The Impact of Artificial Intelligence Policy on Corporate ESG Performance

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Abstract. This paper uses A-share listed companies from 2014 to 2024 as its sample to investigate the impact of artificial intelligence policies on corporate ESG performance. Empirical results indicate that the implementation of artificial intelligence policies significantly enhances corporate ESG performance. Further analysis reveals that the degree of a firm's digital transformation acts as a positive moderator on corporate ESG performance, whilst executive risk appetite acts as a moderator. Heterogeneity tests suggest that the positive impact of artificial intelligence policies on corporate ESG performance is more pronounced in non-state-controlled enterprises and non-heavy-polluting enterprises.

Keywords: artificial intelligence policy, ESG performance, digital transformation, executive risk appetite, multi-period double-difference model.

1 Introduction

Currently, the global technological revolution and industrial transformation have entered a phase of deep development. As a key driver of this new wave of industrial transformation, artificial intelligence has permeated every aspect of corporate production and operations, becoming a critical factor in advancing corporate innovation in digital technology[1], green innovation[2], and sustainable development[3]. The establishment of AI policies has created a vital platform for AI research and development, practical application, and industrial clustering, providing a natural quasi-experimental setting for evaluating the effectiveness of these policies.

Translated with DeepL.com (free version)Against the backdrop of the ongoing deepening of the 'dual carbon' strategy and the widespread societal acceptance of sustainable development principles, ESG performance has become a key metric for assessing the high-quality development of enterprises[4]. Existing research indicates that factors such as digital transformation[5] and green innovation[6] can significantly influence corporate ESG performance; however, there remains a relative scarcity of research examining how AI policies—as a systemic institutional arrangement—can influence corporate ESG performance by guiding technological adoption and management upgrades.

The implementation of AI policies, by improving regional digital infrastructure, can drive enterprises to optimise their production and operational models, enhance the efficiency of labour allocation, and reduce operational and management costs, thereby

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potentially exerting a profound influence on their ESG performance. Examining the relationship between artificial intelligence policy and corporate ESG performance can help provide new insights and pathways for sustainable economic development.

The marginal contributions of this study are primarily reflected in three aspects: Firstly, by examining ESG performance, this study explores a new frontier in AI policy research, offering fresh perspectives on theories related to corporate sustainability; secondly, it reveals the moderating effects of corporate digital transformation and executive risk appetite, clarifying the boundary conditions under which AI policies influence corporate ESG performance; thirdly, through heterogeneity analysis, it provides targeted practical guidance for different types of firms to respond effectively to policies and enhance their ESG performance, whilst also offering empirical evidence to assist the government in optimising policy implementation pathways.

2 Theoretical Analysis and Research Hypotheses

2.1 Artificial Intelligence Policy and Corporate ESG Performance

The establishment of the Artificial Intelligence Pilot Zone, through policy-driven institutional restructuring and the integration of technological factors, influences corporate ESG performance primarily through two mechanisms: improvements in environmental and social performance, and the optimisation of corporate governance structures. With regard to improvements in environmental and social performance, the pilot zones have significantly reduced the marginal investment costs for enterprises in the areas of real-time pollutant monitoring and supply chain compliance management through the allocation of dedicated funds, the development of public data platforms, and the centralised provision of computing infrastructure. This has enabled projects—such as the upgrading of emission-reduction equipment, employee safety measures, and the maintenance of community relations—which were previously suppressed due to financial constraints, to enter the decision-making process and be implemented. Concurrently, policy-driven deep integration of regulatory technology within the region and increasingly stringent disclosure standards have substantially reduced the scope for enterprises to evade external scrutiny through selective disclosure or data manipulation[7]. This has compelled enterprises to shift their approach to environmental governance and social responsibility from peripheral public relations activities to routine arrangements embedded within business processes, thereby accumulating verifiable performance improvements in areas such as emission intensity control, resource recycling and the stability of labour-management relations. With regard to the optimisation of corporate governance structures, the pilot zones have substantially strengthened the board's ability to counterbalance and monitor management's short-sighted decisions by supporting the implementation of artificial intelligence technologies in scenarios such as internal auditing and risk early warning. This has encouraged enterprises to incorporate sustainable development goals into their strategic resource allocation frameworks. Based on the above analysis, this paper proposes the following hypotheses:

H1: The establishment of AI pilot zones significantly enhances corporate ESG performance.

2.2 The Positive Moderating Effect of Corporate Digital Transformation

Corporate digital transformation serves as a vital bridge linking AI policies and ESG performance. Enterprises with a higher degree of digital transformation typically possess more mature digital infrastructure and more adaptable organisational learning mechanisms, enabling them to integrate the AI application scenarios guided by pilot zones into their own operational systems at a lower transition cost, thereby creating a synergistic pattern of 'external policy empowerment and internal efficient transformation'. Conversely, even when faced with equivalent policy incentives, enterprises with weak digital foundations will see the full release of the pilot zone's spillover effects inhibited by their lag in technological deployment efficiency, data governance capabilities, and organisational process adaptation. Based on this, this paper proposes the following hypothesis:

H2: The degree of enterprise digital transformation acts as a positive moderator in the relationship between AI policies and corporate ESG performance

2.3 The Negative Moderating Effect of Executive Risk Appetite

As the key decision-makers within an organisation, executives' risk appetites directly influence corporate decisions regarding the application of artificial intelligence (AI) technology and investment in ESG. Firms with executives who have a higher risk appetite tend to prioritise the maximisation of short-term gains; they may reduce resources allocated to long-term investments such as ESG, redirecting them instead to high-risk, high-return projects, thereby undermining the positive impact of AI policies on ESG performance. Conversely, firms with executives exhibiting lower risk preferences place greater emphasis on long-term sustainable development; they are more likely to actively respond to AI policies and increase investment in the ESG sector, thereby fully leveraging the enabling effects of such policies. Based on this, the paper proposes the following hypothesis:

H3: Executive risk preference acts as a negative moderator in the relationship between AI policies and corporate ESG performance

3 Research Design

3.1 Model Design

To examine the impact of the establishment of artificial intelligence pilot zones on corporate ESG performance, this paper constructs the following multi-period difference-in-differences model for regression analysis:

$$ESG_{it}=\alpha_0+\beta_1 DID_{it}+\gamma Controls_{it}+\mu_i+\lambda_t+\varepsilon_{it} \tag{1}$$

At the same time, to examine the moderating effects of a firm's digital transformation and senior management's risk appetite, this paper introduces interaction terms into the baseline model to construct the following model:

$$ESG_{it} = \alpha_0 + \beta_1 DID_{it} + \beta_2 Digit_{it} + \beta_3 DID_{it} \times Digit_{it} + \gamma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$ESG_{it} = \alpha_0 + \beta_1 DID_{it} + \beta_2 Risk_{it} + \beta_3 DID_{it} \times Risk_{it} + \gamma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Here, i denotes the firm and t denotes the year; ESGit is the dependent variable, representing firm i's ESG performance in year t; DIDit is the key explanatory variable, namely the interaction term between the treatment dummy variable (Treat) and the post-implementation dummy variable (Post). If the city in which the firm is located has been approved to establish an artificial intelligence pilot zone and is in a post-implementation year, DIDit takes the value 1; otherwise, it takes the value 0; Digitit represents the firm's level of digital transformation, Riskit represents executive risk appetite, and Controlsit comprises a set of control variables; μi is the firm-specific fixed effect, λt is the year-specific fixed effect, and εit is the random error term.

3.2 Variable Definitions and Data Sources

3.2.1 Variable Definitions. (1) Dependent variable: Corporate ESG performance (ESGit). Measured using the Huazheng ESG rating data, Huazheng ESG ratings are assigned values from 1 to 9 in ascending order; a higher value indicates a higher ESG rating and better corporate ESG performance.(2) Core Explanatory Variable: The National New Generation Artificial Intelligence Innovation and Development Pilot Zones are used as a proxy variable for AI policy (DID). If listed firm i, based in a city approved to establish an AI pilot zone, is approved as a pilot zone in year t, the firm is assigned a value of 1 in year t and thereafter; otherwise, it is assigned a value of 0.(3) Moderating variables:① Degree of corporate digital transformation (Digit). Drawing on existing research[8], we utilise technologies such as artificial intelligence, big data, cloud computing and blockchain to identify characteristic terms for digital transformation and construct a feature term map. Subsequently, negative and non-corporate-related expressions are filtered out, and Python is used to crawl relevant content from the data pool to perform keyword searches, matching and frequency counting. On this basis, the word frequencies of each key technology term are aggregated and log-transformed, ultimately completing the construction of the corporate digital transformation indicator system.② Executive Risk Appetite (Risk). Drawing on relevant academic research[9-11], Based on five aspects—asset structure, solvency, profit structure, profit distribution and cash flow—six indicators were selected: the proportion of risk assets to total assets, the debt-to-asset ratio, the core profit ratio, the retained earnings ratio, the self-financing ratio and the capital expenditure ratio. Principal component analysis was employed to extract the principal components, and a comprehensive evaluation of their levels was conducted. Theoretically, the six selected financial indicators reflect executives' risk preferences from different dimensions: a higher proportion of risk assets and a higher debt-to-asset ratio indicate that management is willing to assume greater investment and financial risks; a lower core profit ratio implies that the firm relies on non-recurring gains and losses, and that management has a higher tolerance for profit volatility; a higher retained earnings ratio reflects management's preference for using profits for expansionary reinvestment rather than dividends, demonstrating a propensity for risk-taking; an excessively high self-financing ratio suggests overconfidence and a tendency to avoid external oversight; a higher capital expenditure ratio indicates that the firm favours long-term, high-commitment strategic investments. These indicators collectively reveal the risk preferences demonstrated by senior executives through their actual financial decisions.(4) Control variables: Firm size (Size) is measured by the natural logarithm of total assets; firm leverage (Lev) is measured by the debt-to-asset ratio, i.e. the ratio of liabilities to assets; profitability (ROA) is represented by return on assets; Dual is a dummy variable, taking a value of 1 if the chairman and the CEO are held by the same person, and 0 otherwise; Board size (Board) is measured by the logarithm of the number of board members; Shareholding concentration (Top3) is represented by the sum of the shareholding proportions of the top three shareholders; Firm value (Tob) is measured by the Tobin Q ratio; Firm age (Age) is calculated as the number of years since the firm's establishment. Variable descriptions and descriptive statistics are presented in Table 1.

3.2.2 Data Sources. This study utilises data from Chinese A-share listed companies from 2014 to 2024 as the research sample, which was processed as follows: (1) Exclusion of financial sector companies; (2) Exclusion of ST and ST* listed companies; (3) Exclude samples with missing values for the main variables; ultimately, 32,644 observations were obtained. Furthermore, to account for the impact of outliers, all continuous variables were trimmed at the top and bottom 1%. The data used in this study were sourced from the CSMAR and Wind databases. Table 1 presents the descriptive statistics of the data.

Table 1. Results of descriptive statistics

Variable	N	Mean	SD	Min	Max
ESG	32,644	4.088	1.152	1	9
DID	32,644	0.248	0.432	0	1
Size	32,644	22.409	1.337	19.828	26.369
Lev	32,644	0.434	0.201	0.055	0.898
ROA	32,644	0.029	0.066	-0.257	0.191
Dual	32,644	0.278	0.448	0	1
Board	32,644	2.110	0.198	1.609	2.708
Top3	32,644	0.468	0.155	0.155	0.854
Tob	32,644	2.071	1.353	0.8289	8.612
Age	32,644	3.048	0.290	2.197	3.611

4 Empirical Analysis

4.1 Baseline Regression Results

This paper first examines the impact of artificial intelligence on corporate ESG performance. Columns (1) and (2) of Table 2 both control for firm and year fixed effects;

Column (1) does not include any other variables, whilst Column (2) includes control variables. The results indicate that the estimated coefficients for DID are both significantly positive at the 1% level, suggesting that the ESG performance of firms within the pilot zone is significantly better than that of firms outside the pilot zone. This empirical finding validates Hypothesis 1 outlined earlier, demonstrating that the artificial intelligence policy has significantly improved corporate ESG performance.

Table 2. Benchmark regression results

Variable	(1) ESG	(2) ESG
DID	0.168***	0.170***
	(0.029)	(0.027)
control	No	Yes
Observations	32,623	32,623
R-squared	0.460	0.480
Firm FE	Yes	Yes
Year FE	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1; t-values are shown in brackets

4.2 Robustness Tests and Endogeneity Control

4.2.1 Parallel Trends Test. To rule out any potential endogeneity in the selection of pilot areas—that is, unobservable differences in characteristics between the treatment and control groups—this study first tests the parallel trends hypothesist, the results of which are shown in Figure 1. Prior to the introduction of the AI policy, the coefficients of the core explanatory variables were not significant, and the parallel trends test was passed.

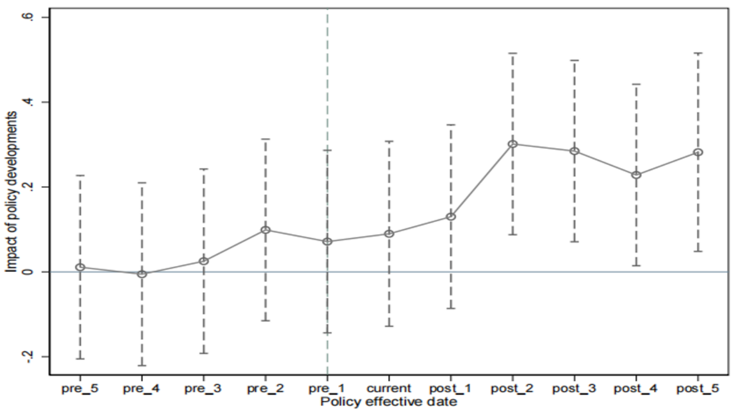

Fig. 1. Parallel Trends Test

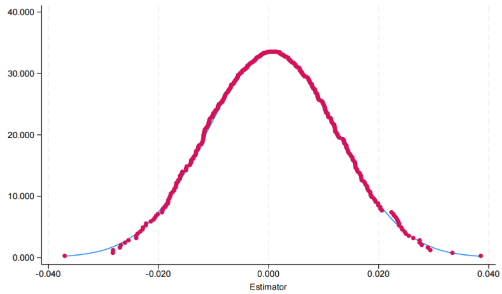

Fig. 2. Placebo test

4.2.2 Placebo Test. This paper uses a placebo test to verify the reliability of the benchmark regression results. Using the permutation test method, the core explanatory variables were randomly assigned 500 times, and the model was re-estimated. The results are shown in Figure 2, which indicates that the simulated coefficients are concentrated around zero and exhibit a symmetrical distribution. The actual estimated coefficients deviate significantly from this random distribution, and p-value tests indicate that fewer than 5% of the simulated results reach the significance level of the baseline regression. This result rules out the possibility of spurious regression caused by random factors, confirming the robustness of the baseline conclusions.

4.2.3 PSM-DID Test. To further mitigate endogeneity issues caused by unobservable time-varying confounding factors, this paper employs a randomised substitution test to assess the placebo effect. To this end, this paper uses control variables as matching variables and conducts PSM-DID estimation based on nearest-neighbour matching, caliper matching and radius matching, respectively. Balance tests indicate that there are no significant differences in characteristics between the groups after matching. As shown in columns (1) to (3) of Table 3, the estimated coefficients of DID are all significantly positive.

Table 3. Results of robustness tests

	(1) ESG	(2) ESG	(3) ESG	(4) ESG	(5) ESG	(6) ESG
DID	0.172*** (6.25)	0.170*** (6.09)	0.170*** (6.09)	0.165*** (6.25)	0.154*** (2.92)	
DID_2018						0.052 (1.62)
Observations	30,312	28,090	32,623	31,530	14,036	13,773
R-squared	0.488	0.493	0.480	0.483	0.480	0.677
control	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1; t-values are shown in brackets

4.2.4 Other robustness tests. ① To ensure that the empirical analysis in this paper is not influenced by other pilot policies, we exclude firms located in green finance policy pilot regions from the regression analysis. The results in Column (4) of Table 3 show that the coefficients of the core explanatory variables remain significantly positive, indicating that the conclusions of this paper are not affected by green finance policies. ② Given that the allocation of pilot regions may be associated with unobserved regional characteristics affecting ESG, this study excludes firms located in municipalities directly under the central government and provincial capitals from the regression analysis. The results in Column (5) of Table 3 show that the coefficients of the core explanatory variables remain significantly positive, indicating that even after controlling for potential confounding effects from municipalities directly under the central government and provincial capitals, the positive impact of the pilot policy on ESG remains robust, thereby supporting the reliability of the conclusions. ③ Given that firms with stronger ESG performance may have chosen to enter pilot regions in advance or adjusted their ESG performance ahead of time in anticipation of the AI policy, this paper assumes that the AI policy began to take effect in 2018. Accordingly, a dummy variable for the AI policy, DID_2018, is defined, and data from 2014 to 2018 are used to examine the impact of this dummy variable on firms' ESG performance. As shown in column (6) of Table 3, the estimated coefficient for DID_2018 is not significant, indicating that prior to the actual implementation of the AI policy, there was no significant trend difference in ESG performance between firms designated as the 'treatment group' and those in the control group.

5 Further Analysis and Heterogeneity Tests

5.1 Analysis of Moderating Effects

To test the moderating effects of corporate digital transformation and executive risk preference, Regression analyses were performed on Model (2) and Model (3) respectively. The specific results are shown in Table 4.

5.1.1 Moderating Effect of Corporate Digital Transformation. As shown in column (1) of Table 4, the coefficient of the interaction term between corporate digital transformation and AI policy is 0.024, which is significantly positive at the 10% level. This indicates that corporate digital transformation positively moderates the promotional effect of AI policy on corporate ESG performance. Hypothesis H2 is thus confirmed.

5.1.2 Moderating Effect of Executive Risk Appetite. As shown in Table 4, column (2), the coefficient of the interaction term between executive risk appetite and AI policy is –0.091, which is significantly negative at the 5% level. This indicates that executive risk appetite negatively moderates the positive effect of AI policy on corporate ESG performance. Hypothesis H3 is supported.

Table 4. Results of the moderation effect test

Variable	(1) ESG	(2) ESG
DID×Digit	0.024* (1.86)	
DID×Risk		-0.091** (-2.48)
Observations	32,623	32,623
R-squared	0.480	0.480
control	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1; t-values are shown in brackets

5.2 Heterogeneity Analysis

To investigate the heterogeneity in the impact of artificial intelligence policies on corporate ESG performance, this paper conducts a grouped regression analysis based on two dimensions: ownership structure and industry pollution levels. The results are shown in Table 5.

5.2.1 Based on the Heterogeneity of Property Rights. Based on differences in the nature of enterprise ownership, the entire sample was divided into two subsamples—state-owned enterprises and non-state-owned enterprises—and regression tests were conducted separately for each. As shown in columns (1) and (2) of Table 5, the results indicate that, in terms of improving corporate ESG performance, the policy has a more significant positive impact on non-state-owned enterprises than on state-owned enterprises. This difference may stem from the inherent divergence between the two types of enterprises in terms of institutional responsiveness and resource allocation logic. Driven by profit maximisation, non-state-owned enterprises have a stronger incentive to adopt technological policies that reduce information asymmetry and enhance operational efficiency. The smart monitoring and data middleware systems introduced in the pilot zones help them achieve environmental compliance and supply chain transparency at a lower cost, which in turn rapidly translates into tangible improvements in ESG ratings. By contrast, whilst state-owned enterprises bear multiple policy objectives, their environmental and social governance practices are already subject to a high degree of administrative regulation, leaving limited scope for marginal improvement through the pilot scheme. Consequently, the catalytic effect of the pilot scheme on the ESG performance of non-state-owned enterprises is more pronounced.

5.2.2 Heterogeneity Based on Enterprise Pollution Levels. To clarify the differing impacts of AI policies on the ESG performance of various enterprise types, this paper categorises enterprises into heavily polluting and non-heavily polluting enterprises. The regression results are presented in Table5 , columns (3) and (4). The results indicate that AI policies are more effective in promoting the ESG performance of non-heavy-polluting enterprises. This suggests that non-heavy-polluting enterprises experience a stronger policy impact compared to heavy-polluting enterprises. This may be because heavy-polluting enterprises face stricter environmental compliance pressures, with management focusing primarily on meeting basic emission standards rather than systematically improving overall ESG performance, In contrast, the production processes and organisational structures of non-heavy-polluting enterprises possess greater flexibility and adaptability, enabling them to integrate AI into environmental data collection, risk assessment and decision-making optimisation at lower transaction costs. Consequently, they can achieve a more rapid improvement in ESG performance, making the impact of AI policies on non-heavy-polluting enterprises more direct and pronounced.

Table 5. Results of heterogeneity analysis

	(1)	(2)	(3)	(4)
	SOEs	non-SOEs	HPEs	non-HPEs
DID	0.081*	0.209***	0.125*	0.147***
	(1.70)	(6.13)	(1.76)	(4.91)
Observations	11,312	21,248	7,213	25,383
R-squared	0.501	0.490	0.491	0.490
control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1; t-values are shown in brackets

6 Conclusions

Firstly, artificial intelligence policies have significantly improved corporate ESG performance; the results remain robust following various tests of reliability, indicating that this systemic institutional arrangement can effectively drive sustainable corporate growth.

Second, the moderating effects reveal that the level of digital transformation positively moderates the relationship between policy and ESG, whilst executive risk appetite acts as a negative moderator; the higher a firm's level of digitalisation and the stronger its executives' risk-averse tendencies, the more pronounced the policy's ESG-enhancing effect.

Third, heterogeneity analysis reveals that the policy's effects vary according to firm characteristics, with a stronger positive impact on non-state-owned enterprises and non-heavy-polluting enterprises.

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