2. DOES ARTIFICIAL INTELLIGENCE INVARIABLY ENHANCE ESG PERFORMANCE?[1]

Yi WANG[2]

Yiting XU[3]*

Yufei ZHONG[4]

Abstract

Understanding the intricate roles of artificial intelligence (AI) is crucial for enhancing environmental, social and governance (ESG) performance. For this purpose, this paper adopts a methodology encompassing full and sub sample approaches to delve into the intricate connection between AI and ESG. The empirical results underline that AI has both a facilitative and an inhibitory influence on ESG. The positive aspect indicates that, under certain circumstances, AI can potentially boost ESG performance. However, negative impacts, such as privacy violations, algorithmic bias, energy consumption, job losses, and regulatory risks, counteract this. In addition, when AI is relatively stable, ESG might improve due to policies, investor preferences, corporate awareness, and scrutiny. Thus, AI does not consistently enhance ESG performance. ESG, in turn, has a two-way impact on AI. While it boosts AI by fostering demand for safe, eco-friendly tech, increased ESG scrutiny and trade wars crowd out investment, harming AI funding and market confidence. Amid a new technological revolution, we formulate targeted policy recommendations designed to leverage the beneficial aspects of AI while minimising its detrimental impacts on ESG performance.

Keywords: *Artificial intelligence; ESG performance; Time-dependent relation*.

JEL classification: *C3,; O33, Q56*

1. Introduction

The aims to explore potential causes and their connections between artificial intelligence (AI) and environmental, social and governance (ESG), ultimately seeking to ascertain if the former invariably enhances the latter's performance. The advent of AI has significantly positive impacts on the ESG landscape (Huang et al., 2024; Liu et al., 2024). In the environmental realm, AI

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[2] *School of Economics and Management, Wuchang Shouyi University, Hubei, China. Research Center for Hubei Agricultural Modernization and Rural Development, Hubei, China. Email: 524196199@qq.com.*

[3] ** Corresponding author. Hunan Academy of Social Sciences, Hunan, China. Email: ytxu12@163.com.*

[4] *School of Economic and Management, Qingdao Preschool Education College, Qingdao, China，266318. Email: zhongyfqd@163.com.*

supports achieving carbon neutrality goals and environmental protection by optimising energy management, fostering resource recycling, and driving green innovation (Qin et al., 2023; Chotia et al., 2024; Zhang et al., 2025). In the social realm, AI enhances decision-making transparency and fairness (Ammeling et al., 2025), promotes equitable distribution of education and healthcare resources (Guan et al., 2025; Khan et al., 2025), and elevates work efficiency and quality of life (Aldakhil, 2024). More fundamentally, on the governance level, AI supports policymakers through its ability to track market dynamics in real time and help increase regulatory effectiveness while supporting corporate compliance and transparency for market order and social stability. As Chen et al. (2024) and David et al. (2024) stated, these positive effects all make AI an important enabler for improving ESG performance.

However, the widespread adoption of AI also poses a series of potential negative challenges to ESG. In the environmental domain, the increasing energy consumption of AI data centres and the issue of electronic waste disposal pose significant pressures on the environment (Masanet et al., 2024). Socially, AI automation could shift the nature of employment structures and therefore create social instability (Qin et al., 2024b); in addition, data privacy breaches and algorithmic biases could aggravate social discrimination and, hence, social inequality and disharmony. Governance levels will see how fast the evolution of AI takes place relative to the update of regulatory frameworks that would eventually result in lags in regulation and hinder effective management of newly emerging AI-related issues (Zhang et al., 2024). Legal and ethical complications engendered by AI also pose formidable tests to existing legal systems (Sienkiewicz-Małyjurek and Zyzak, 2024). For this reason, AI may be inextricably interwoven with ESG and a great area of research, little understood and explored. Conversely, ESG standards have profoundly influenced the development and application of AI, impacting its ethical and moral dimensions, practical uses, and future advancements (Broadstock et al., 2020; Hao et al., 2025).

Conversely, ESG standards demand that AI align with societal ethical standards, guiding its development through environmental, social, and governance principles. This includes minimising environmental impact, respecting privacy and data protection, and adhering to fairness, impartiality, and transparency to avoid discrimination and bias (Wang et al., 2023). As society is focusing more on the ESG standards, AI should align these principles within its research and development and eventually application for increasing environmental performance, data privacy, and algorithmic fairness. ESG opens new areas of climate monitoring, disaster warning, and energy management opportunities with AI while also facing challenges to cope with rising demands of fairness and transparency in societal expectations. So, there may be a significant relationship between ESG and AI. Remarkably, it has to be underlined that the previous research has not adequately discussed this very aspect, and we try to fill this gap in knowledge.

This paper has three contributions: To begin with, existing research has been constrained in its examination of the unilateral effect of AI on ESG (Asif et al., 2023; Chen et al., 2024; Chotia et al., 2024; Huang et al., 2024; Liu et al., 2024; Qin et al., 2024a, b; Guan et al., 2025), and the influence from ESG to innovation (Broadstock et al., 2020; Wang et al., 2023; Hao et al., 2025), neglecting to decipher the complex interplay among various factors comprehensively, and our study innovatively explores the mutual influences between AI and ESG. Secondly, prior research endeavours in the field of artificial intelligence have predominantly utilised metrics such as patent filings (Nguyen and Vo, 2022), robotic systems (Bai et al., 2025), survey questionnaires (Li and Qi, 2022), specific policy (Huang et al., 2024), and Google search keyword analytics (Guliyev et al., 2023) to derive valuable insights. However, these approaches lack comprehensiveness. We introduce an innovative solution to address this shortcoming by employing the S&P Kensho New Economy RAIC Index as a fresh yardstick for assessing AI development. Furthermore, this study introduces another novel aspect by selecting the S&P Global ESG Index to evaluate ESG performance, thereby contributing to the advancement of existing literature. Thirdly, recognizing the complex, non-linear dynamics characterizing the AI-ESG relationship, which is a dimension frequently overlooked in existing literature, we conduct four parameter stability tests. These analyses reveal significant structural breaks, prompting our adoption of an advanced sub sample approach to capture the temporal evolution of this critical relationship, thereby offering novel empirical insights.

Accordingly, we utilise monthly data covering the time frame from January 2015 to December 2024 and discover that AI has enabling and impeding effects on ESG performance. On the one hand, AI can potentially enhance ESG performance under specific conditions. Conversely, negative consequences such as privacy breaches, algorithmic biases, heightened energy consumption, job displacement, and regulatory challenges serve as counteracting forces. Furthermore, when AI is in relative stability, ESG may improve due to factors like supportive policies, investor inclinations towards sustainability, heightened corporate awareness, and rigorous scrutiny. Consequently, AI does not uniformly elevate ESG performance. In turn, ESG has a reciprocal impact on AI. While it stimulates AI development by fostering demand for secure and environmentally friendly technologies, heightened ESG scrutiny and international trade tensions can lead to investment displacement, negatively impacting AI funding and market sentiment. Based on these discoveries, we offer invaluable guidance to harness AI’s positive potential while mitigating its adverse effects on ESG performance. Policymakers should align AI development with ESG principles, enforce data protection, algorithmic fairness, and energy efficiency, and encourage sustainable AI practices. Promoting balanced ESG investing, funding AI research and development, addressing ESG challenges, and fostering international cooperation are key to ensuring AI respects human rights, supports sustainability, and drives global prosperity.

This study is organized as follows: Section 2 conducts a systematic literature review. Sections 3 and 4 detail the methodological framework and data sources respectively. Section 5 presents and interprets the empirical results, while Section 6 concludes with key findings and policy recommendations.

2. Literature Review

In recent years, the impact of AI on ESG has garnered significant attention, leading to various and differing conclusions being drawn. Regarding the environmental effect, Chotia et al. (2024) offer practical insights for organisations, suggesting that by utilising AI-supported Green Business Strategies (GBS), companies can maintain their focus on Green Process Innovation (GPI) at the organisational level, thereby enhancing their environmental performance. Qin et al. (2024a) find that AI has both beneficial and adverse effects on renewable energy. The positive impacts suggest that AI catalyses the development of renewable energy. However, this view cannot be sustained if AI’s effect turns negative, primarily due to the cost-effectiveness of non-renewable energy sources. Zhang et al. (2025) reveal that implementing the AI innovation and development pilot zones (AIPZ) policy significantly decreases urban carbon emissions, achieving an average reduction of 3.4 percent.

Regarding the social effect, Ammeling et al. (2024) suggest that medical diagnosis enhanced by AI provides the opportunity to harness the combined wisdom of contextually aware humans and highly specialised machines, ultimately benefiting patients (Khan et al., 2025). Qin et al. (2024b) identify three temporal phases of AI’s employment impact: short-term job displacement, medium-term labor market equilibrium through new job creation, and long-term net employment growth driven by economic expansion and workforce adaptation. Guan et al. (2025) highlight that integrating AI in education fundamentally transforms how students, teachers, and technology interact, making adopting a collaborative approach rather than a mere mechanical application imperative.

Regarding the governmental effect, David et al. (2024) underline that the rapid development of AI has led many local governments around the globe to contemplate incorporating it into their administrative processes. However, several high-profile AI mishaps have raised ethical alarms, underscoring local governments need to adopt AI-related technologies with a sense of responsibility. Zhang and Yang (2024) demonstrate that the implementation of AI has a pronounced positive influence on both environmental and social performance indicators, yet its impact on governance remains relatively modest. The underlying reason is that governance encompasses organisational structures, decision-making processes, laws, and regulations, among other aspects, which are more intricate and deeply ingrained.

Regarding the overall effect, Asif et al. (2023) confirm that AI is highly beneficial for improving the authenticity of ESG disclosures, transforming them from historical to forward-looking and real-time reports. It also enables the customisation of ESG reports, broadens the reporting scope to include multi-tier supply chains, lowers ESG costs, and enhances the overall effectiveness of such disclosures. Chen et al. (2024) ascertain that AI boosts firms' ESG ratings by elevating their overall productivity and increasing their investments in research and development. In addition, macroeconomic policy uncertainty acts as a moderating factor, amplifying the beneficial effects of AI on ESG performance. Huang et al. (2024) indicate that implementing an AI pilot policy notably enhances the ESG performance of enterprises. An analysis of the underlying mechanisms affirms the pivotal role played by advancements in green technology and research and development expenditure. Liu et al. (2024) discover that AI boosts corporate investment in research and development and accelerates the pace of digital transformation, ultimately enhancing ESG performance. Firms situated in provinces with higher levels of digital financial inclusion experience a more significant impact from AI on their ESG performance.

In turn, ESG's effect on innovation has also attracted attention. Broadstock et al. (2020) align with a process of indirect value creation, where adopting ESG policies would strengthen firms' capacity for innovation and subsequently positively influence their value creation and financial/operational outcomes. Wang et al. (2023) show that firms rated by an ESG agency experience a notable 3.9 percent boost in green innovation output, primarily due to an increase in green invention patents. Hao et al. (2025) indicate that firms with higher ESG ratings exhibit a notable positive correlation with digital technology innovation. These high ESG ratings propel digital innovation by boosting research and development funding, expanding financing avenues, reducing ESG-related uncertainties, and enhancing corporate credibility.

In essence, previous research has mainly focused on the unilateral effects of AI on ESG and the influence of ESG on innovation, neglecting the complex interplay among them. Our study innovatively explores the mutual influences between AI and ESG to address this limitation. Additionally, studies examining the time-varying connection between AI and ESG are scarce. To address this gap, we utilize a sub sample method to uncover the dynamic interaction between AI and ESG, providing empirical support on whether AI contributes to improving ESG performance and highlighting the crucial significance of ESG in the context of AI.

3. Methodology

3.1. Full Sample Technique

Building on Sims' (1980) foundational work, we employ a vector autoregressive (VAR) framework to analyze complex interdependencies among time series variables. However, this approach requires normally distributed series and residuals to ensure validity (Su et al., 2024a,d; 2025). To address potential non-normality, we adopt Shukur and Mantalos' (1997) residual bootstrap (RB) technique, which provides robust critical values for causality testing even with non-normal distribution, especially in small samples (Qin et al., 2024a,c; Qiu et al., 2024). Following their enhanced likelihood ratio (LR) methodology (Shukur and Mantalos, 2000), we examine Granger causal relationships using the following VAR (s) specification:

$$Z_t = \phi_0 + \phi_1 Z_{t-1} + ...+ \phi_s Z_{t-s} + \vartheta_t \tag{1}$$

where s is selected by applying the Schwarz Information Criterion (SIC), a method to determine the most fitting one. Z comprehensively denotes as $Z_t = (\mathrm{AI}_t, \mathrm{ESG}_t)'$, we reformulate the preceding mathematical framework, resulting in the derivation of Equation (2).

$$\begin{bmatrix} \mathrm{AI}_t \\ \mathrm{ESG}_t \end{bmatrix} = \begin{bmatrix} \phi_{10} \\ \phi_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} \mathrm{AI}_t \\ \mathrm{ESG}_t \end{bmatrix} + \begin{bmatrix} \vartheta_{1t} \\ \vartheta_{2t} \end{bmatrix} \tag{2}$$

We begin with a null hypothesis stating that no statistically significant Granger causal relationship exists between AI and ESG in either direction. The testing procedure involves two key examinations: first, for the AI-to-ESG relationship, where failure to reject the null hypothesis would confirm our initial assumption, while statistically significant evidence would lead to its rejection. Second, we apply the same analytical framework to test the reciprocal ESG-to-AI relationship, where the null hypothesis will either be maintained or rejected based on the statistical evidence.

3.2. Stability Test of Parameters

Conventional VAR models rely on the assumption of parameter constancy, which may not adequately capture real-world economic dynamics (Su et al., 2024b, c). When model parameters experience structural shifts, traditional full-sample estimation methods can produce biased results. Our analysis incorporates three complementary approaches to detect parameter instability: the Sup-F test developed by Andrews (1993) identifies discrete structural breaks, while the Ave-F and Exp-F tests (Andrews and Ploberger, 1994) examine more gradual parameter changes. Additionally, we apply the Lc statistics proposed by Nyblom (1989) and Hansen (1992) to test for random walk behavior in parameters. These diagnostic tests consistently reveal time-varying characteristics in the AI-ESG relationship, demonstrating the limitations of full-sample analysis. Consequently, we employ a sub-sample methodology that accounts for temporal variation, providing more reliable estimates of the dynamic interplay between AI development and ESG performance.

3.3. Sub Sample Technique

The subsample approach, as coined by Balcilar et al. (2010; 2013), is another tool in bringing to light the dynamic relationship between AI and ESG, where the original sample is divided into sub-samples with predefined rolling window widths. The great challenge is the choice of an appropriate width of the window: while a wider window can reduce the frequency, a too-narrow width might make it unreasonable. Following Pesaran and Timmermann's (2005), we implement a sub sample approach with a minimum window size of 20 observations.

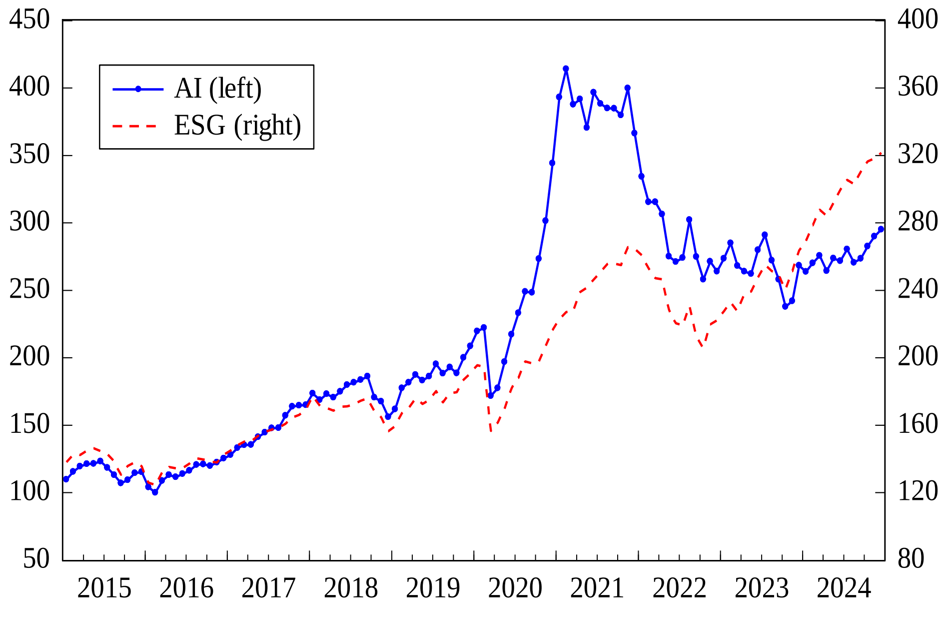
Our methodological implementation proceeds through three systematic stages: First, given a dataset spanning E periods, we establish rolling windows of width r, creating consecutive estimation windows that incrementally advance through the dataset (window positions r, r+1, ..., E). Second, we apply the RB-LR test to each window to examine the evolving AI-ESG relationship dynamics. Third, we calculate and analyze the distribution of LR statistics and their associated p-values across all windows. The mean values of these statistics ($N_b^{-1}\sum_{k=1}^{s}\hat{\phi}^*_{21,k}$ and $N_b^{-1}\sum_{k=1}^{s}\hat{\phi}^*_{12,k}$) quantify the average directional effects, representing AI's influence on ESG and ESG's impact on AI respectively. This approach provides both robust average estimates and crucial insights into how the interdependencies evolve across different time periods.

Furthermore, our analysis incorporates a 90% confidence interval, which serves as a range of uncertainty around our estimates. The 95th quantile defines the upper limit of this interval, while the lower limit corresponds to the 5th quantile, ensuring that our findings are robust and take into account potential variations.

4. Data

The research examines the correlation between AI and ESG applying monthly data from January 2015 to December 2024, investigating whether artificial intelligence invariably enhances ESG performance. 2015 stands as a pivotal juncture in the trajectory of ESG principles, which has witnessed the historic signing of the Paris Agreement by nations across the globe in Paris, underscoring their unified resolve to confront the challenges posed by climate change. This monumental event has catalysed the profound advancement and heightened recognition of ESG principles on a global scale. Meanwhile, international organizations such as the United Nations and the World Bank have strengthened their efforts in promoting ESG principles. In addition, more and more investors have started to use ESG factors in the investment decision-making process. All this rising tide further promotes the wide practice and development of ESG principles around the world. Therefore, beginning research into ESG from 2015 offers a very comprehensive understanding of its historical path, current state, and future course. This paper selects the S&P Global ESG Index as a benchmark to gauge ESG performance, and it is sourced from the S&P Dow Jones Indices Website[5]. This index is a comprehensive, market capitalization-weighted measure that evaluates the performance of securities based on sustainability criteria. A higher ESG score indicates superior ESG performance, whereas a lower score reflects less impressive performance.

Figure 1. The trends of AI and ESG



Source: Authors' calculations.

[5] *https://www.spglobal.com/spdji/zh/indices/sustainability/sp-world-esg-index/#overview*

In 2015, deep learning technologies achieved remarkable breakthroughs in fields such as computer vision and speech recognition, laying a solid foundation for the widespread application of AI technologies and significantly enhancing their ability to process complex information (Qin et al., 2023). With the increasing maturity of technologies and the expansion of application scenarios, many investors have begun to focus on and invest in AI, providing robust financial support for the continuous research and development and widespread adoption of AI technologies. Since then, AI has rapidly developed, and we choose the S&P Kensho New Economy RAIC Index, sourced from the S&P Dow Jones Indices Website[6], as our representative indicator. This index is specifically formulated to gauge the performance across nine industry sectors, encompassing enterprises engaged in robotics, artificial intelligence, and cloud computing, utilising an equal-weight methodology. We aim to examine the correlations among AI and ESG through these selections. The trends exhibited by these two indicators are illustrated in the figure below.

Figure 1 demonstrates that ESG indicators do not evolve in tandem with AI development, indicating a dynamic rather than static relationship between these variables. This temporal divergence renders full-sample analysis inadequate for capturing their complex interdependencies, as such approaches cannot account for time-varying dynamics. Our study consequently implements an advanced sub-sample methodology capable of revealing the evolving nature of AI-ESG relationships while identifying potential structural breaks. This approach enables a rigorous examination of whether AI development consistently enhances ESG performance across different temporal contexts, overcoming the limitations of conventional static models that may obscure important time-sensitive patterns in the data.

Table 1. Descriptive statistics for AI and ESG

	AI	ESG
Observations	120	120
Mean	219.588	198.522
Median	196.063	179.877
Maximum	413.990	321.467
Minimum	100.011	124.311
Standard Deviation	85.698	52.487
Skewness	0.480	0.552
Kurtosis	2.266	2.238
Jarque-Bera	7.298 **	9.002 **
Probability	0.026	0.011

*Note: ** is the significance at a 5% level.*

Source: Authors' calculations.

Table 1 presents descriptive statistics highlighting distinct characteristics between AI and ESG variables. The mean values (AI: 219.588; ESG: 198.522) reflect different measurement scales, while the substantial ranges (AI: 100.011-413.990; ESG: 124.311-321.467) indicate considerable variability. Both series exhibit right-skewed distributions with platykurtic properties, evidenced by positive skewness and kurtosis coefficients. The Jarque-Bera tests confirm non-normal distributions at conventional significance levels ($p<0.05$), rendering standard VAR-based

[6] *https://www.spglobal.com/spdji/zh/indices/equity/sp-kensho-new-economy-raic-index/#overview*

causality tests inappropriate.To address these distributional properties, our methodology incorporates two critical adaptations. First, we implement the residual bootstrap- likelihood ratio test, which maintains robustness against non-normality. Second, we employ a rolling-window approach to account for potential time-varying relationships. Additionally, we apply logarithmic transformations to both series to mitigate scale differences and reduce outlier effects.

5. Empirical Analyses and Discussions

To confirm the stationarity of AI and ESG, we employ three key tests: ADF (Dickey and Fuller, 1981), PP (Phillips and Perron, 1988) and KPSS test (Kwiatkowski et al., 1992). Table 2 summarises the results, showing that at their original levels, both AI and ESG align with the initial hypothesis of a unit root in the ADF and PP methods but contradict the hypothesis of stationarity in the KPSS method. However, when considering their first differences, the results are reversed. We could conclude that the first differences between AI and ESG are stationary.

Table 2. The results of unit root tests

		ADF	PP	KPSS
Levels	AI	-1.224 (1)	-1.295 [2]	1.075 [9] ***
	ESG	-0.034 (1)	-0.063 [5]	1.232 [9] ***
First Differences	AI	-7.409 (1) ***	-8.816 [8] ***	0.134 [3]
	ESG	-7.921 (1) ***	-9.551 [6] ***	0.101 [5]

Source: Authors' calculations.

Building upon Equation (2), we construct a VAR (s) framework to systematically examine the AI-ESG relationship. The analysis employs 10,000 bootstrap iterations for enhanced reliability and determines an optimal lag structure of 2 through SIC. Contrary to theoretical expectations, Table 3 demonstrates statistically insignificant Granger causality in both directions, neither AI significantly influences ESG nor does ESG meaningfully affect AI development based on our model specifications. This finding stands in contrast to existing research, including those by Asif et al. (2023), Chen et al. (2024), Chotia et al. (2024), Huang et al. (2024), Hao et al. (2025), and Guan et al. (2025).

Table 3. The outcomes of the bootstrap full-sample method

H_0: AI is not the Granger cause of ESG		H_0: ESG is not the Granger cause of AI	
Statistic	p-value	Statistic	p-value
0.170	0.950	5.525	0.330

Note: The research computes p-values by utilising 10,000 bootstrap repetitions.

Source: Authors' calculations.

Our full-sample analysis begins with the fundamental assumption of parameter stability in the VAR (s) framework, suggesting time-invariant Granger causal relationships between AI and ESG throughout the observation period. However, we acknowledge that potential structural breaks in either the time series or model parameters could invalidate this assumption and bias the results shown in Table 3. To rigorously test the stability assumption underlying our full-sample approach, we implement diagnostic tests including the Sup-F test for sudden structural breaks, Ave-F and Exp-F tests for gradual parameter changes, and the Lc test for random walk behavior in coefficients. These tests assess the presence of structural changes that could compromise the stability. The results, summarised in Table 4, provide insights into whether our initial hypothesis of constant coefficients and Granger causality holds true or whether we must consider the time-dependant relation between AI and ESG.

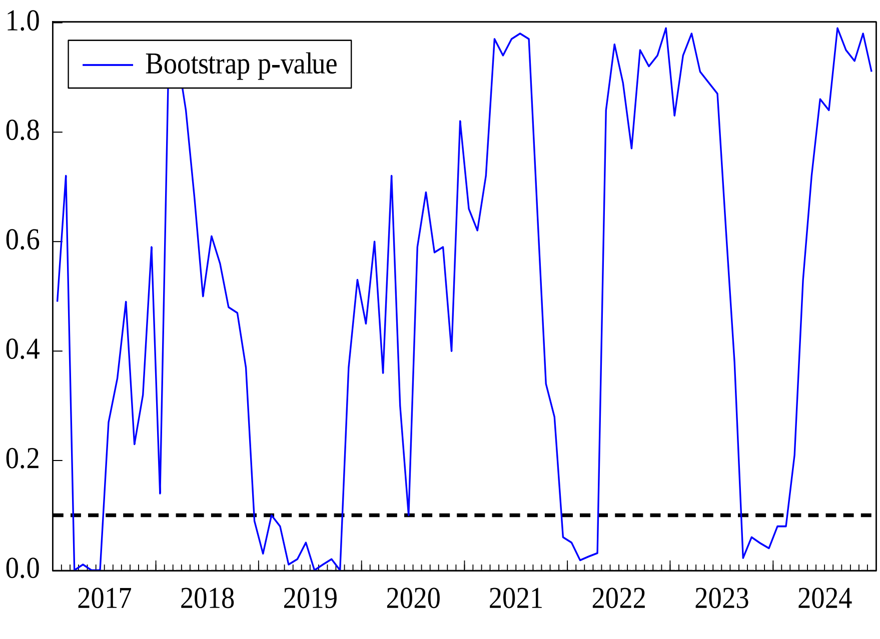
Table 4. The outcomes of parameter stability techniques

Tests	AI		ESG		VAR (s) process	
	Statistics		p-values		Statistics	
Sup-F	45.065 ***	0.000	90.430 ***	0.000	45.148 ***	0.000
Ave-F	14.581 ***	0.001	21.234 ***	0.024	20.091 ***	0.004
Exp-F	18.112 ***	0.000	40.844 ***	0.001	18.426 ***	0.000
Lc					6.496 ***	0.005

Note: *** is the significance at a 1% level.

Source: Authors' calculations.

Figure 2. Testing the absence of Granger causality from AI to ESG

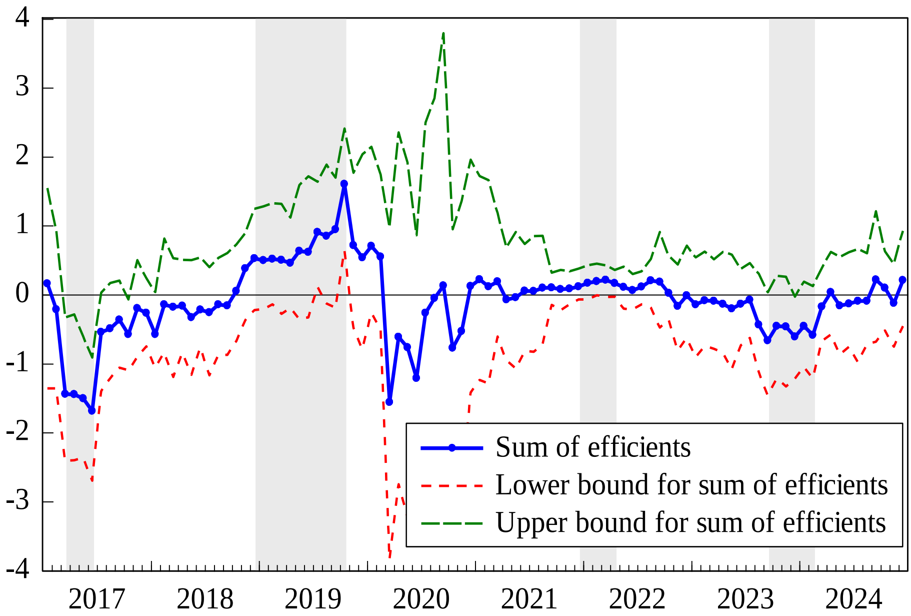


Source: Authors' calculations.

Table 4 reveals significant parameter instability in the AI-ESG relationship, with all structural break tests (Sup-F, Ave-F, Exp-F, and Lc) rejecting stability at the 1% or 5% level. This compelling evidence of time-varying dynamics necessitates our adoption of a 24-month rolling window approach per Pesaran and Timmermann (2005), balancing estimation precision with adaptability to structural changes. Our objective is twofold: firstly, to ascertain whether the alternative hypothesis, proposing a significant Granger causal link between AI and ESG, holds true at a 10% level of significance, and secondly, to identify the precise direction of influence flowing from AI (ESG) to ESG (AI).

Figure 2 shows the statistical significance of Granger causal relation of AI on ESG, highlighting that there is a significant causal link between the two variables at a 10% confidence level during March 2017 to June 2017, December 2018 to October 2019, December 2021 to April 2022, and September 2023 to February 2024. Figure 3 showcases both positive and negative impacts during these four intervals. From December 2018 to October 2019 and from December 2021 to April 2022, AI exerts positive influences on ESG. Conversely, from March 2017 to June 2017 and September 2023 to February 2024, AI negatively impacts ESG.

Figure 3. The coefficients of effect of AI on ESG



Source: Authors' calculations.

The positive impacts indicate that AI could enhance ESG performance. From December 2018 to October 2019, AI significantly enhanced the performance of ESG, a trend fueled by the following reasons. Firstly, AI has witnessed rapid advancements during this timeframe, particularly in Natural Language Processing (NLP) and Machine Learning. These breakthroughs in technology have, therefore, empowered AI to process and analyze unstructured data efficiently, such as corporate reports and news, to extract information of value to ESG appraisals. As digital technology matured, deeper applications within the domain of ESG started accruing, including real-time monitoring of carbon emissions, energy consumption, social responsibility events across the supply chains of corporations. These applications have equipped business operations with more accurate and timely ESG management tools. In particular, Google used AI during this period to optimize its data center cooling systems. Such an innovative approach not only significantly cuts down energy use and increases the operational efficiency of data centers but also minimizes environmental impacts, showcasing the huge potential of AI in advancing environmental sustainability. Meanwhile, the application of IBM Watson Health by International Business Machines Corporation in the medical domain is amazing. It deploys AI in the development of treatment plans that best suit each patient, in improving the quality and efficiency of medical services, thereby facilitating reasonable use and distribution of medical resources. This fully reflects the active role of AI in the perfection of social governance. Besides, BlackRock once rolled out Aladdin, with a view to applying AI into ESG. This platform allowed for real-time monitoring of ESG exposures in investment portfolios while providing ESG analysis and risk management functionalities to help investors lessen investment risks but at the same time improve returns. Thereby, AI helped improve ESG performance in manifold ways during the period from December 2018 to October 2019.

From December 2021 to April 2022, AI enhances ESG performance, and several key areas have innovations and breakthroughs that fuel this trend. Firstly, AI is capable of a great enhancement in data processing and mining. The leading technology companies have introduced some efficient AI-based tools that can accurately identify, extract, and categorize the unstructured ESG-related data, such as corporate reports, news articles, and social media content. It greatly increased the precision and availability of ESG data. For example, some enterprises such as Miaoying Technology utilize AI algorithms in multi-dimension estimation for the core data disclosure of ESG, thus effectively filling in the gap of corporate disclosure. Secondly, AI enhances the real-time monitoring and warning function. Firms have gradually employed AI systems for real-time monitoring of the carbon emission ESG performance of underlying companies or underlying social responsibility events. AI might warn a business through an early warning mechanism when ESG indicators go off the normal trend, and thus quick responses and actions could be taken. This capability not only raises the level of corporate risk management but also supports the achievement of sustainable development goals. Thirdly, AI has great potential in ESG rating and quantitative assessment. In this case, the AI model would integrate multi-source ESG information and use machine-learning algorithms with a deep neural network to give weights for comprehensively scoring ESG factors. This will provide more accurate company ESG ratings and be of immense help to investors, regulators, and others in understanding corporate ESG performance comprehensively. Fourthly, AI also performs an important function in the production and optimization of ESG reporting through automation. Using AI algorithms, companies are able to integrate and analyze the ESG data much faster for the creation of ESG reports according to requirements. AI will optimize reports with readability and usability in mind so that investors and regulators can really understand corporate ESG performance. Fifthly, the wide application of AI in the ESG field has promoted ESG principles throughout and pushed forward sustainable development. With AI, companies can better understand their ESG performance, recognise the importance of improving it, and formulate and implement ESG strategies, moving towards a more sustainable and responsible direction. For instance, AI helps companies identify potential environmental risks and social issues, developing solutions and action plans that lay a solid foundation for their long-term, stable development. Thus, we have evidence that during the period from December 2021 to April 2022, AI significantly improved ESG performance.

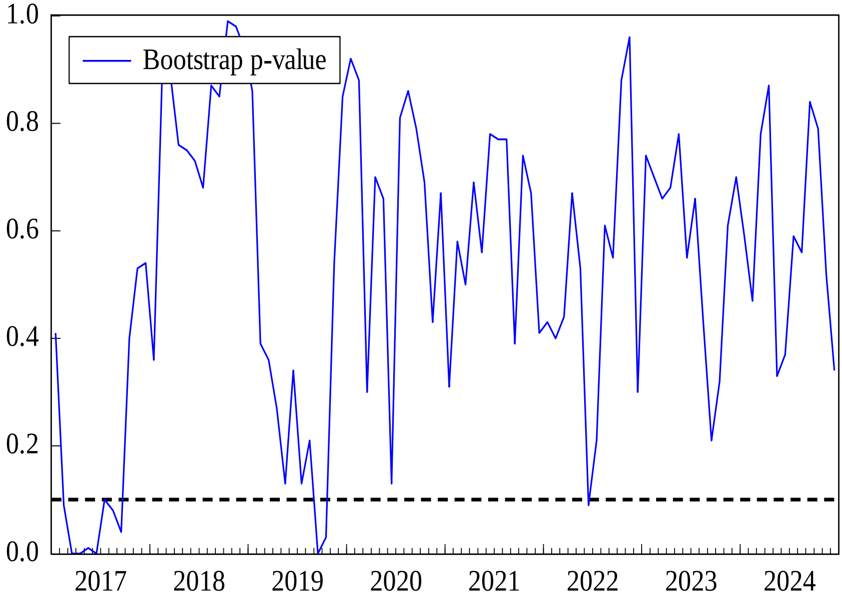
However, evidence of negative impacts demonstrates that AI enhancing ESG performance is not invariable. From March 2017 to June 2017, several factors contribute to the negative impact of AI on ESG performance. First, the intensification of data privacy and security challenges, with several high-profile incidents of data breaches linked to improper AI applications, could undermine corporate social responsibility and public trust. In ESG assessments, data privacy protection is a crucial social indicator, and these negative AI-related incidents undoubtedly have an adverse impact on corporate ESG performance. Second, during this period, AI algorithms are exposed to gender, racial, and other forms of discrimination in areas such as recruitment and credit approval. These issues are concerns of wide social attention and controversy, affecting corporate social responsibility and governance standards. Under the ESG framework, companies are responsible for ensuring technology fairness and non-discrimination, principles that AI algorithm bias clearly violates. Third, in the process where AI contributes to enhancing operational efficiency, the rapid expansion of AI applications in this period leads to higher energy consumption and carbon dioxide emissions from data centers. It influences the environment a lot and weakens the positive role of AI in improving ESG performance. Fourth, the rapid development of AI influences jobs in many traditional industries and raises concerns over unemployment and a shift in employment structures. Employment problems, caused by technology, would influence social stability and harmony, therefore negative impacts on the social dimension of ESG. Fifth, regulatory policies for AI have not fully kept pace with technological advancements, leading to compliance risks for some companies applying AI. These risks potentially damage corporate governance standards and trigger legal disputes and reputational losses, further affecting ESG performance. Hence, we confirm that AI has a negative influence on ESG performance from March to June 2017.

From September 2023 to February 2024, the performance of AI remains relatively stable amidst a backdrop of reaching a technological maturity phase and encountering bottlenecks. This phenomenon is partially attributed to the dwindling returns of profound learning innovations, coupled with constraints in high-quality data resources and the escalating costs associated with computational power and energy. Despite the relatively moderate performance of AI, ESG shows a significant surge, which can be attributed to many factors. On the one hand, policy initiatives across multiple regions, including India, Singapore, the European Union, the United Kingdom, and China, have imposed mandatory regulations and voluntary industry guidelines for ESG disclosure. Amidst this regulatory push, corporate awareness of ESG management has heightened, prompting enterprises to adopt measures such as optimising production processes for carbon reduction, enhancing employee rights protection, and improving supply chain transparency. On the other hand, investors and stakeholders have increasingly prioritised ESG performance as a crucial factor in assessing corporate sustainability, leading to a surge in ESG-themed fund sizes and a heightened market enthusiasm for ESG investments. This, coupled with heightened social and public scrutiny, could compel companies to strengthen their ESG management and actively respond to societal concerns, thereby contributing to the rapid ascent of ESG. Consequently, the negative effect of AI on ESG is proved between September 2023 and February 2024.

Figure 4 details the p-values from ESG to AI, showing that ESG exhibits a significant Granger causality with AI at a 10% level during February 2017 to September 2017 and September 2019 to October 2019. Figure 5 shows the parameters of ESG on AI, underlining the existence of both positive influence (from February 2017 to September 2017) and negative one (from September 2019 to October 2019).

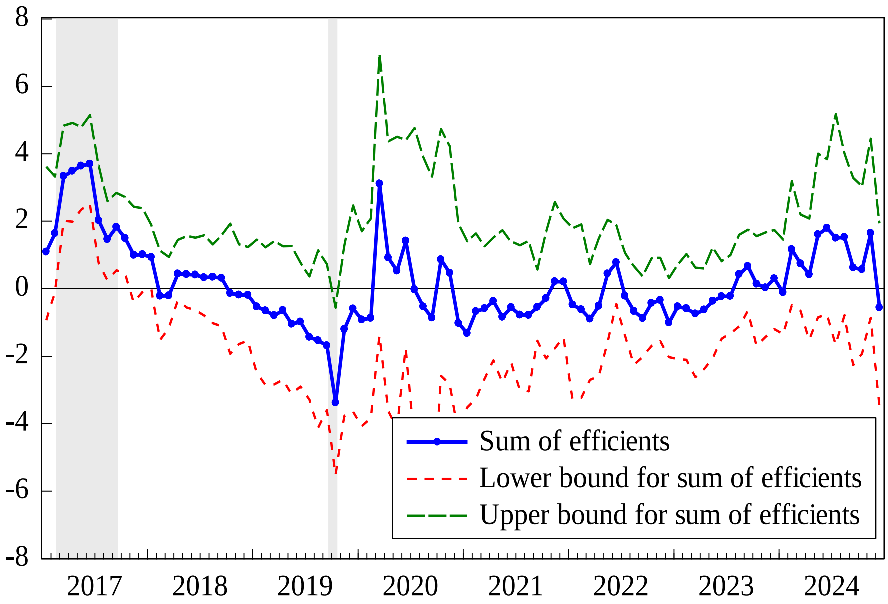
From February 2017 to September 2017, ESG has had a positive impact on AI, with the core reason being the urgent need for safe and environmentally friendly AI in the development of ESG. The ESG framework underscores the importance of environmental protection by mandating enterprises to minimise carbon emissions and enhance resource utilisation efficiency. Consequently, AI is prompted to prioritise energy efficiency and environmental safeguards during its design phase. This includes leveraging optimised algorithms to diminish computational resource consumption, thereby lessening the carbon footprint of data centres. Meanwhile, ESG also includes corporate social responsibility in terms of workers' welfare, security, and data protection. Thus, it places pressure on AI technology to give priority to users' rights and data security when applying technology so as to prevent misuse or leakage of information concerning users. Hence, for adherence to safety standards and protection of the environment by ESG, AI has to reinforce security measures through protocols such as encryption and controlled access. In addition, AI technology should be widely used in intelligent monitoring and data analysis to optimize the production process and reduce energy consumption and waste emissions. Therefore, the ESG framework has provided standards for enterprises to measure their performance in sustainable development and guides AI technology application to meet the requirements of sustainable development. This proves that from February 2017 to September 2017, ESG performance promotes AI.

Figure 4. Testing the absence of Granger causality from ESG to AI



Source: Authors' calculations.

Figure 5. The coefficients of effect of ESG on AI



Source: Authors' calculations.

From September 2019 to October 2019, the investment crowding-out effect became one of the key drivers of ESG's negative impact on AI, especially since the trade wars were making the situation worse. Under the ESG framework, investors have put growing emphasis on the performance of companies in environmental, social, and governance dimensions. As this occurs with some AI companies or projects regarding ESG concerns, in addition to the substantial uncertainty from trade wars, investors would be more inclined to divest from such companies and reinvest in sectors or projects that present better prospects or lesser risk. This reallocation reduces the capital inflow into the AI industry directly and potentially even leads to a decline in the overall market confidence in AI, further exacerbating the capital outflows. Thus, the AI industry has faced greater investment challenges under the dual impact of the trade war and ESG considerations.

6. Conclusion and Policy Implication

6.1. Conclusions

The research explores the intricate connection between AI and ESG, subsequently evaluating whether artificial intelligence invariably enhances ESG performance. This paper utilises full and sub sample approaches to unravel this complex relationship. We find that AI has positive and negative effects on ESG, and the positive one indicates that artificial intelligence, under certain conditions, could improve ESG performance. However, the negative influences refute this notion. On the one hand, when there is a rise in AI, its negative impacts on ESG performance due to privacy breaches, algorithmic bias, increased energy consumption, job displacement, and regulatory compliance risks. On the other hand, when AI remains relatively stable, ESG surges independently due to policy initiatives, investor priorities, heightened corporate awareness, and scrutiny. In turn, ESG has bidirectional influences on AI, and ESG positively influences AI by driving demands for safe and eco-friendly technologies. However, due to heightened ESG scrutiny and ongoing trade wars, the investment crowding-out effect adversely impacts AI funding and market confidence. Upon exploring the time-dependant interactions between AI and ESG, it becomes clear that artificial intelligence cannot enhance ESG performance invariably.

6.2. Policy Implications

Based on the findings above, we will develop relevant policy recommendations that could help realize the positive potential of AI while limiting its negative impacts on ESG performance. Firstly, policymakers must provide clear guidance and regulations with regard to ensuring AI development is aligned with ESG principles. This would include stringent laying down of data protection laws to avoid breaches of privacy, transparency, and fairness in algorithmic decision-making to overcome biases, and energy efficiency standards for AI systems to reduce their carbon footprint. Policies should furthermore support the use of AI in more sustainable practices, such as intelligent monitoring and data analysis, to optimize production processes and minimize waste emissions.

Secondly, governments and regulatory bodies should support a counterbalancing of ESG investing to avoid the crowding-out effect of investments. Educating investors on the long-term benefits of supporting companies with strong ESG profiles-including those in the AI sector-is a necessary step. Similarly, active responsible capital allocation should be encouraged, considering not just short-term financial returns but also social and environmental consequences. Such cooperation between the public and private sectors in developing guidelines for responsible AI investment would go a long way in cushioning the negative impact of trade wars on related funding.

Thirdly, governments should provide incentives and financing for research and development in AI technologies that deliver ESG outcomes, including those with the aim to reduce carbon emissions and enhance energy efficiency, those for monitoring and mitigating environmental impacts, and even those improving social equity. The government should work on various partnerships with a number of different academic institutions, research organizations, and private companies to fast-track the development and deployment of the technology. This can be furthered by the government's encouragement of innovation and research in ways that AI can help to advance ESG goals.

Fourthly, international cooperation in addressing AI and ESG is important; therefore, multilateral dialogues on the development and deployment of internationally accepted standards and best practices that align AI development with ESG principles should be engaged in by governments. Cross-border collaboration can be promoted in the areas of research, industry, and regulators to share knowledge, best practices, and innovative solutions. By fostering international cooperation, governments can ensure that AI technologies are developed and implemented in a way that respects human rights, promotes sustainability, and contributes to global prosperity.

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