average CATEs based on the characteristics of the sample firms, estimated using the causal forest approach. As depicted in Figure 2a, the CATEs of nearly 1300 sample companies are mostly on the left side of 0, with the maximum negative value reaching -4 . The remaining 200 sample firms show positive CATE values, indicating that green innovation capability has a significant negative impact on the enterprise value of most of the sample firms, reducing rather than increasing firm value. Overall, green innovation has a negative “causal effect” on firm value. Figure 2b illustrates that green innovation activities significantly enhance the financial performance of most of the sample enterprises. The CATEs of most sample companies are mostly on the right side of the zero value, ranging from 0 to 50 and exhibiting relative dispersion.

To further measure the heterogeneity effect of green innovation performance, Figure 3 divides the outcome variables into two aspects: firm value (TobinQ) and return on assets (ROA), providing the distribution of HTEs.

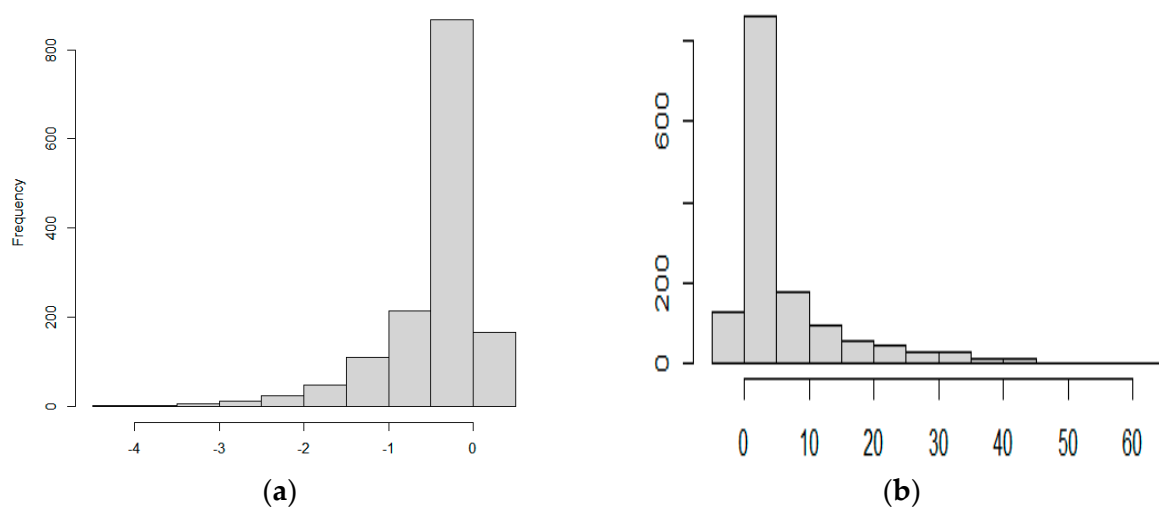


Figure 2. CATE distribution at the level of enterprise characteristics. The *vertical axes* represents the statistical frequency, and the *horizontal axes* represents the causal effect values. (a) CATEs to TobinQ. (b) CATEs to ROA.

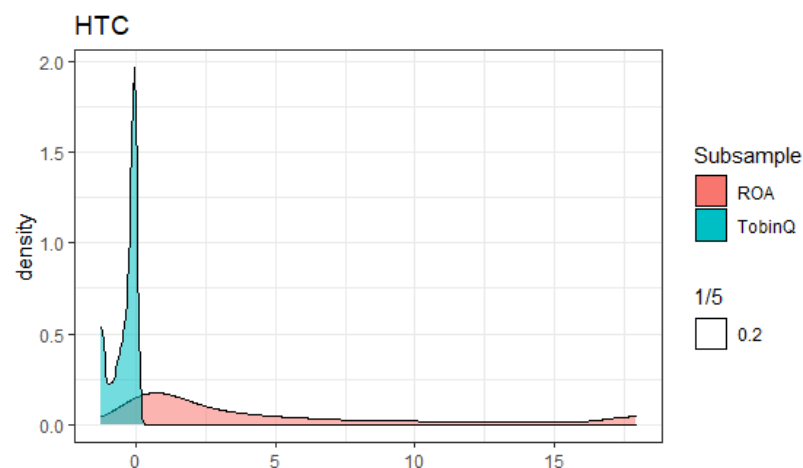


Figure 3. Distribution of heterogeneity treatment effects (HTEs). Note: Different outcome variables were grouped (subsample), and the heterogeneous causal effects were truncated by 10%.

The density plot of HTEs in Figure 3 reveals that the majority of HTEs, as derived from ROA as the outcome variable, are distributed to the right of zero, indicating that green innovation can significantly promote the improvement of financial performance for most enterprises. This result suggests that it takes some time for enterprises to realize positive returns through green technology upgrades and R&D investments. After a period of time, the impact of green innovation becomes mature, leading to a significant enhancement of financial performance. On the other hand, for the outcome variable of firm value (TobinQ), most HTE values are negative, indicating a decline in firm value due to green innovation.

4.4. Mechanism Analysis

The impact of enterprises' green innovation on firm performance is largely dependent on changes in costs, so the next obvious step is to examine the overall effect of corporate operating costs. The effects on operating costs stemming from green innovation are two-fold: on the one hand, high-risk, high-investment green innovation activities may 'crowd out' other innovative resources within the company, leading to an increase in operating costs; on the other hand, green innovation, to some extent, enhances the production and operational efficiency of the enterprise, thereby reducing overall operating

costs. Table 4 presents the average effects of green innovation estimated using the causal forest algorithm.

Table 4. Results of causal forest estimation at the 95% confidence level.

Outcome	Environment Settings	Causal Effect
Operating costs (cost_income)	ATE	-0.012 ± 0.011
	ATT	-0.008 ± 0.009
	ATC	-0.014 ± 0.015
	ATO	-0.009 ± 0.011

Table 4 reports the overall average causal effect of green innovation on firm operating costs. It can be observed that the implementation of green innovation significantly reduces the operating costs of enterprises (ATE = -0.012). Similarly, the ATT, ATC, and ATO provide similar estimates of the impact of green innovation capabilities on operating costs.

The preceding analysis examined the average effect of green innovation capabilities on operating costs. As shown in Figure 4, we estimated the heterogeneous causal effects of green innovation capabilities on enterprise costs using causal forests. Specifically, green innovation reduced the operating costs of most of the sample enterprises, with only a small number of sample enterprises having a positive CATE value between 0 and 0.1, which is relatively concentrated. This indicates that green innovation can reduce the operating costs of enterprises.

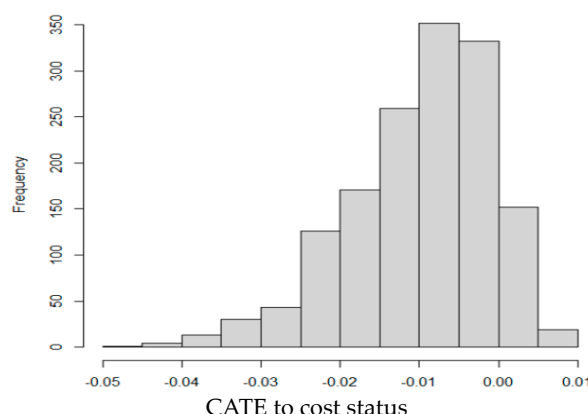


Figure 4. Distribution of enterprise cost to CATE.

4.5. Heterogeneity Analysis

In order to further discuss the heterogeneous effects of green innovation on firm performance and the dependence on firm characteristics, Table 5 presents the importance of different covariates in the process of “planting” causal trees.

The importance ranking of green innovation effects based on enterprise attribute features is shown in Table 5. It can be inferred that the logarithm of firm assets (Lnassets) holds the top position in the importance of covariates, which means that green innovation exhibits heterogeneity due to different enterprise sizes. The sum of the shareholding proportions of the top three shareholders (top3_shareholders), the shareholding proportion of the first-largest shareholder (first_shareholder), the asset–liability ratio (asset_liability), and the total asset turnover rate (asset_turnover) occupy the top five positions in importance. This confirms that equity concentration, debt-paying ability, and operational capability are important sources of heterogeneity in the performance of green innovation for enterprises.

Table 5. Importance of covariates in dependent fruit trees.

Serial Number	Covariates	Importance
1	Lnassets	0.1577
2	top3_shareholders	0.1303
3	first_shareholder	0.1236
4	asset_liability	0.1059
5	asset_turnover	0.0935
6	cash_income	0.0732
7	operat_income	0.0616
8	cost_income	0.0608
9	ndep_director	0.0507
10	manage_ownership	0.0469
11	agency_cost	0.0357
12	net_profit	0.0341
13	stated_shares	0.0143
14	concurrent_post	0.0117

5. Conclusions and Policy Suggestions

With the deepening of ESG concepts, enterprises are gradually becoming the main actors in green governance and green technological innovation. This paper, based on the perspective that green innovation has certain quasi-public goods, delves into the complexity and heterogeneity of the performance of enterprise green innovation. The performance of enterprises mainly revolves around corporate value and financial performance. Starting from the implementation of the “Green Credit Guidelines” in 2012, this paper takes 1510 A-share listed companies from 2013 to 2020 as the research sample. Using the latest machine learning algorithms, we analyzed the heterogeneous causal effects of green innovation capability on enterprise value. The empirical method, combining causal forests with quasi-natural experiments, accurately estimates the causal relationship between green innovation and corporate performance and its related mechanisms. The results can be summarized as follows.

Firstly, green innovation capability has a significant negative impact on corporate value (TobinQ), which means that green innovation not only fails to receive green incentives from the financial markets but also suppresses the improvement of corporate value. Overall, green innovation activities have a negative impact on corporate value, with the average intervention effect being negative ($ATE = -0.358$ and $ATO = -0.377$). From the perspective of heterogeneous individuals, the CATE of nearly 1300 sample companies is mostly less than 0, with the largest negative value reaching -4 . The remaining 200 sample companies have a positive CATE, indicating that green innovation capability has a significant negative impact on the enterprise value of most sample enterprises.

Secondly, green innovation capability significantly improves enterprises’ financial performance. Green innovation activities significantly increase the return on assets (ROA), with an average causal effect of 8.009. Both the treatment group and the control group showed positive average intervention effects on the enterprise’s financial performance ($ATT = 3.551$, $ATC = 11.209$, and $ATO = 5.321$). At the individual level, the CATE of the vast majority of the sample enterprises is mostly greater than 0, ranging from 0 to 50.

Thirdly, the improved financial performance of enterprise green innovation activities mainly stems from the reduction in operating costs. Green technological innovation reduces operating costs by promoting the improvement of financial performance, with $ATE = -0.012$, according to the results of the cost mechanism analysis.

Fourthly, among all enterprise features, enterprise size and equity concentration are the most important factors influencing the heterogeneous performance of enterprise green innovation performance. The larger the enterprise size, the closer the causal effect to zero, indicating that large and medium-sized enterprises can, to some extent, mitigate the negative impact of green innovation on enterprise value. As equity concentration increases,

the negative impact of green innovation activities on corporate value becomes smaller. Because of this, the paper proposes the following policy implications.

Firstly, we must adhere to advocating the concept of green development. Green innovation is conducive to reducing enterprise operating costs and improving financial performance, making it an important way to achieve high-quality development and ecological civilization construction. Secondly, it is necessary to improve the green technological innovation system, enhance the market-oriented mechanism construction of green innovation, give full play to the role of enterprises as the main body of green innovation, and implement fiscal, financial, and taxation policies to reduce enterprise financing costs. Thirdly, we must improve the green financial market and green incentive mechanisms, fully consider the heterogeneity characteristics and needs of enterprises, provide financial policy support to address the green innovation characteristics and demands of different-sized enterprises, reduce the public goods reward pressure of enterprise green innovation, and promote the sustainable development of enterprise green innovation.

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References

1. Cen, J.; Wang, M.; Yang, Y.; Li, J.; Yu, R. Does broader mean more general? Decomposing the effect of knowledge breadth on R&D and spillover of generic technology. *Eur. J. Innov. Manag.* **2023**, *26*, 1214–1234.
2. Luo, Y.; Salman, M.; Lu, Z. Heterogeneous impacts of environmental regulations and foreign direct investment on green innovation across different regions in China. *Sci. Total Environ.* **2021**, *759*, 143744. [\[CrossRef\]](#)
3. Coll-Martínez, E.; Kedjar, M.; Renou-Maissant, P. (Green) Knowledge spillovers and regional environmental support: Do they matter for the entry of new green tech-based firms? *Ann. Reg. Sci.* **2022**, *69*, 119–161. [\[CrossRef\]](#)
4. Zhang, L.; Liu, F.; Zhu, L.; Zhou, H. Research on Carbon Reduction Strategies Considering Retailer Equity Concerns and Advertising Effort Level. *Chin. J. Manag. Sci.* **2021**, *4*, 138–148.
5. Flammer, C. Corporate Green Bonds. *J. Financ. Econ.* **2021**, *142*, 499–516. [\[CrossRef\]](#)
6. Han, L.; Cai, L.; Yin, L. Green Incentives in China's Securities Market: A Four Factor Model. *J. Financ. Res.* **2017**, *1*, 145–161.
7. Choi, D.; Gao, Z.Y.; Jiang, W.X. Attention to global warming. *Rev. Financ. Stud.* **2020**, *33*, 1112–1145. [\[CrossRef\]](#)
8. Pástor, L.; Stambaugh, R.F.; Taylor, L.A. Dissecting green returns. *J. Financ. Econ.* **2022**, *146*, 403–424. [\[CrossRef\]](#)
9. Zhu, J.; Lu, Y.; Song, Z.; Shao, X.; Yue, X.G. The choice of green manufacturing modes under carbon tax and carbon quota. *J. Clean. Prod.* **2023**, *384*, 135336. [\[CrossRef\]](#)
10. Chien, F.; Kamran, H.W.; Nawaz, M.A.; Thach, N.N.; Long, P.D.; Baloch, Z.A. Assessing the prioritization of barriers toward green innovation: Small and medium enterprises Nexus. *Environ. Dev. Sustain.* **2021**, *24*, 1897–1927. [\[CrossRef\]](#)
11. Duque-Grisales, E.; Aguilera-Caracul, J.; Guerrero-Villegas, J.; García-Sánchez, E. Does green innovation affect the financial performance of Multilatinas? The moderating role of ISO 14001 and R&D investment. *Bus. Strategy Environ.* **2020**, *29*, 3286–3302.
12. Zhu, J.; Feng, T.; Lu, Y.; Jiang, W. Using blockchain or not? A focal firm's blockchain strategy in the context of carbon emission reduction technology innovation. *Bus. Strategy Environ.* **2024**. [\[CrossRef\]](#)
13. Shadbegian, R.J.; Gray, W.B. Pollution abatement expenditures and plant-level productivity: A production function approach. *Ecol. Econ.* **2005**, *54*, 196–208. [\[CrossRef\]](#)
14. Amores-Salvadó, J.; Martín-de Castro, G.; Navas-López, J.E. Green Corporate Image: Moderating the Connection Between Environmental Product Innovation and Firm Performance. *J. Clean. Prod.* **2014**, *83*, 356–365. [\[CrossRef\]](#)
15. Zhu, J.; Dou, Z.; Yan, X.; Yu, L.; Lu, Y. Exploring the influencing factors of carbon neutralization in Chinese manufacturing enterprises. *Environ. Sci. Pollut. Res.* **2023**, *30*, 2918–2944. [\[CrossRef\]](#) [\[PubMed\]](#)

16. Palmer, K.; Oates, W.E.; Portney, P.R. Tightening Environmental Standards: The Benefit-Cost or the No-Cost Paradigm? *J. Econ. Perspect.* **1995**, *9*, 119–132. [\[CrossRef\]](#)
17. Climent, F.; Soriano, P. Green and Good? The investment performance of US environmental mutual funds. *J. Bus. Ethics* **2011**, *3*, 275–287. [\[CrossRef\]](#)
18. Jiang, X.; Shen, Z. A Study on the Driving Mechanism and Innovation Performance of Enterprise Ecological Innovation Based on Porter's Hypothesis. *Econ. Manag.* **2015**, *37*, 190–199.
19. Van den Bergh, J.C. Environmental and Climate Innovation: Limitations, Policies and Prices. *Technol. Forecast. Soc. Change* **2015**, *80*, 11–23.
20. Soltmann, C.; Stuck, T.; Woerter, M. The impact of environmentally friendly innovations on value added. *Environ. Resour. Econ.* **2015**, *62*, 457–479. [\[CrossRef\]](#)
21. Zhu, Q.J.S.; Lai, K.H. Green supply chain management innovation diffusion and its relationship to organizational improvement: An ecological modernization perspective. *J. Eng. Technol. Manag.* **2012**, *29*, 168–185. [\[CrossRef\]](#)
22. Kong, T.; Feng, T.W.; Ye, C.M. Advanced Manufacturing Technologies and Green Innovation: The Role of Internal Environmental Collaboration. *Sustainability* **2016**, *8*, 1056. [\[CrossRef\]](#)
23. Walley, N.; Whitehead, B. It's not easy being green. *Harv. Bus. Rev.* **1994**, *72*, 47–52.
24. Jaffe, A.B.; Palmer, K. Environmental Regulation and Innovation: A Panel Data Study. *Rev. Econ. Stat.* **1997**, *79*, 610–619. [\[CrossRef\]](#)
25. Ederington, J. Should Trade Agreements Include Environmental Policy? *Rev. Environ. Econ. Policy* **2010**, *4*, 84–102. [\[CrossRef\]](#)
26. Petersen, H.L.; Vredenburg, H. Morals or Economics? Institutional Investor Preferences for Corporate Social Responsibility. *J. Bus. Ethics* **2019**, *90*, 1–14. [\[CrossRef\]](#)
27. Zhu, J.; Baker, J.S.; Song, Z.; Yue, X.G.; Li, W. Government regulatory policies for digital transformation in small and medium-sized manufacturing enterprises: An evolutionary game analysis. *Humanit. Soc. Sci. Commun.* **2023**, *10*, 1–18. [\[CrossRef\]](#)
28. David, P.; Bloom, M.; Hillman, A.J. Investor activism, managerial responsiveness, and corporate social performance. *Strateg. Manag. J.* **2007**, *28*, 91–100. [\[CrossRef\]](#)
29. Gupta, S.; Goldar, B. Do Stock Markets Penalize Environment-unfriendly Behaviour? Evidence from India. *Ecol. Econ.* **2005**, *52*, 81–95. [\[CrossRef\]](#)
30. Bae, K.H.; Wang, W. What's in a 'China' Name? A Test of Investor Attention Hypothesis. *Financ. Manag.* **2012**, *41*, 429–455. [\[CrossRef\]](#)
31. Chiou, T.Y.; Chan, H.K.; Lettice, F.; Chung, S.H. The Influence of Greening the Suppliers and Green Innovation on Environmental Performance and Competitive Advantage in Taiwan. *Transp. Res. Part E Logist. Transp. Rev.* **2011**, *47*, 822–836. [\[CrossRef\]](#)
32. Hojnik, J.; Ruzzier, M. The Driving Forces of Process Eco-innovation and Its Impact on Performance: Insights from Slovenia. *J. Clean. Prod.* **2016**, *133*, 812–825. [\[CrossRef\]](#)
33. Zhu, J.; Lu, Y.; Feng, T. The influence of the altruistic preferences of e-commerce platforms on the carbon emission reduction of manufacturers. *Electron. Commer. Res.* **2023**, 1–25. [\[CrossRef\]](#)
34. Huang, J.W.; Li, Y.H. Green Innovation and Performance: The View of Organizational Capability and Social Reciprocity. *J. Bus. Ethics* **2017**, *145*, 309–324. [\[CrossRef\]](#)
35. Ambec, S.; Elgie, M.A.C.S.; Lanoie, P. The Porter Hypothesis at 20: Can Environmental Regulation Enhance Innovation and Competitiveness? *Rev. Environ. Econ. Policy* **2013**, *7*, 2–22. [\[CrossRef\]](#)
36. Winblad, B.; Palmer, K.; Kivipelto, M.; Jelic, V.; Fratiglioni, L.; Wahlund, L.O.; Nordberg, A.; Bäckman, L.; Albert, M.; Almkvist, O.; et al. Mild cognitive impairment—Beyond controversies, towards a consensus: Report of the International Working Group on Mild Cognitive Impairment. *J. Intern. Med.* **2004**, *256*, 240–246. [\[CrossRef\]](#)
37. El Ghouli, S.; Guedhami, O.; Kwok, C.C.Y.; Mishra, D.R. Does Corporate Social Responsibility Affect The Cost of Capital? *J. Bank. Financ.* **2011**, *35*, 2388–2406. [\[CrossRef\]](#)
38. Wan, X.; Wang, Y. Research on Promoting Green Innovation through Green Credit Policies. *Manag. World* **2021**, *37*, 173–188.
39. Li, W.; Zheng, M. Substantive innovation or strategic innovation—The impact of macro industrial policies on micro enterprise innovation. *Econ. Res. J.* **2016**, *51*, 60–73.
40. Zhang, D.; Zhao, R.; Qiang, J. Green Innovation and Firm Performance: Evidence from Listed Companies in China. *Resour. Conserv. Recycl.* **2019**, *144*, 48–55. [\[CrossRef\]](#)
41. Fang, X.; Na, J. Research on Green Innovation Incentives of Listed Companies on the ChiNext Board. *Econ. Res. J.* **2020**, *55*, 106–123.
42. Athey, S.; Imbens, G. Recursive Partitioning for Heterogeneous Causal Effects. *Proc. Natl. Acad. Sci. USA* **2016**, *113*, 7353–7360. [\[CrossRef\]](#) [\[PubMed\]](#)
43. Wager, S.; Athey, S. Estimation and inference of heterogeneous treatment effects using random forests. *J. Am. Stat. Assoc.* **2018**, *113*, 1228–1242. [\[CrossRef\]](#)
44. Hu, Z.; Deng, L.; Mao, J.; Xie, J. Heterogeneity in the Effect of Environmental Protection Expenditure in China: Causal Inference from Machine Learning. *Emerg. Mark. Financ. Trade* **2023**, *59*, 623–640. [\[CrossRef\]](#)
45. Athey, S.; Tibshirani, J.; Wager, S. Generalized Random Forests. *Ann. Stat.* **2019**, *47*, 1179–1203. [\[CrossRef\]](#)
46. Nie, X.; Wager, S. Quasi-Oracle Estimation of Heterogeneous Treatment Effects. *Biometrika* **2020**, *108*, 299–319. [\[CrossRef\]](#)

47. Xu, J.; Ye, F.; Li, X. Carbon Intensity Constraint Policy and Firm Green Innovation in China: A Quasi-DID Analysis. *Sustain. Account. Manag. Policy J.* **2024**, *19*, 145–170. [[CrossRef](#)]
48. Rahelliamelinda, L.; Handoko, J. Profitabilitas Sebagai Moderating Pengaruh Kinerja Esg, Green Innovation, Eco-Efficiency Terhadap Nilai Perusahaan. *Jurnal Ilmiah Pendidikan Akuntansi, Keuangan, dan Keuangan Publik* 2024. Available online: <https://www.e-journal.trisakti.ac.id/index.php/jipak/article/view/19191> (accessed on 14 January 2024).

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