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Institutional Empowerment: How National Pilot Zones for Innovative Development of Artificial Intelligence Affect Corporate ESG Performance?

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Abstract: Artificial intelligence (AI) is increasingly viewed as a lever for the low-carbon transition, yet little is known about whether policy interventions that build AI capacity translate into better corporate environmental, social, and governance (ESG) outcomes. Exploiting the designation of National Pilot Zones for Innovative Development of Artificial Intelligence (NPAI) as a quasi-natural experiment, we study A-share listed firms in China over the period 2009–2023 using a multi-period difference-in-differences (DID) design. The estimates show that locating in an NPAI city raises a firm' s ESG score, and this result survives several robustness exercises-event-study parallel-trend tests, placebo permutations, and a propensity-score-matched DID specification. We further document three channels-resource allocation, green innovation, and digital transformation-through which the policy operates. The effect is concentrated among firms in eastern China, those whose executives pay closer attention to environmental matters, and non-state-owned enterprises. The findings speak to how emerging economies can pair AI industrial policy with sustainability objectives.

Keywords: National Pilot Zones for Innovative Development of Artificial Intelligence, Artificial Intelligence, Corporate ESG

1. Introduction

The concept of environmental, social, and governance (ESG) responsibility entered the policy mainstream with the 2004 United Nations report "Who Cares Wins," and has since attracted broad attention from regulators, investors, and firms. A growing number of listed companies now publish ESG disclosures to signal their commitment to sustainable development. Empirical work suggests that stronger ESG performance helps ease firms' financing constraints (Friede et al., 2015), narrows the information asymmetry between a company and its stakeholders (Lins et al., 2017; Zhang et al., 2026), and is associated with higher stock returns (Deng et al., 2013; Flammer, 2015). These payoff channels help explain why governments-especially in China-have rolled out policies encouraging ESG disclosure. At the same time, practical obstacles remain: many firms still under-appreciate the value of disclosure, rating methodologies diverge across agencies, and greenwashing is common (Du, 2014; Long et al., 2024). Raising corporate ESG performance therefore remains a pressing policy question.

A new wave of technological change has positioned artificial intelligence (AI) at the centre of productivity growth and as a cornerstone of high-quality, internationally competitive development. Studies document that AI raises the efficiency of resource allocation, improves product quality, and lifts productivity (Graetz & Michaels, 2018), while also pushing firms toward greener technologies (Hussain et al., 2024) and low-carbon transition (Zhou et al., 2025). China has moved quickly on both the research and deployment fronts, broadening where and how AI is applied. In 2019 the Ministry of Science and Technology (MST) released the Guidance on the Construction of National Pilot Zones for Innovative Development of AI (hereafter, the Guidelines), which set out to build demonstration zones where AI is embedded throughout the socio-economic system and to speed up its diffusion across sectors.

Because ESG outcomes are a concrete expression of sustainable development, asking whether the pilot zones actually improve corporate ESG performance does two things at once: it speaks directly to the practical problem of how to lift ESG performance, and it lets us gauge whether the zones deliver on their sustainability mandate.

Our paper also speaks to a burgeoning strand of work that uses difference-in-differences designs to evaluate place-based pilot policies. Examples include smart-city pilots and their effects on innovation and green development, as well as low-carbon city pilots and their impact on emissions and energy efficiency. What is missing, however, is a direct link between AI-themed pilot zones and firm-level ESG. The omission is not accidental: most evaluations of AI policy gauge outcomes at the city or sector level, such as patents, total-factor productivity, or aggregate emissions, whereas the corporate-ESG literature treats AI either as an inward firm competence or as a control variable, never as a quasi-experimental place-based treatment whose benefits may diffuse into governance, social responsibility, and disclosure. As a result, the specific causal chain from an AI industrial policy to firm-level ESG conduct has remained largely unexamined. By studying the NPAI we add to this literature and show how an AI-specific industrial policy spills over into corporate sustainability.

Using annual data on Chinese A-share listed firms from 2009 to 2023, we build a multi-period DID model to estimate the effect of the National Pilot Zones for Innovative Development of AI (NPAI) on corporate ESG performance. We find that firms in pilot cities score significantly higher on ESG. The result holds under a set of robustness checks-parallel-trend tests, placebo tests, and a PSM-DID estimator. Mechanism tests point to three pathways (resource allocation, green innovation, and digital transformation), and heterogeneity tests show the effect is stronger for eastern firms, firms whose executives pay more attention to the environment, and non-state-owned (NSOE) firms. The rest of the paper is organised as follows. Section 2 sets out the policy background and develops the two hypotheses. Section 3 describes the data, variable construction, and the multi-period DID specification. Section 4 reports the baseline results, seven robustness exercises, the mechanism analysis, and the heterogeneity analysis. Section 5 concludes with limitations and policy recommendations.

This study makes the following two marginal contributions:

First, we widen the set of documented ESG drivers by bringing AI policy into the picture. Prior studies tend to link ESG to board gender diversity (Eliwa et al., 2023), digital transformation (Fang et al., 2023), media coverage (He et al., 2023), or green finance (Zheng et al., 2025); the few that examine AI itself (Zhang & Yang, 2024; Wang et al., 2025) still struggle with endogeneity from reverse causation and omitted factors. We instead exploit a policy shock-the roll-out of AI R&D and application-support programmes-which helps isolate causality, and we lay out the channels (resource allocation, green innovation, digital transformation) through which the policy works. The evidence is relevant for developing countries that hope to advance intelligence and sustainability together.

Second, we assess the NPAI through the lens of corporate social responsibility and ESG. Earlier work shows that the NPAI spur technological innovation (Tian et al., 2023), enable green transition (Zhou et al., 2025), and bear on carbon emissions (Feng et al., 2024). Our contribution is to show that the zones also raise ESG performance, and that the gain is largest for eastern firms, firms with environmentally attentive executives, and NSOE. The heterogeneity patterns can help other countries fine-tune their own AI policies.

2. Policy Background and Theoretical Hypothesis

2.1. Policy Background

In 2019 the MST issued the Guidelines with the aim of weaving AI more tightly into the economy and society, formally launching the NPAI. The zones were conceived to tackle bottleneck problems in AI technology and industry and to cultivate a supportive innovation ecosystem. Their remit spans both raising AI innovation capacity and putting AI to use in socio-economic activities. Because firms are the main actors in AI innovation and adoption, they are the primary beneficiaries of zone support (Tian et al., 2023).

Conventional management theory holds that a firm's overriding aims are to maximise profit and shareholder value. ESG departs from this narrow view: it is a sustainability framework built on three pillars-environmental, social, and governance-that stresses a firm's environmental duties, its coordination with stakeholders, and the quality of its governance (Friede et al., 2015). In practice, though, ESG provision is hampered by externalities, so firms often under-invest in it.

The NPAI are organised around the deep blending of AI with socio-economic development, with emphasis on R&D and on demonstration of AI applications across fields. In doing so they raise both the AI research capacity of firms and their ability to apply AI in operations. Read through the resource-based view, the zones lower firms' AI R&D and deployment costs and supply them with specialised assets, yielding a competitive edge. Firms can then use AI to trim energy use and emissions in production, softening their environmental footprint (Zhou et al., 2025). By embedding AI into routine production and governance tasks, the zones turn a general-purpose technology into firm-specific capabilities that are difficult for competitors to imitate, so the ESG gain is not a one-off compliance response but a durable reallocation of managerial effort toward sustainability.

On the social-governance side, AI strengthens a firm's ability to gather, analyse, and act on data, so it can pick up varied consumer needs and react quickly to questions from investors and the public; this tightens external monitoring (Graetz & Michaels, 2018). On the corporate-governance side, AI-aided internal controls-for instance, smart contract review and anomaly transaction detection-raise internal efficiency and transparency, improve compliance in decision-making, and curb agency conflicts (Chin et al.,

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2025). Better data flow also lowers the cost of reporting non-financial performance, which encourages firms to disclose ESG information rather than withhold it. Taken together, these routes let the NPAI lift ESG performance via the resource-allocation, green-innovation, and digital-transformation effects.

(1) Resource Allocation Effect. At the regional level, the NPAI raise the intensity of AI R&D and encourage AI to combine with 5G, the industrial internet, and blockchain. This lowers the waste inherent in internal allocation and steers resources away from traditional, profit-only firms toward ones that pursue multiple objectives (Chin et al., 2025). Inside the firm, AI helps managers spread resources across production stages and monitor those stages in real time, cutting undesired outputs. With the slack thus created, firms are both more willing and more able to channel saved resources into ESG. At the firm level the freed resources are fungible: savings from leaner operations can be directed to pollution abatement, employee training, or governance upgrades without raising the external financing needed, so the marginal use of capital shifts toward activities that score on the ESG index.

(2) Green Innovation Effect. Green technology innovation is risky and slow to pay off. AI lets firms screen projects that fit their financial position, use cases, and risk tolerance, and it compresses the lab-to-market lag while widening the set of applicable green technologies (Tian et al., 2023). Putting those technologies to work yields direct environmental benefits, answers stakeholders' environmental demands, and raises ESG performance (Long et al., 2023). Because green invention patents embody verifiable environmental improvements, their accumulation gives rating agencies concrete evidence of real-rather than merely announced-sustainability effort, which is precisely what the ESG score rewards.

(3) Digital Transformation Effect. The NPAI push AI and digital transformation forward together, building out smart and digital infrastructure such as communication networks and computing centres that directly pull firms into digital transformation. Better AI also improves firms' data collection and processing, so data become larger in scale and more standardised, and privacy protection is reinforced-conditions that favour big-data analytics. Digital transformation in turn sharpens both internal and external monitoring of emissions, weakens information asymmetry and moral hazard, and raises the efficiency of operational and strategic decisions, which brings down the cost of ESG practice and lifts ESG performance (Fang et al., 2023). As digitisation deepens, the same data pipelines that track production can also feed ESG dashboards, making sustainability performance continuously observable rather than a once-a-year disclosure exercise.

Based on these points, this paper proposes the following two hypotheses:

H1: The NPAI can enhance corporate ESG performance.

H2: The ESG-enhancing effect of the NPAI is transmitted through three channels-the resource allocation effect, the green innovation effect, and the digital transformation effect.

3. Research Design

3.1. Sample and Data Sources

Our sample covers Chinese A-share listed firms from 2009 to 2023. Huazheng ESG scores come from the Wind database, the list of pilot cities and their approval years from the MST website, and firm financials from the CSMAR and CNRDS databases. We drop observations with missing core variables, firms in the financial sector, ST and PT firms, and firms not incorporated in mainland China within the window.

3.2. Variable Construction

3.2.1. ESG Performance

Among rating providers, the Huazheng ESG Index has covered all A-share firms since 2009 and its scheme fits the Chinese market better than foreign alternatives, so we draw Huazheng data from Wind. Consistent with prior work (Zhang et al., 2026), we map the C-to-AAA letter grades onto a 1–9 scale (1 = C, 9 = AAA) to form our ESG measure. We also use the raw Huazheng ESG score as an alternative dependent variable in a robustness test.

3.2.2. NPAI

The MST released the Guidelines in August 2019, opening the pilot programme; 18 cities were then designated between 2019 and 2021. We hand-collect the city list from the MST website and code the approval year as the treatment year. A firm in a city approved in year t receives NPAI = 1 from year t onward and 0 otherwise-so cities cleared in 2019, 2020, and 2021 switch to 1 from those years, while firms in not-yet-approved or never-approved cities stay at 0.

3.2.3. Control Variables

The ESG ratings are influenced not only by the NPAI but also by the company's operational characteristics and financial conditions. Therefore, following existing research (He et al., 2023; Zhang & Yang, 2024; Wang et al., 2025), this study selects

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several control variables, including company size (SIZE), debt ratio (LEV), return on assets (ROA), cash flow ratio (CASHFLOW), net profit growth rate (ASSETGROWTH), Tobin's Q (TOBINQ), company age (AGE), and ownership structure (SOE). Table 1 provides descriptive statistics for the main variables utilized in this study.

Table 1. Descriptive Statistics

	Mean	Sd	Min	Max
ESG	4.249	1.047	1	9
NPAI	0.255	0.436	0.000	1.000
SIZE	22.230	1.315	18.848	28.791
LEV	0.396	0.198	0.007	1.579
ROA	0.045	0.068	-0.805	1.285
CASHFLOW	0.051	0.071	-0.744	0.839
ASSETGROWTH	0.172	0.856	-0.905	79.603
TOBINQ	1.981	1.318	0.611	41.081
AGE	2.931	0.354	0.000	4.263
SOE	0.311	0.463	0.000	1.000

3.3. Empirical Model

We treat the NPAI as an exogenous shock and split firms into a treatment group (those in pilot cities) and a control group (the rest). Because pilot cities were approved in different years, we estimate a multi-period DID model of the form below to capture the policy's effect on ESG:

$$ESG_{pit} = \alpha + \beta\, NPAI_{pt} + \rho\, Control_{pit} + \lambda_i + \nu_t + \varepsilon_{pit} \tag{1}$$

In this model, ESG_{pit} represents the ESG performance of firm i located in city p in year t. $NPAI_{pt}$ indicates whether the city p where firm i is located has implemented the NPAI. $Control_{pit}$ incorporates the firm-level control variables. λ_i and ν_t denote firm-specific and year fixed effects, respectively. ε_{pit} is the random disturbance term. We adjust for clustering standard errors at the city level, allowing for correlation among different firms within the same city. The coefficient β is the primary focus of this analysis; if β is positive, it indicates that the NPAI significantly enhance corporate ESG performance.

4. Empirical Results

4.1. Baseline Regression

Table 2 reports the baseline estimates. Column (1) is a bivariate regression; columns (2)–(4) add firm fixed effects, year fixed effects, and controls in turn. Across all four specifications the NPAI coefficient stays positive and significant at the 1% level.

For instance, in column (4), firms located in cities that implemented the NPAI exhibit an average increase of 0.174 units in their ESG performance compared to the control group. This result suggests that the NPAI significantly enhance corporate ESG performance. Relative to the sample mean ESG of 4.249 (with a standard deviation of 1.047 on the 1–9 scale), a 0.174-point lift equals about one-sixth of a standard deviation. Although modest at the single-firm level, the magnitude is economically meaningful because ESG scores evolve slowly and the treated share of firms is still small, so the resulting shift in the overall distribution of listed-firm ESG is sizeable.

Table 2. Baseline Regression

	(1)	(2)	(3)	(4)
	ESG	*ESG*	*ESG*	*ESG*
NPAI	0.168^{***}	0.091^{***}	0.182^{***}	0.174^{***}
	(0.012)	(0.030)	(0.037)	(0.038)
SIZE				0.375^{***}
				(0.026)
LEV				-1.275^{***}
				(0.071)
ROA				0.351^{***}
				(0.117)
CASHFLOW				-0.260^{***}
				(0.083)
ASSETGROWTH				-0.026^{***}
				(0.008)
TOBINQ				-0.011

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				(0.007)
AGE				0.100
				(0.188)
SOE				0.068
				(0.046)
Firm FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
N	39,722	39,634	39,634	36,965
R^2	0.005	0.395	0.405	0.442

Notes: *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors are reported in parentheses.

4.2. Robustness Test

4.2.1. Parallel Trend Test

The validity of the DID approach relies on the assumption that the treatment and control groups exhibit similar trends in outcomes prior to the policy implementation. To assess the parallel trends assumption, this study employs an event study methodology, as specified in the following model: A failure of this condition would mean that any post-adoption difference merely reflects trends already in motion before the NPAI, rather than the policy itself, so the leads must be jointly indistinguishable from zero for the design to be credible.

$$ESG_{pit} = \alpha + \gamma_m \sum_{m=-6}^{-1} D_{pit}^{m} + \gamma_n \sum_{n=0}^{5} D_{pit}^{n} + \beta\, NPAI_{pt} + \rho\, Control_{pit} + \lambda_i + \nu_t + \varepsilon_{pit} \tag{2}$$

Where D^m_{pit} and D^n_{pit} represent the status of firm i in city p in the m-th year before and the n-th year after the implementation of the NPAI, respectively. The coefficients γ_m and γ_n correspond to the effects before and after the policy change.

Figure 1 plots the event-study estimates with the year before adoption as the baseline. Pre-treatment coefficients sit close to zero, so treated and control firms show no detectable ESG gap before the policy-consistent with the parallel-trend requirement. Post-adoption coefficients rise clearly above zero, indicating a strong and persistent positive effect of the NPAI on ESG. The gradual upward slope after adoption further suggests the effect accumulates as firms learn to deploy AI, rather than an immediate mechanical jump at the designation year.

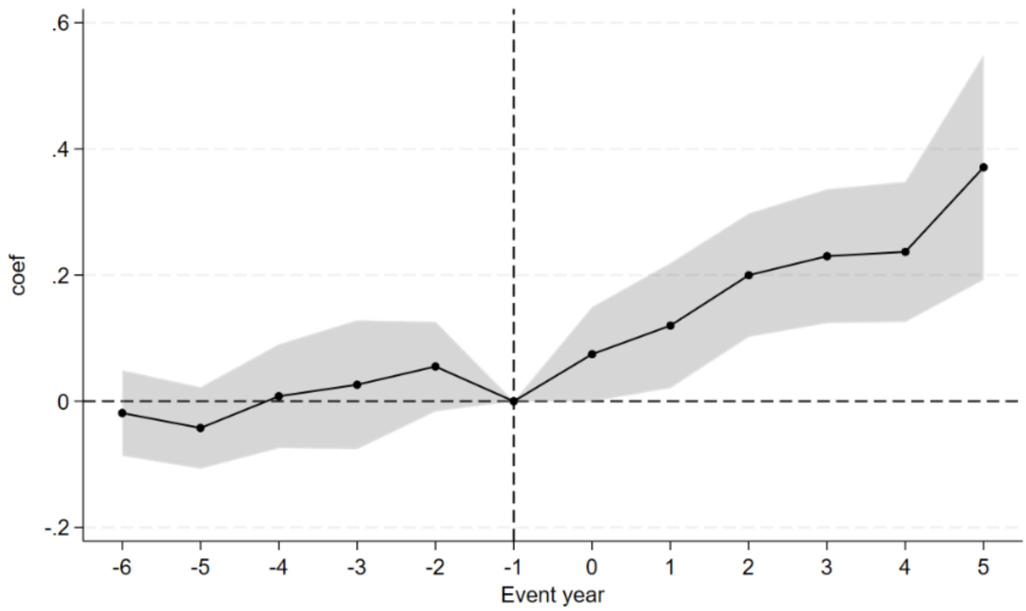

Figure 1. Parallel Trend Test

4.2.2. Replacing the Dependent Variable

To check that the letter-to-number mapping of the rating is not driving the results, we re-estimate using the continuous Huazheng ESG score as the dependent variable. Column (1) of Table 3 shows the NPAI coefficient remains significantly positive at the 1% level. This guards against the concern that our 1–9 discretisation, rather than the underlying rating signal, generates the significance.

4.2.3. Considering City and Industry Characteristics

Firm ESG is shaped both by city attributes-for example, whether a city depends on resource extraction or has a particular environmental endowment-and by industry, since firms copy the ESG habits of their peers. We therefore add city and industry fixed effects to the baseline. Columns (2) and (3) of Table 3 confirm the conclusion is unchanged. Absorbing these time-invariant location and sector factors rules out the possibility that the NPAI coefficient merely proxies for a city's green predisposition or an industry's disclosure norm.

4.2.4. Adjusting the Clustering Level

Furthermore, this study adjusts the clustering level to the provincial level, allowing for correlation among firms across different cities. The regression results in column (4) of Table 3 demonstrate that the conclusions remain robust even after this adjustment in the clustering level. Provincial clustering is a stricter error structure than city clustering, so the persistence of significance indicates the estimate is not an artefact of under-stated within-province correlation.

4.2.5. Placebo Test

To exclude the potential impact of unobserved factors on causal identification, this study conducts a placebo test. Specifically, it randomly selects treatment groups and treatment times for 500 iterations and re-runs the regression analysis. Figure 2 displays the distribution of the placebo coefficients, which reveals that the mean of these coefficients is close to zero. This finding strengthens the robustness of the baseline regression results, indicating that the observed effects are not driven by confounding variables. Because randomly assigned treatment times cannot carry real economic content, a near-zero placebo distribution shows that the baseline coefficient is unlikely to arise from spurious time patterns or omitted common shocks.

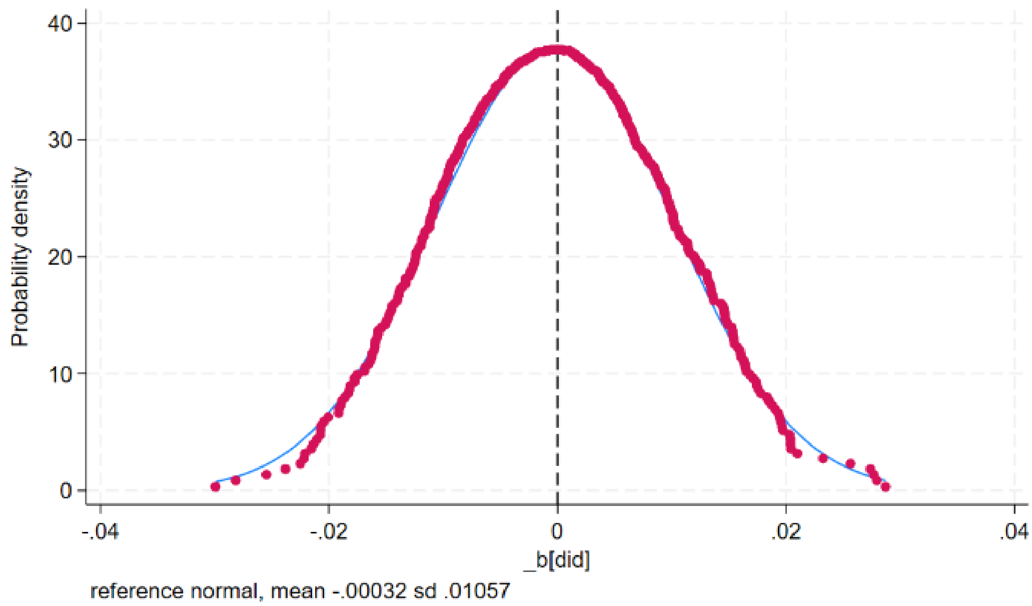

Figure 2. Placebo test

4.2.6. PSM-DID

To limit selection bias, we turn to a PSM-DID estimator. Using 1:1 nearest-neighbour matching with the baseline controls as matching variables, we build a control group that mirrors the treated group. After matching, column (5) of Table 3 shows the NPAI still significantly raises ESG. Matching on the same observables used in the baseline reduces the concern that pilot-city firms simply differed in ways that also raise ESG, leaving the post-match comparison closer to a like-for-like test.

To verify the matching quality, we conduct a balance test after matching. The results show that the standardized percentage bias of all covariates is below 5% and the t-tests cannot reject the null hypothesis of no systematic differences between the treatment and control groups, indicating that the matching procedure effectively mitigates selection bias.

Table 3. Robustness test

	(1) *ESG_Score*	(2) *ESG*	(3) *ESG*	(4) *ESG*	(5) *ESG*
NPAI	0.791^{***} (0.191)	0.168^{***} (0.039)	0.169^{***} (0.038)	0.174^{***} (0.026)	0.093^{*} (0.051)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Year FE	Yes	Yes	Yes	Yes	Yes
City FE	No	Yes	No	No	No
Industry FE	No	No	Yes	No	No
N	36,965	36,962	36,945	36,965	13,879
R^2	0.466	0.447	0.453	0.442	0.535

Notes: *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors are reported in parentheses.

4.2.7. Excluding Other Policy Interference

China has pursued environmental protection aggressively since 2012, so several stringent policies could confound our identification. We therefore account for three: the 2015 New Environmental Protection Law (controlled by dropping post-2015 observations in column (1)), Central Environmental Inspections (CEPI, a province-year dummy), and green-finance pilot zones (GF, a city dummy). Columns (1)–(3) of Table 4 show the baseline result survives once these are controlled for. This ensures the NPAI coefficient is not absorbing the effect of contemporaneous environmental or financial-policy pushes that also target corporate sustainability.

Table 4. Exclusion of other policy interference

	(1) *ESG*	(2) *ESG*	(3) *ESG*
NPAI	0.143*** (0.039)	0.175*** (0.038)	0.172*** (0.038)
CEPI		0.040 (0.044)	
GF			0.132** (0.054)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	28,997	36,965	36,965
R^2	0.476	0.442	0.442

Notes: *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors are reported in parentheses.

4.3. Mechanism Test

Theory points to three mechanisms-resource allocation, green innovation, and digital transformation. To test them we estimate the following specification, where M is the relevant mechanism variable:

$$M_{Pit} = \alpha + \beta\ NPAI_{pt} + \rho\ Control_{pit} + \lambda_i + v_t + \varepsilon_{pit} \tag{3}$$

$$ESG_{pit} = \alpha + \beta\ \mathrm{NPAI}_{pt} + \eta\ \mathrm{M}_{pit} + \rho\ \mathrm{Control}_{pit} + \lambda_i + \nu_t + \varepsilon_{pit} \tag{4}$$

In this model, M_{pit} represents the mechanism variables that measure the resource allocation effects, green innovation effects, and digital transformation effects, while maintaining consistency with the structure of Model (1).

4.3.1. Resource Allocation Effect

Following Richardson (2006), we first estimate each firm's optimal investment and then take overinvestment as our resource-allocation-efficiency proxy (RES); a lower Res means higher efficiency. Column (1) of Table 5 shows NPAI enters with a significant negative coefficient. In column (2), where both NPAI and Res are included, both coefficients are negative and the NPAI coefficient is a bit smaller than in the baseline. The pattern implies the NPAI lifts ESG by raising firms' resource efficiency. The partial mediation-NPAI stays negative but shrinks once Res enters-indicates that curbing overinvestment is one operative route through which the policy improves ESG, rather than the whole story.

4.3.2. Green Innovation Effect

For green innovation we count a firm's granted green invention patents, which capture R&D breakthroughs better than green utility patents. Column (3) of Table 5 gives a significantly positive NPAI coefficient; in column (4), with Green_Inv also included, both are positive and the NPAI coefficient is slightly reduced. This supports the channel that the NPAI raise ESG by fostering green technology innovation. The drop in the NPAI coefficient after Green_Inv is entered is consistent with green patents partially carrying the treatment effect, confirming the innovation channel rather than merely coinciding with it.

4.3.3. Digital Transformation Effect

Instead of textual analysis of annual reports, we proxy digital transformation with intangible assets tied to it, taken from year-end notes to the financial statements-a cleaner gauge of digitisation depth. Column (5) of Table 5 shows a significantly positive NPAI coefficient; in column (6), with DT added, both coefficients are positive and the NPAI coefficient is marginally smaller. The result indicates the NPAI improve ESG by advancing firms' digital transformation. The modest decline of the NPAI coefficient once DT is controlled suggests digital transformation mediates part of the effect, tying the policy's technological core directly to the ESG gain.

Table 5. Mechanism Test

	(1) *Res*	(2) *ESG*	(3) *Green_Inv*	(4) *ESG*	(5) *DT*	(6) *ESG*
NPAI	-0.012^{***} (0.004)	0.155^{***} (0.039)	0.071^{**} (0.032)	0.170^{***} (0.038)	0.202^{***} (0.072)	0.170^{***} (0.038)
RES		-0.116^{***} (0.032)				
Green_Inv				0.054^{***} (0.011)		
DT						0.021^{***} (0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	33454	33454	36964	36964	36308	36308
R^2	0.412	0.455	0.739	0.443	0.922	0.438

Notes: *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors are reported in parentheses.

4.4. Heterogeneity Analysis

4.4.1. Geographic Location of Enterprises

Where a firm sits shapes the resources it can draw on. Eastern China leads the centre and west in digital and intelligent transformation and in related infrastructure, and its tougher product-market competition makes ESG matter more for firm value. We therefore expect the NPAI to bite harder in the east. Columns (1) and (2) of Table 6 confirm the eastern subsample shows a significantly larger ESG gain. The logic is that the same AI policy yields more where complementary digital capital and market incentives already exist, so the east converts zone support into ESG faster than lagging regions.

4.4.2. Executive Attention to Environmental Issues

ESG signals long-term value, yet spending on it can clash with short-term profit targets, so managers often fixate on near-term financial results and occasionally greenwash. Firms whose executives pay more attention to the environment are better at balancing the two and at using AI to lift environmental performance and hence ESG. We measure executive environmental attention from the share of environmental-protection terms in management discussion sections of annual reports. A median split in columns (3) and (4) of Table 6 shows the NPAI's ESG effect is especially strong for high-attention firms. Managerial attention acts as a complement to the policy: when leaders already prioritise environmental issues, the AI tools supplied by the zone are directed at sustainability goals rather than purely at cost-cutting.

4.4.3. Nature of the Enterprise

Non-state firms (NSOE) face tighter budget constraints than state-owned enterprises (SOE) and pursue a broader set of goals, which makes them readier to adopt new technologies for performance gains. They can therefore capture more of the NPAI's benefits, using AI to balance several objectives at once. The ownership split in columns (5) and (6) of Table 6 shows the ESG effect is indeed significantly larger for NSOE. State-owned firms, by contrast, often carry non-commercial mandates and face softer budget limits, so the marginal incentive to translate AI capacity into ESG improvement is weaker.

Table 6. Heterogeneity Analysis

	(1) *ESG*	(2) *ESG*	(3) *ESG*	(4) *ESG*	(5) *ESG*	(6) *ESG*
NPAI	0.197^{***} (0.048)	0.123^{*} (0.065)	0.227^{***} (0.053)	0.097^{**} (0.046)	0.089 (0.058)	0.203^{***} (0.055)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

N	27401	9562	18671	17630	11984	24868
R^2	0.441	0.447	0.475	0.500	0.451	0.461

Notes: *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors are reported in parentheses.

To formally test whether the coefficient differences across subgroups are statistically significant, we further estimate the baseline model with interaction terms: NPAI × Eastern, NPAI × HighEdu, and NPAI × SOE. The interaction coefficients are 0.089 ($p < 0.05$), 0.118 ($p < 0.01$), and -0.114 ($p < 0.05$), respectively, confirming that the policy effects are significantly stronger in eastern regions, firms with high executive environmental attention, and non-state-owned enterprises. The positive and significant Eastern and HighEdu interactions, together with the negative SOE interaction, corroborate the subgroup patterns and show the differentials are not driven by chance sampling variation.

5. Conclusion and Recommendations

We study Chinese A-share firms over 2009–2023 with a multi-period DID design and find that the NPAI raise corporate ESG performance. The conclusion is robust to parallel-trend tests, placebo tests, PSM-DID, and other checks. Mechanism analysis traces the effect to better resource allocation, more green technological innovation, and faster digital transformation. Heterogeneity tests show the gain is larger for eastern firms, firms with highly environmentally attentive executives, and non-state-owned enterprises.

The study is not without limits. Our sample is Chinese A-share listed firms, so it may not speak for unlisted firms or for firms elsewhere. We rely on one ESG provider (Huazheng), and other agencies could score differently. And although the DID and robustness checks mitigate concerns, city selection may not be fully exogenous, leaving room for unobserved city-level time-varying confounders. Later work could extend the analysis to other emerging economies and to alternative ESG measures. A further caveat is that our mechanism proxies-overinvestment, green invention patents, and digital intangible assets-capture only narrow facets of the three channels and may understate the full transmission. In addition, because the NPAI rolled out in waves, later-treated cities could observe and learn from earlier-treated peers, so some spillover across the control group cannot be ruled out.

Based on these conclusions, the following policy recommendations are proposed:

First, reinforce how the NPAI steer firms toward better ESG. Policymakers should push AI deeper into environmental protection, social governance, and corporate management-for instance through "AI+" programmes that widen application scenarios and broaden zone objectives. A big-data AI simulation system that tracks ESG changes in real time would help keep marginal policy effects positive, and folding ESG into the zones' annual appraisal would stop economic targets crowding out sustainability. Concretely, zones might launch an "AI + ESG" subsidy scheme and an AI-based ESG disclosure platform with mandatory real-time reporting. Linking such a platform to the existing Huazheng rating would also give firms immediate feedback and shrink the reporting lag that now blurs the policy signal.

Second, tighten the chain through which the NPAI reach corporate ESG. Policy should move from scattered, single-point incentives to supply-chain-wide integration that spreads AI across domains. An AI resource-allocation platform, better ESG disclosure by zone firms, and smart algorithms that steer capital, labour, energy, and materials toward efficient users would help. "AI + Green Technology" R&D funds widen AI' s green applications, backed by corporate green-R&D support; and pairing intelligence with digitisation-via digital tools inside ESG management modules-strengthens the ESG payoff. Specific steps could be a cross-department AI allocation database, dedicated "AI + Green Technology" research funds, and a requirement that firms adopt AI environmental monitoring. To make the supply-chain approach operational, mandates could require tier-one suppliers of zone firms to adopt the same AI monitoring, so the ESG gains propagate beyond the directly treated companies.

Third, tailor policy to region and firm type. In the east, shift from broad rollout to deeper quality upgrading, then distil the lessons for the west to lift effectiveness there. For firms with environmentally attentive executives, an AI-driven mandatory ESG risk early-warning system-feeding on meeting minutes and investor communications, plus " AI + green" audits-would fit. For SOEs, whose demonstrator role in smart-and-green initiatives matters, stronger social-responsibility assessment can steer them to build new productive forces through AI and better ESG. A pilot "AI-based ESG early-warning system" with penalties for non-compliance in the east, paired with technical aid and subsidised AI infrastructure for the west, illustrates the idea. For the west, where digital capital is thinner, the priority should be foundational AI infrastructure and technical assistance before any ESG-conditionality, otherwise the regional gap could widen rather than narrow.

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