

5 DIGITALLY POWERED ESG EVALUATION: MITIGATING RATING DIVERGENCE THROUGH ARTIFICIAL INTELLIGENCE

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Abstract

Despite the growing integration of environmental, social, and governance (ESG) principles into corporate and investment strategies, ESG rating systems remain plagued by significant inter-agency discrepancies, undermining their reliability and comparability. This study investigates whether artificial intelligence (AI) can alleviate the ESG rating divergence by improving the quality, transparency, and consistency of corporate ESG disclosures. Using a panel dataset of Chinese A-share listed firms from 2015 to 2024, we construct an AI adoption index based on patent filings and textual analytics, and examine its impact on the ESG rating divergence across six major rating agencies. The results reveal that AI adoption significantly reduces ESG rating inconsistency. Mechanism tests further show that this effect is primarily driven by three channels: enhanced information transparency, improved internal coordination, and strengthened stakeholder communication. Specifically, AI technologies automate data collection, standardize disclosure formats, support cross-departmental ESG governance, and facilitate clearer engagement with external stakeholders. These mechanisms reduce information asymmetry and minimize subjective interpretation by rating agencies. Heterogeneity analysis demonstrates that the divergence-mitigating effect of AI is more pronounced in high-tech firms, non-state-owned firms, companies audited by non-Big Four auditors, financially constrained firms, and those in digitally advanced regions. These findings highlight the governance value of AI in ESG systems and offer practical implications for enhancing rating alignment in emerging markets.

Keywords: ESG Rating Divergence, Artificial Intelligence, Information Transparency, Internal Coordination, Stakeholder Communication

JEL Classification: G30

1. Introduction

As society places increasing emphasis on Environmental Protection, Social Responsibility, and Corporate Governance (ESG), companies face growing expectations to demonstrate their long-term value and sustainability to investors, consumers, and regulators. According to the Global Sustainable Investment Alliance, global sustainable investment assets reach \$30.300 trillion in

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2022. ESG integration refers to the systematic consideration of Environmental, Social, and Governance factors in investment analysis and decision-making in order to enhance risk-adjusted returns. It currently accounts for over 30 percent of total sustainable investment strategies in Canada, Australia and New Zealand, and Japan. This trend reflects the global progress in promoting sustainable financial practices. In this context, ESG ratings serve as an increasingly important benchmark for assessing the sustainability performance of companies. However, different rating agencies often produce significantly inconsistent evaluations for the same company, making rating divergence a growing concern. To improve the consistency and reliability of ESG ratings, AI (Artificial intelligence) technologies play an increasingly important role in ESG data processing and analysis. AI improves the efficiency of data collection, enhances the accuracy of information extraction, and identifies key ESG indicators from large volumes of unstructured data. These capabilities help address inconsistencies caused by information asymmetry, subjective interpretation, and differences in disclosure practices. As a result, AI contributes to improved transparency and credibility in ESG ratings. Despite these advances, the ESG rating landscape continues to face substantial challenges. Chatterji et al. (2016) identify considerable divergence in ESG assessments across six major rating agencies. These inconsistencies hinder the accurate evaluation of corporate performance, distort capital allocation decisions, and undermine the effectiveness of investment portfolios. They also weaken the core purpose of ESG assessments. Furthermore, fragmented ratings may reduce firms' incentives to improve their ESG practices and weaken the link between executive compensation and ESG outcomes (Berg et al., 2022).

Compared with countries such as the United States and the United Kingdom, where ESG systems are relatively mature, China is still in the process of improving its ESG rating mechanisms, corporate disclosure standards, and sustainability strategies (Su et al., 2024). As a result, the ESG rating divergence is more prevalent in the Chinese context. Against this backdrop, investigating the role of AI in mitigating ESG rating discrepancies is of greater practical and policy relevance. On the one hand, Chinese firms are accelerating the adoption of AI technologies as part of their digital transformation, providing a solid foundation for evaluating AI's impact on ESG disclosure and assessments (Su et al., 2025a). On the other hand, regulatory bodies and capital markets in China are placing increasing emphasis on ESG transparency and consistency, creating strong institutional incentives for AI-enabled ESG governance. Therefore, exploring the relationship between AI and ESG ratings from a Chinese perspective not only supports sustainable development among domestic firms but also offers valuable insights for other emerging markets.

In the realm of firm innovation and economic growth, AI investments have been shown to drive product innovation, improve operational efficiency, and enhance firms' market competitiveness (Qin et al., 2024). Beyond these economic benefits, the strategic deployment of AI also plays a critical role in addressing the ESG rating divergence. By improving the quality, consistency, and timeliness of ESG data through automated collection and intelligent analysis, AI reduces the informational asymmetries and subjective interpretations that often lead to discrepancies among ESG rating agencies (Zhou et al., 2025). As such, AI serves not only as a catalyst for innovation and growth, but also as a technological enabler that enhances ESG transparency, facilitates more consistent assessments, and ultimately contributes to narrowing ESG rating gaps. By integrating AI into ESG rating standards, scoring systems, and disclosure processes, firms can significantly reduce inconsistencies in ESG assessments. This integration not only enhances ESG evaluation frameworks but also promotes sustainable development within companies, offering investors more reliable and valuable information, thereby strengthening the theoretical and practical significance of ESG metrics. Building on this premise, this study empirically investigates the relationship between AI adoption and ESG rating discrepancies, using data from Chinese A-share listed companies spanning from 2015 to 2024. The findings reveal two major insights: First, the adoption of AI technologies leads to a significant reduction in ESG rating discrepancies,

underscoring AI's pivotal role in mitigating inconsistencies in ESG assessments. Second, the effect of AI adoption is heterogeneous, varying across industries, external governance structures, financing constraints, and the level of digital infrastructure development.

This study makes three key contributions to the existing literature on ESG ratings and AI. First, it incorporates AI adoption into the analytical framework of the ESG rating divergence, addressing a critical gap in current research on the role of AI in enhancing rating consistency. In contrast to prior studies that primarily examine the general impact of digital technologies on ESG performance, this study focuses on how AI improves rating comparability by optimizing data processing, enhancing information quality, and minimizing subjective interpretation. Second, it uncovers the heterogeneous effects of AI adoption across industries and organizational settings. The impact of AI differs markedly between heavily regulated sectors, such as finance and energy, and less regulated or smaller-scale industries, offering valuable insights into the context-dependent effectiveness of AI in ESG governance. Third, the study provides robust empirical evidence that AI adoption contributes to greater consistency and accuracy in ESG ratings, offering practical implications for corporate managers, rating agencies, and investors seeking to enhance sustainability evaluations in the digital era.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on the ESG rating divergence and the role of artificial intelligence in corporate governance, and proposes the research hypotheses based on prior studies. Section 3 introduces the data and empirical model. Section 4 presents the baseline regression results along with a series of robustness checks. Section 5 provides further analysis, including mechanism testing and heterogeneity analysis. Finally, Section 6 concludes the study and discusses its policy implications.

2. Literature review and hypotheses

2.1. Artificial Intelligence and the ESG rating divergence

The ESG rating divergence refers to the inconsistent assessments of a firm's ESG performance by different rating agencies. These discrepancies primarily arise from subjective evaluation standards, non-unified disclosure formats, and information asymmetries (Su et al., 2025b). Existing literature, both domestic and international, has primarily examined this issue from four key dimensions: executive characteristics, internal control systems, ESG disclosure quality, and technological innovation. Among these, the role of technology, particularly AI, in reducing rating inconsistencies has gained growing academic attention.

AI technologies, including natural language processing (NLP) and machine learning, have been shown to improve the accuracy, timeliness, and comparability of ESG information disclosure. For example, Wang (2025) utilize ChatGPT-4 sentiment scores to assess ESG disclosures and found that AI-generated indicators were strongly aligned with formal ESG ratings in China, suggesting the potential of AI to standardize ESG evaluations (Zhou et al., 2024a). Other studies argue that AI helps automate data collection, reduce subjectivity, and process large volumes of unstructured information in real time (Li et al., 2024a; Liu et al., 2024). However, while digital transformation more broadly has been empirically shown to enhance ESG rating alignment (Yang and Han, 2023; Ren, 2025), the specific role of AI, distinct from other digital tools, remains underexplored. Addressing this gap, our study examines how AI affects the ESG rating divergence, particularly in the context of Chinese listed firms, and proposes the following central hypothesis:

H1: AI adoption reduces the ESG rating divergence.

2.2. Artificial Intelligence, information transparency, and the ESG rating divergence

AI adoption significantly enhances the transparency of ESG information. By leveraging NLP and automated data collection systems, firms can extract, process, and standardize ESG-related content from internal records, sustainability reports, and third-party sources. This not only reduces reliance on manual reporting, which is prone to error and bias, but also increases the objectivity and timeliness of disclosures (Cai et al., 2024; Li et al., 2024a). In particular, AI minimizes the selective disclosure behavior observed in traditional ESG reporting practices and supports full-spectrum reporting across environmental, social, and governance dimensions. Greater information transparency lowers the uncertainty faced by ESG rating agencies and reduces their need for subjective judgment, leading to more consistent assessments across rating providers. As demonstrated by Li (2022) and Shimamura et al. (2025), low-readability and complex ESG reports exacerbate interpretive differences. Conversely, AI-enabled disclosure mechanisms can simplify language, structure key indicators, and reduce ambiguity, thereby improving inter-rater agreement and narrowing the ESG rating divergence.

H2: AI adoption reduces the ESG rating divergence by improving information transparency.

2.3. Artificial Intelligence, internal coordination, and the ESG rating divergence

AI facilitates stronger internal coordination in ESG management. ESG performance data are typically sourced from various departments such as finance, operations, human resources, and compliance, making consistent aggregation challenging. AI systems enable the integration of multi-source datasets in real time, aligning internal metrics and ensuring consistency of ESG performance indicators across functional units (Himeur et al., 2023). Furthermore, AI enhances intra-organizational communication through dashboard interfaces and automated alerts, ensuring timely and uniform dissemination of ESG data across departments. Improved internal coordination reduces fragmented or contradictory information in ESG disclosures, which is a key contributor to rating inconsistencies (Maroun, 2022). Boulhaga et al. (2023) found that high-quality internal control enhances the reliability of disclosures and supports greater alignment in ESG ratings. Similarly, AI indirectly strengthens internal control by synchronizing data flows and minimizing manual intervention, thereby improving the consistency and credibility of ESG information submitted to rating agencies (Harasheh and Provasi, 2023; Bao et al., 2024). These improvements help mitigate divergences in ESG assessments that stem from uncoordinated internal practices.

H3: AI adoption reduces the ESG rating divergence by enhancing internal coordination.

2.4. Artificial Intelligence, stakeholder communication, and the ESG rating divergence

AI enhances firms' capacity to communicate ESG strategies and progress with external stakeholders (Aljohani, 2025). Through applications such as AI-powered investor relations portals and real time ESG dashboards, companies can deliver tailored, transparent, and easily accessible information to investors, analysts, regulators, and rating agencies (Zhou et al., 2024b). These tools foster greater engagement and bolster firms' credibility in the eyes of external evaluators. In contrast to static disclosures, AI facilitates dynamic updates of ESG metrics, offering stakeholders a clearer and more timely view of sustainability performance (Pesqueira and Sousa, 2024). Improved stakeholder communication helps mitigate ESG rating divergence by aligning external perceptions of a firm's ESG approach (Clementino and Perkins, 2021; Li and Su, 2024). When

rating agencies receive timely and reliable data directly from companies through AI-enhanced communication channels, their dependence on inconsistent third-party sources and speculative assumptions diminishes. This contributes to greater convergence in evaluation results, particularly in settings where ESG disclosure standards remain fragmented, as is often the case in emerging markets such as China (Eng et al., 2022; Liu, 2022; He et al., 2023).

H4: AI adoption reduces ESG rating divergence by strengthening stakeholder communication.

3. Data and model

3.1. Sample, data, and model

Given the limitations in ESG data availability, this study focuses on A-share listed companies in China between 2015 and 2024. The following sample exclusions apply: (1) firms classified as ST, *ST, PT, newly listed companies in their IPO year, and those with negative net assets; (2) firms in the financial sector; and (3) firms with significant missing data. After applying these criteria, the final sample comprises approximately 9,000 firm-year observations. The ESG rating data are obtained from six major rating agencies: China Securities Index (CSI), Wind, Ftse Russell, SynTao Green Finance, Susallwave, and Bloomberg. Data on AI-related patents are collected from the China National Intellectual Property Administration (CNIPA) and manually compiled by the authors. Additional financial and control variables at the firm level are obtained from the China Securities Market and Accounting Research Database (CSMAR) and Wind databases.

To examine the impact of AI adoption on corporate the ESG rating divergence, this study constructs the following econometric model:

$$ESGdif_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_j Controls_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (1)$$

where i denotes the firm, and t denotes the year. $ESGdif_{it}$ represents the ESG rating divergence index of the firm i in the year t . AI_{it} indicates the level of AI adoption in the firm i in year t . $Controls_{it}$ represents the control variables used in this study. λ_i and μ_t denote firm and year fixed effects, respectively. ε_{it} is the stochastic error term.

Following the methodology of Jiang et al. (2025), this study selects ESG ratings from six prominent agencies: CSI, WIND, FTSE Russell, SynTao Green Finance, Susallwave, and Bloomberg. Since the rating scales differ across these agencies, a standardization process is employed to ensure comparability. ESG scores from CSI, WIND, and SynTao Green Finance are rescaled to a 0–9 scale. Susallwave scores, originally ranging from 0 to 26, are adjusted by multiplying by 9/26 to align with the 0–9 scale. FTSE Russell scores, which range from 0 to 3.6, are similarly rescaled by multiplying by 9/3.6. Bloomberg's ESG scores are normalized by taking the top 10% of scores and rescaling them to a 0–9 range. After these adjustments, all scores are rounded, and the standard deviation is calculated to quantify rating divergence.

Based on the approach proposed by Fujii and Managi (2018) and grounded in the Classification System of Core Digital Technology Patents, this study identifies AI-related patents using designated classification codes under the “AI” category. Data from the CNIPA is used to retrieve annual AI patent applications for each firm. We measure AI adoption as the natural logarithm of one plus the number of AI-related patent applications, following standard practice in prior literature.

Drawing on the study of He et al. (2025), this study controls for a range of firm-level characteristics that may influence the ESG rating divergence, including firm size (Size), leverage (Lev), current ratio (Liq), CEO duality (Dual), ownership concentration (First), firm age (Age), administrative

expense ratio (Man), Big Four auditor involvement (Big4), board size (Board), and operating cash flow level (Opcf). In addition, both firm fixed effects and year fixed effects are incorporated into the model to account for unobserved heterogeneity.

Table 1 presents the descriptive statistics of the main variables. The mean value of AI is 1.963, indicating that the overall level of AI development among Chinese companies is relatively favorable. The minimum and maximum values of AI are 1.265 and 8.362, respectively, suggesting considerable variation in AI adoption across firms. The mean value of ESGdif is 1.044. The minimum and maximum values of ESGdif are 0.713 and 3.536, respectively, further highlighting the extent of rating discrepancies. The mean value of Size is 1.416, with a maximum of 26.452, a minimum of 20.166, and a median of 22.339, suggesting relatively limited variation in firm size. The descriptive statistics for the remaining control variables are generally consistent with existing literature and are therefore not discussed in detail here.

Table 1. Definition of variables and descriptive statistics

<i>Variable</i>	<i>Symbol</i>	<i>Definition</i>	<i>N</i>	<i>Mean</i>	<i>Sd</i>	<i>Min</i>	<i>Max</i>
The ESG rating divergence	ESGdif	Six rating agencies' ESG standard deviation	11250	1.044	0.713	0.713	3.536
Artificial intelligence	AI	ln (artificial intelligence patents +1)	11250	1.964	1.265	1.265	8.362
Firm size	Size	ln (total assets +1)	11250	22.659	1.416	1.416	26.452
Gearing ratio	Lev	Total liabilities/total assets	11250	0.421	0.195	0.195	0.902
Current ratio	Liq	Expressed as the ratio of current assets to current liabilities	11250	2.519	2.355	2.356	18.700
Dual career	Dual	1 for both chairman and general manager, 0 otherwise	11250	0.322	0.467	0.467	0.500
Shareholding concentration	First	The shareholding ratio of the first-largest shareholder	11250	32.138	15.078	15.078	74.824
Years of listing	Age	Statistics date minus listing date taken as the logarithm	11250	2.100	0.879	0.879	3.401
Management expense ratio	Man	Measured by the ratio of administrative expenses to operating income	11250	0.086	0.067	0.067	0.589
Big 4 audit	Big4	Annual reports audited by the Big Four accounting firms take 1, otherwise take 0	11250	0.088	0.283	0.283	1.000
Board size	Board	Natural logarithm of the number of board members	11250	2.116	0.202	0.202	2.708
Cash flow level	Opcf	Net cash flow from operating activities/total assets	11250	0.049	0.065	0.065	0.267

3.2 Correlation analysis

Table 2 presents the correlation coefficients among all variables. Most of the coefficients are statistically significant at the 5% level, and the majority are below 0.3000, indicating that multicollinearity is not a major concern and supporting the robustness of the regression analysis. In particular, the explanatory variable AI shows a statistically significant correlation with the dependent variable ESGdif, which provides preliminary evidence in support of the study's hypothesis regarding the potential effect of AI on mitigating the ESG rating divergence.

Table 1. Correlation test

	ESGdif	AI	Size	Lev	Liq	Dual	First	Age	Man	Big4	Board	Opcf
ESGdif	1											
AI	0.152 ***	1										
Size	0.210 ***	0.293 ***	1									
Lev	0.081 ***	0.085 ***	0.548 ***	1								
Liq	-0.066 ***	-0.038***	-0.390 ***	-0.689 ***	1							
Dual	-0.030 ***	0.0140	-0.231 ***	-0.179 ***	0.156 ***	1						
First	0.011	-0.005 00	0.255 ***	0.112 ***	-0.078 ***	-0.077 ***	1					
Age	0.192 ***	0.058***	0.481 ***	0.352 ***	-0.353 ***	-0.276 ***	-0.027**	1				
Man	-0.179 ***	-0.066***	-0.401 ***	-0.332 ***	0.247 ***	0.077 ***	-0.164***	-0.146***	1			
Big4	0.079 ***	0.176***	0.396 ***	0.135 ***	-0.072 ***	-0.079***	0.151 ***	0.048***	-0.106 ***	1		
Board	0.024 **	0.010	0.295 ***	0.176 ***	-0.160 ***	-0.215 ***	0.030 ***	0.175***	-0.094 ***	0.095***	1	
Opcf	0.100 ***	0.032 ***	0.128 ***	-0.132 ***	0.025 **	-0.008	0.117 ***	0.010	-0.161 ***	0.095***	0.030***	1

Note: ***p < 0.01, **p<0.05, *p<0.1.

4. Empirical study

4.1. Benchmark regression analysis

Table 3 presents the regression results for the baseline model. The coefficient of the key independent variable, AI, remains consistently negative and statistically significant at the 1% level across all specifications. This finding indicates that AI adoption is associated with a reduction in the ESG rating divergence. A possible explanation is that AI improves data processing and disclosure quality, thereby reducing information asymmetry and enhancing the consistency of ESG evaluations across rating agencies. Specifically, a 1% increase in AI adoption corresponds

to a 0.031% decrease in the ESG rating divergence, providing empirical support for the core hypothesis of this study.

Table 3. Benchmark regression results

<i>Variable</i>	(1)	(2)	(3)	(4)	(5)	(6)
	ESGdif	ESGdif	ESGdif	ESGdif	ESGdif	ESGdif
AI	-0.045*** (0.010)	-0.040*** (0.011)	-0.042*** (0.011)	-0.031*** (0.010)	-0.031*** (0.010)	-0.031*** (0.010)
Size		-0.045** (0.022)	-0.044** (0.022)	-0.128*** (0.021)	-0.142*** (0.022)	-0.147*** (0.022)
Lev		0.745*** (0.084)	0.577*** (0.096)	0.501*** (0.093)	0.523*** (0.093)	0.543*** (0.093)
Liq			-0.024*** (0.007)	-0.001 (0.006)	0.001 (0.007)	0.002 (0.007)
Dual			-0.029 (0.024)	-0.016 (0.023)	-0.017 (0.023)	-0.013 (0.023)
First				-0.004** (0.002)	-0.004** (0.002)	-0.003** (0.002)
Age				0.558*** (0.028)	0.555*** (0.028)	0.560*** (0.028)
Man					-0.596*** (0.175)	-0.547*** (0.175)
Big4					0.060 (0.064)	0.051 (0.064)
Board						0.159** (0.065)
Opcf						0.353*** (0.124)
_cons	1.133*** (0.021)	1.820*** (0.480)	1.939*** (0.481)	2.753*** (0.470)	3.108*** (0.481)	2.824*** (0.491)
Year fe	Yes	Yes	Yes	Yes	Yes	Yes
Firm fe	Yes	Yes	Yes	Yes	Yes	Yes
N	11250	11250	11250	11250	11250	11250
R ²	0.460	0.466	0.467	0.497	0.498	0.499

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are reported in parentheses. The same applies to the tables below.

4.2. Robustness Test

In this subsection, we use five methods to do the robustness test. First, in the baseline regression, this study primarily measures the divergence of various ESG rating indices, including the CSI ESG rating index, WIND ESG rating index, SynTao Green Finance ESG rating index, Allied Wave FIN-ESG rating index, Bloomberg ESG rating scores, and FTSE Russell ESG rating scores, using the standard deviation (Wong et al., 2021; Wang and Li, 2023; Li et al., 2024b; Lu and Li, 2024). This defines the core explanatory variable, ESGdif. In the robustness test, an alternative measure of the ESG rating divergence is employed by calculating the extreme variance ESG range for the

six ESG rating categories. Regression analyses are then conducted using this measure, while controlling for industry and year fixed effects. Second, this study uses the natural logarithm of the number of AI-related keywords in the MD&A section of the annual report, plus one (AI_MD&A), to re-measure the level of AI adoption by firms. The regression coefficient of AI remains significantly negative after substituting this variable, which supports the findings of this study. Moreover, relying solely on the number of patents to measure AI adoption may overlook the actual effectiveness of AI implementation. Accordingly, this study utilizes the knowledge breadth approach to quantify patent quality, thereby serving as a substitute indicator of AI adoption. The regression results, presented in columns (2) to (3) of Table 4, indicate that after replacing the core independent variable, the coefficient remains significantly negative, further confirming the robustness of the core conclusion. Third, to account for potential interference from industry characteristics and differences in industry evolution over time, this study incorporates industry fixed effects and year-industry interaction fixed effects (Li et al., 2024b; Zhang and Yang, 2024). The results remain robust after accounting for these fixed effects. Four, to address the potential influence of omitted variables on the baseline regression results, this study further includes industry-level and firm-level characteristics by adding industry-level carbon emission intensity and firm-level ESG reporting frequency as additional control variables (Sætra, 2023). As shown in Column (5) of Table 4, the regression coefficient remains significantly negative after incorporating these additional controls, suggesting that the main findings are robust. At last, Due to the unique administrative hierarchy and economic scale of municipalities, which may lead to biased regression results, firms located in municipalities are excluded from the study sample (Asif et al., 2023). As shown in Column (6) of Table 4, As shown in Column (6) of Table 4, the coefficient of AI remains significantly negative at the 5% level after excluding these firms, consistent with the main findings. This result confirms that the relationship between AI adoption and the ESG rating divergence is not driven by the unique characteristics of firms in municipalities, thereby further enhancing the robustness and generalizability of the study's conclusions. The above results from five robustness tests are given in Table 4.

Table 2. Robustness test

Variable	(1) ESGrange	(2) ESGdif	(3) ESGdif	(4) ESGdif	(5) ESGdif	(6) ESGdif
AI	-0.043** (0.018)			-0.033*** (0.010)	-0.045*** (0.012)	-0.024** (0.012)
AI_MD&A		-0.030* (0.018)				
AI_quality			-0.168*** (0.022)			
Carbon					-0.002 (0.002)	
ESG					0.499** (0.203)	
_cons	2.151** (0.846)	2.022** (0.843)	3.128*** (0.491)	3.502*** (0.521)	2.734*** (0.488)	2.910*** (0.562)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fe	Yes	Yes	Yes	Yes	Yes	Yes
Firm fe	Yes	Yes	Yes	Yes	Yes	Yes
N	11250	11250	11250	11250	11250	6811
R ²	0.584	0.584	0.499	0.499	0.501	0.494

4.3 Endogeneity test

To address potential endogeneity concerns, this study employs two instrumental variables within a two-stage least squares (2SLS) framework. The first instrument (Bartik_iv) follows the Bartik approach (Goldsmith-Pinkham et al., 2020) and is defined as the interaction between a firm's deviation from the annual industry-average number of AI patent applications and the one-period lag of the firm's AI adoption level. This instrument satisfies the relevance condition, as the deviation captures firm-level heterogeneity in AI adoption, while the annual industry average reflects broader technological trends not driven by any single firm. Its exogeneity is justified by the fact that neither the national average nor the firm-specific deviation is likely to be directly influenced by the firm's the ESG rating divergence, thus meeting the exclusion restriction. The second instrument (iv2), inspired by Huang et al. (2022), is constructed as the interaction between the number of fixed-line telephones per 100 people in 1984 and the current national revenue of the information technology services sector. This variable reflects a path-dependent relationship between historical communication infrastructure and modern digital development, which plausibly influences a firm's capacity to adopt AI technologies. Since both components are macro-level variables unrelated to firm-specific ESG outcomes, the instrument is unlikely to be endogenous. Both instruments pass the underidentification and weak identification tests, and the second-stage regression results remain consistent with the baseline findings, reinforcing the robustness and credibility of the main conclusions.

Table 5. Instrumental variable approach and heckman two-stage approach

Variable	Instrumental Variable		Instrumental Variable		Heckman Two-Stage Approach	
	First stage	Second stage	First stage	Second stage	Aldum	ESGdif
AI		-0.352** (0.172)		-0.672** (0.226)		-0.032*** (0.012)
Bartik_iv	0.845*** (0.007)					
iv2			0.001*** (0.000)			
AI_IV					0.022*** (0.004)	
IMR						-0.016 (0.036)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fe	Yes	Yes	Yes	Yes	Yes	Yes
Firm fe	Yes	Yes	Yes	Yes	Yes	Yes
N	5972	5972	8989	8989	11250	11250
R ²	0.747	0.056	0.502	0.016		0.593
F-test	1819.410***		55.647***			
LM Statistic	1309.989***		28.806***			
Wald F	150.217		22.366			
Statistic	[16.380]		[16.380]			

Note: The Wald F-statistic value of [16.380] is derived from the weak instrument test, verifying the relevance of the instrumental variable used in the second stage regression. The result exceeds the Stock-Yogo critical value threshold at the 10% level, indicating that the instrumental variable is not weak.

Table 6. Balance test results

Variable	Before Match / After Match	Average value		Difference between treated and control groups (%)	T-test	
		process group	control subjects		t-value	p-value
Size	Before Match	22.911	22.436	33.900	16.110	0.000
	After Match	22.905	22.898	0.500	0.220	0.823
Lev	Before Match	0.427	0.415	6.400	3.040	0.002
	After Match	0.428	0.433	-2.600	-1.190	0.236
Liq	Before Match	2.435	2.592	-6.700	-3.160	0.002
	After Match	2.429	2.363	2.800	1.350	0.177
Dual	Before Match	0.312	0.332	-4.300	-2.020	0.044
	After Match	0.312	0.301	2.400	1.110	0.267
First	Before Match	32.344	31.955	2.600	1.220	0.222
	After Match	32.321	32.432	-0.700	-0.330	0.740
Age	Before Match	2.229	1.987	27.900	13.140	0.000
	After Match	2.227	2.251	-2.800	-1.330	0.184
Man	Before Match	0.078	0.094	-24.500	-11.510	0.000
	After Match	0.078	0.077	0.600	0.300	0.761
Big4	Before Match	0.107	0.071	12.400	5.910	0.000
	After Match	0.106	0.115	-3.200	-1.320	0.187
Board	Before Match	2.117	2.107	5.000	2.3800	0.017
	After Match	2.117	2.115	1.000	0.430	0.668
Opcf	Before Match	0.055	0.043	18.000	8.540	0.000
	After Match	0.055	0.055	-1.200	-0.540	0.589

Given that some firms in the sample do not adopt AI technologies and that the decision to adopt AI may be influenced by various factors, the estimated empirical results could be subject to sample selection bias. To mitigate this issue, the study employs the Heckman two-stage approach. In the first stage, the industry-year average level of AI adoption (AI_IV) is treated as an exogenous variable, and a dummy variable (Aldum) is constructed to indicate whether a firm has adopted AI. The inverse Mills ratio (IMR) is then computed. As shown in Column (5) of Table 5, the coefficient of AI_IV is significantly positive at the 1% level. In the second stage, the regression results presented in Column (6) of Table 7 indicate that, after controlling for IMR, the coefficient of AI remains significantly negative, consistent with the baseline regression. This suggests that the core conclusion of this study holds even after addressing potential sample selection bias.

To address potential endogeneity issues arising from omitted variables, this study employs the Propensity Score Matching (PSM) method and re-estimates the regression using the matched sample (Kim and Park, 2023; Chen et al., 2024). Specifically, the median value of the AI variable

is used as a threshold to divide the sample into a treatment group and a control group: firms with AI levels above the median are assigned to the treatment group (coded as 1), while those below the median are assigned to the control group (coded as 0). A 1:1 nearest-neighbor matching is then conducted using all control variables as covariates. After matching, a covariate balance test is performed. The results indicate that the differences between the treatment and control groups are all within 5%, and the corresponding t-statistics are substantially reduced, suggesting good matching quality.

Table 6 shows that the absolute values of standardized deviations for all matched variables are controlled within 10% after PSM treatment, indicating excellent matching quality. Furthermore, after examining the probability values in the t-test, it is found that the t-statistic is no longer significant, confirming that the hypothesis of equal mean values between the matched groups is valid. This further substantiates that the PSM method effectively eliminates systematic bias between the samples, ensuring that the systematic differences are appropriately addressed. Table 7 presents the regression results based on the PSM sample (Model 1), showing that the AI level significantly reduces the ESG rating divergence, with a negative coefficient significant at the 1% level. This result is consistent with previous findings and strengthens the robustness of the main effect, suggesting that sample selection bias does not materially affect the study's conclusions. Moreover, this finding is consistent with the baseline regression results, where firm-level clustered standard errors were already controlled. The consistency of results after PSM further strengthens the robustness of the main effect and suggests that sample selection bias does not materially affect the study's conclusions.

Table 7. Propensity score matching regression results

<i>Variable</i>	(1)	(2)	(3)
	ESGdif	ESGdif	ESGdif
AI	-0.057*** (0.016)	-0.042*** (0.016)	-0.042** (0.018)
_cons	1.230*** (0.034)	3.028*** (0.771)	3.028*** (0.998)
Control variable	N	Yes	Yes
Year fe	Yes	Yes	Yes
Firm fe	Yes	Yes	Yes
Firm clustering	N	N	Yes
N	4240	4240	4240
R ²	0.433	0.469	0.469

5. Further analysis

5.1 Mechanism test

To clarify the internal mechanisms through which AI adoption influences the ESG rating divergence, this section conducts a mechanism test using a two-step regression approach. Specifically, it evaluates three potential mediating channels: information transparency, internal coordination, and stakeholder communication. These mechanisms reflect key aspects of corporate ESG management that AI technologies are most likely to influence. Corresponding

proxy variables are constructed based on ESG disclosure data, internal governance indicators, and external communication metrics.

Information transparency is a critical determinant of ESG rating accuracy, as it directly affects how rating agencies perceive and interpret corporate sustainability performance. In this study, transparency is measured by the total number of ESG-related disclosures voluntarily published by a firm, including standalone ESG reports, environmental bulletins, and third-party assurance documents. A higher frequency of disclosures indicates stronger transparency and openness. AI improves transparency by automating ESG data collection from internal systems and external sources, standardizing disclosure formats, and enabling real-time updates. These capabilities reduce manual intervention, eliminate noise, and enhance the credibility and timeliness of reported data. Regression results in Column (1) of Table 8 show that the coefficient on AI is significantly positive at the 1% level (0.221), suggesting that AI adoption substantially enhances a firm's information transparency. As transparency increases, information asymmetry is reduced and ESG narratives become more consistent, limiting the scope for subjective interpretation by rating agencies and ultimately narrowing rating divergence.

Internal coordination reflects the ability of a firm to align ESG practices and reporting across multiple departments, ensuring unified data flow and decision-making. This study constructs an internal coordination index based on whether firms disclose the establishment of ESG governance structures - such as sustainability committees, cross-functional ESG task forces, and internal control mechanisms that span departments. AI technologies promote internal coordination by integrating ESG data from disparate systems and facilitating cross-departmental collaboration through centralized platforms and decision-support tools. This allows companies to monitor ESG performance in real time and ensure consistent information flow from operations to disclosure. Column (2) of Table 8 reports a significantly positive coefficient for AI at the 1% level (0.173), confirming that AI adoption improves internal coordination. Enhanced coordination leads to more coherent ESG actions across departments and standardized disclosures, minimizing intra-firm inconsistencies that could confuse or mislead rating agencies.

Stakeholder communication plays a vital role in shaping how external parties - particularly ESG rating agencies - understand and evaluate a firm's sustainability strategy. This mechanism is proxied by the number of publicly disclosed interactions with stakeholders on ESG matters, such as investor dialogues, regulatory consultations, and media engagements reported in annual or sustainability reports. AI strengthens stakeholder communication by enabling firms to respond more quickly to external inquiries, tailor their ESG messaging through sentiment analysis and predictive analytics, and standardize language across platforms. These improvements enhance message clarity and frequency, reducing ambiguity and reinforcing stakeholder confidence. As shown in Column (3) of Table 8, the coefficient on AI is significantly positive at the 1% level (0.295), indicating that AI adoption significantly enhances communication with external stakeholders. Better communication helps align external perceptions with a firm's actual ESG efforts, thus reducing interpretive discrepancies across rating agencies and promoting more consistent ESG evaluations.

Table 8. Mechanism Variables Regressed on AI

Variable	(1)	(2)	(3)
	Information transparency	Internal Coordination	Stakeholder Communication
AI	0.221*** (0.031)	0.173*** (0.029)	0.295*** (0.0351)
Control variable	Yes	Yes	Yes

<i>Variable</i>	(1)	(2)	(3)
	Information transparency	Internal Coordination	Stakeholder Communication
_cons	0.382*** (0.062)	0.538*** (0.053)	0.603*** (0.064)
Year fe	Yes	Yes	Yes
Firm fe	Yes	Yes	Yes
N	11250	11250	11250
R ²	0.413	0.420	0.427

5.2 Heterogeneity analysis

Compared to non-high-tech firms, high-tech firms typically possess stronger technological capabilities, a more skilled talent base, and higher upfront Research and Development (R&D) investments (Wang et al., 2025). These advantages facilitate deeper and more effective digital transformation, enabling high-tech firms to better leverage AI technologies to enhance the efficiency and accuracy of information dissemination. As a result, AI in high-tech firms is more effective in reducing the ESG rating divergence. To empirically test this hypothesis, we use the classification criteria for high-tech firms from the CSMAR (Cathay Pacific) database and conduct subgroup regressions for high-tech and non-high-tech firms. As shown in Table 9, the absolute value of the AI coefficient is larger and statistically significant in the high-tech group, indicating that AI adoption in high-tech firms plays a more significant role in mitigating the ESG rating divergence.

The quality of external auditing not only enhances the accuracy and transparency of ESG disclosures but also moderates the effectiveness of AI in reducing the ESG rating divergence - where weaker external oversight creates greater space for AI to improve data quality and mitigate inconsistency across ratings (Kim and Lu, 2011; Asante-Appiah and Lambert, 2023). In this study, sample firms are grouped based on whether they are audited by the "Big Four" accounting firms, and the heterogeneity in external governance levels is examined. As shown in Table 9, the coefficient of AI is larger and more significant for firms audited by non-Big Four firms. For firms audited by the Big Four, corporate ESG information tends to be accurate and transparent, and managerial "greenwashing" behavior is more effectively monitored and suppressed, leading rating agencies to assign more consistent ratings. In contrast, non-Big Four audited firms exhibit more pronounced the ESG rating divergence.

Ownership heterogeneity is a critical factor influencing the effectiveness of AI in mitigating the ESG rating divergence (Wang et al., 2023; Zhang, 2024). Differences in ownership structures lead to varying levels of managerial autonomy, strategic flexibility, and responsiveness to market incentives, all of which affect how AI is applied to enhance ESG information quality and alignment across rating agencies. This study categorizes sample firms based on ownership type. As shown in Table 9, the coefficient of AI is significantly negative for non-state-owned firms, whereas it is statistically insignificant for state-owned firms. A possible explanation is that state-owned firms operate within more complex incentive systems that incorporate not only economic performance but also social objectives and policy implementation. Management compensation and promotion are subject to stringent oversight by government authorities, with incentives often focused on policy compliance and social stability. Consequently, in non-state-owned firms, the application of AI is typically driven by market-based incentives, competitive pressures, and a stronger focus on maximizing shareholder value. These firms often have more flexible governance structures and

greater autonomy in decision-making, enabling them to quickly adopt and integrate AI technologies to enhance their ESG performance. AI can be leveraged to streamline ESG data collection, improve the accuracy of disclosures, and detect discrepancies or inefficiencies in ESG reporting. Moreover, AI-driven analytics allow non-state-owned firms to identify and respond to emerging sustainability risks more proactively, thereby aligning their ESG practices with international standards and reducing the divergence in ratings across different agencies. As a result, AI adoption tends to significantly improve the consistency and transparency of ESG information, leading to a reduction in the ESG rating divergence in these firms.

Table 9. Heterogeneity Analysis

Variable	High-tech industries	Non-high-tech industries	The 'Big Four' audits	Non-Big four audits	Non-state-owned firms	State-owned firms
	ESGdif	ESGdif	ESGdif	ESGdif	ESGdif	ESGdif
AI	-0.041*** (0.013)	0.002 (0.024)	0.010 (0.030)	-0.029** (0.012)	-0.016 (0.017)	-0.024* (0.013)
_cons	3.816*** (0.739)	-2.105* (1.142)	1.226 (3.073)	3.294*** (0.639)	-1.339 (0.903)	4.373*** (0.632)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fe	Yes	Yes	Yes	Yes	Yes	Yes
Firm fe	Yes	Yes	Yes	Yes	Yes	Yes
N	8750	2500	771	8188	2950	5167
R ²	0.517	0.461	0.406	0.510	0.476	0.519

This study further investigates heterogeneity in the relationship between AI adoption and the ESG rating divergence by considering corporate financing constraints. Prior studies (Shao et al., 2022; Babina et al., 2024) suggest that firms facing tighter financial constraints are more reliant on internal efficiency tools, such as digital technologies and AI, to optimize operations and enhance non-financial performance indicators, including ESG outcomes. Moreover, firms under greater financing pressure often face stricter scrutiny from investors and are more motivated to improve their ESG profiles to access sustainable financing or reduce perceived risk. In this study, financing constraint levels are measured using the absolute value of the SA index, with firms above the industry median classified as highly constrained and those below as less constrained. As shown in Table 10, AI adoption has a significantly stronger negative effect on the ESG rating divergence in firms with higher financing constraints. This indicates that financially constrained firms tend to make more targeted and efficient use of AI tools to enhance data quality, reduce disclosure inconsistencies, and thereby improve alignment across ESG rating agencies. In contrast, firms with lower financing pressure may not prioritize ESG-related digitalization, resulting in a weaker moderating role of AI. These findings highlight that financing constraints serve as an important contextual factor shaping the effectiveness of AI in narrowing the ESG rating divergence, offering

practical insights into how firms with limited capital can leverage technological tools to strengthen sustainable governance and credibility.

China has implemented the "Big Data Pilot Zones" initiative in phases to enhance digital infrastructure, promote the application of information technology, and improve digital policy support. These efforts have facilitated greater AI adoption by firms, thereby helping to reduce the ESG rating divergence. In this study, we categorize sample firms based on whether the city in which they are registered has been designated as a Big Data Pilot Zone, to explore the heterogeneity resulting from regional variations in digital infrastructure development (Yang et al., 2023; Yu et al., 2025). As shown in Table 10, firms located in areas with Big Data Pilot Zones demonstrate a more pronounced negative relationship between AI adoption and the ESG rating divergence, indicating that strong digital infrastructure provides substantial external support for the effective application of AI. In contrast, for firms located in non-pilot areas, the mitigating effect of AI on the ESG rating divergence is weaker and only marginally significant. This may be due to limited access to digital resources, lower technological readiness, and weaker policy incentives in these regions, which restrict the depth and scope of AI implementation. The comparison highlights that regional digital infrastructure not only affects AI adoption rates but also moderates its effectiveness in improving ESG data quality and rating alignment. These findings underscore the importance of external digital conditions in shaping the impact of internal technological capabilities.

To formally test whether the difference in coefficients between the two groups is statistically significant, we construct an interaction model. Specifically, we introduce a binary indicator for Big Data Pilot Zones and an interaction term ($AI \times BigData$), and re-estimate the following regression:

$$ESGdif_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 BigData_{it} + \beta_3 (AI_{it} \times BigData_{it}) + \beta_j Controls_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (2)$$

The coefficient on the interaction term β_3 , captures the difference in the effect of AI between pilot and non-pilot regions. As shown in Table 11, the interaction term is significantly negative at the 5% level, confirming that the divergence-mitigating effect of AI is significantly stronger in regions with more advanced digital infrastructure. These results reinforce the notion that digital infrastructure not only promotes the adoption of AI but also enhances its capacity to improve ESG data quality and rating alignment across agencies.

Table 10. Heterogeneity analysis

Variable	High financing constraints	Low financing constraints	Big Data Pilot	Non-big data pilot
	ESGdif	ESGdif	ESGdif	ESGdif
AI	-0.032** (0.015)	-0.014 (0.015)	-0.037*** (0.014)	-0.027* (0.016)
_cons	2.777*** (0.747)	1.947** (0.818)	3.024*** (0.710)	3.007*** (0.712)
Control variable	Yes	Yes	Yes	Yes
Year fe	Yes	Yes	Yes	Yes
Firm fe	Yes	Yes	Yes	Yes
N	4300	4300	4700	4200
R ²	0.557	0.476	0.503	0.494

Table 11. Interaction test for heterogeneity in digital infrastructure development

Variable	ESGdiff
AI	-0.027*** (0.009)
BigData	0.014 (0.011)
AI × BigData	-0.010** (0.005)
Control variables	Yes
Year fe	Yes
Firm fe	Yes
N	8900
R ²	0.517

6. Conclusions

This study investigates the effect of corporate AI adoption on ESG rating divergence in China’s capital market, against the backdrop of growing digital governance and sustainability imperatives. Based on panel data from A-share listed firms between 2015 and 2024, we employ multiple regression models, robustness checks, and instrumental variable methods to identify the mitigating effect of AI on ESG rating inconsistency. Empirical results demonstrate that AI adoption significantly reduces ESG rating divergence, with stronger effects observed in high-tech firms, non-state-owned enterprises, companies audited by non-Big Four auditors, financially constrained firms, and those operating in regions with better digital infrastructure. These heterogeneous patterns reveal that both firm-level characteristics and local digital ecosystems condition the effectiveness of AI in improving ESG information quality. The findings underscore AI’s potential as a governance-enhancing tool to resolve the misalignment between ESG disclosure and rating interpretation, particularly in the context of China’s fragmented ESG standards and accelerating digital transformation.

Our conclusions give rise to several practical managerial and policy implications. For corporate management, AI-enabled strategies, such as natural language processing for ESG disclosure standardization and machine learning-based ESG risk detection, should be embedded in sustainability governance processes. High-tech and non-state firms should further integrate AI into real-time ESG monitoring, improving transparency and responsiveness in a competitive and regulation-sensitive market. In regions with robust digital foundations, enterprises can exploit AI-driven dynamic reporting to align more effectively with investor and regulatory expectations. For less digitally developed areas, efforts should be made to localize and simplify AI applications, thereby avoiding regional disparities in ESG evaluation quality. For policy development, digital infrastructure investment and interregional ESG resource coordination should be prioritized. In particular, promoting AI knowledge sharing from digitally advanced eastern firms to underdeveloped western firms may catalyze national ESG convergence. Standardization agencies and rating institutions should accelerate the development of AI-based disclosure frameworks to ensure interpretative consistency. Furthermore, financial institutions are encouraged to adopt AI-derived ESG indicators in credit scoring and investment screening

processes, particularly when assessing firms with constrained financing access, thereby improving capital allocation and facilitating sustainable finance at scale.

The contributions of this research are threefold. Conceptually, we expand the understanding of how AI functions as a new quality productivity to address ESG rating misalignment, enhancing firm transparency and market trust. Methodologically, we bridge ESG studies with applied AI techniques, enriching empirical ESG evaluation through algorithmic modeling and robustness-oriented econometric design. Contextually, our analysis captures how AI deployment interacts with firm heterogeneity and regional digital capacity, providing a referential model for aligning digital governance with ESG advancement in emerging markets.

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