

Does Artificial Intelligence Promote Corporate Green Transformation? — Empirical Evidence from the “AI Innovation and Application Pilot Zone”

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Article

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Posted Date: October 5th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10570606/v1>

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Additional Declarations: No competing interests reported.

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— Empirical Evidence from the “AI Innovation and Application Pilot Zone”

Abstract

Based on a set of A-share companies traded in Shanghai and Shenzhen stock exchanges during the years of 2010-2023, the paper uses a Difference-in-Differences (DID) framework to examine how the AI Pilot Zone policy affected Corporate Green Transformation. The empirical evidence indicates that the creation of the AI Pilot Zone significantly promotes Corporate Green Transformation and even after a battery of parallel trend and placebo tests, it is still a strong result. In terms of mechanisms, the policy contributes to Corporate Green Transformation through improved Resource Allocation Efficiency, better Credit Availability, reduced Agency Costs and increased Green Innovation Numbers, Green Innovation Quality and Green Investment. Besides, other considerations like ESG, Green Finance Development Level, Digital Corporate Transformation and the degree of the Digital economy are major positive mediators of this relationship. The heterogeneity analysis shows that the positive impact of the policy is stronger in state-owned companies, companies in recessionary stages, in high-pollution sectors, in first-tier cities, and in companies without a previous green or digitized history. Taken together, the overall implications of these findings imply that the AI Pilot Zone has been quite successful in driving Corporate Green Transformation using multi-dimensional linkages and thus presents theoretical backing and policy lessons on how to improve the artificial intelligence policy structure and streamline the way towards green growth.

keywords: *Artificial Intelligence Pilot Zone; Corporate Green Transformation; Difference-in-Differences; Green Innovation; Emerging Markets*

1. Introduction

As climate change worsens and resources dwindle, ecological civilization has become a key global socioeconomic goal. Green low-carbon transformation is critical to high-quality development, addressing resource and environmental crises, and promoting human-nature harmony. As core economic actors, enterprises drive industrial upgrading and enhance national competitiveness. China's 13th and 14th Five-Year Plans have promoted green manufacturing and industrial systems through policy tools including the Green Industry Guidance Catalogue and Circular Economy Development Plan, offering direction and institutional support. Driven by these strategies, since 2012, China's energy consumption per unit of GDP and carbon emission intensity have decreased by more than 26% and 35% respectively, and the downward trend continues. China is among the countries with the fastest energy intensity reduction globally. In 2024, the carbon dioxide emission per 10,000 yuan of output value (operating income) of central enterprises

decreased by 2.4%, 13.9% lower than 2020. In 2024, there were 6,430 nationally accredited green factories in China's manufacturing industry, whose output accounted for about 20% of total manufacturing output, up 2 percentage points year-on-year. However, challenges including flawed corporate governance, insufficient market penetration of green technologies, unstandardized green definitions, and supply chain emission reduction barriers still hinder the effective implementation of modern corporate green transformation.

Artificial intelligence (AI), a foundational element of contemporary industrial systems, is an interdisciplinary field that studies methods, theories and application systems for simulating and expanding human intelligence. It is widely held that AI technologies and products will be a core driver of the Fourth Industrial Revolution (Agrawal et al., 2019). Currently, AI-based disruptive technologies are continuously generating new industries, business models and growth engines. China has launched multiple initiatives to promote AI development and technological innovation, releasing the New Generation Artificial Intelligence Development Plan in 2017. On May 21, 2019, the Ministry of Industry and Information Technology (MIIT) and the Shanghai Municipal People's Government launched the first pilot zone: the Shanghai (Pudong New Area) Artificial Intelligence Innovation and Application Pilot Zone, marking the official launch of the National Artificial Intelligence Innovation and Application Pilot Zone initiative (hereinafter referred to as the AI policy). In October 2019, Shenzhen and Qingdao joined Shanghai as the first batch of pilot cities; in February 2021, Beijing, Tianjin, Hangzhou, Guangzhou, and Chengdu were announced as the second batch; in September 2022, Nanjing, Wuhan, and Changsha were approved. By July 2025, 11 cities nationwide had been approved to establish these zones. In AI Pilot Zones, enterprises can adopt AI technology to improve resource efficiency, reduce environmental pollution, enhance production sustainability, and address the challenge of green transformation.

This paper establishes a Difference-in-Differences (DID) model based on the set of A-share firms traded on the Shanghai and Shenzhen stock exchanges between 2010 and 2023, which will systematically examine the effect of the AI Pilot Zone policy on Corporate Green Transformation. The results are tested on parallel trends and placebo testing. In the mechanism analysis part of this paper, the author concentrates on intermediary pathways such as Resource Allocation Efficiency, Credit Availability, Agency Costs, Green Innovation Number, Green Innovation Quality and Green Investment as well as the inclusion of ESG, Green Finance Development Level, Digital Corporate Transformation and the Level of Digital Economy as variables of moderation and heterogeneity analysis.

The marginal contributions of this paper are mainly manifested in three aspects. To start with, it has introduced a new integration of AI Pilot Zone policy and Corporate Green Transformation hence expanding the scope of research on economic implications of AI policies. Secondly, it clarifies the underlying mechanisms that the policy uses to support Corporate Green Transformation in several dimensions, and enhances the theoretical connection between science and technology policies and green development. Thirdly, based on heterogeneity analysis, it performs systematic analysis on both enterprise, industry, and regional levels providing new empirical data to assess the impact of AI policy.

2. Literature Review

2.1 Corporate Green Transformation

The idea of the so-called Corporate Green Transformation did not originate from any one researcher, but is an academic consensus that has been developing over more than half a century. The crucial change happened in the 1990s, when scholars started to systematize the criticism of the formerly prevailing position that environmental and economic improvements are naturally divergent concepts, and formed the conceptual basis of green transformation (Porter and van der Linde, 1995; Hart, 1995). According to modern mainstream research, Corporate Green Transformation is a process of change that is systemic in nature, motivated by corporate strategy and focused on green innovation in order to attain synergistic gains in environmental, economic, and social performance metrics (Bansal and Roth, 2000; Hart and Milstein, 2003).

Due to the complexity of Corporate Green Transformation, its measurements are broadly divided into two methodological categories. The first category uses single-dimensional proxy variables. Green innovation measurement is dominant here, which is commonly measured by proxies including the volume of green patent applications (Li et al., 2023), the proportion of green patents in all patents (Wang and Ning, 2020), or citation numbers (Chen Guojin et al., 2021). Another common method measures production efficiency: it applies Green Total Factor Productivity (GTFP) (Zhou et al., 2021), which accounts for negative environmental externalities, or traditional Total Factor Productivity (TFP) (Hao et al., 2024), to capture quality and efficiency improvement brought by transformation. The second category adopts multi-dimensional comprehensive indices to better reflect the systemic nature of transformation. This includes researcher-built theoretical assessment systems, such as the comprehensive index by Li et al. (2023) covering environmental, economic and green innovation dimensions. With the development of data science, text analysis methods have emerged, which measure corporate green development orientation by counting the frequency of relevant keywords in annual reports (Zhang et al., 2025).

In terms of the determinants of Corporate Green Transformation, current literature focuses on four aspects: external pressure, internal drivers, managerial cognition, and digital empowerment. From the external pressure perspective, government regulation, market forces and societal forces are the main motivations. Most studies support the "Porter Hypothesis" (Porter and van der Linde, 1995), which holds that reasonably designed market-incentive regulations are more effective in promoting corporate green innovation than command-and-control regulations (Guenther et al., 2016). Meanwhile, social and market forces from consumers, supply chains, and non-governmental organizations directly catalyze transformation through reputation mechanisms. For internal drivers, corporate governance frameworks and resource capacities are the core factors determining transformation feasibility. Active governance arrangements such as institutional investor participation and board members' overseas experience enable effective implementation of corporate environmental responsibility (Lin et al., 2021), while technological capacity and capital are necessary material conditions, with capital shortage being the primary obstacle (Li et al., 2019). For managerial cognition, based on Upper Echelons Theory (Hambrick and Mason, 1984), top management teams' perception of the environment ultimately determines corporate strategy. When managers view environmental issues as value-creating opportunities rather than compliance costs, corporate endogenous motivation becomes a lasting driver (Martin et al., 2011). For digital empowerment, digital technologies provide new paths for transformation.

Shi and Chang (2024) found that digitalization can promote green innovation by improving information processing capacity and resource allocation efficiency. However, this effect requires caution: digital technology's own energy consumption may bring a rebound effect (Sorrell, 2009), leaving uncertainty about its overall environmental impact.

2.2 AI Policy

National Artificial Intelligence Innovation and Application Pilot Zone (also known as AI Pilot Zone) is a demonstration sector established by China's Ministry of Industry and Information Technology to strengthen the connection between artificial intelligence and the real economy. Driven by open application scenarios, AI Pilot Zones are built as AI innovation sources and industrial highlands through core technological breakthroughs, computing power infrastructure layout, and industrial ecosystem development. Starting from 2019, Shanghai, Shenzhen, and Jinan-Qingdao became the first batch of national pilot zones. By 2025, there are 11 national pilot zones across China: Shanghai, Shenzhen, Jinan-Qingdao, Beijing, Tianjin, Hangzhou, Guangzhou, Chengdu, Nanjing, Wuhan and Changsha. Each zone focuses on different fields such as smart manufacturing, smart city, healthcare and autonomous driving, aiming to promote the in-depth integration of artificial intelligence and the real economy. All zones develop based on regional resource endowments and form diversified development models, as shown in Table 1.

Table 1: Overview of China National Artificial Intelligence Innovation and Application Pilot Zones

<i>batch</i>	<i>Approval time</i>	<i>Pilot Zone Name</i>	<i>Key Application Areas and Development Priorities</i>
<i>the first batch of</i>	<i>May/October 2019</i>	<i>Shanghai (Pudong)</i>	<i>The focus lies in AI chips (Zhangjiang), smart finance (Lujiazui), intelligent manufacturing, and smart healthcare. Efforts will be made to promote the deep integration of AI algorithms, chips, and application scenarios.</i>
<i>the first batch of</i>	<i>May/October 2019</i>	<i>Shenzhen</i>	<i>Leveraging its robust electronic information industry, the region prioritizes the advancement of AI chips, smart hardware (particularly smart terminals), intelligent finance, and AI-assisted urban governance.</i>
<i>the first batch of</i>	<i>May/October 2019</i>	<i>Jinan-Qingdao</i>	<i>This is a dual-core pilot zone. Jinan concentrates on smart healthcare and intelligent software; Qingdao, drawing on enterprises such as Haier, focuses on the industrial internet and smart home applications, while concurrently pursuing the development of smart ocean technologies.</i>
<i>Second batch</i>	<i>February 2021</i>	<i>Beijing</i>	<i>Capitalizing on its pool of top-tier research talent, the organization directs its efforts toward</i>

<i>batch</i>	<i>Approval time</i>	<i>Pilot Zone Name</i>	<i>Key Application Areas and Development Priorities</i>
			<i>algorithmic innovation and security, smart city systems (urban brain), smart governance, and intelligent connected vehicles.</i>
<i>Second batch</i>	<i>February 2021</i>	<i>Tianjin (Binhai)</i>	<i>Capitalizing on its port and manufacturing strengths, the region will prioritize developing smart ports (Tianjin Port), smart manufacturing, and information technology innovation industries.</i>
<i>Second batch</i>	<i>February 2021</i>	<i>Hangzhou</i>	<i>Capitalizing on the strengths of the digital economy (e.g., Alibaba), the focus will be on developing the City Brain (the birthplace), smart retail/e-commerce, smart finance (FinTech), and smart healthcare.</i>
<i>Second batch</i>	<i>February 2021</i>	<i>Guangzhou</i>	<i>Capitalizing on its established trade and automotive industry, the region will prioritize the development of intelligent connected vehicles, smart logistics, smart cities (including transportation governance), and smart healthcare.</i>
<i>Second batch</i>	<i>February 2021</i>	<i>Chengdu</i>	<i>Capitalizing on the central role of the western region in healthcare and cultural tourism, the focus will be on developing smart healthcare (e.g., West China Hospital), smart cultural tourism, smart finance, and smart agriculture.</i>
<i>The third batch</i>	<i>September 2022</i>	<i>Nanjing</i>	<i>With its strong software industry foundation, the focus is on developing intelligent software, smart chips, smart manufacturing, and smart grids.</i>
<i>The third batch</i>	<i>September 2022</i>	<i>Wuhan</i>	<i>Relying on "China Optics Valley" and scientific and educational resources, the focus will be on developing intelligent manufacturing (especially intelligent optoelectronics), intelligent remote sensing, intelligent connected vehicles, and smart healthcare.</i>
<i>The third batch</i>	<i>September 2022</i>	<i>Changsha</i>	<i>Capitalizing on its distinctive industries, the region prioritizes the development of intelligent construction machinery (e.g., Sany Heavy Industry), smart connected vehicles, and smart cultural and creative media (e.g., Malanshan).</i>

When it comes to analyzing the economic implications of artificial intelligence policies, there are four major perspectives that have been widely used in the available literature on the issue and

these are regional economic development, firm-level performance, labor market dynamics and corporate green transformation.

In terms of regional economy, AI Pilot Zone policy effectively develops industrial clusters and innovation ecosystems by gathering innovation-related factors. Studies show that through fiscal and taxation incentives, talent support and application scenario construction, the policy gathers leading AI enterprises, R&D centers and venture capital, generating significant agglomeration economy effects (Marshall, 2009). This agglomeration promotes the development of upstream and downstream of the AI industry chain, drives the transformation of traditional industries through technology diffusion, and finally promotes the coordinated development of regional economy (Klein & Crafts, 2020).

In terms of firm performance, AI policies boost corporate production efficiency and innovation capability by promoting AI technology application. Empirical studies show that AI technological innovation significantly improves corporate total factor productivity (Chen et al., 2019). The effect works through multiple channels: AI reduces labor input and management costs via automation and intelligent transformation (Wang and Dong, 2020), optimizes marketing and other processes through data-driven precision decision-making, realizing overall cost reduction and efficiency improvement (Cheng, 2021). This AI-based transformation is generally regarded as a core driving force for developing New Quality Productive Forces (Qi et al., 2023; Jiang, 2024).

AI application causes significant structural changes in the labor market. As a type of Skill-Biased Technological Change (SBTC), AI simultaneously creates new job demands and replaces repetitive routine work, leading to the coexistence of substitution and creation effects (Acemoglu and Restrepo, 2019). Existing literature shows that AI has different impacts on workers with different skills, causing labor market polarization: employment in high-skill and low-skill positions grows, while employment in middle-skill positions declines (Autor et al., 2021; Goos and Manning, 2022).

In the context of corporate green development, the economic impact of AI policies extends to the environmental field, producing both positive and negative dual effects. First, AI technologies can transform the corporate green industry through accurate monitoring, production process optimization and green R&D promotion, bringing significant environmental co-benefits (Kaginalkar et al., 2021). Studies also show that AI is positively correlated with corporate ESG performance, helping enterprises turn green development goals into practical innovation outcomes (Yin and Zeng, 2023). On the contrary, large AI model training and data center operation consume huge amounts of energy, and their inherent carbon footprint is a severe challenge, forming an efficiency paradox (Chu et al., 2024).

Overall, existing relevant literature can be summarized into two distinct but increasingly integrated research lines. The first focuses on Corporate Green Transformation, constructing a multi-level analysis framework covering external pressures (regulation, market), internal factors (governance, capability), managerial cognition and digital empowerment, and deeply analyzes the multiple driving factors for corporate sustainable development. The second focuses on evaluating the social and economic impacts of AI policies, confirming that AI policies can promote regional

industrial agglomeration and improve corporate productivity, while also revealing their impact on labor market structure changes and initially discussing their dual environmental effects.

Theoretical Analysis and Research Hypotheses

This research suggests that national-level artificial intelligence policies, as exogenous institutional forces, constitute a systematic strategy to promote corporate green transformation. The core transmission mechanism is as follows: AI policies promote the application of applicable technologies, which effectively improve internal resource allocation efficiency and reduce agency costs, thus freeing organizational resources and financial support for green strategic planning (Liu et al., 2025). Meanwhile, such policies support R&D activities, significantly improving the quantity and quality of green innovation and providing necessary technological impetus for transformation (Shen et al., 2024).

In terms of cost saving and productivity improvement, AI policies guide enterprises to adopt machine learning, predictive analytics and other technologies, which optimize supply chain management and production processes, and reduce resource misallocation and waste through accurate prediction and real-time control (Hassanein and Tharwat, 2023). Under policy incentives, AI-based intelligent monitoring and data analysis systems improve operational transparency, reduce information asymmetry between managers and shareholders, and enhance the effectiveness of internal supervision. The resulting improvement in resource allocation efficiency and reduction in agency costs form an important resource foundation for corporate green transformation. As a capital-intensive long-term initiative, green transformation requires sufficient idle resource support to start and maintain (Hina et al., 2024a; Hina et al., 2024b). Lower agency costs ensure that new resources can be more effectively directed to green development goals that serve the long-term interests of shareholders.

In terms of investment and finance, AI policies improve credit availability and corporate green investment potential by increasing information transparency. Driven by policies, AI systems integrate and process massive internal and external data, conduct more accurate dynamic assessment of corporate operating conditions and environmental performance, significantly reducing information asymmetry between enterprises and external capital providers (Zhou & Zhu, 2024). Improved credit availability directly promotes corporate green transformation. Corporate green transformation is capital-intensive: it requires technology R&D and equipment upgrading, and is highly dependent on external financing (Kumar et al., 2025). AI policies expand corporate financing scale, especially for green credit, by improving information disclosure and data analysis capabilities, removing financial constraints for large-scale green projects and accelerating the transition to sustainable development models.

From the perspective of green innovation, AI policies improve both the quantity and quality of green innovation by optimizing the R&D process. As a policy-supported general-purpose technology, AI significantly reduces R&D time by automating repetitive research tasks, accelerating large-scale data processing and simulating complex processes, promoting the growth of green innovation patents (Zhao and Wang, 2025). Improved quantity and quality of green innovation form the core technological foundation for corporate green transformation. Policies

can guide enterprises to shift from traditional end-of-pipe treatment to proactive source prevention and circular economy models via green innovation, which is a core symbol of in-depth green transformation (Anim, Mahmoud and Odoom, 2025a). High-quality green innovation reduces corporate carbon emission intensity, and is the most direct way to fundamentally improve environmental footprints and achieve balanced development of economic benefits and environmental protection (Naeem and Siddique, 2024).

Based on the foregoing analysis, this paper proposes Hypothesis 1 and Hypothesis 2:

H1: The AI Pilot Zone policy can improve the level of Corporate Green Transformation.

H2: The AI Pilot Zone policy has the potential to enhance the degree of Corporate Green Transformation through decreasing Agency Costs, enhancing the efficiency of Resource Allocation, boosting the availability of Credit and Green Investments, and raising the count and quality of Green Innovations.

Better ESG performance indicates that a company has endogenous strategic willingness to pursue sustainable development, and its transformation direction is highly consistent with the incentive orientation of AI policies (Eccles, Ioannou and Serafeim, 2014). This strategic consistency enables the technological potential brought by policies to be effectively integrated with enterprises' existing green structures, generating synergistic effects. Companies with better ESG performance generally have complete green governance frameworks and can integrate AI technologies into management systems more quickly (Grewal and Serafeim, 2020). Therefore, good ESG performance creates conditions for effective policy implementation, maximizes the absorption and transformation of policy dividends, and thus significantly enhances the promoting effect of AI policies on Corporate Green Transformation.

Based on absorptive capacity theory, a company's Digital Corporate Transformation level is a fundamental factor affecting its ability to identify, absorb and apply new external technologies (Cohen and Levinthal, 1990). Highly digitized companies have built digital infrastructure and data management capabilities, enabling them to integrate new technologies and solutions brought by AI policies more quickly. This first-mover advantage of digitalization reduces the barriers and costs of AI technology adoption, helping companies convert policy orientation into actual results in green innovation and operational efficiency more effectively (Zahra and George, 2002). Therefore, as an organizational capability, higher level of Digital Corporate Transformation improves the implementation effect of AI policies.

Per the Porter Hypothesis, appropriate environmental regulations and intense industry competition force enterprises to gain new competitive advantages through innovation (Porter and van der Linde, 1995). AI policies clarify that green transformation is the strategic path to cost reduction, efficiency improvement and differentiated competitiveness. Adopting AI to achieve green transformation is not only an option under high industry competition (proxied by HHI), but also a key strategy to maintain competitiveness. Peer pressure pushes enterprises to respond more actively to policy incentives to avoid falling behind in green technology competition, thus amplifying the overall policy effect (DiMaggio and Powell, 1983).

City-level Green Finance Development Level is an important external support environment for enterprises to respond to national policies (Salazar, 1998). Cities with mature green financial markets provide local enterprises with more diverse green financing tools at lower costs. This positive external financial ecosystem strengthens the investment and financing transmission process of national AI policies, helping enterprises translate technical improvement and credit enhancement into capital support for green initiatives (Chassagnon and Haned, 2015). Therefore, urban green finance development enhances the impact of national policies on green investment and transformation by reducing the friction cost of capital allocation.

A city's overall Digital Economy level brings significant positive externalities to local enterprises, forming a supportive innovation ecosystem (Audretsch & Feldman, 1996). Enterprises can obtain more complete digital infrastructure, sufficient AI talent stock and knowledge spillovers through connections with technology enterprises and research institutions. This favorable local environment reduces the cost and risk of individual enterprises implementing and applying AI technologies, making enterprises respond more strongly to national policies (Jaffe, Trajtenberg and Henderson, 1993). Thus, a better-developed urban digital economy improves enterprises' ability to obtain policy dividends, and strengthens the positive effect of AI policies on Corporate Green Transformation.

Based on the above analysis, Hypothesis 3 is proposed:

H3: ESG, Digital Corporate Transformation, HHI (industry competition level), Green Finance Development Level, and the Level of Digital Economy may enhance the promotional impact of the policy on Corporate Green Transformation.

3. Research Design

3.1 Model Specification

3.1.1 Benchmark Regression Model

To examine the impact of the AI Pilot Zone on Corporate Green Transformation, the following regression model is constructed:

$$CGT_{it} = \alpha_0 + \alpha_1 inter_{it} + \alpha_2 Control_{it} + \delta_i + \rho_t + \varepsilon_{it} \quad (1)$$

In the above equation, i represents the firm and t represents the year. The dependent variable is Corporate Green Transformation (CGT_{it}), and the explanatory variable is the AI Pilot Zone. $Control_{it}$ represents relevant control variables. δ_i denotes firm fixed effects, ρ_t denotes time fixed effects, and ε_{it} is the random disturbance term.

3.1.2 Mediation Effect Model

To investigate the process of the AI Pilot Zone on Corporate Green Transformation, the mediation effect analysis method will be used in this paper. Since the endogeneity estimation bias associated

with the traditional stepwise regression method of mediation effects (Jiang, 2022) will be present, this paper will test whether or not the mediation path exists and is valid by replacing the dependent variable with the mediating variable to see how the core explanatory variable influences the mediator. The mediation effect model is defined as follows:

$$M = \theta_0 + \theta_1 inter_{it} + \theta_2 Control_{it} + \delta_i + \rho_t + \varepsilon_{it} \quad (2)$$

When M symbolizes the mediators, which are the Resource Allocation Efficiency, Credit availability, Agency Costs, the number of green innovations, quality of green innovations, and green investments. The rest of the variables are compatible with Equation (1).

3.1.3 Moderation Effect Model

To examine the influence of various moderating variables on the results, the following model is constructed for in-depth discussion:

$$CGT_{it} = \vartheta_0 + \vartheta_1 inter_{it} + \vartheta_2 Z + \vartheta_3 inter_{it} \times Z + \vartheta_4 Control_{it} + \delta_i + \rho_t + \varepsilon_{it} \quad (3)$$

where Z represents the moderating variables, specifically including ESG, Level of Internal Control, HHI, Green Finance Development Level, Digital Corporate Transformation, and Level of Digital Economy. The remaining variables are consistent with Equation (1).

3.2 Variable Selection

3.2.1 Dependent Variable

The concept of Corporate Green Transformation (CGT): This is the main dependent variable of our study. The indicator of Corporate Green Transformation is defined as the indicator that directly considers negative externalities related to environmental pollution by the term Corporate Green Total Factor Productivity. In particular, measurement is done on the non-radial SBM-ML index model. Indicators of inputs include: Labor (measured as total number of employees), Capital (measured as net fixed assets), and Energy (urban industrial electricity consumption scaled based on the proportion of the enterprise workforce). The output indicators are divided into two groups: Desired Output (operating income), and Undesired Output (industrial sulfur dioxide, wastewater, and soot emissions scaled by the enterprise workforce ratio).

3.2.2 Explanatory Variable

The AI Pilot Zones ($inter$): These are national pilots used to foster the intensive adoption of artificial intelligence into the real economy. $Treat \times Post$ is the variable defined as the treatment group identifier ($Treat = 1$, if the company is registered in an AI pilot zone, and 0, otherwise). $Post$ means the timeline of the policy implementation ($Post = 1$, when the city was approved in the current year or later years, and 0, otherwise).

3.2.3 Mediating Variables

Resource Allocation Efficiency (RAE): In line with the methodological framework proposed by Richardson (2006), we use investment efficiency as a proxy in measuring the effectiveness of resource allocation. The indicator mainly reflects the degree of the corporate overinvestment. We will estimate a reasonable level of investment first and then determine the difference (residual) between the actual investment and this estimated level. The residuals which are positive are kept to indicate over-investment and those which are negative (meaning under-investment) are marked as zero.

Credit Availability (Flex): The variable reflects the ability of a company to borrow credit resources of banking institutions. It is estimated as the sum of the long-term borrowings and short-term borrowings of the firm at the end of the year divided by the total assets in the respective period. Higher ratio values are associated with greater ability to raise external debt financing.

Agency Costs (AC): The given indicator is a measure of how much interest conflict exists between owners and managers in the corporate structure. The proxy measurement used in this research is the Management Expense Ratio (the ratio of management expense to operating income). Higher ratios usually imply greater concerns about managerial perquisite consumption or inefficiency in operations, which in turn imply more serious agency problems.

Green Innovation Number (GIN): The variable measures the scope of corporate green research and development output. In this work, Green Innovation Number is measured in terms of the number of green patents applied to the enterprise throughout the current year as it represents the activity level and investment commitment of the enterprise in green innovation activities.

Quality of Green Innovations (GIQ): Green Innovation Quality is a measure of the technological quality and industrial contribution of the outcomes of corporate green innovations. In this research, the number of subsequent citations to green patents will be used as the measure. Higher rates of citations mean increased technological development and better market awareness of the patented invention.

Green Investment (GI): It indicates how much capital has been invested in environmental protection and green production. The green investment ratio is calculated as a part of this paper, which involves adding up the total number of projects concerning environmental protection, desulfurization, sewage treatment, etc., listed on the item of construction in progress in the financial statements of the company and then dividing the sum by the total assets of the company at the end of the period.

3.2.5 Control Variables

Based on the previous research, the variables that can influence Corporate Green Transformation are chosen as below:

Firm Size: Represented by the natural logarithm of the firm's total assets at the end of the year.

Top Shareholder's Ownership Ratio: Represented by the shareholding of the largest shareholder divided by the total share capital of the company.

Leverage Ratio: Represented by the firm's total liabilities at the end of the year divided by total assets at the end of the year.

Return on Assets = Net Profit / Total assets. Firm Age = -ln(current year - year of establishment + 1). Cash Holdings: It is measured as a ratio of net cash flow from operating activities to total assets. GDP of the Region: The Gross Domestic Product of the region. Industrial Upgrading of the Region: It is calculated as value-added of the tertiary industry divided by the value-added of the secondary industry in the region.

CEO-Chairman Duality: A value of 1 if the chairman and general manager are the same person, otherwise 0.

3.3 Data Source and Processing

*The research sample of this paper consists of A-share listed companies on the Shanghai and Shenzhen stock exchanges during the period of 2010-2023. Financial institution listed company samples, ST and *ST samples, and samples with missing corporate social responsibility data were eliminated. Continuous variables were all winzorized at the 1 percent and 99 percent. Finally, 30,582 observations were obtained. Pilot cities for the major explanatory variable AI Pilot Zone were derived based on the list of pilot cities provided by the Ministry of Industry and Information Technology (MIIT). The firm level data were extracted with the help of WIND and CSMAR databases. Stata 18.0 helped process data and perform regression analysis. Descriptive statistics of variables are presented in Table 2.*

Table 2 Descriptive Statistics

<i>VarName</i>	<i>Obs</i>	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Median</i>	<i>Max</i>
<i>CGT</i>	30582	1.0261	0.1076	0.8108	1.0375	1.2246
<i>inter</i>	30582	0.1156	0.3197	0.0000	0.0000	1.0000
<i>RAE</i>	30582	0.1215	0.1121	0.0000	0.0941	0.5565
<i>AC</i>	30582	0.0837	0.0639	0.0081	0.0677	0.3835
<i>GIN</i>	30582	0.6194	1.0321	0.0000	0.0000	4.5747
<i>GIQ</i>	30582	0.5421	0.2148	0.1483	0.5286	0.9868
<i>Flex</i>	30582	0.1733	0.1517	0.0000	0.1455	0.6001
<i>GI</i>	30582	19.5470	1.1345	17.2608	19.4073	23.0177
<i>DCG</i>	30582	1.2932	1.3659	0.0000	1.0986	5.0434
<i>ESG</i>	30582	4.2918	0.0668	4.0782	4.2955	4.4332
<i>LIC</i>	30582	6.4823	0.1332	5.7713	6.5050	6.7586
<i>HHI</i>	30582	0.1914	0.1669	0.0404	0.1402	0.9341
<i>GF</i>	30582	0.4156	0.1219	0.0917	0.4233	0.6466
<i>LDE</i>	30582	0.1581	0.2128	0.0020	0.0763	0.8621
<i>CASH</i>	30582	0.2244	0.3548	-0.4845	0.1448	1.8422
<i>SIZE</i>	30582	22.3473	1.2874	20.0116	22.1588	26.4045

<i>LEV</i>	30582	0.4357	0.1992	0.0628	0.4291	0.8967
<i>ROA</i>	30582	0.0384	0.0622	-0.2076	0.0362	0.2210
<i>DUAL</i>	30582	0.2629	0.4402	0.0000	0.0000	1.0000
<i>AGE</i>	30582	2.3271	0.6578	1.0986	2.3979	3.4012
<i>TOP</i>	30582	0.3367	0.1475	0.0822	0.3131	0.7382
<i>GDP</i>	30582	10.6125	0.7552	8.2253	10.6807	11.8180
<i>RIU</i>	30582	2.4761	0.1440	2.2272	2.4449	2.8461

4. Empirical Results

4.1 Benchmark Regression Results

Table 3 displays the benchmark regression findings of AI Pilot Zone regarding Corporate Green Transformation. The columns (1) and (2) represent regression models without and with control variables respectively. *Inter* is a core explanatory variable and its regression coefficients are identical (0.0032), and statistically significant at the 1 percent level. It means that irrespective of whether or not control variables are introduced, the AI Pilot Zone implementation has led to a significant improvement of Corporate Green Transformation.

4.2 Parallel Trend Test

Table 3 Benchmark Regression Results

	(1) CGT	(2) CGT
<i>inter</i>	0.0032*** (6.925)	0.0032*** (6.797)
<i>CASH</i>		-0.0000 (-0.010)
<i>SIZE</i>		-0.0004 (-1.492)
<i>LEV</i>		-0.0004 (-0.389)
<i>ROA</i>		-0.0034 (-1.504)
<i>DUAL</i>		-0.0009*** (-2.630)
<i>AGE</i>		-0.0002 (-0.366)
<i>TOP</i>		0.0001 (0.065)
<i>GDP</i>		-0.0021 (-1.162)
<i>RIU</i>		-0.0053 (-0.941)
<i>_cons</i>	0.8217***	0.8641***

	(1713.938)	(38.118)
<i>FE</i>	<i>Yes</i>	<i>Yes</i>
<i>Year</i>	<i>Yes</i>	<i>Yes</i>
<i>N</i>	30582	30582
<i>R</i> ²	0.9791	0.9791

*Note: ***, **, and * indicate significance levels of 1%,5%, and 10%, respectively. The same applies to the table below.*

*The establishment of a Difference-in-Differences (DID) model assumes that the parallel trend assumption holds; i.e., no statistically significant difference between the treatment group and the control group exists before the policy affects them. Unless it is done so, the approach to the analysis of the DID model can lead to incorrect estimates of the policy impact. Thus, this paper has chosen the year before policy implementation as its base period since a parallel trend test is conducted. The change in trends of Corporate Green Transformation before and after policy implementation is illustrated in Figure 1 by the treatment and control group. It is evident from the figure that all the time points before the implementation of the policies (*pre_5* to *pre_2*), CGT coefficients between treatment and control groups oscillate near zero with their confidence intervals containing zero. It means that there is no significant difference in trends between them, so the parallel trend assumption is met. Following the introduction of the policy (*post_1* and beyond), Corporate Green Transformation experiences a considerable shift, and the difference becomes bigger over time, indicating that the policy has had a long-term promotional impact on Corporate Green Transformation since its introduction.*

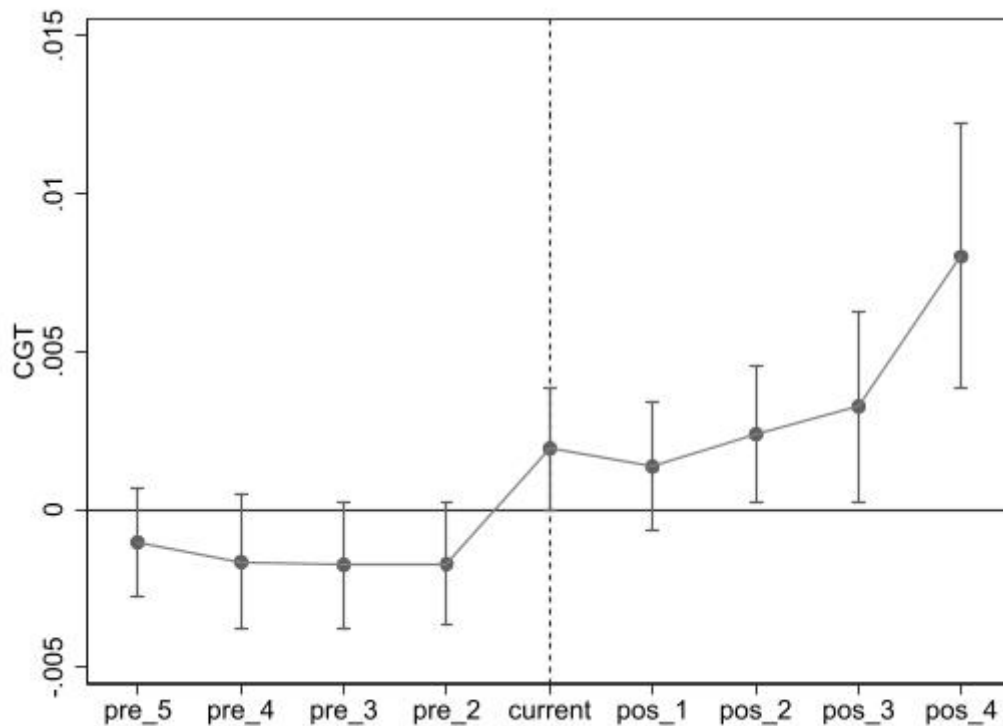


Figure 1 Parallel trend test

Alt Text: Line chart showing the dynamic effects of the AI Pilot Zone policy on Corporate Green Transformation (CGT) before and after implementation. The horizontal axis represents event time (pre_5 to post_5), and the vertical axis represents the estimated coefficients. Before the policy (pre_5 to pre_2), coefficients fluctuate around zero with confidence intervals containing zero, indicating no pre-trend differences between treatment and control groups. After policy implementation (post_1 and beyond), coefficients turn positive and increase over time, demonstrating a sustained promotional effect.

4.3 Placebo Test

To rule out interference from unobservable omitted variables on policy evaluation results, this paper conducts a placebo test following existing research to confirm whether the policy's impact on Corporate Green Transformation is caused by other unobservable factors. The study adopts a multi-period DID model. This paper randomly selects samples of the same size as the original treatment group, constructs two pseudo-treatment groups (Rd_Treat) and a pseudo-policy shock dummy variable (Rd_Post) with randomized firms and policy timings. Specifically, this paper constructs 500 random pseudo-innovative pilot policy shocks on the full sample; treatment group and policy shock time are randomly generated in each iteration, obtaining 500 samples of the virtual treatment group interaction term $Rd_Treat \times Rd_Post$. Results are shown in Figure 2. The estimated coefficient distribution of randomized interaction terms clusters near 0, with most P -values > 0.1 , and most coefficients lie to the left of the actual coefficient value 0.001. This indicates that after double randomization, both the significance and magnitude of the policy effect are significantly reduced, indirectly confirming the robustness of this paper's findings.

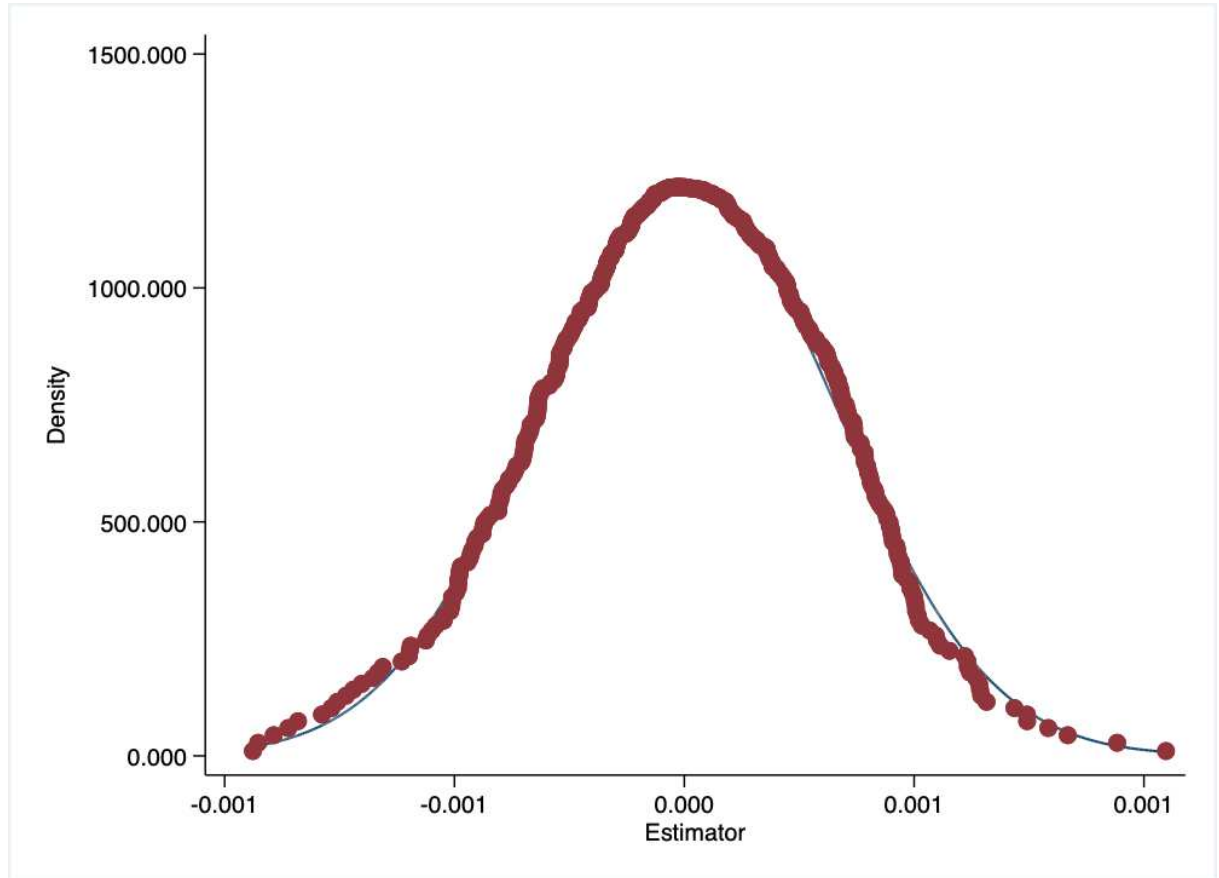


Figure 2 Placebo Test

Alt Text: Kernel density distribution of estimated coefficients from 500 random placebo tests. The distribution is centered near zero, with most p-values greater than 0.1. The vertical dashed line marks the true coefficient value (0.001) from the benchmark regression, which falls to the right of the main distribution, indicating that the actual policy effect is unlikely to be driven by unobservable factors.

4.4 Robustness Tests

4.4.1 Propensity Score Matching (PSM)

*As an attempt to reduce possible interference caused by sample selection bias on the results of the benchmark regression, the current paper uses Propensity Score Matching (PSM) as a robustness test to confirm if the effect of the AI Pilot Zone on Corporate Green Transformation is strong. In particular, we build a matched sample using the basic characteristics of the enterprises and use the 1:3 nearest neighbour matching approach to re-pair the enterprises in the pilot zone with those that are not. Following up, regression estimation is conducted using the matched sample. Table 4 presents the findings of the regression analysis following propensity score matching. As it can be seen in the table, the regression coefficients of the policy variable *inter* are 0.0043 in both columns (1) and (2) and are significant at the 1 percent level. It means that even when considering the sample selection bias, the AI Pilot Zone is still significantly promoting Corporate Green*

Transformation, which in turn further confirms the strength of the benchmark regression findings and credibility of the policy impacts.

Table 4 Score results of propensity matching

	(1)	(2)
	CGT	CGT
<i>inter</i>	0.0043*** (4.326)	0.0043*** (4.292)
<i>CASH</i>		-0.0001 (-0.079)
<i>SIZE</i>		-0.0000 (-0.045)
<i>LEV</i>		-0.0022 (-0.658)
<i>ROA</i>		-0.0120** (-2.136)
<i>DUAL</i>		-0.0005 (-0.489)
<i>AGE</i>		0.0025 (1.237)
<i>TOP</i>		0.0019 (0.340)
<i>GDP</i>		-0.0207 (-1.029)
<i>RIU</i>		0.0470* (1.664)
<i>_cons</i>	0.8209*** (186.610)	0.9138*** (3.976)
<i>FE</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>N</i>	7618	7618
<i>R²</i>	0.9677	0.9678

4.4.2 Alternative Regression Method

To further confirm the validity of our results, we re-examine the main effect again by using another regression model. The outcome shown in Column (1) of Table 5 indicates that the coefficient of the core explanatory variable \$inter is 0.0221 and statistically significant at the 1 percent level. Such consistency with the benchmark regression results achieved by applying the alternative method is a powerful indicator of the robustness of our principal findings.

4.4.3 Excluding the Impact of the Pandemic

In order to evaluate further the stability of the results of the benchmark regression, we discuss the possible confounding due to the COVID-19 pandemic as a shock that was external and could also

have affected the Corporate Green Transformation efforts and the effectiveness of the policy implementation. Therefore, we omit the data of the year 2020 to reduce the effects of the pandemic. The results of the regression estimates given in Column (2) of Table 5 show that the value of the coefficient of “inter” is 0.0038 and it is significant at the 1 percent level. That the positive effect persists even with the exclusion of the pandemic year indicates that the promotional effect of the AI Pilot Zone on the Corporate Green Transformation is independent of this out of the ordinary occurrence.

4.4.4 Adding Control Variables

In order to consider other possible confounders related to corporate governance systems and operational attributes, we add to our regression specification by adding Board Size (MBOARD) and Firm Growth (GROWTH) as other control variables. The estimation outcomes shown in Column (3) of Table 5 indicate that the coefficient of \$inter\$ also is equal to 0.0032 and statistically significant at the 1 percent level. Such a consistency in the derived effect despite the inclusion of these extra governance and growth aspects strengthens our certainty in the resilience of the AI Pilot Zone influence on Corporate Green Transformation.

Table 5 Robustness Testing

	(1)	(2)	(3)
	CGT	CGT	CGT
<i>inter</i>	0.0221*** (33.235)	0.0038*** (7.475)	0.0032*** (6.804)
<i>CASH</i>	0.0025*** (3.956)	0.0001 (0.162)	0.0000 (0.010)
<i>SIZE</i>	0.0029*** (7.319)	-0.0004 (-1.316)	-0.0004 (-1.523)
<i>LEV</i>	-0.0194*** (-11.446)	-0.0003 (-0.236)	-0.0006 (-0.504)
<i>ROA</i>	-0.0177*** (-5.148)	-0.0038 (-1.565)	-0.0039* (-1.708)
<i>DUAL</i>	-0.0015*** (-2.754)	-0.0009** (-2.548)	-0.0009*** (-2.626)
<i>AGE</i>	0.0443*** (48.131)	-0.0003 (-0.483)	-0.0002 (-0.332)
<i>TOP</i>	0.0089*** (3.369)	-0.0002 (-0.089)	0.0001 (0.071)
<i>GDP</i>	0.2383*** (170.742)	-0.0024 (-1.332)	-0.0020 (-1.138)
<i>RIU</i>	0.2244*** (33.315)	-0.0049 (-0.844)	-0.0052 (-0.924)
<i>MBOARD</i>			-0.0006 (-0.628)
<i>GROWTH</i>			0.0002* (1.825)

<i>_cons</i>	-2.2231*** (-178.172)	0.8665*** (36.826)	0.8650*** (38.111)
<i>FE</i>	Yes	Yes	Yes
<i>Year</i>	No	Yes	Yes
<i>N</i>	30582	27861	30582
<i>R²</i>	0.9514	0.9803	0.9791

5. Mechanism Analysis

5.1 Mediation Effect Analysis

5.1.1 Resource Allocation Efficiency (RAE)

Estimates in column (2) of Table 6 show that the AI Pilot Zone policy has a negative, statistically significant impact on Resource Allocation Efficiency, with a coefficient of -0.0106 significant at 1 percent. This finding indicates the policy reduces corporate resource misallocation and thus improves Resource Allocation Efficiency. This improvement is a material condition for enterprises to carry out green transformation. As a long-term strategy requiring large capital input, green transformation needs adequate resource support. After intelligent technologies help cut resource misallocation and waste in production and operation, enterprises will obtain valuable slack resources. These released resources can be invested in long-term strategic green initiatives with high investment and high risk, providing internal financial support for enterprises to launch and maintain green transformation activities (Hina et al., 2024a; Hina et al., 2024b). Therefore, Resource Allocation Efficiency acts as a transmission channel between the policy and Corporate Green Transformation, supporting the existence of a mediation effect.

Table 6 Mediation Effect of Resource Allocation Efficiency

	(1) CGT	(2) RAE
<i>inter</i>	0.0032*** (6.797)	-0.0106*** (-4.736)
<i>CASH</i>	-0.0000 (-0.010)	-0.0018 (-0.910)
<i>SIZE</i>	-0.0004 (-1.492)	0.0001 (0.054)
<i>LEV</i>	-0.0004 (-0.389)	-0.0043 (-0.787)
<i>ROA</i>	-0.0034 (-1.504)	0.0663*** (6.026)
<i>DUAL</i>	-0.0009*** (-2.630)	-0.0034** (-2.005)
<i>AGE</i>	-0.0002 (-0.366)	0.1193*** (37.600)
<i>TOP</i>	0.0001 (0.065)	0.0148* (1.758)

<i>GDP</i>	-0.0021 (-1.162)	0.0018 (0.212)
<i>RIU</i>	-0.0053 (-0.941)	0.0692** (2.547)
<i>_cons</i>	0.8641*** (38.118)	-0.2762** (-2.521)
<i>FE</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>N</i>	30582	30582
<i>R²</i>	0.9791	0.5512

5.1.2 Credit Availability (Flex)

Based on Column (2) in Table 7, the AI Pilot Zone policy has a positive, slightly significant effect on Credit Availability, with a coefficient of 0.0030 significant at 10%. This result indicates that the policy improves enterprises' access to credit. Sufficient Credit Availability is a key external mechanism for corporate green transformation. Corporate green transformation initiatives, including technological R&D and equipment renewal, are highly capital-intensive and rely heavily on external funding (Kumar et al., 2025). Financing constraints are a major barrier to corporate green innovation (Li et al., 2019). Increased Credit Availability helps enterprises overcome financing hurdles and obtain capital required for large-scale green projects. Thus, Credit Availability is an important channel through which the policy affects Corporate Green Transformation, confirming the mediation effect.

Table 7 Intermediary of Credit Availability

	(1) <i>CGT</i>	(2) <i>Flex</i>
<i>inter</i>	0.0032*** (6.797)	0.0030* (1.828)
<i>CASH</i>	-0.0000 (-0.010)	-0.0170*** (-11.555)
<i>SIZE</i>	-0.0004 (-1.492)	0.0219*** (23.886)
<i>LEV</i>	-0.0004 (-0.389)	0.5231*** (132.576)
<i>ROA</i>	-0.0034 (-1.504)	-0.1542*** (-19.270)
<i>DUAL</i>	-0.0009*** (-2.630)	-0.0005 (-0.403)
<i>AGE</i>	-0.0002 (-0.366)	0.0031 (1.360)
<i>TOP</i>	0.0001 (0.065)	0.0309*** (5.054)
<i>GDP</i>	-0.0021 (-1.162)	-0.0064 (-1.024)

<i>RIU</i>	-0.0053 (-0.941)	-0.0785*** (-3.973)
<i>_cons</i>	0.8641*** (38.118)	-0.2688*** (-3.375)
<i>FE</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>N</i>	30582	30582
<i>R2</i>	0.9791	0.8704

5.1.3 Agency Costs (AC)

As shown in Column (2) of Table 8, the core explanatory variable has a statistically significant negative impact on Agency Costs, with a coefficient of -0.0036 and 1% significance level. This indicates that the AI Pilot Zone reduces corporate Agency Costs, and such reduction provides governance guarantee for enterprises to implement green transformation strategies. Per classical agency theory, conflicts of interest exist between managers and shareholders: under short-term performance pressure and personal factors, managers may reject green transformation, which requires large investments with slow returns (Jensen and Meckling, 1976). AI technology restricts managerial opportunism by improving operational transparency, ensuring that efficiency-released resources are used for long-term shareholder value-aligned green development (Liu et al., 2025). Therefore, Agency Costs plays a partial mediating role in the policy's impact on Corporate Green Transformation, confirming the validity of this mediation path.

Table 8 Intermediary of Agency Costs

	(1) <i>CGT</i>	(2) <i>AC</i>
<i>inter</i>	0.0032*** (6.797)	-0.0036*** (-3.687)
<i>CASH</i>	-0.0000 (-0.010)	-0.0051*** (-5.841)
<i>SIZE</i>	-0.0004 (-1.492)	-0.0152*** (-27.734)
<i>LEV</i>	-0.0004 (-0.389)	-0.0376*** (-15.962)
<i>ROA</i>	-0.0034 (-1.504)	-0.2107*** (-44.173)
<i>DUAL</i>	-0.0009*** (-2.630)	0.0003 (0.382)
<i>AGE</i>	-0.0002 (-0.366)	-0.0128*** (-9.325)
<i>TOP</i>	0.0001 (0.065)	-0.0082** (-2.259)
<i>GDP</i>	-0.0021 (-1.162)	-0.0006 (-0.158)
<i>RIU</i>	-0.0053	-0.0155

	(-0.941)	(-1.314)
<i>_cons</i>	0.8641***	0.5117***
	(38.118)	(10.777)
<i>FE</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>N</i>	30582	30582
<i>R2</i>	0.9791	0.7407

5.1.4 Green Innovation Number (GIN) and Quality (GIQ)

As shown in Column (2) of Table 9, the policy has a significant positive effect on Green Innovation Number, with a coefficient of 0.0507 significant at the 1% level, meaning it accelerates enterprises' intelligent upgrading and green innovation. Table 9 Column (3) shows the policy's coefficient on Green Innovation Quality is 0.0094, significant at the 5% level. Simultaneous improvement of green innovation quality and quantity is an essential intermediate path for Corporate Green Transformation. More green innovations provide alternative technical solutions for enterprises to shift from end-of-pipe treatment to source prevention (Anim, Mahmoud and Odoom, 2025a). Meanwhile, quality improvement acts as the core engine of profound change, generating "innovation compensation" to help enterprises radically change their environmental impact and achieve both financial and environmental benefits (Porter and van der Linde, 1995; Naeem and Siddique, 2024). Therefore, the policy effectively promotes Corporate Green Transformation by boosting both quantitative and qualitative green innovation.

Table 9 Mediation of Quantity and Quality of Green Innovation

	(1) CGT	(2) GIN	(3) GIQ
<i>inter</i>	0.0032*** (6.797)	0.0507*** (3.066)	0.0094** (2.426)
<i>CASH</i>	-0.0000 (-0.010)	-0.0081 (-0.546)	-0.0013 (-0.370)
<i>SIZE</i>	-0.0004 (-1.492)	0.2822*** (30.342)	-0.0020 (-0.897)
<i>LEV</i>	-0.0004 (-0.389)	0.0131 (0.327)	-0.0061 (-0.651)
<i>ROA</i>	-0.0034 (-1.504)	-0.0342 (-0.422)	-0.0267 (-1.399)
<i>DUAL</i>	-0.0009*** (-2.630)	0.0290** (2.321)	0.0006 (0.196)
<i>AGE</i>	-0.0002 (-0.366)	-0.1651*** (-7.072)	0.0001 (0.016)
<i>TOP</i>	0.0001 (0.065)	-0.1170* (-1.890)	-0.0105 (-0.724)
<i>GDP</i>	-0.0021 (-1.162)	0.1238** (1.970)	0.0023 (0.154)
<i>RIU</i>	-0.0053	-0.4207**	0.0083

	(-0.941)	(-2.102)	(0.176)
<i>_cons</i>	0.8641***	-5.7912***	0.2408
	(38.118)	(-7.181)	(1.268)
<i>FE</i>	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes
<i>N</i>	30582	30582	30582
<i>R2</i>	0.9791	0.7130	0.6328

5.1.5 Green Investment (GI)

As shown in Column (2) of Table 10, the AI Pilot Zone policy has a positive effect on Green Investment, with a coefficient of 0.0156 that is statistically significant at the 10% level. This indicates the policy raises corporate Green Investment levels. Green Investment is the most direct foundational form of Corporate Green Transformation. Green transformation is not merely a strategic concept, but requires specific investment actions including purchasing environmental protection facilities, installing clean production lines and investing in pollution control infrastructure (Kumar et al., 2025). Increased Green Investment means enterprises substantially shift resources from traditional production models to sustainable development paradigms, and acts as a key link between corporate green intentions and actual environmental performance improvement (Li et al., 2019). Therefore, Green Investment is an essential transmission channel that connects the policy to Corporate Green Transformation, confirming the existence of a mediation effect.

Table 10 Intermediary of Green Investment

	(1) CGT	(2) GI
<i>inter</i>	0.0032*** (6.797)	0.0156* (1.708)
<i>CASH</i>	-0.0000 (-0.010)	0.0796*** (9.673)
<i>SIZE</i>	-0.0004 (-1.492)	0.6029*** (117.517)
<i>LEV</i>	-0.0004 (-0.389)	-0.0267 (-1.211)
<i>ROA</i>	-0.0034 (-1.504)	-1.0011*** (-22.399)
<i>DUAL</i>	-0.0009*** (-2.630)	0.0057 (0.823)
<i>AGE</i>	-0.0002 (-0.366)	0.1624*** (12.609)
<i>TOP</i>	0.0001 (0.065)	-0.1513*** (-4.430)
<i>GDP</i>	-0.0021 (-1.162)	0.0464 (1.340)
<i>RIU</i>	-0.0053	-0.4964***

	(-0.941)	(-4.496)
<i>_cons</i>	0.8641***	6.4369***
	(38.118)	(14.467)
<i>FE</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>N</i>	30582	30582
<i>R²</i>	0.9791	0.9277

5.2 Heterogeneity Analysis

5.2.1 ESG — Organizational

Empirical evidence shows that better current ESG performance makes the AI Pilot Zone policy more effective in promoting Corporate Green Transformation, highlighting the role of strategic alignment. High-quality ESG performance means enterprises have endogenous willingness for sustainable development, consistent with the orientation of AI policies (Eccles, Ioannou, and Serafeim, 2014). For these enterprises, green development is part of their strategic focus, and they generally have mature green governance infrastructure to introduce AI technologies more quickly (Grewal and Serafeim, 2020), thus translating policy benefits into practical results more effectively.

To test the moderating role of ESG, we need to define the measurement of ESG performance. Existing literature commonly uses 1-9 coded Huazheng ESG ratings, but this approach produces discontinuous scores and loses the variability and dynamism of ESG performance, reducing comparability. In fact, per Huazheng Index Company's Huazheng ESG Rating Methodology (V2.0), ratings are generated based on underlying ESG scores: nine grades from AAA to C correspond to scores ranging from ≥ 95 to < 60 , with higher corporate ESG scores indicating better performance and higher ratings. Following Fang and Hu (2023) and Yang et al. (2023), this paper directly uses the 0-100 scaled Huazheng corporate ESG score to measure corporate ESG practice. This measurement supports both horizontal cross-firm comparison and longitudinal dynamic comparison, enhancing the robustness of research conclusions.

*By analyzing column (2) of Table 11, we can see that the AI Pilot Zone policy has a positive and statistically significant effect on Corporate Green Transformation (coefficient=0.0030, $p < 0.01$). It is worth noting that the interaction variable *ESG_inter* comes up with a coefficient value of 0.0135 ($p < 0.05$) which means that ESG performance positively moderates the association between policy and Corporate Green Transformation. This result confirms our theoretical predictions about the synergistic nature of effective sustainability governance in increasing the effectiveness of policies.*

5.2.2 HHI — Environmental

The Porter Hypothesis states that well-designed environmental policies paired with high industry competition push firms to seek innovative competitive advantages (Porter and van der Linde, 1995). AI policies provide a strategic path for firms to cut costs, improve efficiency, and achieve

differentiation via green transformation. In highly competitive environments, applying AI to environmental improvement is a strategic necessity for maintaining competitiveness. Institutional theory holds that peer rivalry in the same industry encourages firms to adopt AI for green transformation to maintain market legitimacy and competitive position (DiMaggio and Powell, 1983), which amplifies the policy's overall effect. We thus expect higher industry competition strengthens the policy's promotional effect on Corporate Green Transformation.

To explore this moderating effect, we adopt the established Herfindahl-Hirschman Index (HHI) to measure industry concentration. HHI is the weighted sum of squared firm market share percentages calculated by industry total revenue or total assets (Cheng and Zhu, 2015). Higher HHI indicates higher industry concentration and lower competition, while lower HHI indicates more intense competition.

*Column (4) of Table 11 shows the AI Pilot Zone policy has a positive impact on Corporate Green Transformation, with a coefficient of 0.0032 ($p < 0.01$). By contrast, the interaction term *HHI_inter* has a coefficient of -0.0034 and is not statistically significant. This result indicates HHI does not moderate the relationship between the policy and transformation, failing to support the hypothesis that industry competition improves policy efficacy.*

5.2.3 Green Finance Development Level (GF) — Environmental

Urban Green Finance development level is a key external support for enterprises to respond to national AI policies (Salazar, 1998). Cities with developed green finance provide more green financing tools and lower capital costs for local enterprises, strengthening the investment and financing transmission mechanism of national AI policies. When AI policies raise firms' green investment value and credit rating, efficient local green finance markets can quickly meet corporate financing demands, converting technological advantages into green project capital (Chassagnon and Haned, 2015) and enhancing the policy's driving effect on green investment and transformation. We therefore hypothesize that higher Urban Green Finance development levels strengthen the policy's promotional effect on Corporate Green Transformation.

We use the Green Finance Index to accurately measure urban green finance development levels. Following the methodology of Liu and He (2021), we calculate the index via the entropy method, which determines indicator weights by indicator dispersion, where higher dispersion indicates greater influence on the comprehensive evaluation. Higher index values correspond to higher urban Green Finance development levels.

*As shown in column (5) of Table 11, the AI Pilot Zone policy has a positive effect on Corporate Green Transformation, with a coefficient of 0.0017 ($p < 0.05$). The interaction term *GF_inter* has a coefficient of 0.0111 ($p < 0.01$), indicating that Green Finance development level positively moderates the relationship between the policy and transformation, which is consistent with our theoretical prediction.*

5.2.4 Digital Corporate Transformation (DCG) — Technical

Per absorptive capacity theory, a firm's Digital Corporate Transformation level determines its ability to recognize, assimilate and apply new external technologies (Cohen and Levinthal, 1990). Highly digitized companies own existing digital infrastructure, standardized data governance systems and professional technical talent pools, making it easier to adopt technologies and solutions from AI policies. This first-mover digital advantage reduces AI adoption barriers and costs, helping firms translate policy guidance into tangible outcomes in green innovation and operational optimization (Zahra and George, 2002), thus strengthening the effect of policy implementation. We hypothesize that a higher Digital Corporate Transformation level strengthens the policy's empowering effect on Corporate Green Transformation.

To measure this moderator, following Wu Fei et al. (2021), we count the frequency of 76 digitization-related terms in five categories (artificial intelligence technologies, big data technologies, cloud computing technologies, blockchain technologies, digital technology applications) in corporate annual reports. We take the natural logarithm of this frequency as the measure of Digital Corporate Transformation level: higher values indicate more advanced digital transformation and stronger absorptive capacity for AI technologies.

As shown in Column 6 of Table 11, the AI Pilot Zone policy has a positive impact on Corporate Green Transformation, with a coefficient of 0.0027 ($p < 0.01$). The interaction term DCG_inter has a coefficient of 0.0005 ($p < 0.10$), indicating that Digital Corporate Transformation positively moderates the policy-transformation relationship, which is consistent with our theoretical prediction.

5.2.5 Level of Digital Economy (LDE) — Environmental

A city's overall Level of Digital Economy generates positive externalities for local enterprises and forms a beneficial innovation ecosystem (Audretsch and Feldman, 1996). Well-developed digital economies provide enterprises with stronger support via more complete digital infrastructure, richer AI talent pools, and knowledge spillovers from local tech firms and research institutions. This favorable ecosystem reduces the cost and risk for individual enterprises to adopt AI, helping them better respond to national AI policies (Jaffe, Trajtenberg and Henderson, 1993) and strengthening the policy's promotional effect on green transformation. We expect that as the urban Level of Digital Economy rises, the policy's driving effect on Corporate Green Transformation will be stronger.

To test this moderating effect, we adopt the Digital Financial Inclusion Index processed via logarithmic transformation following Zhao et al. (2020) to measure regional Level of Digital Economy. This index reflects regional digital infrastructure development and digital application maturity, and serves as an effective indicator for digital economy measurement, with higher values corresponding to more advanced urban digital economy development.

Column (7) of Table 11 shows the AI Pilot Zone policy has a positive impact on Corporate Green Transformation, with a coefficient of 0.0049 ($p < 0.01$). The interaction term LDE_inter has a coefficient of 0.0215 ($p < 0.01$), indicating that the Level of Digital Economy significantly

moderates the policy-transformation relationship, which strongly supports our theoretical prediction.

Table 11 Results of Moderating Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CGT	CGT	CGT	CGT	CGT	CGT	CGT
<i>inter</i>	0.0032**	0.0030***	0.0032***	0.0032***	0.0017**	0.0027***	0.0049***
	*						
	(6.797)	(6.423)	(6.909)	(6.888)	(2.537)	(5.191)	(8.424)
<i>CASH</i>	-0.0000	-0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000
	(-0.010)	(-0.013)	(0.007)	(0.020)	(0.016)	(-0.008)	(-0.084)
<i>SIZE</i>	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004
	(-1.492)	(-1.410)	(-1.508)	(-1.416)	(-1.448)	(-1.497)	(-1.486)
<i>LEV</i>	-0.0004	-0.0005	-0.0004	-0.0004	-0.0005	-0.0004	-0.0006
	(-0.389)	(-0.446)	(-0.398)	(-0.380)	(-0.481)	(-0.386)	(-0.513)
<i>ROA</i>	-0.0034	-0.0033	-0.0034	-0.0035	-0.0033	-0.0033	-0.0032
	(-1.504)	(-1.454)	(-1.486)	(-1.540)	(-1.431)	(-1.441)	(-1.426)
<i>DUAL</i>	-0.0009**	-0.0009**	-0.0009***	-0.0009**	-0.0009**	-0.0009**	-0.0009**
	*	*		*	*	*	
	(-2.630)	(-2.667)	(-2.627)	(-2.642)	(-2.590)	(-2.655)	(-2.551)
<i>AGE</i>	-0.0002	-0.0003	-0.0002	-0.0003	-0.0002	-0.0003	-0.0002
	(-0.366)	(-0.402)	(-0.329)	(-0.455)	(-0.349)	(-0.452)	(-0.345)
<i>TOP</i>	0.0001	0.0001	0.0002	0.0001	0.0002	0.0002	0.0001
	(0.065)	(0.048)	(0.100)	(0.071)	(0.137)	(0.127)	(0.059)
<i>GDP</i>	-0.0021	-0.0020	-0.0020	-0.0020	-0.0020	-0.0021	-0.0023
	(-1.162)	(-1.153)	(-1.155)	(-1.153)	(-1.149)	(-1.167)	(-1.330)
<i>RIU</i>	-0.0053	-0.0051	-0.0053	-0.0057	-0.0035	-0.0052	-0.0035
	(-0.941)	(-0.905)	(-0.945)	(-1.012)	(-0.613)	(-0.932)	(-0.609)
<i>ESG</i>		-0.0018					
		(-0.862)					
<i>ESG_inter</i>		0.0135**					
		(2.120)					
<i>LIC</i>			-0.0000				
			(-0.001)				
<i>LIC_inter</i>			0.0050*				
			(1.839)				
<i>HHI</i>				-0.0023**			
				(-2.174)			
<i>HHI_inter</i>				-0.0034			
				(-1.534)			
<i>GF</i>					0.0037		
					(0.994)		
<i>GF_inter</i>					0.0111***		
					(2.857)		

<i>DCG</i>						0.0000 (0.314)	
<i>DCG_inte</i>						0.0005*	
<i>r</i>						(1.752)	
<i>LDE</i>							0.0003 (0.278)
<i>LDE_inter</i>							0.0215*** (7.980)
<i>_cons</i>	0.8641** *	0.8709***	0.8641***	0.8650***	0.8579***	0.8641***	0.8623***
	(38.118)	(36.072)	(37.178)	(38.159)	(37.702)	(38.075)	(38.005)
<i>FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	30582	30582	30582	30582	30582	30582	30582
<i>R²</i>	0.9791	0.9791	0.9791	0.9791	0.9791	0.9791	0.9792

6. Heterogeneity Analysis

6.1 Ownership Nature

In order to explore whether ownership structure determines the effectiveness of policies, this paper sorts out enterprises as state-owned enterprises (SOEs) and non-state-owned enterprises according to the nature of ownership. The regression estimates shown in columns (1) and (2) of Table 12 show coefficients of 0.0043 and 0.0023 respectively and are statistically significant at the 1 percent level. These results indicate that the AI Pilot Zone policy has a meaningful influence on both ownership types. Comparison of the coefficients reveals slightly greater influence on the state-owned holding companies. The discrepancy can be explained by various reasons: SOEs are subjected to stricter policy limitations and are able to allocate resources better, thus they are more prone to green development instructions. Also, their extended social accountability requirements produce different policy demonstration implications, and they experience less bureaucratic opposition as they combine green aspects with their digital transformation projects.

Table 12 Heterogeneity of Enterprise Nature

	(1) <i>belong to the state</i>	(2) <i>non-state-owned</i>
<i>inter</i>	0.0043*** (6.019)	0.0023*** (3.719)
<i>CASH</i>	-0.0002 (-0.218)	0.0001 (0.183)
<i>SIZE</i>	-0.0005 (-1.181)	-0.0004 (-1.035)
<i>LEV</i>	0.0008 (0.443)	-0.0017 (-1.106)
<i>ROA</i>	-0.0060	-0.0024

	(-1.529)	(-0.839)
<i>DUAL</i>	-0.0011*	-0.0009**
	(-1.831)	(-1.987)
<i>AGE</i>	-0.0024**	0.0011
	(-2.104)	(1.276)
<i>TOP</i>	0.0003	0.0001
	(0.124)	(0.038)
<i>GDP</i>	-0.0062***	0.0036
	(-2.719)	(1.342)
<i>RIU</i>	0.0009	-0.0148*
	(0.124)	(-1.714)
<i>_cons</i>	0.8960***	0.8275***
	(29.612)	(24.533)
<i>FE</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>N</i>	12189	18393
<i>R²</i>	0.9808	0.9769

6.2 Life Cycle

In order to investigate the differences in the stages of corporate development, the presented paper breaks down the sample into the growth stage, maturity, and recession stage using the life cycle framework. The findings in the columns (1) to (3) of Table 13 indicate that the policy has a significant effect on firms of various life cycles with the coefficient values of 0.0015, 0.0038 and 0.0050 respectively. The impact is not statistically significant in the case of the growth stage but statistically significant at the 1 percent level in the case of the maturity and recession stages. By comparing the coefficients, the value is somewhat higher in enterprises in the recession stage, which demonstrates that this policy also has the most evident promotional impact on Corporate Green Transformation of these companies. It is possible that companies in the recession period are experiencing transformation pressure and require urgent technological empowerment to lower costs and improve their efficiency. Artificial intelligence assists in optimizing energy use and emissions, which helps eliminate survival crises, and green transformation becomes one of the essential ways to get out of challenges.

Table 13 Life Cycle Heterogeneity

	(1) <i>grow up</i>	(2) <i>ripe</i>	(3) <i>fail</i>
<i>inter</i>	0.0015 (1.460)	0.0038*** (4.177)	0.0050*** (5.954)
<i>CASH</i>	-0.0006 (-0.694)	0.0012 (1.493)	-0.0009 (-1.236)
<i>SIZE</i>	-0.0009* (-1.723)	-0.0006 (-1.161)	-0.0005 (-1.061)
<i>LEV</i>	-0.0009 (-0.391)	0.0010 (0.465)	-0.0010 (-0.478)

<i>ROA</i>	0.0004 (0.089)	-0.0032 (-0.719)	-0.0056 (-1.161)
<i>DUAL</i>	-0.0012* (-1.656)	-0.0011* (-1.690)	-0.0009 (-1.384)
<i>AGE</i>	0.0003 (0.243)	0.0000 (0.037)	-0.0013 (-0.912)
<i>TOP</i>	0.0021 (0.599)	0.0014 (0.406)	0.0021 (0.646)
<i>GDP</i>	-0.0021 (-0.480)	-0.0030 (-0.903)	-0.0026 (-0.849)
<i>RIU</i>	-0.0135 (-1.050)	0.0168 (1.569)	-0.0165* (-1.660)
<i>_cons</i>	0.8938*** (16.556)	0.8233*** (18.790)	0.9008*** (23.154)
<i>FE</i>	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes
<i>N</i>	9238	10748	10596
<i>R²</i>	0.9841	0.9832	0.9820

6.3 Pollution Intensity

By exploring the way in which industry environmental variables influence the policy outcomes, the paper divides the sample into two groups: high-pollution industries and non-high-pollution industries. Impact coefficients of 0.0065 and 0.0026 respectively are obtained with regression results reported in Columns (1) and (2) of Table 14, and they are significant at the 1% level. The significantly higher coefficient of high-pollution industries indicates that the policy has a greater normative effect on companies with significant pollution levels and increased pressure to govern. The reasonable cause may be the increased cost of environmental compliance faced by the high-pollution industries, which makes the urgent need to substitute the technologies necessary. The AI technology itself is used to reduce the costs of pollution control by intelligent monitoring and optimization of processes, and policy support helps to speed up the penetration of the technology and simplify implementing it into these spheres.

Table 14 Heterogeneity Analysis by Pollution Intensity

	(1) High pollution	(2) Non-high pollution
<i>inter</i>	0.0065*** (5.672)	0.0026*** (4.966)
<i>CASH</i>	-0.0012 (-1.408)	0.0003 (0.666)
<i>SIZE</i>	-0.0004 (-0.716)	-0.0004 (-1.304)
<i>LEV</i>	-0.0042* (-1.878)	0.0008 (0.582)
<i>ROA</i>	-0.0040	-0.0034

	(-0.877)	(-1.291)
<i>DUAL</i>	-0.0022***	-0.0005
	(-2.975)	(-1.313)
<i>AGE</i>	0.0014	-0.0007
	(0.993)	(-0.891)
<i>TOP</i>	0.0004	0.0002
	(0.125)	(0.080)
<i>GDP</i>	-0.0028	-0.0012
	(-0.911)	(-0.576)
<i>RIU</i>	0.0069	-0.0116*
	(0.695)	(-1.687)
<i>_cons</i>	0.8419***	0.8713***
	(20.917)	(31.723)
<i>FE</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>N</i>	7501	23081
<i>R2</i>	0.9793	0.9791

6.4 City Tier

This investigation examines whether there are differences between the levels of urban development and how policy is transmitted; it divides cities into two groups, the first tier and non-first tier. The data shown in Table 15 indicate that the AI Pilot Zone policy has a great positive effect on Corporate Green Transformation in first-tier cities with the regression coefficient of 0.0042 significant at 1 percent. On the contrary, policy impacts have been found to have no statistical significance to companies operating in non-first-tier cities. This trend indicates slightly better effectiveness of policies in first-tier urban environments. This occurrence may be explained by good infrastructure, capacity to implement policies and stronger supervisory systems that are typical of first-tier cities. Moreover, such urban centers have access to large volumes of data sources and specialized technical experts, which allows companies to access more effective AI solutions and implementation assistance, thus reducing the level of threshold of transformations.

Table 15 Urban Line-Level Heterogeneity

	(1)	(2)
	<i>First-tier</i>	<i>Non-first-tier</i>
<i>inter</i>	0.0042***	0.0009
	(6.955)	(0.303)
<i>CASH</i>	0.0006	-0.0006
	(1.036)	(-1.000)
<i>SIZE</i>	0.0000	-0.0008**
	(0.087)	(-2.138)
<i>LEV</i>	-0.0021	0.0010
	(-1.324)	(0.622)
<i>ROA</i>	-0.0053*	-0.0012

	(-1.659)	(-0.365)
<i>DUAL</i>	-0.0009*	-0.0010*
	(-1.725)	(-1.944)
<i>AGE</i>	-0.0009	0.0006
	(-1.013)	(0.656)
<i>TOP</i>	0.0007	-0.0004
	(0.274)	(-0.155)
<i>GDP</i>	-0.0030	-0.0021
	(-0.642)	(-1.089)
<i>RIU</i>	0.0010	-0.0078
	(0.103)	(-1.105)
<i>_cons</i>	0.8515***	0.8767***
	(14.685)	(34.608)
<i>FE</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>N</i>	15353	15229
<i>R2</i>	0.9801	0.9782

6.5 Green Background Heterogeneity

This paper divides the sample into two groups according to the existence of non-existence of executive green backgrounds in order to investigate the impact of executive characteristics on policy responsiveness. The values shown in Columns (1) and (2) of Table 16 demonstrate influence coefficients of 0.0017 and 0.0034 in case of enterprises with and without executive green backgrounds respectively, which are significant at the 10% and 1% level. Comparison of the coefficients suggests stronger policy influences on enterprises without green backgrounds. Such a trend is probably due to the fact that companies that do not have developed green expertise have less strong underlying capabilities, which makes the marginal effects of policies more significant. The pilot zone has access to technology imports and finance, which make up the natural defects and allow leapfrog green improvements in some of these businesses.

Table 16 Green Background Heterogeneity

	(1) have	(2) not have
<i>inter</i>	0.0017*	0.0034***
	(1.724)	(6.288)
<i>CASH</i>	-0.0002	0.0004
	(-0.256)	(0.859)
<i>SIZE</i>	0.0002	-0.0005
	(0.237)	(-1.584)
<i>LEV</i>	0.0011	-0.0007
	(0.415)	(-0.566)
<i>ROA</i>	0.0061	-0.0055**
	(1.259)	(-2.077)
<i>DUAL</i>	-0.0008	-0.0012***

	(-1.130)	(-2.941)
AGE	-0.0034**	0.0009
	(-2.328)	(1.220)
TOP	-0.0081**	0.0026
	(-2.068)	(1.264)
GDP	0.0009	-0.0026
	(0.202)	(-1.294)
RIU	0.0073	-0.0047
	(0.588)	(-0.706)
_cons	0.8003***	0.8679***
	(14.743)	(32.850)
FE	Yes	Yes
Year	Yes	Yes
N	7246	23336
R2	0.9820	0.9801

6.6 Digital Background Heterogeneity

As a way of exploring how prior digital capacities can influence the results of policies, the research divides the sample into organizations that have and do not have significant digital backgrounds. The estimates given in Columns (1) and (2) of Table 17 produce -0.0013 and 0.0035 as the influence coefficients of these two categories. Although statistically insignificant in digitally-sophisticated businesses, policy impact is significant at the 1 percent level in businesses not having developed digital capacity, which suggests significantly larger impacts in the second group. Such inconsistency can be accounted by the typical technological accumulation gaps and transformation capabilities gaps common to those enterprises that are devoid of digital foundations. AI Pilot Zone The AI Pilot Zone significantly reduces the green transformation threshold of individuals by offering them policy support, enabling them to use technology and align resources. These businesses have a large margin of improvement and are very efficient when it comes to absorbing the benefits of policies, and therefore, AI empowerment is especially evident in assisting them in their green transformation paths.

Table 17 Heterogeneity of Digital Background

	(1) have	(2) not have
inter	-0.0013 (-0.712)	0.0035*** (7.093)
CASH	-0.0002 (-0.125)	-0.0001 (-0.141)
SIZE	-0.0032** (-2.083)	-0.0003 (-1.015)
LEV	0.0026 (0.474)	-0.0003 (-0.252)
ROA	-0.0066 (-0.657)	-0.0023 (-0.951)

<i>DUAL</i>	0.0025 (1.635)	-0.0012*** (-3.329)
<i>AGE</i>	0.0008 (0.244)	-0.0005 (-0.664)
<i>TOP</i>	-0.0150 (-1.258)	0.0000 (0.015)
<i>GDP</i>	0.0136 (1.181)	-0.0022 (-1.237)
<i>RIU</i>	-0.0293 (-0.939)	-0.0047 (-0.811)
<i>_cons</i>	0.8280*** (5.674)	0.8622*** (37.193)
<i>FE</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>N</i>	2095	28487
<i>R²</i>	0.9800	0.9795

7. Research Conclusions and Policy Implications

7.1 Research Conclusions

Using the sample of A-share companies traded on the Shanghai and Shenzhen exchanges between 2010 and 2023, this paper applies the Difference-in-Differences (DID) approach to examine the association between AI Pilot Zone policy and Corporate Green Transformation. The analysis reveals a number of important results.

Firstly, the creation of AI Pilot Zones has a statistically meaningful promotional impact on Corporate Green Transformation. This finding can be strongly validated by using parallel trend tests and placebo tests as it indicates that the effect noted is a result of systematic policy changes and not a false correlation.

Secondly, based on a mechanistic point of view, the AI Pilot Zone will enable Corporate Green Transformation via various interrelated channels, including minimizing the misallocation of resources (thus improving Resource Allocation Efficiency), increasing Credit Accessibility, reducing Agency Costs, promoting Green Innovation Quantity as well as Green Innovation Quality, and growing Green Investment.

Third, the empirical findings indicate that ESG performance, Green Finance Development Level, Digital Corporate Transformation, and level of digital economy in the city are strong positive moderators in the association between the AI Pilot Zone policy and Corporate Green Transformation.

Lastly, there are heterogeneous effects amongst various enterprise attributes. The policy shows increased efficiency in transmission between state owned enterprises, businesses during recessionary cycles, businesses in high pollution industries, companies in first tier cities, and

companies that do not have any previous green or digital infrastructure. Taken all together, these findings suggest that the AI Pilot Zone is successful in facilitating corporate green transformation through multi-dimensional connections. The findings give a theoretical basis as well as practical direction to enhance the AI Pilot Zone structure and reinforce Corporate Green Transformation efforts.

7.2 Policy Recommendations

One key recommendation is to build intelligent governance systems for enterprises. Government programs shall guide enterprises to apply AI in optimizing decision-making and control systems to cut agency costs, and support them in introducing AI-based performance assessment and risk warning systems to improve management transparency, address principal-agent problems, and strengthen endogenous motivation for corporate green transformation. Meanwhile, it is necessary to develop lightweight AI governance solutions for enterprises of all sizes, to lower technical adoption thresholds and realize universal access to agency cost management. In addition, support shall be given to enterprises for building AI-enabled dynamic resource allocation platforms to track and schedule production factors such as energy and capital in real time. Policy mechanisms shall guide enterprises to connect to industrial internet and big data systems, to improve the accuracy of resource allocation, reduce misallocation, and increase green total factor productivity. Furthermore, the establishment of regional resource coordination and scheduling centers can promote resource complementarity and recycling among enterprises, and enhance the economies of scale and environmental advantages of efficient resource allocation.

Secondly, it is suggested to increase fiscal and tax support for the integrated innovation of AI and green technologies. Special funds shall be set up to encourage enterprises to increase green innovation patents. AI-enabled R&D systems can cut innovation costs and boost enterprises' green technology R&D vitality. Meanwhile, encouraging open-source green technology communities and patent sharing systems can promote knowledge spillover and collaborative innovation, and form a sound innovation ecosystem. An AI-centered intellectual property evaluation and trading system shall be established to identify and commercialize high-level green technologies. Support shall focus on the cooperation between enterprises and research institutions, which applies AI to optimize technical paths and evaluate innovation results, so as to improve the technical complexity and market value of green innovation. In addition, it is required to introduce international advanced green technology certification standards to ensure that enterprises' green innovation meets global requirements and improves its international competitiveness.

Next, financial organizations shall be encouraged to develop AI-based green credit smart risk management systems to improve the quality of green project identification and lending. Policies shall guide banks to set up special green loan programs and use AI to dynamically evaluate corporate environmental records, thus improving credit accessibility for environmentally responsible enterprises. Meanwhile, inter-departmental green information sharing platforms integrating multi-source data from environmental protection, taxation, industry and commerce authorities shall be supported to eliminate information asymmetry between financial institutions and enterprises. Enterprises shall be guided to use AI to screen green investment projects and evaluate benefits, so as to improve the scientificity of investment decisions. The government can

boost green investment in environmental protection equipment and clean technologies through a combination of green investment subsidies and tax incentives. In addition, the establishment of green industry investment funds shall be encouraged to attract social capital, and form a green investment and financing pattern led by the government and supplemented by the market.

Fourth, it is worth considering integrating AI technology into ESG rating systems, especially promoting enterprises to implement intelligent ESG data disclosure and management systems. Policy incentives shall aim to improve the quality and transparency of ESG information, raise awareness of green transformation enterprises among the market and investors, and expand policy impact. Meanwhile, support shall be given to third-party institutions to develop AI-based ESG rating tools, to ensure more objective and timely ratings and provide reliable basis for corporate green transformation. It is recommended that enterprises use AI to improve internal control systems, and achieve intelligent risk detection and automatic process monitoring. Promoting intelligent internal control systems will improve compliance and operational efficiency, and provide reliable institutional guarantee for green transformation. In addition, industry-specific principles for building intelligent internal control can help organizations optimize internal control processes, reduce operational risks, and increase potential for sustainable development.

Fifth, it is necessary to increase government support for enterprise Digital Corporate Transformation programs to promote the in-depth integration of AI, big data and green technologies. Through technical training and financial support, the government can help enterprises establish digital green production systems and improve their sensitivity to green policies. At the same time, Digital Corporate Transformation demonstration projects shall be built to promote excellent practices and support the overall digital and green upgrading of industrial chains. In highly concentrated industries, the promotion of AI and green technologies shall be coordinated, with leading enterprises playing a demonstration role. The establishment of industrial green technology sharing networks shall be encouraged to promote technology diffusion and collaborative innovation, and reduce the negative impact of market concentration on green transformation. In addition, clusters and alliances shall be formed to encourage small and medium-sized enterprises to join relevant platforms, so as to improve the overall level of industrial green innovation and the efficiency of resource allocation.

Sixth, local governments shall consider building AI-based integrated green finance service systems to integrate financial data and ecological information. Through intelligent matching between enterprises and appropriate green financial solutions, capital allocation efficiency can be improved, which strengthens the supporting role of green finance development in regional green economic transformation. In addition, green finance reform and innovation pilots can be carried out to test the integration of financial technology and green finance and sum up replicable experience models. The construction of urban digital infrastructure shall be promoted to realize the deep integration of AI, the Internet of Things and the green economy. Developing smart environmental protection platforms and digital twin systems can improve urban digital governance capabilities, and create a favorable external environment with a high-level digital economy for corporate green transformation. Meanwhile, the coordinated development of the

regional digital economy shall be strengthened to remove data barriers, promote cross-regional flow and rational allocation of resources, and thus boost green transformation.

7.3 Limitations and Future Research

Although this study provides robust empirical evidence on the impact of AI Pilot Zones on corporate green transformation, several limitations warrant consideration. First, the empirical sample is restricted to Chinese A-share listed companies due to data availability; future research could extend the investigation to non-listed small and medium-sized enterprises (SMEs) or cross-country contexts. Second, while this paper covers multi-dimensional transmission channels (agency costs, resource allocation, and credit availability), future studies could further explore micro-operational mechanisms using high-frequency environmental disclosure data or granular corporate telemetry.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The macroeconomic and micro-financial datasets generated and analyzed during the current study are derived from publicly available databases, including the China Stock Market & Accounting Research (CSMAR) database, WIND database, and official policy announcements from the Ministry of Industry and Information Technology (MIIT) of China. The cleaned empirical dataset and Stata replication scripts (Do-files) supporting the conclusions of this article are uploaded as Supplementary Information files accompanying this submission to enable full peer-review verification and empirical replication.

addendum

type of variable	variable	Variable explanation	variable declaration
Dependent Variable	CGT	Corporate Green Transformation	The paper uses the green total factor productivity of enterprises to measure the environmental pollution of enterprises, and uses the non-radial SBM-ML index to measure the environmental pollution of enterprises.
Core Explanatory Variable	inter	AI Pilot Zone	The equation "equal to" is expressed as $Treat \times Post$, where <i>Treat</i> is a dummy variable for policy grouping: 1 for enterprises in cities designated as AI pilot zones, 0 otherwise. <i>Post</i> is a dummy variable for policy duration: 1 for years when the city was approved as an AI pilot zone, 0 otherwise.
Mediating	Flex	Credit Availability	(Long-term loans + short-term loans) / total

<i>Variable</i>			<i>assets</i>
	<i>RAE</i>	<i>Resource Allocation Efficiency</i>	<i>The investment efficiency is measured by estimating the reasonable investment level of the enterprise and calculating the residual between the actual investment and the expected investment.</i>
	<i>GI</i>	<i>Green Investment</i>	<i>Environmental protection construction in progress/total assets at the end of the period</i>
	<i>AC</i>	<i>Agency Costs</i>	<i>management expense ratio</i>
	<i>GIN</i>	<i>Green Innovation Number</i>	<i>Number of green patent applications</i>
	<i>GIQ</i>	<i>Green Innovation Quality</i>	<i>Number of citations for green patents</i>
<i>Moderating Variable</i>	<i>ESG</i>	<i>ESG</i>	<i>Huazheng ESG Score</i>
	<i>LIC</i>	<i>Level of Internal Control</i>	<i>Dibo Internal Control Index.</i>
	<i>DCG</i>	<i>Digital Corporate Transformation</i>	<i>This paper analyzes the frequency of 76 digital-related words in the annual reports of enterprises from five dimensions: artificial intelligence technology, big data technology, cloud computing technology, blockchain technology, and digital technology. The natural logarithm of the frequency is used to measure the level of enterprise digitalization.</i>
	<i>HHI</i>	<i>HHI</i>	<i>Herfindahl-Hirschman Index (HHI)</i>
	<i>GF</i>	<i>Green Finance Development Level</i>	<i>entropy evaluation method</i>
	<i>LDE</i>	<i>Level of Digital Economy</i>	<i>digital inclusive finance index logarithm</i>
<i>Control Variables</i>	<i>SIZE</i>	<i>Firm Size</i>	<i>Ln (Total assets at the end of the year)</i>
	<i>TOP</i>	<i>Top Shareholder's Ownership Ratio</i>	<i>shareholding of largest shareholder / total share capital</i>
	<i>LEV</i>	<i>Leverage Ratio</i>	<i>Year-end total liabilities to total assets ratio</i>
	<i>ROA</i>	<i>Return on Assets</i>	<i>net profit/total assets</i>
	<i>AGE</i>	<i>Firm Age</i>	<i>Ln (Current Year - Establishment Year + 1).</i>
	<i>CASH</i>	<i>Cash Holdings</i>	<i>net cash flow from operating activities/total assets</i>
	<i>GDP</i>	<i>Regional GDP</i>	<i>Ln(City GDP)</i>
	<i>RIU</i>	<i>Regional Industrial Upgrading</i>	<i>Value added of the tertiary industry / Value added of the secondary industry in the region.</i>
	<i>DUAL</i>	<i>CEO-Chairman Duality</i>	<i>Equals 1 if the Chairman and CEO are the same person, 0 otherwise.</i>

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