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Estimating the Impact of Government Green Subsidies on Corporate ESG Performance: Double Machine Learning for Causal Inference

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Abstract

In this study, we examine the impact of government green subsidies on corporate ESG performance. We employ the method of double machine learning for causal inference. We use all A-share listed companies in China from 2013 to 2023 as the research sample. After excluding financial and insurance companies, those in ST/*ST/PT status, and those with missing key indicators, we ultimately obtain 2,337 sample observations. Our baseline results based on double machine learning reveal government green subsidies significantly enhance corporate ESG performance. The findings suggest that this reduction occurs notably through the mediating variables of digital technology innovation and technology conversion efficiency. We also introduce heterogeneous dimensions such as the level of digital inclusive finance, the intensity of environmental regulations, and the scale of enterprises. Meanwhile, we adopt multiple robustness test methods, including changing the dependent variable, excluding data from special years, controlling for exogenous policy shocks, using instrumental variable methods, and resetting the double machine learning model—adjusting the sample partition ratio from the original 1:4 to 1:9 and replacing the prediction algorithm from random forest to gradient boosting, lasso regression, and ensemble machine learning methods—to ensure the reliability and scientific nature of the research conclusions. Additional tests indicate that the regression coefficient remains positive and is significant, indicating the robustness of our conclusions. This research offers implications for further optimizing the design of government green subsidy policies, and to promote the improvement of enterprises' ESG performance and economic green transformation.

Keywords: double machine learning; government green subsidies; corporate ESG performance; digital technology innovation; technology conversion efficiency

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1. Introduction

Government green subsidies are financial support measures implemented by governments through funding grants, tax reductions, and other means to encourage enterprises to invest in green innovation, green technologies, and green management practices, thereby promoting environmental protection and sustainable development (C. Wang et al., 2022). China has long neglected environmental costs in economic development, resulting in an extensive industrial growth model that has led to increasingly severe environmental pollution. To achieve harmonious coexistence between the economy and the environment, the Chinese government has increasingly emphasized green innovation and industrial green transformation in recent years (Imperiale et al., 2023). The core objective of government green subsidies is to alleviate financial pressures on enterprises in green technology R&D and management innovation through financial support, thereby enhancing their capacity for green development (X. Yu et al., 2022). However, implementation challenges remain in

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the process of government green subsidies. Some enterprises may develop dependency on government funds after receiving subsidies, reducing their enthusiasm for independent innovation (Han et al., 2024). The efficiency of subsidy utilization may vary depending on differences in enterprise scale and green management capabilities, with some companies potentially underutilizing allocated funds (Y. Li et al., 2020). When formulating green subsidy policies, governments fully consider heterogeneous characteristics of enterprises, such as pollution intensity, factor intensity, and lifecycle factors, to improve policy precision and effectiveness (Song & Yan, 2023).

Environmental, Social and Governance (ESG) performance is a crucial indicator for measuring a company's sustainable development capabilities and social responsibility fulfillment. ESG performance reflects a company's efforts and achievements in environmental protection, social responsibility, and corporate governance, which helps enhance its social image and brand value (Cai et al., 2023). Good ESG performance can attract more investor attention, especially from institutional investors who prioritize long-term value and social responsibility, thereby reducing corporate financing costs and improving capital market recognition (Bin-Feng et al., 2024). ESG performance is also closely related to a company's risk management and long-term profitability. By optimizing ESG performance, companies can better identify and address environmental and social risks, thereby achieving sustainable development (Imperiale et al., 2023). With global emphasis on environmental protection, green transformation, and sustainable development, corporate ESG performance has become a key indicator for assessing their comprehensive strength and growth potential (Madison & Schiehll, 2021). In this context, governments encourage companies to improve ESG performance through policy measures such as green subsidies, promoting corporate green transformation. Therefore, how to advance corporate green transformation during economic growth to enhance ESG performance has become a significant challenge and unavoidable issue for China's high-quality economic development.

Under the green development strategy, government green subsidies serve as a key policy tool that drives corporate low-carbon transitions and supports sustainable economic growth. These subsidies provide financial support to guide enterprises in environmental R&D, energy conservation, emission reduction, and green production, with potential to enhance environmental performance and accelerate green upgrades. They act as a safeguard for the transformation of traditional high-energy-consuming enterprises (J. Wang, Ma, et al., 2023). Zahid et al. (2022) suggests that their effectiveness and value should be assessed through scientific methods like cost-benefit analysis to measure how subsidies boost corporate green investments and pollutant reductions. Existing empirical studies on accounting treatment and information disclosure of government green subsidies have proposed solutions such as separate reporting and establishing special accounting mechanisms, providing robust support for corporate standardization of green financial accounting and government strengthening of subsidy supervision (Jiang et al., 2021). The promoting effect of government green subsidies on corporate green development has been thoroughly validated (Li et al., 2020). However, the intrinsic relationship between government green subsidies and corporate ESG performance remains underexamined. Methodologically, traditional econometric models (e.g., DID, fixed effects model) remain mainstream tools for analyzing green subsidy effects (Mahesh, 2020), while cutting-edge models like dual machine learning are gradually expanding research paradigms, offering new pathways to precisely identify causal relationships between subsidy policies and corporate green performance.

ESG has achieved vigorous development since its inherent nature of sustainable development and long-term value growth perfectly aligns with the intrinsic needs of value creation in current business practices. Zhao and Cai (2023) proposed that ESG indicators are not an evaluation metric based on corporate financial fundamentals, but rather a novel assessment system measuring a company's green development philosophy, corporate social responsibility, and management capabilities. Therefore, ESG indicators provide certain guidance for investment (D. Zhang et al., 2023). In contrast, Western scholars' research on ESG tends to focus more on practical aspects such as responsible investment and corporate performance (Clément et al., 2022), while China's ESG studies

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predominantly explore the necessity of ESG disclosure and the consequential impacts of ESG (L. Yu et al., 2024). Existing literature on corporate ESG performance research mostly concentrates on analyzing the economic consequences of ESG performance, which primarily include financial performance, corporate value, and efficiency (H. Liu & Lyu, 2022). Most studies hold a positive and affirmative attitude toward the impact of ESG (Dai & Zhu, 2024). However, research on the antecedent factors influencing corporate ESG performance remains relatively limited. Traditional methods mainly involve Ordinary Least Squares (OLS), Difference-in-Differences (DID), and fixed effects models (Tan et al., 2024), but in recent years, cutting-edge models such as Dual Machine Learning (DML) have been increasingly applied (Janiesch et al., 2021).

In the dual context of digital transformation and green development, most existing research focuses on the direct impact of government subsidies on green technology investments or emission outcomes (C. Wang et al., 2022). However, limited attention has been paid to the influence of government green subsidies on ESG performance. Methodologically, current empirical strategies still predominantly rely on traditional regression methods (Han et al., 2024), which demonstrate limited capacity to handle high-dimensional confounding variables and nonlinear relationships, while failing to fully leverage the advantages of dual-machine learning in causal discovery and policy evaluation. Regarding mediation effect analysis and heterogeneity analysis, existing studies neglect critical mediating variables such as corporate digital economy patents and technology transfer efficiency, and rarely conduct heterogeneity analyses from dimensions like environmental regulation intensity, digital inclusive finance, firm size, and financing constraints (Y. Li et al., 2020; Santín & Sicilia, 2017; X. Wang, Zhang, et al., 2023)

Building upon existing research, this research examines the impact of government green subsidies on corporate ESG performance. Three key innovations emerge: first, in terms of research perspective, it reveals how government green subsidies influence corporate ESG outcomes. Second, methodologically, the study employs a dual-machine learning model to enhance parameter estimation robustness and causal identification accuracy. Third, through mediating effect analysis and heterogeneity analysis, the paper constructs two mediating variables—digital economy patent and technology transfer efficiency—while incorporating environmental regulation intensity, digital inclusive finance, firm size, and financing constraints. This approach examines the differential impacts of multidimensional factors on core effects, providing empirical evidence to refine the sustainable development theory of government green subsidies driving corporate ESG performance.

2. Theoretical Analysis and Research Hypotheses

2.1. Government Green Subsidies and Corporate ESG Performance

The resource dependency theory posits that enterprises are fundamentally resource-dependent organizations whose survival and development rely heavily on continuously acquiring critical resources from external environments (Cao et al., 2022). In this process, the government, as a key actor in institutional environments, often plays the pivotal role of resource provider. Government-provided green subsidies not only deliver much-needed financial support to enterprises but also strategically guide their transition toward sustainable development (Lee & Li, 2022). These special-purpose funds directly alleviate financial pressures faced by companies in environmental governance, energy conservation, emission reduction, and green technology innovation, helping them overcome resource constraints (C. Yang et al., 2024). Subsidized enterprises can more confidently adopt advanced eco-friendly technologies, optimize production processes, and enhance pollution control, thereby significantly improving environmental performance. Government green subsidies incentivize companies to establish robust internal governance structures, improve information disclosure quality, and strengthen social responsibility practices, achieving comprehensive performance enhancement (X. Zhang et al., 2023). Therefore, government green subsidies are not merely fiscal transfers but crucial policy instruments and institutional resources. By alleviating corporate resource dilemmas and reducing green transition costs, they effectively guide enterprises to transform external environmental pressures into internal governance drivers, ultimately promoting coordinated development across environmental, social, and governance (ESG) dimensions. Based on this analysis, this paper proposes:

H1: Government green subsidies can enhance corporate ESG performance.

2.2. Mediating Effects

2.2.1. Digital Technology Innovation

According to the digital empowerment theory, digital technologies support ESG management by enhancing corporate information processing capabilities and optimizing decision-making efficiency (Zahid et al., 2023). Through the adoption of technologies like blockchain, big data, and AI in digital transformation, enterprises can improve the accuracy and transparency of environmental data collection, strengthen internal governance efficiency, enhance the quantification of social responsibility management, and drive green innovation transitions (J. Wang, Hong, et al., 2023). Digital technological innovations boost ESG performance by elevating green technology standards, increasing information transparency, and optimizing resource allocation efficiency (Mu et al., 2023). Government green subsidies alleviate financing constraints for digital technology innovation, further stimulating its role in corporate ESG improvement (Cai et al., 2023). These funds can be specifically allocated for enterprises to purchase digital equipment, recruit technical talent, or develop ESG data management systems, accelerating the integration of digital technologies with practical applications. Based on the above analysis, this research proposes:

H2: Government green subsidies improve corporate ESG performance by promoting digital technology innovation.

2.2.2. Technical Conversion Efficiency

Based on the theory of technological externalities, corporate technological innovation generates knowledge spillover effects that not only drive internal development but also create positive or negative externalities on society and the environment (Clément et al., 2022). Effective technological innovation can significantly reduce the negative externalities of production activities by improving resource efficiency, reducing pollution emissions, and promoting green transformation, thereby laying the foundation for enhanced ESG performance (H. Wang, Jiao, et al., 2023). Digital technology innovation elevates corporate ESG performance by boosting market value, facilitating green transition, and mitigating information asymmetry. Technological innovation empowers enterprises to develop more environmentally friendly production processes and products, minimizing environmental impacts (D. Zhang et al., 2023). Government green subsidies alleviate financing pressures for corporate green technology innovation, reducing costs and risks associated with such initiatives (Lu et al., 2024). The relationship between government green subsidies and substantive green technological innovation exhibits a U-shaped pattern: when subsidies reach a critical threshold, they facilitate the transition from strategic to substantive innovation (Jia et al., 2022). Additionally, government subsidies attract more social capital into green technology sectors through signaling effects, further strengthening the role of technological innovation in enhancing ESG performance. Based on this analysis, this research proposes:

H3: Government green subsidies improve corporate ESG performance by promoting technological innovation.

2.3. Heterogeneity Effects

According to data assetization theory, enterprises with varying levels of digital financial inclusion development demonstrate differing effectiveness in leveraging government green subsidies to enhance ESG performance (Manita et al., 2018). Organizations with advanced or moderate digital financial inclusion capabilities typically possess more sophisticated data infrastructure and efficient processing capacities, enabling them to allocate green subsidies more precisely toward R&D in eco-friendly technologies, energy efficiency improvements, and ESG governance system development (Dai & Zhu, 2024). These enterprises can utilize data-driven approaches to monitor subsidy allocation processes and evaluate implementation effectiveness, thereby driving comprehensive ESG performance enhancement (Menicucci & Paolucci, 2022). Conversely, organizations with limited digital financial inclusion capabilities face challenges in systematically converting data assets into decision-support tools (W. Wang et al., 2022). Even when receiving government green subsidies, they often lack the technical expertise to optimize resource allocation, resulting in minimal marginal improvements in ESG outcomes from such subsidies.

According to information economics theory, the effectiveness of government green subsidies in enhancing corporate ESG performance varies across regions with different environmental regulation intensities (Kumar, 2023). In areas with stringent environmental regulations, companies already possess strong ESG implementation motivation due to clear compliance requirements and regulatory pressure, making the marginal utility of green subsidies relatively limited. Instead, they primarily serve as supplementary incentives (Chen et al., 2022). Conversely, in regions with weaker or moderate environmental regulations, companies often lack both initiative and institutional constraints for ESG practices (Zhong et al., 2023). In such cases, government green subsidies can effectively compensate for the lack of internal motivation caused by insufficient regulation through financial support and policy guidance. These subsidies not only alleviate financial constraints for corporate ESG implementation but also enhance market recognition and stakeholder endorsement via signaling mechanisms, creating implicit incentives. Information economics posits (Xu et al., 2021) that subsidies, as policy information tools, optimize corporate decision-making processes by directing funds toward environmental management, social responsibility, and governance structure optimization, thereby improving ESG performance (Albitar et al., 2023). Therefore, in environments with weaker regulations, green subsidies achieve more significant enhancement effects on corporate ESG performance through dual mechanisms of economic compensation and information empowerment.Based on the above analysis, this research proposes that:

H4: In enterprises with different environmental regulation intensity, digital inclusive finance, enterprise size and financing constraints, the effect of government green subsidy on the improvement of enterprise ESG performance is heterogeneous.

3. Research Design

3.1. Variable Selection

3.1.1. Dependent Variable

Corporate ESG Performance (ESG). The independent variable in this study is ESG performance. As the ESG framework continues to develop, more and more companies have opted to voluntarily disclose their ESG performance. Currently, there are more than 600 specialized institutions globally that provide ESG performance ratings for companies (Albitar et al., 2023). We adopt the average value of Sino Securities Index ESG ratings as a core indicator to measure corporate ESG performance, aiming to comprehensively evaluate a company's overall sustainability performance and long-term value, ensuring consistency and comparability of assessment results.

On one hand, as an independent third-party rating agency, Sino Securities Index is subject to rigorous oversight by various stakeholders in the market such as investors, regulators, and the public (Zhu et al., 2023). This external checks-and-balances mechanism grants it high independence, effectively avoiding potential conflicts of interest and ensuring the fairness and transparency of the rating process. On the other hand, Sino Securities Index deeply integrates international mainstream

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ESG frameworks like GRI or SASB standards into its evaluation system (Z. Hu & Ge, 2014), while precisely incorporating China's unique economic environment, policy context, and local corporate case studies. This ensures its data not only aligns with the actual needs of the Chinese market but also demonstrates excellent timeliness, broad industry coverage, and in-depth corporate insights, enabling dynamic tracking of the latest developments in environmental, social, and governance dimensions (K. Zhang et al., 2022).

Therefore, we select the average score of Sino Securities Index's composite index to assess corporate ESG performance, as this weighted average method comprehensively and balancedly reflects the stability and progress of a company's overall ESG performance, thereby providing a solid decision-making foundation for sustainable investment.

3.1.2. Independent Variable

Government Green Subsidies (Subsidy). Government Green Subsidies refer to financial support funds provided by governments to enterprises specifically designed to promote environmental protection and sustainable development (Tu et al., 2023). These subsidies aim to incentivize companies to adopt green production technologies and emission reduction measures, aligning with national environmental policies while fostering coordinated economic and ecological development (Fang & Zhao, 2023). The allocation of government green subsidies is determined by analyzing details of government subsidy projects in corporate annual reports' appendices (D. Hu et al., 2021). Through manual organization, we systematically identify and aggregate projects explicitly labeled as green-related. During implementation, we meticulously review each report's detailed entries, record subsidy amounts item by item, and cross-verify data. We employ standardized classification criteria to systematically identify green attributes using keywords like "green," "environmental subsidies," "environment," "sustainable development," "clean," and "energy-saving," while extending to terms such as "low-carbon" and "ecological compensation." This approach minimizes human bias and ensures data accuracy and consistency.

To comprehensively assess subsidy impacts, we adopt scale-adjusted relative green subsidy levels as evaluation metrics—measured by dividing subsidy amounts by enterprise scale indicators (total assets and revenue) to eliminate biases caused by varying company sizes. This adjustment method standardizes analytical frameworks, prevents large enterprises from dominating results, and authentically reflects the relative contributions of subsidies. Given that original subsidy amounts are typically small, we present them as percentages. This approach not only facilitates intuitive data comparison and analysis but also highlights the relative importance of green subsidies in corporate operations. For instance, calculating the proportion of subsidies to operating revenue makes research findings more applicable in academic reports and policy evaluations, thereby supporting in-depth interpretation of corporate green performance.

3.1.3. Mediating Variables

Digital Technology Innovation (DTI). Research on measuring digital technology innovation has emerged as a cutting-edge topic in contemporary academia. While existing literature primarily focuses on qualitative theoretical explorations, empirical studies using quantitative approaches to assess digital technological innovation remain underdeveloped. The core challenge lies in accurately capturing the essential characteristics of digital technologies. This research synthesizes the theoretical consensus on the conceptual characteristics of digital technology innovation from Yoo et al., (2012) and Nambisan et al., (2017), innovatively constructing a digital technology innovation measurement model based on the International Patent Classification (IPC) system (WIPO, 2023). We employ a triple-coding correspondence method, systematically integrating the "Statistical Classification of Digital Economy and Its Core Industries (2021)" (H. Zhang et al., 2023) and the "Reference Relationship Table between International Patent Classification and National Economic Industry Classification (2018)" (Xiong & Li, 2024) to establish a cross-standard mapping system of "digital economy core industry codes-national economic industry SIC4 codes-IPC subgroups." The unique value of this framework is derived from its use of the technical characterization benefits of patent IPC classification, enabling precise identification of enterprise digital technology innovation activities (WIPO, 2023).

Technical Conversion Efficiency (TCE). Research on measuring technology transfer efficiency remains a pivotal topic in innovation economics. Existing literature predominantly focuses on qualitative analysis of technology transfer pathways, specifically manifested in three dimensions: First, theoretical interpretations of technology transfer mechanisms from an innovation value chain perspective (Pénin et al., 2011); Second, frameworks for influencing technology transfer efficiency based on innovation ecosystem theory (Autio et al., 2023); Third, case study methodologies revealing dynamic characteristics of technology transfer processes(Purbasari et al., 2020). However, compared to the substantial progress in theoretical research, consensus on quantitative measurement of technology transfer efficiency at the macro level has yet to emerge. The core challenge lies in developing evaluation indicators that balance theoretical rationality with data availability. We adopt technology transaction activity as a proxy variable for technology transfer efficiency. This indicator is constructed based on Jaffe et al.'s, (2000) "innovation input-market output" theoretical framework, incorporating Z. L. He et al.'s (2006) research on signal transmission mechanisms in technology trading markets. Technology transaction activity is defined as the ratio of technology market transaction volume to regional GDP. This scientific basis stems from the fact that measuring actual technology market transactions relative to regional economic output not only effectively captures the efficiency of market-based allocation of technological factors but also eliminates measurement biases caused by regional scale differences.

3.1.4. Control Variables

To mitigate the influence of confounding factors on corporate ESG performance exposure and bolster the robustness of our findings, we carefully selected control variables groundedJ. Wang, Ma, et al. (2023) in established research on corporate ESG performance and accountability(W. Wang et al., 2022). This selection process rigorously incorporated both theoretical foundations and practical insights from the existing literature. Within the fundamental characteristics dimension, empirical evidence Asante-Appiah & Lambert (2023)Burke & Hoitash (2019)reveals that corporate debt levels, life cycle stages, and growth capabilities profoundly shape environmental strategic decisions, thereby dictating ESG performance levels. Consequently, we designated financial leverage (Lev), listing duration (Age), and revenue growth rate (Growth) as core control variables. Shifting to the governance mechanism dimension, studies Albitar et al. (2023) García-Sánchez et al. (2019) Manita et al. (2018) demonstrate that internal and external governance structures significantly impact ESG disclosure quality and implementation effectiveness. Therefore, this study integrated key internal governance controls: equity structure (Equity concentration, OC), board governance efficacy (board size, Board; proportion of independent directors, Indep), checks-and-balances mechanisms (shareholder balance degree, Balance), and institutional investor ownership (Institution) (Orazalin, 2019). Finally, to eliminate potential interference from temporal fluctuations and industry heterogeneity, this study incorporated year and industry fixed effects, meticulously controlling for underlying time trends and sector-specific variations.

3.2. Models Specification

We aim to study the impact of government green subsidies on corporate ESG performance. Existing literature demonstrates that studies employing traditional causal inference frameworks frequently encounter significant methodological constraints. Using the difference-in-differences (DID) model as an example, its core parallel trends assumption critically depends on specific data structures, necessitating strictly synchronized trajectories between treatment and control groups prior to policy intervention—a stringent condition often unmet in practical applications (Y. Liu et al., 2021). While the synthetic control method (SCM) mitigates pressure on the parallel trends assumption through the construction of a virtual control group, its efficacy is constrained by dual limitations: it

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requires that treatment units exhibit no extreme characteristic values and is restricted to matching a single treated unit with multiple control units (Ben-Michael et al., 2021). Furthermore, propensity score matching (PSM) is compromised by significant subjective dependency in covariate selection, rendering model robustness susceptible to researchers' theoretical priors (Yuan et al., 2021).

In response to the inherent limitations of traditional models, the academic community has proactively examined the integration of machine learning with causal inference in recent years (Chernozhukov et al., 2018; Athey et al., 2019; Knittel & Stolper, 2021). Among these integrative approaches, Double Machine Learning demonstrates distinctive advantages: it decouples high-dimensional variable selection from parameter estimation, maintaining adaptability to complex data structures while ensuring statistical consistency in causal effect estimation. Specifically, Double Machine Learning (Sarker, 2021) constitutes a statistical methodology that synergistically combines machine learning models with causal inference frameworks, primarily employed to estimate causal effects in contexts characterized by high-dimensional confounding variables. Its core conceptual framework involves a two-stage modeling procedure designed to eliminate confounding variable influences, thereby yielding more precise estimates of the causal effect of treatment variables on outcome variables. Critically, the incorporation of machine learning algorithms should not be construed as substituting traditional econometric methods; rather, it enhances the precision of confounding factor control and elevates model generalization capabilities through data-driven feature extraction and algorithmic optimization (J. C. Yang et al., 2020).

In order to test the impact of government green subsidies on corporate ESG performance, we construct a dual machine learning model as follows:

$$ESG_{it} = \beta_0 Subsidy_{it} + g(X_{it}) + U_{it} \quad (1)$$

$$E(U_{it} \mid Subsidy_{it}, X_{it}) = 0 \quad (2)$$

Here, ESG_{it} represents the corporate ESG performance, $Susidy_{it}$ denotes government green subsidies, and β_0 is the disposal coefficient we primarily focus on. X_{it} represents a series of control variables, for which the specific functional form $\hat{g}(X_{it})$, needs to be estimated using machine learning algorithms. U_{it} is the error term with a conditional mean of 0. By directly estimating equations (1) and (2), we obtain the estimated values of the disposal coefficients as:

$$\hat{\beta}_0 = \left(\frac{1}{n}\sum_{i\in I,\, t\in T} Subsidy_{it}^{\,2}\right)^{-1} \frac{1}{n}\sum_{i\in I,\, t\in T} Subsidy_{it} \left(ESG_{i+1} - \hat{g}(X_{it}) \right) \quad (3)$$

where n is the sample size.

Based on the aforementioned estimators, their estimation bias can be further examined:

$$\sqrt{n}\left(\hat{\beta}_0 - \beta_0\right) = \left(\frac{1}{n}\sum_{i\in I,\, t\in T} Subsidy_{it}^{\,2}\right)^{-1} \frac{1}{\sqrt{n}}\sum_{i\in I,\, t\in T} Subsidy_{it} + U_{it} + \left(\frac{1}{n}\sum_{i\in I,\, t\in T} Subsidy_{it}^{\,2}\right)^{-1} \frac{1}{\sqrt{n}}\sum_{i\in I, i\in T} Subsidy_{it} \left[g(X_{it}) - \hat{g}(X_{it})\right] \quad (4)$$

Among them, $a = \left(\frac{1}{n}\sum_{i\in I,\, t\in T} Subsidy_{it}^{2}\right)^{-1} \frac{1}{\sqrt{n}} \sum_{i\in I,\, t\in T} Subsidy_{it} U_{it}$, follow a normal distribution with mean 0 $b = \left(\frac{1}{n}\sum_{i\in I,\, t\in T} Subsidy_{it}^{2}\right)^{-1} \frac{1}{\sqrt{n}}\sum_{i\in I,\, t\in T} Subsidy_{it} \left[g(X_{it}) - \hat{g}(X_{it})\right]$. It should be emphasized that double machine learning utilizes machine learning techniques and regularization algorithms to estimate a specific functional form $\hat{g}(X_{it})$, inevitably introducing "regularization bias". While this mitigates excessive variance in the estimator, it concurrently leads to a loss of unbiasedness, specifically evidenced by a slower convergence rate $\hat{g}(X_{it})$ to $g(X_{it})$. Consequently, $n^{-\varphi_g} > n^{-\frac{1}{2}}$ as the sample nsize tends to infinity, bthe bias also tends to infinity, $\hat{\beta}_0$ hindering convergence to β_0 the true parameter.

To boost the convergence rate and guarantee unbiasedness for the treatment coefficient estimator in small-sample scenarios, the auxiliary regression is specified as follows:

$$Subsidy_{it} = m(X_{it}) + J_{it} \quad (5)$$

$$E\left(J_{it} \mid X_{it}\right) = 0 \quad (6)$$

Among them, $m(X_{it})$ is the regression function of the treatment variable on the high-dimensional control variables, and its specific form $\hat{m}(X_{ii})$ also needs to be estimated using machine learning algorithms. J_{dx} is the error term, with a conditional mean of 0.

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The specific operational procedure is as follows: first, employ a machine learning algorithm to estimate the auxiliary regression $\widehat{m}(X_{it})$, taking its residual $\hat{J}_{it} = Subsidy_{it} - \widehat{m}(X_{it})$; second, similarly use a machine learning algorithm to estimate $\hat{g}(X_{it})$, transforming the main regression into the form $ESG_{it+1} - \hat{g}(X_{it}) = \beta_0 Subsidy_{it} + U_{it}$; finally, regress using $\hat{J}_{it}$ as the instrumental variable for $Subsidy_{it}$ to obtain an unbiased coefficient estimator as follows:

$$\widehat{\beta}_0 = \left(\frac{1}{n}\sum_{i\in I,\ t\in T}\hat{J}_{it}\, Subsidy_{it}\right)^{-1}\frac{1}{n}\sum_{i\in I,\ t\in T}\hat{J}_{it}\left(ESG_{it+1} - \hat{g}(X_{it})\right) \quad (7)$$

Similarly, Equation (7) can also be approximately expressed as:

$$\sqrt{n}(\widehat{\beta}_0-\beta_0) = [E(J_{it}^2)]^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I\ i\in T} J_{it}\, U_{it}$$

$$+ [E(J_{it}^2)]^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I,\ t\in T}[m(X_{it})-\widehat{m}(X_{it})]\,[g(X_{it})-\hat{g}(X_{it})] \quad (8)$$

Here, $E(J_{it}{}^2)]^{-1}\frac{1}{\sqrt{n}}\Sigma_{i\in I,t\in T}J_{it}U_{it}$ follows a normal distribution with mean 0. Since machine learning estimation is applied twice, the overall convergence rate of $[E(J_{it}{}^2)]^{-1}\frac{1}{\sqrt{n}}\Sigma_{i\in I,t\in T}$ $[m(X_{it})-\widehat{m}(X_{it})][g(X_{it})-\hat{g}(X_{it})]$ depends on the convergence rates of $\widehat{m}(X_{it})$ to $m(X_{it})$ and $\hat{g}(X_{it})$ to $g(X_{it})$, namely $n^{-(\varphi_g+\varphi_m)}$. Compared to equation (4), the convergence rate of $\sqrt{n}(\hat{\beta}_0 - \beta_0)$ to 0 is faster, thereby enabling unbiased estimation of the treatment coefficient.

Theoretical analysis indicates that corporate technological innovation and financing constraints are two channels affecting ESG performance exposure. We employ a two-step mediation effect test and construct the following model (9) for verification:

$$Mechanism_{it} = \gamma_0 + \gamma_1 Subsidy_{it} + \gamma_2 X_{it} + \mu_i + \varepsilon_{it} \quad (9)$$

Among them, X_{it} represents a series of control variables, μ_i denotes the fixed effects term, and ε_{it} is the random disturbance term.

3.3. Data Sources and Descriptive Statistics

Through reading annual reports, it is found that the disclosure of data assets currently covers almost the entire stock market, and digital tools began to be widely used after 2010. Based on data availability and research objectives, we select all A-share listed companies in China from 2013 to 2023 as the research sample. Financial and insurance companies, as well as listed companies with *ST, ST, or PT status and those lacking key indicators, are excluded, resulting in a final sample of 2337 observations. The relevant data for empirical analysis are sourced from the Sino Securities Index ESG Rating, Corporate annual report, CSMAR Database and with missing data supplemented using interpolation methods. Descriptive statistics of the main variables are detailed in Table 1.

Table 1. Descriptive Statistics.

Variables	Obs	Mean	Std.dev.	Min	Max
ESG	2337	4.9276	0.9436	2.25	6.75
Subsidy	2337	14.7674	3.4312	0	19.0947
Lev	2337	0.5542	0.2247	0.074	0.9363
Age	2337	2.4304	0.7178	0	3.3673
Growth	2337	0.197	0.4998	-0.6888	2.6055
OC	2337	0.367	0.1659	0.0838	0.733
Board	2337	2.2314	0.2455	1.6094	2.7081
Indep	2337	0.3848	0.0591	0.3333	0.5714
Balance	2337	0.4317	0.297	0.026	0.9953
Institution	2337	0.6487	0.207	0.0976	0.9338
DTI	2337	3.1221	2.2419	0	8.3354
TCE	2337	0.0527	0.0605	0.0006	0.191

4. Empirical Results

4.1. Main Analysis

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We employ a dual machine learning model to evaluate the impact of government green subsidies on corporate ESG performance, with a sample split ratio of 1:4. The random forest algorithm was used for both principal and auxiliary regression predictions, with results presented in Table 2. Model (1) retained no fixed effects and only included the linear term of control variables across the full sample range, showing positive regression coefficients that remained statistically significant at the 1% level. This confirms the substantial positive influence of government green subsidies on corporate ESG performance. Building upon Model (1), Model (2) further controlled for the quadratic term of control variables, maintaining positive regression coefficients with minimal numerical variation. Expanding from Model (2), Model (3) incorporated firm fixed effects across the full sample range, preserving statistically significant positive coefficients. Following Model (3), Model (4) added industry fixed effects, maintaining positive coefficients. Finally, Model (5) introduced annual fixed effects across the full sample range, sustaining significant positive coefficients. All five models yielded consistent positive regression coefficients across all samples, demonstrating that higher government environmental subsidy scores correspond to better corporate ESG performance. This evidence validates Hypothesis H1.

Table 2. The Regression Results of H1.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	ESG	**ESG**	**ESG**	**ESG**	**ESG**
Subsidy	0.0816 ***	0.0793 ***	0.0667 ***	0.0675 ***	0.0513 ***
	(5.426)	(5.414)	(4.433)	(4.360)	(3.361)
_cons	0.0035	0.0038	-0.0221	-0.0204	-0.0237
	(0.230)	(0.246)	(-1.529)	(-1.445)	(-1.642)
CV First-order	Yes	Yes	Yes	Yes	Yes
CV Second-order	No	Yes	Yes	Yes	Yes
Enterprise FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes
Year FE	No	No	No	No	Yes
Obs	2586	2586	2586	2586	2586

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors in parentheses.

Government green subsidies alleviate financial pressures on enterprises undergoing green transformation, encouraging increased investment in environmental governance and technological innovation (Y. Li et al., 2020). By acquiring eco-friendly equipment and developing clean technologies, companies can effectively reduce energy consumption and emissions while improving environmental performance. However, subsidy recipients typically face stricter environmental compliance requirements and disclosure obligations, which drive enterprises to refine internal management systems and strengthen environmental risk control, thereby optimizing governance structures (D. Zhang et al., 2023). Green transformation helps businesses establish responsible social images, enhance employee engagement and community support, and improve social performance. Environmental subsidies serve as policy signals, guiding market resources toward companies with strong ESG performance (Ma et al., 2022). To sustain support, enterprises actively improve ESG management capabilities, creating a virtuous cycle. Government green subsidies not only directly incentivize environmental improvements but also comprehensively boost ESG performance through institutional guidance and market feedback, serving as an effective policy tool for achieving economic and environmental win-win outcomes.

4.2. Roustness Tests

4.2.1. Changing the Dependent Variable

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In the robustness test of variable substitution, we replace the mean of annual ESG ratings in the Sino Securities Index with the standard deviation of annual ESG ratings in the Sino Securities Index to verify the stability of the impact of government green subsidies on ESG performance. The regression results are detailed in Table 3 (1). It is evident that the regression coefficients remain significantly positive after the variable substitution. This indicates that the conclusion demonstrates strong robustness, unaffected by specific measurement dimensions of ESG performance.

Table 3. The Results of Robustness Tests.

Variable	(1) ESG	(2) ESG	(3) ESG	(4) ESG	(5) ESG	(6) ESG
Subsidy	0.016**	0.0192***	0.0134**	0.0144**	0.0136**	0.1825**
	(2.44)	(2.577)	(2.110)	(2.479)	(2.486)	(2.463)
_cons	-0.026	-0.026	-0.027*	-0.036**	-0.027*	-0.025
CV First-order	Yes	Yes	Yes	Yes	Yes	Yes
CV Second-order	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	2337	1481	2070	2337	2337	2337

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors in parentheses.

4.2.2. Excluding 2020 Data

Considering that the COVID-19 pandemic in 2020 had a significant impact on China's economic development, conducting regression analysis using all years may lead to estimation bias. Therefore, we exclude the data from 2020 and retained other years' data for regression analysis. The specific regression results are detailed in Table 3 (2). It can be observed that after excluding the 2020 data, the regression coefficients remain positive and are statistically significant at the 1% level.

4.2.3. Elimination of Extreme Values

Given that outliers in the regression sample could introduce bias into the estimation results—particularly since Beijing, Tianjin, Shanghai, and Chongqing implemented government green subsidies earlier, which might affect the regression outcomes—we exclude their data for regression analysis. The specific results are detailed in Table 3 (3). It is evident that even after removing outliers, the regression coefficients remain significantly positive at the 5% level.

4.2.4. Excluding Policy Shocks

Another challenge regarding our regression results lies in the inevitable interference from exogenous policies during the same period when verifying the impact of government green subsidies on corporate ESG performance. To ensure the accuracy of the regression estimates, we controlled for the "Broadband China Policy" (BCP) during the same period. Accordingly, we construct a dummy variable for the Broadband China Policy (BCP) and incorporated it into the regression analysis. The specific regression results are detailed in Tables 3 (4). After excluding the influence of exogenous policies, the regression coefficients remain positive and statistically significant at the 5% level. This demonstrates the robustness of our conclusions.

Additionally, we analyze policies from the concurrent "National Big Data Comprehensive Pilot Zone" (Bigdata). Based on this, we construct a policy dummy variable for the "National Big Data Comprehensive Pilot Zone" (Bigdata) and incorporated it into the regression analysis. The detailed regression results are presented in Table 3 (5). After excluding the influence of exogenous policies,

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the regression coefficients remain positive and statistically significant at the 5% level. This demonstrates the robustness of our conclusions.

4.2.5. Endogeneity Analysis

Due to the limitations of the data, the regression analysis may have omitted certain variables, thus facing endogeneity issues. However, the instrumental variables method can effectively mitigate this problem. We construct a partially linear instrumental variables model using double machine learning, with the specific setup as follows:

$$ESG_{it} = \beta_0 Subsidy_{it} + g(X_{it}) + U_{it} \quad (10)$$

$$Z_{it} = \beta_0 Subsidy_{it} + J_{it} \quad (11)$$

In this study, Z_{it} as an instrumental variable for $Subsidy_{it}$, we construct it by using the mean value of government green subsidies from other enterprises within the same province, incorporating it into the regression analysis. This variable satisfies the exogeneity and correlation assumptions of instrumental variables. Detailed regression results are presented in Table 3 (6). After introducing the instrumental variable, the regression coefficients remain positive and statistically significant at the 5% level. This fully validates the robustness of our conclusions.

4.2.6. Reset the Double Machine Learning Models

To address potential biases in the conclusions caused by configuration errors in the dual machine learning model, we conduct two validation approaches: first, adjusting the sample partition ratio from the original 1:4 to 1:9 to examine its impact on results. Second, replacing the prediction algorithm from random forest to gradient boosting, lasso regression, and ensemble machine learning methods to assess their influence. The updated regression results are detailed in Table 4. Notably, both the adjusted sample partition ratio and algorithm changes yielded significantly positive regression coefficients, maintaining the conclusion that government green subsidies enhance corporate ESG performance. These findings conclusively demonstrate the robustness of the original conclusions.

Table 4. The Results of Double Machine Learning Robustness Tests.

Variable	Sample Splitting Ratio 1： 9	Gradient Boosting	Lasso Regression	Ensemble Machine Learning
	(1)	(2)	(3)	(4)
	ESG	ESG	ESG	ESG
Subsidy	0.0131**	0.0232***	0.0138***	0.0151***
	(2.2114)	(4.2547)	(2.9627)	(3.3568)
_cons	-0.0273*	-0.0064	-0.0316**	-0.0186
	(-1.8157)	(-0.3851)	(-2.2823)	(-1.3776)
CV First-order	Yes	Yes	Yes	Yes
CV Second-order	Yes	Yes	Yes	Yes
Enterprise FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	2337	2337	2337	2337

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors in parentheses.

5. Further Discussion

5.1. Mediating Effeccts

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5.1.1. Digital Technology Innovation

To examine how government green subsidies enhance digital technology innovation and subsequently improve corporate ESG performance, we develop a measurement model based on the International Patent Classification System (IPC) to assess digital technological innovation through regression analysis. The regression results of government green subsidies on digital technological innovation are presented in Tables 5 (1) and 5 (2), with statistically significant positive coefficients. These findings confirm that government green subsidies effectively boost digital technological innovation.

Table 5. The Results of Mediators.

Variable	(1) DTI	(2) ESG	(3) TCE	(4) ESG
Subsidy	0.2346***	0.0338**	0.0015**	0.0503***
	(9.0115)	(2.0390)	(2.3745)	(3.1038)
DTI		0.0788***		
		(5.4654)		
TCE				1.4800***
				(2.9236)
_cons	0.0059	-0.0204	0.0047***	-0.0269*
	(0.2796)	(-1.3979)	(8.4926)	(-1.7800)
CV First-order	Yes	Yes	Yes	Yes
CV Second-order	Yes	Yes	Yes	Yes
Enterprise FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	2586	2586	2586	2586

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors in parentheses.

Government green subsidies effectively enhance corporate Environmental, Social, and Governance (ESG) performance by supporting digital technology innovation. Technologies such as the Internet of Things (IoT), big data analytics, and artificial intelligence (AI) enable businesses to monitor resource consumption in real-time, optimize energy efficiency, and reduce carbon emissions (Zhao & Cai, 2023). For instance, smart sensors can track factory energy usage, promptly identify and resolve waste issues, thereby improving environmental performance. Through blockchain and big data technologies, companies gain greater transparency in supply chain management, ensuring legal sourcing of raw materials and compliance with social responsibility standards (Zahid et al., 2023). This not only strengthens corporate social image but also boosts their reputation in societal dimensions. Cloud computing and collaborative platforms support enterprises in establishing more efficient governance structures, enhancing decision-making transparency and risk management capabilities (J. Wang, Hong, et al., 2023). Digital management systems, for example, can detect potential operational risks in real-time, allowing timely strategy adjustments to improve governance effectiveness. These advancements fully validate how government green subsidies empower digital innovation to optimize resource allocation, increase information transparency, and strengthen governance capacity, ultimately elevating corporate ESG performance. H2 has been validated.

5.1.2. Technical Conversion Efficiency

To examine how government green subsidies enhance corporate ESG performance through improved technology transfer efficiency, we measure this efficiency using technology transaction activity and conducted regression analysis. The regression results of government green subsidies on

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technology transaction activity are presented in Tables 5 (3) and 5 (4), with positive regression coefficients that are statistically significant at the 1% level.

Government green subsidies can significantly enhance corporate ESG performance by improving technology transfer efficiency. These subsidies provide enterprises with financial and resource support to facilitate the practical application of environmental technologies. For instance, they can fund R&D and promotion of clean energy technologies, energy-saving equipment, and pollution control facilities (J. Wang, Hong, et al., 2023). Such support reduces costs and risks during technology transfer, accelerating the transition from lab to production lines. Through technological transformation, companies can optimize resource utilization and boost productivity (Clément et al., 2022). The adoption of automation and smart technologies helps minimize resource waste, lower energy consumption, and reduce carbon emissions. Moreover, technology transfer enables enterprises to recycle waste materials, thereby minimizing environmental impact. The efficiency gains from technology transfer directly translate into improved ESG performance (Bin-Feng et al., 2024). Environmentally, companies can cut carbon footprints and pollutant emissions while enhancing environmental management capabilities. Socially, it fosters greater social responsibility through initiatives like community impact reduction and employee welfare improvement. Governance-wise, it allows enterprises to establish more robust environmental management systems with increased transparency and accountability. This fully demonstrates that government green subsidies can elevate corporate ESG performance by boosting technology transfer efficiency. H3 is validated.

5.2. Heterogeneity Analysis

5.2.1. Fintech Digitalization Level

The digitalization process of China's fintech industry exhibits a gradient pattern, and the impact of government green subsidies on corporate ESG performance shows significant heterogeneity under different levels of technological penetration. To examine the differences in how government green subsidies affect corporate ESG performance across varying levels of fintech digitalization, we divide all sample enterprises into three tiers, lower, moderate, and higher, based on the mean value of Peking University's Digital Inclusive Finance Index, and conducted grouped regression analysis. The specific regression results are shown in Table 6. It can be observed that in the subgroup regression with corporate ESG performance as the dependent variable for enterprises with low fintech digitalization levels, the regression coefficient of government green subsidies is not statistically significant. However, for enterprises with high and medium fintech digitalization levels, the regression coefficient shows a significantly positive correlation. This indicates that government green subsidies significantly enhance the ESG performance of enterprises with high fintech digitalization levels, but fail to effectively improve the ESG performance of enterprises with low fintech digitalization levels.

Table 6. The Heterogeneity Results of Fintech Digitalization Level.

Variable	**Low**	**Medium**	**High**
	(1)	**(2)**	**(3)**
	ESG	**ESG**	**ESG**
Subsidy	-0.0092	0.0450***	0.0286***
	(-0.8653)	(4.3804)	(3.3681)
_cons	-0.0520**	-0.0271	-0.0274
	(-2.0093)	(-0.9263)	(-1.0189)
CV First-order	Yes	Yes	Yes
CV Second-order	Yes	Yes	Yes
Enterprise FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

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Year FE	Yes	Yes	Yes
Obs	780	780	777

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors in parentheses.

Government green subsidies play a pivotal role in driving corporate digital transformation by enhancing data processing capabilities, optimizing resource allocation efficiency, and improving information transparency, thereby boosting ESG performance (X. Wang, Zhang, et al., 2023). This effectiveness is closely tied to the level of fintech digitalization within enterprises. Companies with advanced or moderate digitalization can better integrate environmental subsidies into their transformation processes, strengthening green innovation capabilities and achieving higher levels of sustainable development (Ma et al., 2022). In contrast, firms with underdeveloped fintech digitalization often face limitations in utilizing government subsidies effectively due to insufficient overall digital infrastructure, making it difficult to convert financial support into momentum for ESG improvement. Particularly in regions or industries with concentrated such enterprises, the potential of subsidies remains underutilized, resulting in minimal positive impact on ESG outcomes. Therefore, the effectiveness of government green subsidies in elevating corporate ESG performance proves more pronounced among enterprises with high fintech digitalization levels.

5.2.2. Environmental Regulation Intensity

Under varying environmental regulation intensities, government green subsidies demonstrate differentiated effects on corporate ESG performance. We measure regulatory intensity using the percentage of industrial pollution control investments relative to added value. To examine differences in subsidy impacts across regulatory tiers, we categorized firms into three groups based on average regulatory intensity: low, moderate, and high levels. The analysis reveals heterogeneous effects of Subsidy on ESG outcomes, as shown in Table 7. In the low-regulation group (Column 1), Subsidy's coefficient reaches 0.0287, statistically significant at the 1% level, indicating substantial regulatory-enhanced ESG improvements. The moderate-regulation group (Column 2) shows a 0.0152 coefficient at the 10% level, with both magnitude and significance markedly reduced compared to low-regulation firms. For high-regulation firms (Column 3), Subsidy's coefficient jumps to 0.0282, achieving statistical significance at the 5% level. This demonstrates that moderate regulatory intensity weakens the subsidy's ESG-enhancing effects, while high-regulation firms maintain similar coefficients to low-regulation counterparts.

Table 7. The Heterogeneity Results of Environmental Regulation Intensity.

Variable	**Low**	**Medium**	**High**
	(1)	**(2)**	**(3)**
	ESG	**ESG**	**ESG**
Subsidy	0.0287***	0.0152*	0.0282**
	(3.6138)	(1.8069)	(2.4945)
_cons	-0.0273	-0.0236	-0.0290
	(-1.0738)	(-0.7556)	(-1.0380)
CV First-order	Yes	Yes	Yes
CV Second-order	Yes	Yes	Yes
Enterprise FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	834	741	762

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors in parentheses.

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In scenarios with lenient environmental regulations, companies face minimal external pressure to engage in ESG-related activities. Government subsidies effectively supplement corporate investments in environmental governance, social responsibility fulfillment, and corporate governance optimization, thereby significantly enhancing ESG performance (Xia et al., 2022). Under moderate regulatory conditions, enterprises face external compliance pressures without reaching stringent constraints. The resource incentive effects of subsidies and corporate ESG strategy adjustments enter a "transitional coordination phase," weakening the direct promoting effect of subsidies on ESG (Shi & Li, 2022). When environmental regulations are stringent, rigorous external requirements compel companies to increase ESG investments to meet compliance and sustainability demands. Government subsidies effectively alleviate resource constraints during this process, thereby reinforcing the promoting effect of subsidies on ESG. Thus, environmental regulation levels exhibit heterogeneous effects on the relationship between Subsidy and corporate ESG performance (Lin et al., 2022). When environmental regulations are low or high, Subsidy's promoting effect on ESG performance is more pronounced; in moderate regulatory environments, this promoting effect becomes relatively weaker.

5.2.3. Enterprise Scale

The impact of government green subsidies on corporate ESG performance varies across enterprises with different scales, as measured by asset levels. To examine how subsidy effects differ across enterprise sizes, we categorized firms into three groups based on scale: small, medium, and large. As shown in Table 8, the coefficient for Subsidy is 0.0339 in the small-scale group (Column 1), statistically significant at the 1% level, indicating substantial ESG-enhancing effects for smaller enterprises. In the medium-sized group (Column 2), the coefficient drops to 0.0001, showing negligible statistical significance. For large-scale enterprises (Column 3), the coefficient remains insignificant at 0.0046, suggesting similar limited promotional effects of green subsidies.

Table 8. The Heterogeneity Results of Enterprise Scale.

Variable	Low	Medium	High
	(1)	(2)	(3)
	ESG	ESG	ESG
Subsidy	0.0339***	0.0001	0.0046
	(3.2211)	(0.0144)	(0.7142)
_cons	-0.0043	-0.0110	-0.0010
	(-0.1599)	(-0.4100)	(-0.0393)
CV First-order	Yes	Yes	Yes
CV Second-order	Yes	Yes	Yes
Enterprise FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	779	779	779

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, with robust standard errors in parentheses.

Small and medium-sized enterprises (SMEs) typically face constraints such as limited resources (funding, technology, etc.) and higher barriers to ESG-related investments (e.g., environmental governance equipment, social responsibility projects, governance structure optimization) (S. Li et al., 2022). Government green subsidies effectively bridge these resource gaps, driving SMEs to engage in ESG initiatives, thereby significantly enhancing their ESG performance. While larger enterprises generally have weaker resource constraints than SMEs, their resources remain insufficient and they may be in transitional development phases (Ade et al., 2020). The prioritization of ESG strategies or resource allocation efficiency often fails to align with subsidy mechanisms, making it difficult for

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government incentives to take effect. Large enterprises, however, possess relatively abundant resources where internal motivation for ESG investment or regular budgets can cover most needs (Tuffour et al., 2022). The incremental resources from government subsidies offer minimal marginal improvement to ESG performance. Moreover, the complexity of corporate governance structures in large enterprises may complicate subsidy allocation alignment with ESG objectives, further diminishing the impact of subsidies. Thus, the relationship between enterprise size and government green subsidies/ESG performance shows heterogeneity (Xia et al., 2022). Subsidies only enhance ESG performance when enterprises are small. For medium or large enterprises, the promoting effect becomes negligible. This reflects scale-dependent impacts of government green subsidies on ESG, where SMEs more readily access resources to boost ESG through subsidies.

6. Conclusions and Implications

6.1. Conclusions

This research takes all A-share listed companies in China from 2013 to 2023 as the research sample. After excluding financial and insurance companies, ST/*ST/PT status companies, and those with missing key indicators, a final sample of 2,337 observations is obtained. Using a dual machine learning model combined with baseline regression, robustness tests, mechanism tests, and heterogeneity analysis, this study systematically examines the impact of government green subsidies on corporate ESG performance. During the research process, we construct a digital technology innovation measurement model based on the International Patent Classification System (IPC), measure technology transformation efficiency through technology transaction activity, and introduce heterogeneity dimensions such as digital inclusive finance level, environmental regulation intensity, and firm size. Additionally, multiple robustness testing methods are employed, including replacing dependent variables, removing special-year data, controlling for exogenous policy shocks, using instrumental variable methods, and resetting the dual machine learning model, to ensure the reliability and scientific validity of the research conclusions.

The core research conclusions of this research are as follows:

Government green subsidies demonstrate a significant positive impact on corporate ESG performance. Baseline regression analysis reveals that the coefficient of government green subsidies remains statistically significant at the 1% level, regardless of whether control variables (including quadratic terms, firm fixed effects, industry fixed effects, and year fixed effects) are controlled. This indicates that through green subsidies, governments can effectively alleviate financial pressures for corporate green transitions, encouraging enterprises to increase investments in environmental governance, social responsibility fulfillment, and organizational structure optimization. Consequently, these measures enhance overall ESG performance, thereby validating Research Hypothesis H1.

Government green subsidies enhance the ESG performance of enterprises through digital technology innovation and technical conversion efficiency. The mediating effect results show that, on the one hand, the regression coefficient of government green subsidies on enterprise digital technology innovation is 0.2346***, and the regression coefficient of digital technology innovation on ESG performance is 0.0788***, indicating that government green subsidies can support enterprises in developing Internet of Things, big data, AI and other digital technologies, optimize resource allocation and information transparency, and improve ESG performance. On the other hand, the regression coefficient of government green subsidies on technical conversion efficiency is 0.0015**, and the regression coefficient of technical conversion efficiency on ESG performance is 1.4800***, suggesting that government green subsidies can accelerate the transformation of green technologies from laboratories to production lines, reduce pollution emissions and resource waste, and promote the improvement of ESG performance. This verifies research hypotheses H2 and H3.

The impact of government green subsidies on the ESG performance of enterprises shows heterogeneity. The results of heterogeneity analysis indicate that, in terms of the level of digital

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inclusive finance, the positive effect of government green subsidies on ESG is significant only in the medium and high-level groups, while it is not significant in the low-level group. In terms of the intensity of environmental regulations, the promoting effect of government green subsidies is more significant in the low and high-intensity groups, while it is weakened in the moderate-intensity group. In terms of enterprise scale, the positive effect of government green subsidies is significant only in the small-scale enterprise group, while it is not significant in the medium and large-scale enterprise groups, verifying research hypothesis H4.

6.2. Implications

Based on the above research conclusions, to further optimize the design of government green subsidy policies and more precisely promote the improvement of enterprises' ESG performance and economic green transformation, this research offers the following implications:

6.2.1. Differentiate the Design of Green Subsidy Policies

In view of the feature that the subsidy effect for "small-scale enterprises" and "enterprises in regions with low levels of digital inclusive finance" in heterogeneity analysis is more dependent on policy support, a differentiated subsidy system needs to be established.

Small and medium-sized enterprises (SMEs), facing challenges such as funding shortages and weak technological foundations, represent a "potential group" for ESG enhancement. It is recommended to expand green subsidy coverage for SMEs by lowering application thresholds, including streamlining approval processes and relaxing project initiation standards. A dedicated "Special Green Subsidy Fund for SMEs" should be established to support essential initiatives like purchasing environmental governance equipment and building ESG disclosure systems. This initiative aims to help SMEs overcome resource constraints and rapidly improve their ESG performance.

To address the challenges in digital inclusive finance for enterprises in underdeveloped regions, governments should collaborate with financial institutions to enhance digital infrastructure. For instance, fiscal subsidies could support local banks in developing "ESG + Digital Credit" products that link companies' green subsidy eligibility to their digital financing quotas. Simultaneously, establishing a "Digital Technology Empowerment Special Fund" would provide enterprises with subsidies for digital skills training and ESG data management system development. This initiative aims to boost data processing capabilities, ensuring green subsidies effectively translate into momentum for ESG enhancement.

6.2.2. Improve the Supervision of Subsidy Funds

Building a green subsidy fund tracking platform using blockchain technology requires enterprises to disclose in real-time the allocation of subsidy funds (such as R&D investments in digital technologies and procurement amounts for technology transfer equipment), while linking fund utilization efficiency to future subsidy eligibility. Companies failing to use funds for green innovation or technology transfer as mandated will have their subsidy application qualifications revoked for the next 3-5 years. Additionally, third-party institutions will conduct regular assessments of corporate ESG improvement outcomes, with evaluation results serving as critical criteria for subsidy disbursement. This mechanism aims to prevent the overemphasis on application but neglect of implementation phenomenon.

Governments should strengthen supporting incentives for technological innovation and commercialization. On one hand, enterprises engaged in digital technology innovation should receive not only direct financial subsidies but also additional tax benefits, such as increasing the R&D expense super deduction ratio to 100% and providing patent application fast-track support, to encourage greater adoption of IoT and AI technologies in ESG management. On the other hand, establishing a "government-enterprise-research" technology transfer platform is crucial. The

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government should cover pilot-scale production costs through subsidies, facilitating the alignment between green technologies from research institutions and corporate production needs. Furthermore, enterprises demonstrating high activity in technology transactions should receive additional subsidies and rewards to accelerate the transition of technologies from "laboratories" to "production lines".

6.2.3. Adjust the Relationship Between Environmental Regulation and Subsidy Policy Dynamically

Enterprises in low-regulation areas lack sufficient motivation for ESG investments. To address this, we should boost green subsidy standards (implementing tiered subsidies based on enterprises' ESG improvement levels) to incentivize corporate engagement. Simultaneously, we should gradually raise environmental access thresholds (establishing regional pollutant emission limits) to prevent companies from relying solely on subsidies while neglecting environmental compliance. This creates a dual-driven mechanism combining "subsidy incentives + regulatory pressure" to ensure sustainable progress.

To address the diminishing effectiveness of subsidies in moderately regulated regions, we should identify companies with outstanding ESG performance as benchmark enterprises. By publicly disclosing their subsidy utilization and ESG improvement cases, this approach will guide other enterprises to optimize resource allocation. Simultaneously, subsidy policies should be tailored according to industry characteristics (prioritizing energy-saving technologies for high-energy-consuming sectors and social responsibility initiatives for service industries) to enhance policy precision.

While enterprises in high-regulation regions face pressure to invest in ESG initiatives, the substantial compliance costs necessitate redirecting subsidies toward cost compensation (including subsidies for pollution control equipment upgrades and ESG disclosure expenses). Simultaneously, streamlining approval processes through a one-time environmental compliance verification system will enable businesses to meet stringent regulatory requirements while reducing operational costs. This approach ensures that subsidies effectively alleviate resource constraints while maintaining operational efficiency.

6.2.4. Promote the Linkage Between ESG Information Disclosure and Subsidy Policies

Referring to the Sino Securities Index ESG Rating, formulate unified corporate ESG disclosure guidelines for China, clarify the core disclosure indicators in the dimensions of environment (carbon emissions, energy consumption), society (employee welfare, supply chain responsibility), and governance (board independence, information transparency), and require enterprises to publicly disclose ESG reports annually to ensure that subsidy effects are measurable and assessable. Enterprises demonstrating complete and truthful ESG disclosures will be prioritized for green subsidies. Those with non-compliant disclosures or data falsification will have their subsidy eligibility suspended and face penalties. Meanwhile, the government regularly publishes reports on corporate ESG performance and subsidy utilization, subjecting these materials to public scrutiny to enhance policy transparency and credibility.

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References

1. Ade, I., Joseph, M., & Francis, D. (2020). Enterprise Risk Management Practices and Survival of Small and Medium Scale Enterprises in Nigeria. Studies in Business and Economics, 15(1). https://doi.org/10.2478/sbe-2020-0007
2. Albitar, K., Abdoush, T., & Hussainey, K. (2023). Do corporate governance mechanisms and ESG disclosure drive CSR narrative tones? International Journal of Finance and Economics, 28(4). https://doi.org/10.1002/ijfe.2625
3. Asante-Appiah, B., & Lambert, T. A. (2023). The role of the external auditor in managing environmental, social, and governance (ESG) reputation risk. Review of Accounting Studies, 28(4). https://doi.org/10.1007/s11142-022-09706-z
4. Athey, S., Tibshirani, J., & Wager, S. (2019). Generalized random forests. Annals of Statistics, 47(2). https://doi.org/10.1214/18-AOS1709
5. Autio, S., Laitala, E., & Kallio-Mannila, K. (2023). Evaluation of the Finnish action plan for the sustainable use of pesticides 2018–2022. Agricultural and Food Science, 32(1). https://doi.org/10.23986/afsci.122220
6. Ben-Michael, E., Feller, A., & Rothstein, J. (2021). The Augmented Synthetic Control Method. Journal of the American Statistical Association, 116(536). https://doi.org/10.1080/01621459.2021.1929245
7. Bin-Feng, C., Mirza, S. S., Ahsan, T., & Qureshi, M. A. (2024). How uncertainty can determine corporate ESG performance? Corporate Social Responsibility and Environmental Management, 31(3). https://doi.org/10.1002/csr.2695
8. Burke, J. J., & Hoitash, R. (2019). Auditor response to negative media coverage of client environmental, social, and governance practices. Accounting Horizons, 33(3). https://doi.org/10.2308/acch-52450
9. Cai, C., Tu, Y., & Li, Z. (2023). Enterprise digital transformation and ESG performance. Finance Research Letters, 58. https://doi.org/10.1016/j.frl.2023.104692
10. Cao, J., Li, W., & Xiao, S. (2022). Does mixed ownership reform affect private firms' ESG practices? Evidence from a quasi-natural experiment in China. Financial Markets, Institutions and Instruments, 31(2–3). https://doi.org/10.1111/fmii.12164
11. Chen, G., Han, J., & Yuan, H. (2022). Urban digital economy development, enterprise innovation, and ESG performance in China. Frontiers in Environmental Science, 10. https://doi.org/10.3389/fenvs.2022.955055
12. Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., & Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. Econometrics Journal, 21(1). https://doi.org/10.1111/ectj.12097
13. Clément, A., Robinot, É., & Trespeuch, L. (2022). Improving ESG Scores with Sustainability Concepts. Sustainability (Switzerland), 14(20). https://doi.org/10.3390/su142013154
14. Dai, J., & Zhu, Q. (2024). ESG performance and green innovation in a digital transformation perspective. American Journal of Economics and Sociology, 83(1). https://doi.org/10.1111/ajes.12541
15. Fang, L., & Zhao, S. (2023). On the green subsidies in a differentiated market. International Journal of Production Economics, 257. https://doi.org/10.1016/j.ijpe.2022.108758
16. García-Sánchez, I. M., Suárez-Fernández, O., & Martínez-Ferrero, J. (2019). Female directors and impression management in sustainability reporting. International Business Review, 28(2). https://doi.org/10.1016/j.ibusrev.2018.10.007
17. Han, F., Mao, X., Yu, X., & Yang, L. (2024). Government environmental protection subsidies and corporate green innovation: Evidence from Chinese microenterprises. Journal of Innovation and Knowledge, 9(1). https://doi.org/10.1016/j.jik.2023.100458
18. He, Z. L., Lim, K., & Wong, P. K. (2006). Entry and competitive dynamics in the mobile telecommunications market. Research Policy, 35(8 SPEC. ISS.). https://doi.org/10.1016/j.respol.2006.09.004
19. Hu, D., Qiu, L., She, M., & Wang, Y. (2021). Sustaining the sustainable development: How do firms turn government green subsidies into financial performance through green innovation? Business Strategy and the Environment, 30(5). https://doi.org/10.1002/bse.2746
20. Hu, Z., & Ge, Y. (2014). The geopolitical energy security evaluation method and a China case application based on politics of scale. Sustainability (Switzerland), 6(9). https://doi.org/10.3390/su6095682
21. Imperiale, F., Pizzi, S., & Lippolis, S. (2023). Sustainability reporting and ESG performance in the utilities sector. Utilities Policy, 80. https://doi.org/10.1016/j.jup.2022.101468

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 17 October 2025 doi:10.20944/preprints202510.1410.v1

22. Jaffe, A. B., Trajtenberg, M., & Fogarty, M. S. (2000). Knowledge Spillovers and Patent Citations: Evidence from a Survey of Inventors. American Economic Review, 90(2). https://doi.org/10.1257/aer.90.2.215
23. Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. Electronic Markets, 31(3). https://doi.org/10.1007/s12525-021-00475-2
24. Jia, F., Li, Y., Cao, L., Hu, L., & Xu, B. (2022). Institutional Shareholders and Firm ESG Performance: Evidence from China. Sustainability (Switzerland), 14(22). https://doi.org/10.3390/su142214674
25. Jiang, Z., Zhao, X., & Zhou, J. (2021). Does the Supervision Mechanism Promote the Incentive Effects of Government Innovation Support on the RD Input of Agricultural Enterprises? IEEE Access, 9. https://doi.org/10.1109/ACCESS.2020.3047839
26. Knittel, C. R., & Stolper, S. (2021). Machine Learning about Treatment Effect Heterogeneity: The Case of Household Energy Use. AEA Papers and Proceedings, 111. https://doi.org/10.1257/pandp.20211090
27. Kumar, S. (2023). A Review of ESG Performance as a measure of stakeholder's theory. Academy of Marketing Studies Journal, 27(S3).
28. Lee, E. T., & Li, X. (2022). Too much of a good thing? Exploring the curvilinear relationship between environmental, social, and governance and corporate financial performance. Asian Journal of Business Ethics, 11(2). https://doi.org/10.1007/s13520-022-00157-y
29. Li, S., Li, X., Zhao, Q., Zhang, J., & Xue, H. (2022). An Analysis of the Dimensional Constructs of Green Innovation in Manufacturing Enterprises: Scale Development and Empirical Testing. Sustainability (Switzerland), 14(24). https://doi.org/10.3390/su142416919
30. Li, Y., Tong, Y., Ye, F., & Song, J. (2020). The choice of the government green subsidy scheme: innovation subsidy vs. product subsidy. International Journal of Production Research, 58(16). https://doi.org/10.1080/00207543.2020.1730466
31. Li, Z., Pan, Y., Yang, W., Ma, J., & Zhou, M. (2021). Effects of government subsidies on green technology investment and green marketing coordination of supply chain under the cap-and-trade mechanism. Energy Economics, 101. https://doi.org/10.1016/j.eneco.2021.105426
32. Lin, T., Wang, L., & Wu, J. (2022). Environmental Regulations, Green Technology Innovation, and High-Quality Economic Development in China: Application of Mediation and Threshold Effects. Sustainability (Switzerland), 14(11). https://doi.org/10.3390/su14116882
33. Liu, H., & Lyu, C. (2022). Can ESG Ratings Stimulate Corporate Green Innovation? Evidence from China. Sustainability (Switzerland), 14(19). https://doi.org/10.3390/su141912516
34. Liu, Y., Failler, P., & Chen, L. (2021). Can mandatory disclosure policies promote corporate environmental responsibility?—quasi-natural experimental research on China. International Journal of Environmental Research and Public Health, 18(11). https://doi.org/10.3390/ijerph18116033
35. Lu, Y., Xu, C., Zhu, B., & Sun, Y. (2024). Digitalization transformation and ESG performance: Evidence from China. Business Strategy and the Environment, 33(2). https://doi.org/10.1002/bse.3494
36. Ma, W., Ren, Z., & Ke, H. (2022). Green Housing Subsidy Strategies Considering Consumers' Green Preference. Sustainability (Switzerland), 14(5). https://doi.org/10.3390/su14052748
37. Madison, N., & Schiehll, E. (2021). The effect of financial materiality on esg performance assessment. Sustainability (Switzerland), 13(7). https://doi.org/10.3390/su13073652
38. Mahesh, B. (2020). Machine Learning Algorithms - A Review. International Journal of Science and Research (IJSR), 9(1). https://doi.org/10.21275/art20203995
39. Manita, R., Bruna, M. G., Dang, R., & Houanti, L. (2018). Board gender diversity and ESG disclosure: evidence from the USA. Journal of Applied Accounting Research, 19(2). https://doi.org/10.1108/JAAR-01-2017-0024
40. Menicucci, E., & Paolucci, G. (2022). Board Diversity and ESG Performance: Evidence from the Italian Banking Sector. Sustainability (Switzerland), 14(20). https://doi.org/10.3390/su142013447
41. Mu, W., Liu, K., Tao, Y., & Ye, Y. (2023). Digital finance and corporate ESG. Finance Research Letters, 51. https://doi.org/10.1016/j.frl.2022.103426
42. Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management: Reinventing innovation management research in a digital world. MIS Quarterly: Management Information Systems, 41(1). https://doi.org/10.25300/MISQ/2017/41:1.03

43. Orazalin, N. (2019). Corporate governance and corporate social responsibility (CSR) disclosure in an emerging economy: evidence from commercial banks of Kazakhstan. Corporate Governance (Bingley), 19(3). https://doi.org/10.1108/CG-09-2018-0290
44. Pénin, J., Hussler, C., & Burger-Helmchen, T. (2011). New shapes and new stakes: a portrait of open innovation as a promising phenomenon. Journal of Innovation Economics & Management, n°7(1). https://doi.org/10.3917/jie.007.0011
45. Purbasari, R., Muhyi, H. A., & Sukoco, I. (2020). Actors and Their Roles in Entrepreneurial Ecosystem: A Network Theory Perspective: Cooperative Study in Sukabumi, West Java. Review of Integrative Business and Economics Research, 9(3).
46. Santín, D., & Sicilia, G. (2017). Dealing with endogeneity in data envelopment analysis applications. Expert Systems with Applications, 68. https://doi.org/10.1016/j.eswa.2016.10.002
47. Sarker, I. H. (2021). Machine Learning: Algorithms, Real-World Applications and Research Directions. In SN Computer Science (Vol. 2, Issue 3). https://doi.org/10.1007/s42979-021-00592-x
48. Shi, Y., & Li, Y. (2022). An Evolutionary Game Analysis on Green Technological Innovation of New Energy Enterprises under the Heterogeneous Environmental Regulation Perspective. Sustainability (Switzerland), 14(10). https://doi.org/10.3390/su14106340
49. Song, J., & Yan, X. (2023). Impact of Government Subsidies, Competition, and Blockchain on Green Supply Chain Decisions. Sustainability (Switzerland), 15(4). https://doi.org/10.3390/su15043633
50. Tan, X., Liu, G., & Cheng, S. (2024). How does ESG performance affect green transformation of resource-based enterprises: Evidence from Chinese listed enterprises. Resources Policy, 89. https://doi.org/10.1016/j.resourpol.2023.104559
51. Tu, J., Du, J., & Huang, M. (2023). Competition between Green and Non-Green Travel Companies: The Role of Governmental Subsidies in Green Travel. Sustainability (Switzerland), 15(9). https://doi.org/10.3390/su15097712
52. Tuffour, J. K., Amoako, A. A., & Amartey, E. O. (2022). Assessing the Effect of Financial Literacy Among Managers on the Performance of Small-Scale Enterprises. Global Business Review, 23(5). https://doi.org/10.1177/0972150919899753
53. Wang, C., Chen, P., Hao, Y., & Dagestani, A. A. (2022). Tax incentives and green innovation—The mediating role of financing constraints and the moderating role of subsidies. Frontiers in Environmental Science, 10. https://doi.org/10.3389/fenvs.2022.1067534
54. Wang, H., Jiao, S., Bu, K., Wang, Y., & Wang, Y. (2023). Digital transformation and manufacturing companies' ESG responsibility performance. Finance Research Letters, 58. https://doi.org/10.1016/j.frl.2023.104370
55. Wang, J., Hong, Z., & Long, H. (2023). Digital Transformation Empowers ESG Performance in the Manufacturing Industry: From ESG to DESG. SAGE Open, 13(4). https://doi.org/10.1177/21582440231204158
56. Wang, J., Ma, M., Dong, T., & Zhang, Z. (2023). Do ESG ratings promote corporate green innovation? A quasi-natural experiment based on SynTao Green Finance's ESG ratings. International Review of Financial Analysis, 87. https://doi.org/10.1016/j.irfa.2023.102623
57. Wang, W., Yu, Y., & Li, X. (2022). ESG performance, auditing quality, and investment efficiency: Empirical evidence from China. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.948674
58. Wang, X., Zhang, J., Ma, D., & Sun, H. (2023). Green Agricultural Products Supply Chain Subsidy Scheme with Green Traceability and Data-Driven Marketing of the Platform. International Journal of Environmental Research and Public Health, 20(4). https://doi.org/10.3390/ijerph20043056
59. WIPO. (2023). Guide to the International Patent Classification. In World Intelelctual Property Organization.
60. Xia, Q., Quan, M., Li, H., & Hao, X. (2022). Is environmental regulation works on improving industrial resilience of China? Learning from a provincial perspective. Energy Reports, 8. https://doi.org/10.1016/j.egyr.2022.03.168
61. Xiong, W., & Li, J. (2024). The Knowledge Spillover Effect of Multi-Scale Urban Innovation Networks on Industrial Development: Evidence from the Automobile Manufacturing Industry in China. Systems, 12(1). https://doi.org/10.3390/systems12010005

 doi:10.20944/preprints202510.1410.v1

62. Xu, J., Liu, F., & Shang, Y. (2021). R&D investment, ESG performance and green innovation performance: evidence from China. Kybernetes, 50(3). https://doi.org/10.1108/K-12-2019-0793
63. Yang, C., Zhu, C., & Albitar, K. (2024). ESG ratings and green innovation: A U-shaped journey towards sustainable development. Business Strategy and the Environment, 33(5). https://doi.org/10.1002/bse.3692
64. Yang, J. C., Chuang, H. C., & Kuan, C. M. (2020). Double machine learning with gradient boosting and its application to the Big N audit quality effect. Journal of Econometrics, 216(1). https://doi.org/10.1016/j.jeconom.2020.01.018
65. Yoo, Y., Boland, R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. Organization Science, 23(5). https://doi.org/10.1287/orsc.1120.0771
66. Yu, L., Xu, J., & Yuan, X. (2024). Sustainable Digital Shifts in Chinese Transport and Logistics: Exploring Green Innovations and Their ESG Implications. Sustainability (Switzerland) , 16(5). https://doi.org/10.3390/su16051877
67. Yu, X., Xu, Y., Zhang, J., & Sun, Y. (2022). The Synergy Green Innovation Effect of Green Innovation Subsidies and Carbon Taxes. Sustainability (Switzerland), 14(6). https://doi.org/10.3390/su14063453
68. Yuan, Y., Deng, Z., Chen, M., Yin, D., Zheng, J., Liu, Y., Liu, X., Zou, H., Zhang, C., & Sun, C. (2021). Changes in mental health and preventive behaviors before and after COVID-19 vaccination: A propensity score matching (PSM) study. Vaccines, 9(9). https://doi.org/10.3390/vaccines9091044
69. Zahid, R. M. A., Khan, M. K., Anwar, W., & Maqsood, U. S. (2022). The role of audit quality in the ESG-corporate financial performance nexus: Empirical evidence from Western European companies. Borsa Istanbul Review, 22. https://doi.org/10.1016/j.bir.2022.08.011
70. Zahid, R. M. A., Taran, A., Khan, M. K., & Chersan, I. C. (2023). ESG, dividend payout policy and the moderating role of audit quality: Empirical evidence from Western Europe. Borsa Istanbul Review, 23(2). https://doi.org/10.1016/j.bir.2022.10.012
71. Zhang, D., Meng, L., & Zhang, J. (2023). Environmental subsidy disruption, skill premiums and ESG performance. International Review of Financial Analysis, 90. https://doi.org/10.1016/j.irfa.2023.102862
72. Zhang, H., Liu, Q., & Wei, Y. (2023). Digital product imports and export product quality: Firm-level evidence from China. China Economic Review, 79. https://doi.org/10.1016/j.chieco.2023.101981
73. Zhang, K., Hu, M., & Dang, C. N. (2022). The Potential of Sino-Russian Energy Cooperation in the Arctic Region and Its Impact on China's Energy Security. Scientific Programming, 2022. https://doi.org/10.1155/2022/8943314
74. Zhang, X., Zhang, J., & Feng, Y. (2023). Can companies get more government subsidies through improving their ESG performance? Empirical evidence from China. PLoS ONE, 18(10 October). https://doi.org/10.1371/journal.pone.0292355
75. Zhao, X., & Cai, L. (2023). Digital transformation and corporate ESG: Evidence from China. Finance Research Letters, 58. https://doi.org/10.1016/j.frl.2023.104310
76. Zhong, Y., Zhao, H., & Yin, T. (2023). Resource Bundling: How Does Enterprise Digital Transformation Affect Enterprise ESG Development? Sustainability (Switzerland), 15(2). https://doi.org/10.3390/su15021319
77. Zhu, Y., Yang, H., & Zhong, M. (2023). Do ESG Ratings of Chinese Firms Converge or Diverge? A Comparative Analysis Based on Multiple Domestic and International Ratings. Sustainability (Switzerland), 15(16). https://doi.org/10.3390/su151612573