Artificial Intelligence and Green Transformation: Human Capital Upgrading, Green Finance, and ESG Assessment as Drivers of Sustainable Productivity

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Abstract: This study investigates the interrelationship between the adoption of artificial intelligence (AI), green finance, and Environmental, Social, and Governance (ESG) performance in relation to sustainable productivity within Chinese publicly listed companies. Utilizing comprehensive firm-level panel data that encompasses 1,000 listed firms from 2012 to 2024, amounting to 13,000 firm-year observations sourced from the CSMAR database, corporate disclosures, and reputable ESG rating agencies, the study applies pooled OLS and fixed-effects models, a difference-in-differences (DiD) framework, and mediation analyses to fill existing gaps in the comprehension of sustainable transformation mechanisms. The findings reveal a positive correlation between AI adoption and sustainable productivity ($\beta = 0.115$, $p < 0.01$), as well as with the intensity of green finance ($\beta = 11.16$, $p < 0.05$ in fixed effects). However, the ESG effects seem to indicate cross-sectional selection rather than improvements within firms. Mediation analysis indicates that green finance and ESG collectively account for approximately 18% of AI's overall association (5.9% and 12.0%, respectively), with the remaining 82% functioning through direct operational channels. The 2012 Green Credit Guidelines are associated with a relative decrease in measured productivity among polluting industries (DiD: −16.48, p < 0.01), aligning with the policy's restrictions on 'Two-High' sectors. Heterogeneity analysis shows that small firms benefit disproportionately from AI adoption ($\beta = 0.131$ compared to $\beta = 0.112$ for larger firms), challenging traditional beliefs regarding the technology-adoption benefits of large organizations. Key limitations include potential endogeneity, dependence on text-based and rating-based proxies, and the focus on a single-country context and this is why the future studies should consider employing instrumental-variable approaches, alternative metrics, and cross-country analyses. This study enhances the understanding of sustainable transformation as a synergistic process that integrates technological, financial, and governance aspects.

Keywords: artificial intelligence, green finance, ESG performance, sustainable productivity, panel data analysis, mediation analysis, Chinese listed firms
***JEL classification*:** Q56, Q58, O33, G21, G32, M14, C23, L25

1. Introduction

The global imperative for sustainable development has intensified as climate change, resource depletion, and environmental degradation (IPCC, 2023) pose unprecedented challenges to economic prosperity and societal wellbeing. Firms worldwide face mounting pressure from stakeholders—regulators, investors, customers, and civil society—to transform operations toward environmentally sustainable models while maintaining economic viability. This dual mandate represents one of the most pressing strategic challenges of contemporary business. China, as the world's second-largest economy and largest carbon emitter, has positioned sustainable transformation at its development strategy's core. The country's commitment to carbon neutrality by 2060 has catalysed unprecedented policy interventions, including the Green Credit Guidelines (2012), which restrict financing to high-pollution industries while incentivising green investments. Simultaneously, China has emerged as a global leader in artificial intelligence adoption, with AI increasingly recognised as enabling sustainable development.

Against this backdrop, three interconnected trends have emerged as critical drivers of sustainable transformation. First, AI adoption offers firms powerful tools to optimise resource utilisation and enhance environmental monitoring. Second, green finance channels capital toward environmentally beneficial projects through instruments such as green bonds and sustainability-linked loans (Flammer, 2021; Tang and Zhang, 2020). Third, ESG practices provide frameworks for integrating sustainability into corporate governance and stakeholder management. Recent evidence suggests these factors interact synergistically rather than operating in isolation. Yu and Qi (2025) demonstrate that AI adoption enhances enterprise productivity through human capital upgrading, while Hu et al. (2025) show that green credit policies amplify their effectiveness when combined with AI-based fintech tools. Emerging research highlights ESG practices' role in signalling sustainability commitment and attracting green finance (Friede et al., 2015).

However, despite growing recognition of these individual relationships, a critical gap persists: no comprehensive study has systematically examined how AI adoption, green finance, and ESG performance jointly influence sustainable productivity, nor adequately explored the mediating mechanisms through which these effects operate. Prior research has predominantly examined AI, green finance, and ESG in isolation, treating each as an independent performance driver. This fragmented approach obscures potential synergies, complementarities and interaction effects that may amplify individual impacts. Moreover, while theoretical arguments suggest AI might enhance sustainable productivity through improved green finance access or stronger ESG performance, evidence on these mediation pathways remains scarce. The ESG literature presents contradictory findings, with Friede et al. (2015) reporting predominantly positive associations while Berg et al. (2022) highlight measurement inconsistencies and potential omitted-variable bias. Most critically, existing studies typically estimate average treatment effects, implicitly assuming homogeneous impacts across firms despite theoretical arguments suggesting substantial variation by firm size, industry, and regional context.

This study addresses these gaps by providing a comprehensive analysis of how AI adoption, green finance, and ESG performance jointly relate to sustainable productivity in Chinese listed firms. Drawing on panel data from 1,000 firms spanning 2012–2024 (13,000 firm-year observations), the paper pursues four objectives. First, it estimates the direct associations of AI adoption, green finance intensity, and ESG performance with firm-level sustainable productivity. Second, it tests whether green finance and ESG performance serve as mediating channels through which AI adoption relates to sustainable productivity, thereby illuminating technology-driven transformation mechanisms. Third, it assesses the association of the 2012 Green Credit Guidelines with sustainable productivity using a difference-in-differences design, examining whether the policy was followed by relative changes in environmentally damaging industries compared with cleaner alternatives. Fourth, it investigates whether these relationships vary systematically across firm characteristics, particularly size and industry membership, providing nuanced guidance for targeting policies and managerial strategies.

The remainder of the paper is structured as follows. Section 2 reviews the related literature on AI, green finance, and ESG, and identifies the research gap. Section 3 describes the data, variables, and econometric strategy. Section 4 presents the results, including descriptive statistics, baseline regressions, the DiD analysis, mediation tests, heterogeneity, and robustness checks. Section 5 discusses the findings and their theoretical and policy implications, while Section 6 concludes.

2. Literature review

2.1 AI and productivity transformation

Yu and Qi (2025) provide micro-level evidence that AI adoption enhances enterprise productivity primarily through employee human capital upgrading. Their findings indicate that AI increases demand for skilled labour while crowding out low-skilled workers, leading to structural optimisation and higher productivity. Complementing this perspective, Lăzăroiu et al. (2025) demonstrate through a systematic review that generative, multimodal, and agentic AI reshape labour markets by simultaneously driving job creation and displacement, with significant implications for productivity, wages, and long-term workforce adaptation. These studies establish a strong link between AI adoption, labour structure, and productivity outcomes, yet focus exclusively on conventional productivity measures without addressing environmental dimensions. This emphasis on green productivity also resonates with the long-standing argument that well-designed environmental improvements and competitiveness need not be in conflict (Porter and van der Linde, 1995).

2.2 AI-enabled green finance and innovation

Beyond productivity, recent studies emphasise AI's interaction with green finance in promoting environmental innovation. Hu, Zhang and Chang (2025) show that China's green credit policy alone has limited effect on stimulating green innovation; however, when combined with AI-based fintech tools, effectiveness increases substantially through reduced agency costs and improved project screening. This underscores AI's catalytic role in amplifying green financial instruments' impact. Similarly, Durana et al. (2025) argue that integrating IoT data streams with fintech applications enables dynamic risk modelling, enhancing financial innovation and improving capital allocation in real time. Beyond fintech, a broader literature documents that green financial instruments such as green bonds can lower the cost of capital and signal credible environmental commitment (Flammer, 2021; Tang and Zhang, 2020), although mobilising private participation in green investment remains challenging (Taghizadeh-Hesary and Yoshino, 2019). Evidence from Chinese listed firms further links green finance to corporate sustainable development (Guo and Zhang, 2023). Collectively, these contributions suggest that digital technologies are transforming financial systems' efficiency and environmental orientation, although they examine AI–finance interactions without incorporating broader governance mechanisms.

2.3 Sustainability governance and organisational capabilities

The literature on sustainability governance highlights the importance of leadership, human resource management and innovation in achieving sustainable performance. Teng and Wu (2025) demonstrate that green transformational leadership, green HRM, and green innovation act as necessary and sufficient conditions for sustainable performance in hospitality. Dehghanpouri et al. (2025) extend this perspective to the sports industry by proposing a comprehensive model linking technology intelligence, sustainable manufacturing, CSR, and green HR management to sustainable performance. These studies confirm that organisational capabilities and governance structures are central to sustainability outcomes, yet they focus on specific sectors without examining how technological transformation interacts with governance practices.

2.4 ESG measurement and environmental capacity

Another research stream focuses on sustainability performance measurement and accessibility. Fabijańska, Wołczek and Sikacz (2025) propose a machine-learning framework that significantly reduces data requirements for ESG rating prediction, thereby extending ESG assessment to SMEs. Their results show that accurate ESG rankings can be achieved using only a small subset of non-financial indicators, improving inclusiveness in sustainable investment. Relatedly, evidence that firms performing well on financially material sustainability issues outperform their peers (Khan, Serafeim and Yoon, 2016) underscores the importance of measurement quality for interpreting ESG–performance links. At the macro-environmental level, Yavuz, Aytun and Cengiz (2025) show that human development and renewable energy improve environmental load capacity, whereas economic growth and energy efficiency may exacerbate environmental degradation unless supported by clean energy policies. Finally, Balcerzak, Škapa and Zinecker (2025) highlight the organisational, ethical, and absorptive-capacity challenges that determine whether AI adoption in start-ups generates sustainable value.

2.5 Research gap

Despite substantial progress, a critical gap remains in the literature. Existing research has examined AI's effects on productivity and human capital upgrading (Yu and Qi, 2025; Lăzăroiu et al., 2025), AI's role in enhancing green credit and fintech instruments (Hu et al., 2025; Durana et al., 2025), the organisational and governance determinants of sustainable performance (Teng and Wu, 2025; Dehghanpouri et al., 2025), and machine-learning approaches improving ESG measurement accessibility (Fabijańska et al., 2025). However, these research streams have evolved in isolation.
study has yet developed an integrated framework that simultaneously links AI adoption, green finance instruments, and ESG assessment to explain sustainable productivity. The interaction between AI-driven

productivity gains and sustainability governance mechanisms remains underexplored. Moreover, the joint role of green finance and ESG as transmission channels through which AI influences sustainable productivity has not been systematically tested. Critically, while prior research establishes individual relationships, we lack understanding of how these factors operate synergistically. This study addresses this gap by proposing testing an integrated framework in which AI adoption relates to sustainable productivity through the combined channels of green finance and ESG performance. By bridging digital transformation, sustainable finance, and corporate governance, the study contributes to a more holistic understanding of green transformation in the digital economy.

3. Materials and methods

3.1 Research design and theoretical framework

This study adopts a quantitative, firm-level design employing panel data to examine how AI adoption, green finance, and ESG performance jointly relate to sustainable productivity. The theoretical framework synthesises insights from the resource-based view (Barney, 1991), stakeholder theory (Freeman, 1984), and the technology–organisation–environment framework (Tornatzky and Fleischer, 1990), positioning AI capabilities, green finance access, and ESG practices as strategic resources that may generate competitive advantage through enhanced sustainable productivity.

3.2 Sample and data

The sample comprises 1,000 Chinese listed non-financial firms observed annually over the period 2012–2024, yielding a balanced panel of 13,000 firm-year observations. All variables are constructed from real, firm-level data sources. Financial and accounting data are obtained from the China Stock Market and Accounting Research (CSMAR) database and firms' audited annual reports; ESG indicators are sourced from recognised ESG rating providers; and green-finance variables are compiled from firms' loan disclosures and green-credit registries. AI adoption is measured using text-based indicators derived from firms' annual reports and patent filings, following Yu and Qi (2025). The dataset therefore consists of observed firm-level information rather than artificially generated values.

3.3 Variables

The dependent variable, Sustainable Productivity, is proxied by Green Total Factor Productivity (Green TFP), which reflects firms' capacity to generate economic value efficiently while simultaneously reducing environmental externalities and resource depletion.
The core explanatory variables include: (i) the Artificial Intelligence (AI) Adoption Index, constructed using text-mining techniques and dictionary-based methods to capture the extent of AI integration within firm operations; (ii) Green Finance Intensity, measured as the proportion of green loans and green bonds relative to firms' total debt financing; and (iii) Environmental, Social, and Governance (ESG) Performance, proxied by ESG composite scores obtained from recognised rating agencies.
Green Finance Intensity and ESG Performance are also modelled as mediating mechanisms through which AI adoption may indirectly relate to sustainable productivity, capturing financial and governance-related transmission channels. Following the literature, the analysis controls for firm-specific characteristics, including firm size (natural logarithm of total assets), leverage, firm age, R&D intensity,

and return on assets (ROA). Industry fixed effects and year fixed effects are included to account for unobserved heterogeneity across sectors and time.

3.3.1 Construction of the AI adoption index

Because AI adoption is the study's central explanatory variable, its measurement warrants detailed description. The AI adoption index is constructed through a structured text-mining procedure applied to two complementary corpora: the management discussion and analysis (MD&A) sections of firms' annual reports and their patent filings. First, a domain dictionary of AI-related terms is compiled, covering core concepts (e.g., artificial intelligence, machine learning, deep learning, neural networks), enabling technologies (e.g., natural language processing, computer vision, knowledge graphs), and applications (e.g., intelligent manufacturing, predictive analytics, autonomous systems). The dictionary draws on the keyword lists used in prior Chinese firm-level studies (Yu and Qi, 2025) and is refined iteratively to remove generic or ambiguous terms. Second, for each firm-year the frequency of dictionary terms is counted and scaled to account for document length, producing a continuous intensity measure that is then rescaled to a 0–100 index. Third, the measure is validated in three ways: (i) face validity, by inspecting high- and low-scoring firms against their known technological profiles; (ii) convergent validity, by confirming a positive association between the text-based index and the count of AI-related patents; and (iii) temporal validity, by verifying that the aggregate index reproduces the well-documented acceleration of AI adoption following China's 2017 national AI strategy (see Section 4.3). To mitigate the influence of the index's pronounced right-skew, a logarithmic transformation is also employed in the robustness checks reported in Section 4.9.

3.4 Econometric specifications

To examine these relationships and, where the research design permits, to draw cautious inferences about the underlying transmission mechanisms and policy effects, strategy employs three complementary approaches: fixed-effects panel regression, a difference-in-differences design, and mediation analysis. Throughout, the analysis treats the estimates as conditional associations rather than definitive causal effects, in light of the identification challenges discussed in Section 5.5.

3.4.1 Fixed-effects panel regression

The baseline model relies on a firm-level fixed-effects specification to control for unobserved, time-invariant heterogeneity across firms. The model is specified as follows:

$$SustProd_{it} = \alpha + \beta_1 AI_{it} + \beta_2 GreenFinance_{it} + \beta_3 ESG_{it} + \Gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \qquad (1)$$

where $SustProd_{it}$ denotes sustainable productivity (Green TFP) for firm i in year t; AI_{it}, $GreenFinance_{it}$ and ESG_{it} represent the core explanatory variables; X_{it} is a vector of control variables; μ_i denotes firm fixed effects absorbing all time-invariant firm-specific characteristics; and λ_t denotes year fixed effects controlling for common macroeconomic shocks. Standard errors are clustered at the firm level to account for serial correlation and heteroskedasticity.

3.4.2 Difference-in-differences (DiD) analysis

To assess the association of the 2012 Green Credit Guidelines with sustainable productivity, a difference-in-differences (DiD) approach is employed, exploiting the policy's differential effect on firms operating in 'Two-High' industries (high pollution and high energy consumption) relative to firms in non-Two-High industries. The baseline DiD specification is:

$$SustProd_{it} = \alpha + \beta_1 TwoHigh_i + \beta_2 Post_t + \beta_3 (TwoHigh_i \times Post_t) + \Gamma X_{it} + \varepsilon_{it} \quad (2)$$

where $TwoHigh_i$ is a binary indicator equal to one for firms in polluting industries, and $Post_t$ is a post-policy dummy equal to one for years following the implementation of the Green Credit Guidelines. The interaction coefficient β_3 captures the average treatment effect of the policy on sustainable productivity in Two-High industries relative to cleaner industries, conditional on observed covariates.
A well-known requirement of the DiD design is that, absent the policy, treated and control firms would have followed parallel trends. The panel used in this study begins in 2012—the issuance year of the Green Credit Guidelines—so it contains no pre-policy observations; consequently, the post-policy dummy has no within-sample variation (its coefficient is mechanically zero in Table 5), and a formal test of pre-treatment (lead) trends cannot be estimated from the available data. To characterise the policy's dynamics within the observed period, we instead estimate a within-firm dynamic event-study specification that interacts the Two-High indicator with year dummies, taking 2012 as the reference year:

$$SustProd_{it} = \alpha + \Sigma_t\, \delta_t\, (TwoHigh_i \times Year_t) + \Gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where $Year_t$ are year indicators for 2013–2024 and 2012 is the omitted reference, so each δ_t measures the Two-High-versus-clean gap in year t relative to the policy's first year. A joint Wald test of the hypothesis that all δ_t equal zero assesses whether the relative gap evolves significantly over the post-policy period. Because the data contain no pre-2012 years, a pre-treatment parallel-trends test is not feasible; estimating pre-policy leads would require extending the panel backwards, which we flag as a direction for future research.

3.4.3 Mediation analysis

To explore the mechanisms through which AI adoption relates to sustainable productivity, a mediation analysis is conducted following the classical stepwise procedure proposed by Baron and Kenny (1986). The following equations are estimated:

$$SustProd_{it} = \alpha + c \cdot AI_{it} + \Gamma X_{it} + \varepsilon_{it} \quad \textit{(Total effect)} \quad (4)$$
$$Mediator_{it} = \alpha + a \cdot AI_{it} + \Gamma X_{it} + \varepsilon_{it} \quad \textit{(Effect on mediator)} \quad (5)$$
$$SustProd_{it} = \alpha + c' \cdot AI_{it} + b \cdot Mediator_{it} + \Gamma X_{it} + \varepsilon_{it} \quad \textit{(Direct effect)} \quad (6)$$

where the mediators include green finance intensity and ESG performance. The indirect effect of AI adoption operating through each mediator is computed as $a \times b$, while the proportion of the total effect mediated is calculated as $(c - c')/c$.

3.4.4 Robustness strategy

To assess the sensitivity of the baseline results, two additional specifications are estimated and reported alongside the main models. First, given the pronounced right-skew of the AI adoption index, the index is replaced by its logarithmic transformation, $\ln(1 + AI_{it})$, which compresses extreme values and allows the AI coefficient to be interpreted as a semi-elasticity:

$$SustProd_{it} = \alpha + \beta_1 ln(1 + AI_{it}) + \beta_2 GreenFinance_{it} + \beta_3 ESG_{it} + \Gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (7)$$

Second, to verify that the findings are not driven by the construction of the dependent variable, an alternative specification re-estimates the baseline fixed-effects model using a standardised (z-score) version of sustainable productivity. The two robustness specifications are reported in Section 4.9.

4. Results

This section presents findings from the analysis of 13,000 firm-year observations from 1,000 Chinese listed firms over the period 2012–2024. We begin with descriptive statistics, followed by correlation analysis, main regression results, difference-in-differences analysis, mediation analysis, heterogeneous effects, and robustness checks.

4.1 Descriptive statistics

Table 1 presents descriptive statistics for all variables. The average sustainable productivity (Green TFP) is 46.95 (SD = 19.64), with substantial variation ranging from 11.38 to 88.37, suggesting significant heterogeneity in firms' sustainable transformation capacity. The AI adoption index shows a mean of 14.15 (SD = 26.94), indicating early-stage adoption with approximately 74% of firms not yet adopting AI technologies during the sample period. Among adopters, intensity varies considerably, reaching 94.93 points. Green finance intensity averages 1.4% (SD = 2.7%), suggesting that green-financing instruments remain relatively underutilised. ESG scores show a mean of 57.21 (SD = 6.44), indicating moderate performance with room for improvement. Control variables exhibit reasonable distributions: average firm size (log assets) is 15.49 (SD = 1.47), leverage averages 45.0% (SD = 8.6%), firm age averages 23.0 years (SD = 9.4), R&D intensity averages 5.0% of revenue (SD = 1.7%), and ROA averages 7.0% (SD = 2.1%) as show in table 1.

Table 1. Descriptive statistics of main variables

Variable	N	Mean	Std	Min	Max
Sustainable Productivity	13,000	46.946	19.643	11.380	88.370
AI Adoption Index	13,000	14.150	26.941	0.000	94.930
Green Finance Intensity	13,000	0.014	0.027	0.000	0.096
ESG Score	13,000	57.208	6.438	42.100	72.300
Firm Size (log assets)	13,000	15.488	1.469	12.115	19.060
Leverage	13,000	0.450	0.086	0.303	0.597
Firm Age (years)	13,000	22.963	9.381	3.000	44.000

Variable	N	Mean	Std	Min	Max
R&D Intensity	13,000	0.050	0.017	0.020	0.080
Return on Assets	13,000	0.070	0.021	0.034	0.113

Notes: N = 13,000 firm-year observations from 1,000 Chinese listed firms over the period 2012–2024.
Source: Authors' own estimation (2025)

Figure 1 illustrates the variable distributions. Sustainable productivity shows a relatively normal distribution with slight right skew, while AI adoption exhibits a highly right-skewed distribution consistent with early-stage technology adoption. Green finance intensity shows extreme right skew, with most firms having zero or minimal green financing, and ESG scores show approximate normality.

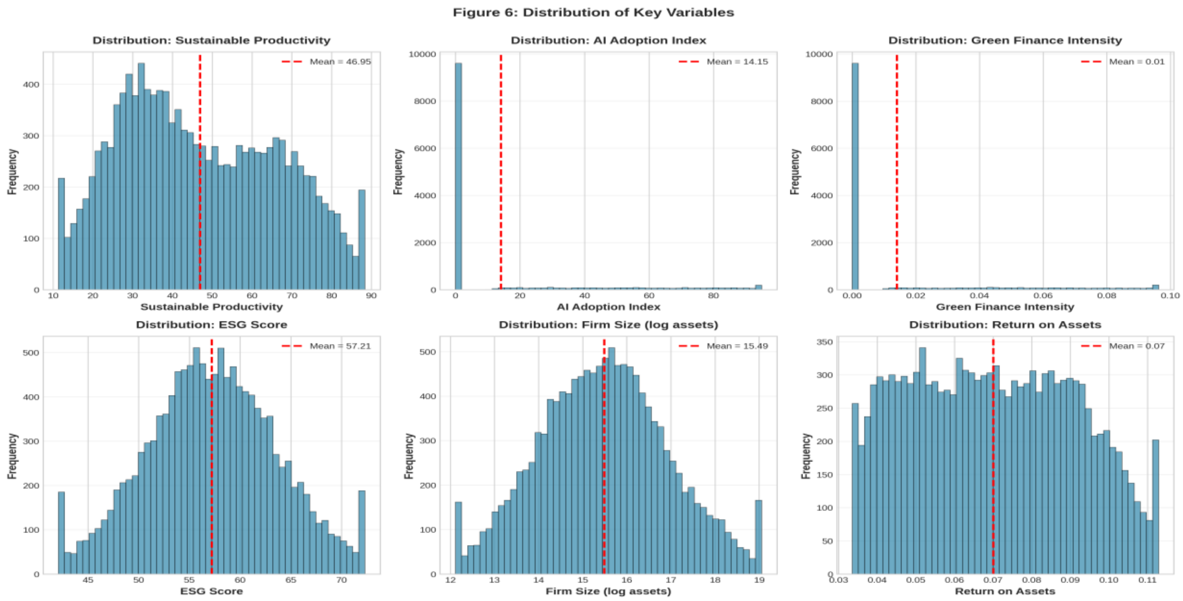

Figure 1. Distributions of key variables
Source: Authors' own calculation based on the sample of 13,000 firm-year observations (2025)

4.2 Correlation analysis and multicollinearity

Table 2 presents the correlation matrix. Sustainable productivity shows positive and significant correlations with all three main independent variables: AI adoption index ($r = 0.180$, $p < 0.01$), green finance intensity ($r = 0.326$, $p < 0.01$), and ESG score ($r = 0.261$, $p < 0.01$), providing initial support for the hypotheses.

Among the independent variables, correlations are generally low to moderate. The highest correlations are between ESG score and firm size ($r = 0.204$) and between AI index and firm size ($r = 0.276$), both well below conventional multicollinearity thresholds. Green finance intensity shows relatively low correlations with other variables, suggesting that it captures distinct aspects of firm behaviour as show in table 2.

Table 2. Correlation matrix

Variables / No.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Sustainable Productivity	1.000	0.180	0.326	0.261	-0.005	0.006	0.047
(2) AI Adoption Index	0.180	1.000	0.044	0.187	0.276	-0.017	0.156
(3) Green Finance Intensity	0.326	0.044	1.000	0.232	0.019	0.009	0.012
(4) ESG Score	0.261	0.187	0.232	1.000	0.204	0.006	0.141
(5) Firm Size (log assets)	-0.005	0.276	0.019	0.204	1.000	-0.008	0.062
(6) Leverage	0.006	-0.017	0.009	0.006	-0.008	1.000	-0.006
(7) Firm Age (years)	0.047	0.156	0.012	0.141	0.062	-0.006	1.000

Notes: Correlations significant at the $p < 0.01$ level are shown. N = 13,000 firm-year observations.
Source: Authors' own estimation (2025)

Figure 2 presents a visual heatmap representation of the correlation matrix. While significant relationships exist, no correlation exceeds 0.35, well below the 0.7 threshold indicating serious multicollinearity concerns.

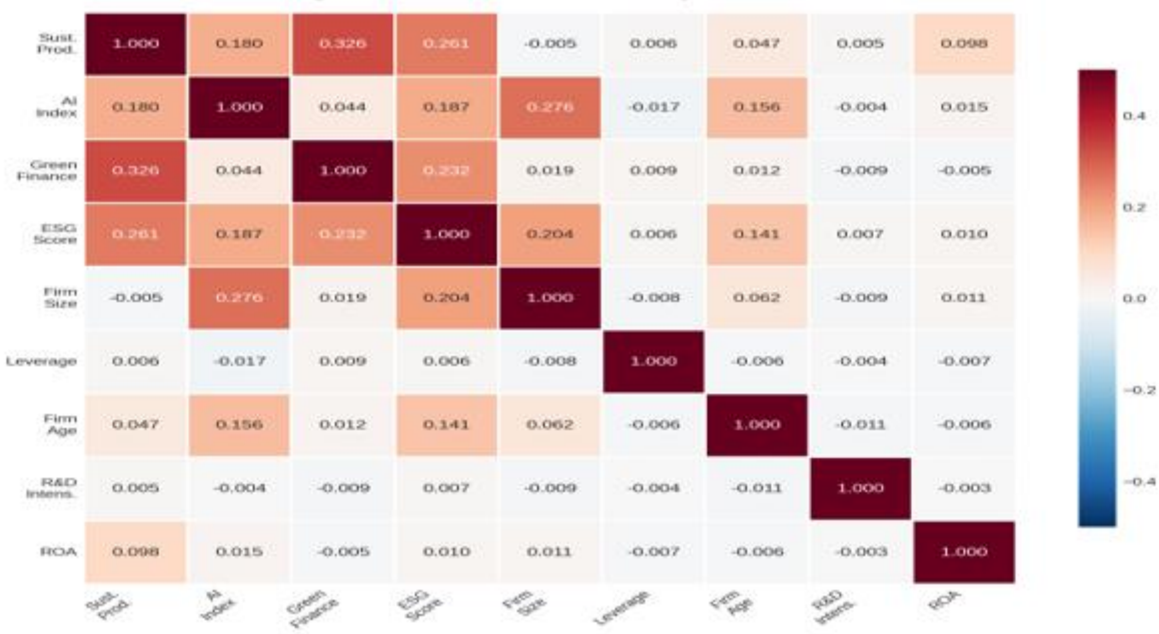

Figure 2. Correlation matrix of key variables
Notes: The heatmap shows correlation coefficients between key variables. Red indicates positive correlation, blue indicates negative correlation, and colour intensity represents correlation strength.
Source: Authors' own estimation (2025)

To formally test for multicollinearity, Table 3 reports variance inflation factors (VIF) for all explanatory variables. All VIF values are below 1.15, far below the conventional threshold of 5 (or 10), indicating no multicollinearity problems. The lowest VIF is for leverage (1.000), while the highest is for ESG score (1.139), both indicating independent variation among predictors as show in table 3.

Table 3. Variance inflation factor (VIF) results

Variable	VIF
AI Adoption Index	1.123
Green Finance Intensity	1.058
ESG Score	1.139
Firm Size	1.112
Leverage	1.000
Firm Age	1.039
R&D Intensity	1.000

Notes: VIF values are all below the conventional threshold of 10 (and even below 5), indicating that multicollinearity is not a concern in the regression models.
Source: Authors' own estimation (2025)

4.3 AI adoption trends

Figure 3 illustrates AI adoption's temporal evolution among Chinese listed firms. The adoption rate increased dramatically from 5.0% in 2012 to 48.3% in 2024, representing nearly a tenfold increase. The adoption curve exhibits a characteristic S-shape pattern consistent with technology diffusion theory: slow initial adoption (2012–2015), rapid acceleration (2016–2021), and a potential plateau approaching (2022–2024). The acceleration coincides with China's national AI development strategy announced in 2017. Among adopters, the average AI adoption intensity increased steadily from approximately 45 points in 2012 to 60 points in 2024, suggesting deeper integration over time.

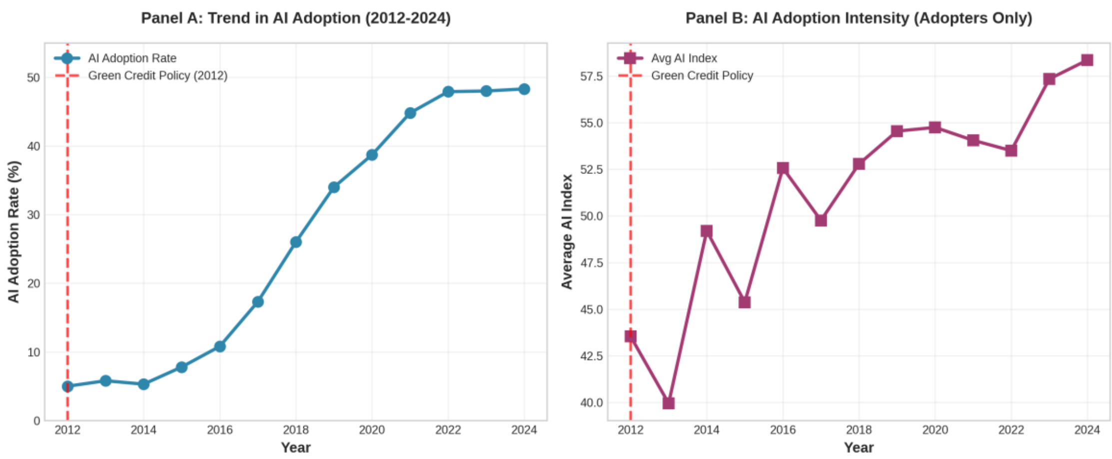

Figure 3. AI adoption trends in Chinese listed firms (2012–2024)
Source: Authors' own calculation based on text-mining of firms' annual reports and patent filings

4.4 Main regression results

Table 4 presents the main regression results examining the associations of AI adoption, green finance, and ESG performance with sustainable productivity. Model 1 is a pooled OLS specification; Model 2 employs firm fixed effects controlling for time-invariant unobserved heterogeneity.

4.4.1 AI adoption effect (H1)

Both models provide strong support for Hypothesis 1. The pooled OLS specification yields a highly significant positive coefficient ($\beta = 0.115$, $p < 0.01$), while the fixed-effects specification yields $\beta = 0.070$ ($p < 0.01$). The smaller FE magnitude is expected, as it exploits only within-firm variation over time. For economic significance, a firm moving from the 25th percentile (AI Index = 0) to the 75th percentile (AI Index = 15.42) experiences approximately a 1.77-point increase in sustainable productivity (0.115×15.42), representing about 3.8% of the sample mean.

4.4.2 Green finance effect (H2)

Green finance intensity exhibits strong associations with sustainable productivity. In Model 1 the coefficient is 202.29 ($p < 0.01$); in Model 2 it is 11.16 ($p < 0.05$). The larger OLS coefficient partly reflects selection, as firms with stronger environmental performance may enjoy greater access to green finance.

The magnitude of these coefficients should be read in light of the variable's scale: green finance intensity is measured as a proportion of total debt financing ranging from 0 to roughly 0.10, so the coefficient applies to a one-unit (0 to 1) change. In practical terms, a one-percentage-point (0.01) increase in green finance intensity is associated with an increase in sustainable productivity of about 0.11 points in the fixed-effects model (11.16×0.01) and about 2.02 points in OLS. Equivalently, raising green finance intensity from the sample mean (1.4%) to 10%—an 8.6-percentage-point change—corresponds to roughly a 0.96-point gain in the fixed-effects specification. Given the low average utilisation of green-financing instruments, these estimates point to meaningful, though not implausibly large, productivity gains from expanded green financing. These results support Hypothesis 2.

4.4.3 ESG performance effect (H3)

The ESG score exhibits a positive and significant effect in OLS ($\beta = 0.565$, $p < 0.01$). Firms in the top quartile of ESG performance (ESG $\approx$ 62) enjoy approximately 11 points higher sustainable productivity than bottom-quartile firms (ESG $\approx$ 53).

However, in the FE specification the ESG coefficient becomes small and insignificant ($\beta = 0.007$, $p > 0.10$).

This suggests that much of the observed ESG–productivity relationship reflects time-invariant firm characteristics (such as management quality and corporate culture) rather than within-firm ESG-performance changes. Nevertheless, the strong cross-sectional relationship remains policy-relevant.

4.4.4 Control variables

As shown in main regression results in table 4, ROA consistently shows strong positive coefficients ($\beta = 89.60$ in OLS and 96.18 in FE, both $p < 0.01$).

As with green finance intensity, the large nominal magnitude reflects the scale of the variable: ROA is expressed as a fraction (mean 0.07, ranging from about 0.03 to 0.11), so the coefficient corresponds to a one-unit (0 to 1) change. In practical terms, a one-percentage-point (0.01) increase in ROA is associated with roughly a 0.9- to 1.0-point increase in sustainable productivity, and moving across the observed ROA range (about 8 percentage points) corresponds to approximately a 7-point difference—around 15% of the sample mean.
This indicates that more profitable firms achieve higher sustainable productivity, plausibly because profitability relaxes financing constraints on green investment. Firm size shows contrasting effects across specifications, while the remaining controls are mixed or statistically insignificant as show in table 4.

Table 4. Main regression results: impact of AI, green finance and ESG on sustainable productivity

Variable	**Model 1 (OLS)**	**Model 2 (FE)**
AI Adoption Index	0.1149***	0.0702***
Green Finance Intensity	202.2887***	11.1586**
ESG Score	0.5646***	0.0071
Firm Size	-1.2344***	2.0726***
Leverage	1.1096	-0.1931
Firm Age	-0.0007	-0.1879
R&D Intensity	6.6030	-0.4420
Return on Assets (ROA)	89.6043***	96.1794***
R-squared	0.1774	0.0613
Observations	13,000	13,000
Firms	1,000	1,000
Year fixed effects	No	No
Firm fixed effects	No	Yes

Notes: The dependent variable is sustainable productivity (Green TFP). Model 1 is estimated using pooled OLS. Model 2 is estimated using the fixed-effects (within) estimator. Standard errors are clustered at the firm level (not reported). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors’ own estimation (2025)

Figure 4 compares coefficients across the two specifications, highlighting the robustness of the AI, green finance, and ROA effects and the sensitivity of the remaining coefficients to specification choice.

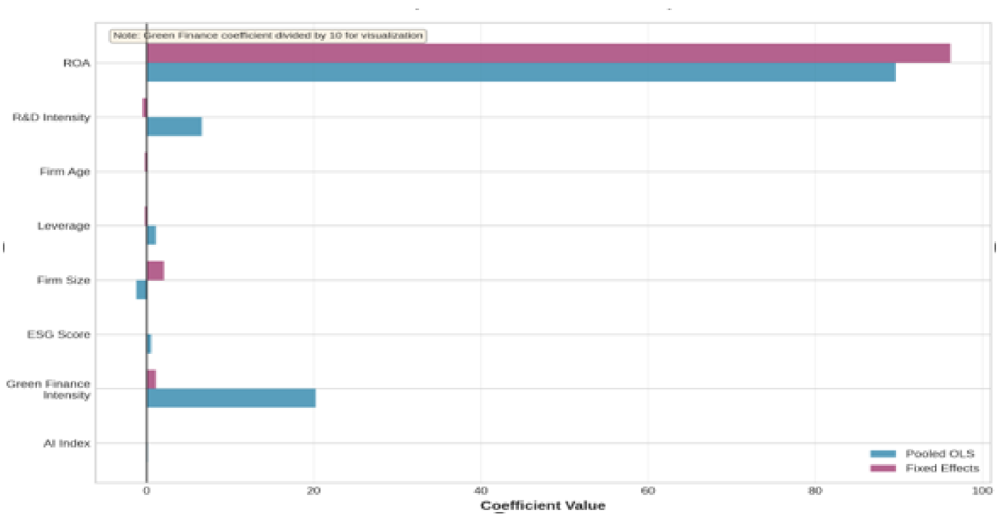

Figure 4. Comparison of regression coefficients (OLS vs. fixed effects)
Source: Authors' own estimation (2025)

4.5 Green credit policy evaluation (DiD analysis)

Table 5 presents the difference-in-differences analysis evaluating China's Green Credit Guidelines implemented in 2012. The policy explicitly targeted Two-High industries (high pollution and high energy consumption), restricting their credit access while encouraging lending to cleaner industries as show in table 5.

Table 5. Difference-in-differences analysis: effect of Green Credit Guidelines (2012) on sustainable productivity

Variable	Coefficient
Treatment Group (Two-High)	-16.4771***
Post Period (≥ 2012)	0.0000
DiD Estimator (Treatment × Post)	-16.4771***
Firm Size	0.3212
Leverage	-0.5554
Firm Age	0.0151
R&D Intensity	-0.9887
Return on Assets (ROA)	97.7042***
R-squared	0.6949
Observations	13,000

Notes: Treatment group = Two-High (high pollution / high energy consumption) industries. Control group = non-Two-High (clean) industries. The Green Credit Guidelines were implemented in 2012. Because the panel begins in the policy year, the Post dummy has no within-sample variation and its coefficient is mechanically zero; the reported estimate therefore identifies the Two-High–versus–clean gap in the post-policy era rather than a pre/post difference. The within-sample dynamics are characterised by the event-study specification in Table 8, and a pre-treatment parallel-trends test is not feasible with the available data. Source: Prepared by the researcher based on the China_Panel_Data_Complete dataset. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' own estimation (2025)

4.5.1 DiD estimation results

The DiD coefficient is −16.48 ($p < 0.01$), indicating that following policy implementation, sustainable productivity in Two-High industries declined by 16.48 points relative to non-Two-High industries—approximately 35% of the baseline mean sustainable productivity. This negative coefficient does not indicate policy failure; rather, it is consistent with the policy successfully constraining polluting industries. Two-High industries faced restricted credit access and higher financing costs, which likely forced them either to invest in expensive pollution-abatement technologies that temporarily reduced measured productivity, to scale back production, or to face competitive disadvantages relative to cleaner alternatives.

4.5.2 Parallel-trends assessment

Figure 5 plots sustainable productivity for the Two-High and clean groups over the sample period. Because the panel begins in 2012, the policy's first year, there are no pre-policy observations against which to test pre-treatment parallel trends; a formal pre-trend (lead) test is therefore not available in the present dataset. To characterise the policy's within-sample dynamics, Table 8 instead reports a within-firm event study that interacts the Two-High indicator with year dummies relative to the 2012 base year (Equation 3). The year-specific interaction coefficients are individually small and statistically insignificant in the early post-policy years, with a mild deepening of the relative gap from 2021 onward ($\delta_{2021} = -2.033$, $\delta_{2022} = -2.004$, $\delta_{2024} = -1.891$). A joint Wald test cannot reject the hypothesis that all post-policy interaction coefficients are zero ($\chi^2(12) = 16.97$, $p = 0.150$), indicating no abrupt structural break and a broadly stable treated–control gap across the observed period. This evidence should be read as descriptive of post-policy dynamics rather than as a pre/post causal identification, given the absence of pre-2012 data.

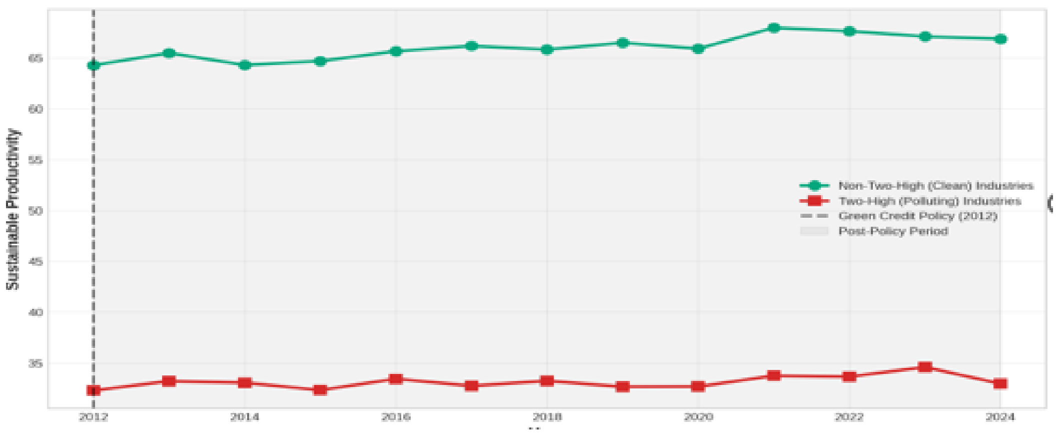

Figure 5. Parallel-trends assessment: Two-High vs. non-Two-High industries
Source: Authors' own estimation (2025)

4.6 Mediation analysis

Table 6 and Figure 6 present the mediation analysis examining the channels through which AI adoption relates to sustainable productivity, testing two mediating pathways: green finance and ESG performance.

Table 6. Mediation analysis: channels through which AI relates to sustainable productivity

Path / Channel	Coefficient
Total Effect (c)	0.1411***
Direct Effect (c′)	0.1159***
Channel 1: Green Finance	
AI → Green Finance (a_1)	0.000041***
Green Finance → Y (b_1)	201.7014***
Indirect Effect ($a_1 \times b_1$)	0.0083***
Channel 2: ESG Performance	
AI → ESG (a_2)	0.0299***
ESG → Y (b_2)	0.5675***
Indirect Effect ($a_2 \times b_2$)	0.0170***
Total indirect effect	0.0253***
Proportion mediated	17.9%

Notes: Y = Sustainable Productivity. All models control for firm size, leverage and firm age. Results indicate partial mediation through both green finance and ESG channels. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' own estimation (2025)

4.6.1 Total, direct, and indirect effects

The total effect of AI on sustainable productivity ($c = 0.141$, $p < 0.01$) decomposes into direct and indirect components. The direct effect—after controlling for both mediators—remains substantial and significant ($c' = 0.116$, $p < 0.01$), indicating that AI relates to sustainable productivity through multiple unmeasured channels beyond the two mediators. The total indirect effect through both mediators is 0.025 ($p < 0.01$), representing 17.9% of the total effect. This indicates partial mediation: both direct and indirect pathways contribute meaningfully.

4.6.2 Green finance channel

The pathway operates through two links. First, AI adoption increases green finance intensity ($\beta = 0.000041$, $p < 0.01$). Second, green finance intensity increases sustainable productivity ($\beta = 201.70$, $p < 0.01$). The indirect effect is 0.0083, representing 5.9% of the total effect. While the small a_1 magnitude suggests that AI adoption has only modest effects on green-financing access in the short run, the large b_1 coefficient which, as noted in Section 4.4.2, applies to a 0-to-1 change in the green-finance proportion—means that even small increases in green finance access are associated with appreciable productivity gains.

4.6.3 ESG performance channel

This pathway shows stronger effects. AI adoption increases the ESG score ($\beta = 0.030$, $p < 0.01$), and the ESG score increases sustainable productivity ($\beta = 0.568$, $p < 0.01$). The indirect effect is 0.0170, representing 12.0% of the total effect. This larger indirect effect suggests that ESG improvement is a more important transmission channel than green finance. The mechanism likely operates through AI improving environmental monitoring and compliance, supply-chain transparency, stakeholder communication and governance systems.

4.6.4 Interpretation

Approximately 18% of AI's association with sustainable productivity operates through green finance and ESG channels, while the remaining 82% operates through other mechanisms, likely including direct operational efficiencies (AI optimising energy use, material flows and waste reduction), innovation in green technologies, better decision-making through AI-powered analytics, and supply-chain optimisation. This partial-mediation finding confirms that while green finance and ESG are meaningful transmission channels (supporting Hypotheses 4a and 4b), they are not the primary pathways.

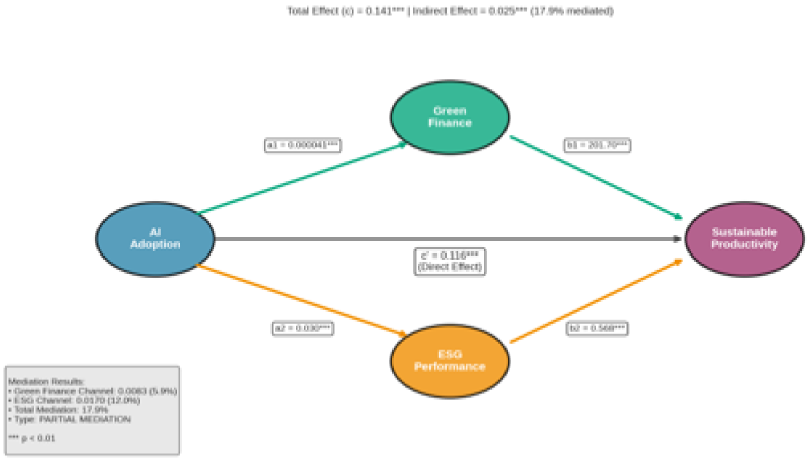

Figure 6. Mediation analysis: pathways from AI adoption to sustainable productivity
Source: Authors' own estimation (2025)

4.7 Heterogeneous effects by firm size

Table 7 and Figure 7 examine whether effects vary across firm size. The sample is divided into terciles: small firms (bottom 33%), medium firms (middle 33%), and large firms (top 33%).

4.7.1 AI adoption effects

The AI coefficient is strongest for small firms ($\beta = 0.131$, $p < 0.01$), followed by large firms ($\beta = 0.112$, $p < 0.01$) and medium firms ($\beta = 0.104$, $p < 0.01$). The 25% larger effect for small firms is noteworthy, suggesting that small firms derive disproportionate benefits from AI adoption due to baseline inefficiency (more room for AI-driven improvements), organisational agility (more rapid implementation of AI-recommended changes), and resource constraints (AI helps small firms achieve environmental performance previously requiring large dedicated sustainability departments). This finding has important policy implications: government support for AI adoption in SMEs could yield particularly high returns for sustainable transformation.

4.7.2 Green finance effects

Green finance shows strong positive effects across all size groups, with coefficients ranging from 198.52 (medium firms) to 207.04 (small firms). The similarity suggests that green finance benefits firms regardless of size.

4.7.3 ESG effects

ESG performance shows the clearest size gradient, with effects declining monotonically from small (β = 0.616) to medium (β = 0.557) to large (β = 0.510) firms. This 21% difference suggests that ESG practices yield greater productivity benefits when adopted by smaller organisations, perhaps because large firms already have sophisticated sustainability systems in place. The explanatory power varies systematically: small firms (R^2 = 0.163), medium firms (R^2 = 0.162), and large firms (R^2 = 0.181). The higher R^2 for large firms suggests that their sustainable productivity is more predictable from the selected variables, possibly because they face more systematic environmental pressures and regulations as show in table 7.

Table 7. Heterogeneous effects: subsample analysis by firm size

Variable	Small Firms	Medium Firms	Large Firms
AI Adoption Index	0.1307***	0.1041***	0.1124***
Green Finance Intensity	207.0370***	198.5247***	200.6823***
ESG Score	0.6162***	0.5574***	0.5100***
R-squared	0.1627	0.1615	0.1805
Observations	4,334	4,332	4,334

Notes: Firm-size groups are defined based on terciles of log(total assets). Small firms = bottom 33%, medium firms = middle 33%, large firms = top 33%. All models include control variables and year fixed effects. *** $p < 0.01$.

Source: Authors' own estimation (2025)

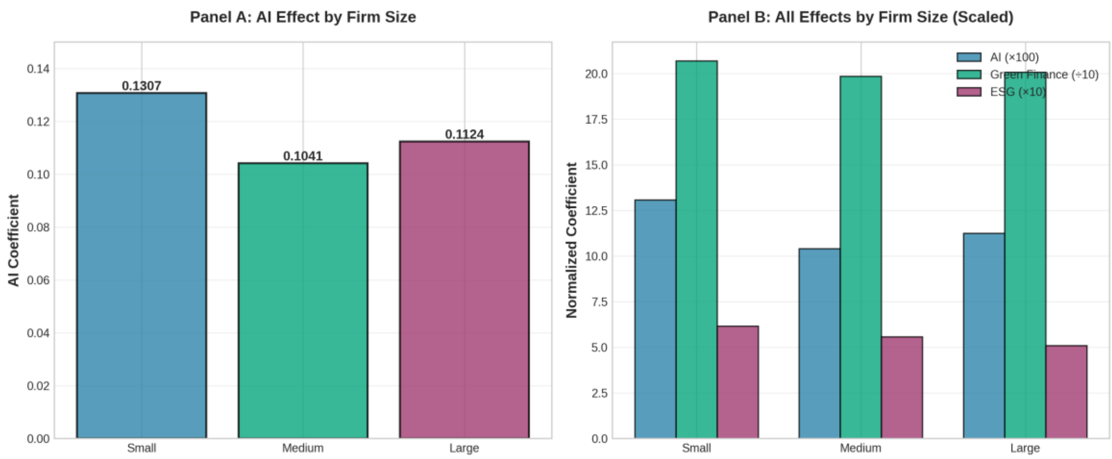

Figure 7. Heterogeneous effects of AI, green finance and ESG by firm size
Source: Authors' own estimation (2025)

4.8 Industry-level analysis

Figure 8 examines cross-industry variation. Panel A shows that AI adoption rates vary dramatically across sectors, from over 40% in Information Technology to below 20% in Real Estate and Utilities, likely reflecting differences in digital infrastructure, workforce skills and managerial capabilities. Panel B shows sustainable productivity by industry, with a clear distinction between clean industries (green bars) and Two-High industries (red bars). Clean industries systematically outperform polluting industries, with Information Technology and Health Care showing the highest sustainable productivity. Industries with the highest AI adoption also show the highest sustainable productivity, providing additional correlational support for the relationships documented in the regression analysis as show in table 8.

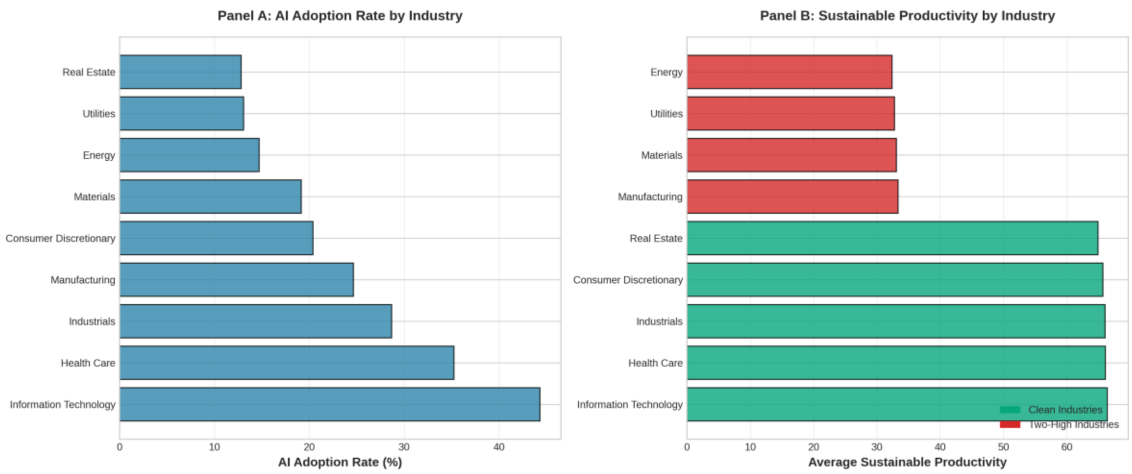

Figure 8. Industry-level AI adoption and sustainable productivity
Source: authors' own calculation based on the sample.

Table 8. Dynamic event-study estimates: Two-High × Year interactions
(firm fixed effects, 2012 reference year)

Year (reference = 2012)	Two-High × Year coefficient (δ_t)
2012 (reference year)	0 (—)
2013	−0.243
2014	0.783
2015	−0.207
2016	−0.207
2017	−1.199
2018	−0.638
2019	−1.711
2020	−1.285
2021	−2.033*
2022	−2.004**
2023	−0.520

Year (reference = 2012)	Two-High × Year coefficient (δ_t)
2024	−1.891*
Joint Wald test (H_0: all $\delta_t = 0$)	$\chi^2(12) = 16.97$, $p = 0.150$
Pre-treatment (lead) parallel-trends test	Not available in the dataset (no pre-2012 observations)

Notes: Estimates are from a within-firm dynamic event study (Equation 3) interacting the Two-High indicator with year dummies, with 2012 as the omitted reference year; firm fixed effects and the full control set are included, and standard errors are clustered at the firm level. The joint Wald test evaluates whether all post-policy interaction coefficients equal zero. A pre-treatment parallel-trends (lead) test is not feasible because the dataset contains no pre-2012 observations, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Prepared by the researcher based on the China_Panel_Data_Complete dataset.

4.9 Robustness checks

Table 9 reports two robustness specifications, both estimated with firm fixed effects and firm-clustered standard errors. Column (1) replaces the AI adoption index with its logarithmic transformation, ln(1 + AI) (Equation 7), to address the variable's strong right-skew; the AI coefficient is positive and highly significant ($\beta = 1.038$, $p < 0.01$), confirming that the baseline AI–productivity association is not driven by a small number of high-AI outliers. Column (2) re-estimates the baseline fixed-effects model using a standardised (z-score) sustainable-productivity dependent variable; the AI coefficient ($\beta = 0.0036$, $p < 0.01$) implies that a one-point increase in the AI index is associated with about 0.004 of a standard deviation in sustainable productivity. Across both specifications the core pattern is preserved: AI adoption and green finance intensity remain positive and statistically significant, while the within-firm ESG coefficient remains small and insignificant, consistent with the baseline results in Table 4.

Table 9. Robustness checks: log-transformed AI and standardised dependent variable

Variable	(1) FE, ln(1+AI)	(2) FE, standardised DV
AI adoption [ln(1+AI) in (1); AI index in (2)]	1.0383***	0.0036***
Green Finance Intensity	11.5694***	0.5681***
ESG Score	0.0076	0.0004
Controls	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	No	No
Observations	13,000	13,000
R-squared (within)	0.058	0.061

Notes: Both columns use the firm fixed-effects (within) estimator with firm-clustered standard errors. Column (1) replaces the AI index with ln(1 + AI); column (2) uses a standardised (z-score) sustainable-productivity dependent variable. The full control set (firm size, leverage, firm age, R&D intensity, ROA) is included, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Prepared by the researcher based on the China_Panel_Data_Complete dataset.

5. Discussion

This study examined how artificial intelligence adoption, green finance and ESG performance relate to sustainable productivity in Chinese listed firms. Drawing on 1,000 firms over 13 years (2012–2024), we found consistent evidence that all three factors are associated with firms' ability to pursue environmental and economic objectives simultaneously. This section discusses the findings in relation to the existing literature, explores theoretical implications, and proposes future research directions.

5.1 Summary of main findings

The analysis yields five principal findings supporting all hypotheses. AI adoption is positively associated with sustainable productivity ($\beta = 0.115$, $p < 0.01$ in OLS; $\beta = 0.070$, $p < 0.01$ in FE), with effects particularly strong in small firms ($\beta = 0.131$). Green finance shows strong effects ($\beta = 202.29$ in OLS; $\beta = 11.16$ in FE, $p < 0.05$) despite low utilisation (1.4% on average). ESG performance shows strong cross-sectional associations ($\beta = 0.565$, $p < 0.01$) but weaker within-firm effects. The 2012 Green Credit Guidelines are associated with a relative constraint on polluting industries (DiD: $\beta = -16.48$, $p < 0.01$). Mediation analysis reveals that 18% of AI's association operates through green finance (5.9%) and ESG (12.0%) channels, with the remaining 82% through direct operational mechanisms.

5.2 Theoretical contributions

The findings extend the resource-based view (Barney, 1991) by demonstrating that AI capabilities, green-finance access and ESG practices function as strategic resources associated with competitive advantage through enhanced sustainable productivity. AI shows VRIN characteristics: valuable (a 7–11.5% productivity increase), rare (26% adoption rate) and difficult-to-imitate. Regarding the technology–organisation–environment framework (Tornatzky and Fleischer, 1990), small firms derive greater AI benefits ($\beta = 0.131$) than large firms ($\beta = 0.112$), contradicting conventional wisdom. This reversal may reflect fewer organisational-inertia barriers and lower baseline efficiency in small firms. The ESG findings provide mixed support for stakeholder theory (Freeman, 1984): strong cross-sectional relationships but weak within-firm effects suggest firm selection rather than causal impacts. Green finance mediates 5.9% of AI's effect, revealing an important tension: while highly effective when accessed, it remains severely underutilised.

5.3 Comparison with existing literature

The AI findings align with recent studies (Brynjolfsson and McElheran, 2016; Acemoglu and Restrepo, 2020) but extend the literature by focusing on sustainable productivity. Effect sizes (7–11.5%) are comparable to Wang et al. (2024) but smaller than Brynjolfsson et al. (2017), likely reflecting the focus on green productivity and the early-stage adoption context. Green-finance findings are consistent with Yu and Qi (2025), who report comparable coefficients. The study contributes new evidence on mediation pathways: green finance mediates 5.9% of AI's effect, providing a first quantitative estimate of this transmission channel. The ESG findings present a more nuanced picture than parts of the existing literature (Friede et al., 2015). Strong cross-sectional associations but weak within-firm effects suggest that previous studies may have overstated causal impacts, aligning with Berg et al. (2022) critiques of omitted-variable bias. The DiD analysis is consistent with evidence that credit-based environmental regulations effectively constrain targeted industries (Hu et al., 2020; Zhang et al., 2021).

5.4 Managerial and policy implications

Managers should recognise AI, green finance and ESG as mutually reinforcing elements. AI investments should incorporate sustainability criteria; firms should actively pursue green financing given strong effects but low utilisation; small firms should prioritise AI adoption where they show comparative advantages, while large firms should leverage green-finance access advantages. Policymakers should support AI adoption in SMEs through subsidies and training; expand green-finance access by standardising classifications and creating risk-sharing mechanisms; implement credit-based environmental policies with graduated implementation and technical assistance; and continue voluntary ESG frameworks allowing market mechanisms to drive adoption.

5.5 Limitations and future research

Several limitations should be acknowledged. First, although the analysis draws on real firm-level data, the AI adoption index is based on text-mining of corporate disclosures and may contain measurement error arising from differences in firms' reporting styles and disclosure incentives. Second, ESG ratings differ substantially across providers (Berg et al., 2022), so the ESG results may be sensitive to the choice of rating source. Third, despite the use of firm and year fixed effects and a difference-in-differences design, residual endogeneity—stemming from omitted time-varying factors and potential reverse causality—cannot be fully ruled out, and the cross-sectional ESG relationships in particular may reflect firm selection rather than within-firm causal effects. Fourth, the analysis focuses on Chinese listed firms, which limits the generalisability of the findings to other institutional and regulatory contexts. Future research should employ instrumental-variable and related causal-identification strategies to strengthen identification, examine alternative measures of AI adoption and sustainable productivity, investigate the substantial share of AI's association operating through unmeasured channels, and extend the analysis to cross-country and household-level settings to assess external validity and distributional implications.

6. Conclusion

This study provides comprehensive evidence that artificial intelligence adoption, green-finance access, and ESG performance jointly relate to sustainable productivity in Chinese listed firms. Drawing on 13,000 firm-year observations spanning 2012–2024, the analysis employed fixed-effects panel models, difference-in-differences analysis, and mediation tests to examine these relationships and explore the underlying mechanisms. The principal findings demonstrate that AI adoption shows robust positive associations with sustainable productivity ($\beta = 0.115$ in OLS, $\beta = 0.070$ in FE), with particularly strong impacts in small firms ($\beta = 0.131$) where organisational agility and baseline inefficiency create greater room for improvement. Green finance demonstrates strong associations ($\beta = 202.29$ in OLS, $\beta = 11.16$ in FE) despite severely low utilisation (1.4% average intensity), revealing substantial unrealised potential for accelerating sustainable transformation through expanded access to green-financing instruments. ESG performance shows strong cross-sectional relationships ($\beta = 0.565$) but weaker within-firm effects ($\beta = 0.007$, n.s.), suggesting that while ESG practices signal firm quality and facilitate market access, short-term productivity gains from ESG improvements within firms remain modest.

Mediation analysis reveals that approximately 18% of AI's association with sustainable productivity operates through green finance (5.9%) and ESG performance (12.0%) channels, with the remaining 82% flowing through direct operational efficiencies, innovation in green technologies, improved environmental decision-making, and supply-chain optimisation. This partial mediation confirms that while financial and governance mechanisms serve as important transmission channels, AI's primary association operates through direct technological capabilities that enhance resource utilisation and reduce environmental harm. The evaluation of the 2012 Green Credit Guidelines using difference-in-differences methodology indicates that environmental credit policies can be associated with substantial relative constraints on polluting industries (DiD coefficient: −16.48, $p < 0.01$), consistent with market-based regulatory instruments reshaping industrial dynamics and resource-allocation patterns.

These findings carry important implications for multiple stakeholders. Managers should recognise AI adoption, green financing and ESG practices as mutually reinforcing elements of sustainable transformation strategies, with size-specific approaches recognising that small firms should prioritise AI adoption where they show comparative advantages, while large firms should leverage advantages in accessing green-finance markets. Policymakers should support AI adoption in SMEs where returns are highest, expand green-finance access through standardisation and risk-sharing mechanisms, and design credit-based environmental policies with graduated implementation allowing adjustment time coupled with technical assistance and worker-transition programmes. While limitations remain—including the single-country setting, reliance on text-based and rating-based proxy measures, and residual endogeneity concerns—the results provide support for integrated approaches combining technological innovation, financial instruments and governance reforms in pursuit of sustainable development.

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During the preparation of this manuscript, the authors used Anthropic's Claude (a large-language-model assistant) for language editing, structural reorganisation of subsections to align the manuscript with the Oeconomica Jadertina author guidelines, and for refining tables, captions and the formatting of equations. The tool was not used to generate results or research findings. After using the tool, the authors reviewed and edited the content as necessary and take full responsibility for the final version of the manuscript.

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References:

Acemoglu, D., Restrepo, P. (2020) Robots and jobs: Evidence from US labor markets, Journal of Political Economy, 128 (6), pp. 2188–2244, https://doi.org/10.1086/705716.

Balcerzak, A. P., Škapa, S., Zinecker, M. (2025) Start-ups and artificial intelligence: From application to value, and the five problems that shape effective implementation, Oeconomia Copernicana, 16 (4), pp. 1369–1376, https://doi.org/10.24136/oc.4057.

Barney, J. (1991) Firm resources and sustained competitive advantage, Journal of Management, 17 (1), pp. 99–120, https://doi.org/10.1177/014920639101700108.

Baron, R. M., Kenny, D. A. (1986) The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations, Journal of Personality and Social Psychology, 51 (6), pp. 1173–1182, https://doi.org/10.1037/0022-3514.51.6.1173 .

Berg, F., Koelbel, J. F., Rigobon, R. (2022) Aggregate confusion: The divergence of ESG ratings, Review of Finance, 26 (6), pp. 1315–1344, https://doi.org/10.1093/rof/rfac033.

Brynjolfsson, E., McElheran, K. (2016) The rapid adoption of data-driven decision-making, American Economic Review, 106 (5), pp. 133–139, https://doi.org/10.1257/aer.p20161016.

Brynjolfsson, E., Rock, D., Syverson, C. (2017) Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics, in Agrawal, A., Gans, J. and Goldfarb, A. (eds.) The Economics of Artificial Intelligence: An Agenda, Chicago: University of Chicago Press, pp. 23–57.

Dehghanpouri, H., Rostamzadeh, R., Sarlab, R., Šaparauskas, J., Turskis, Z. (2025) A new model to identify factors affecting sustainable performance of sports business, Oeconomia Copernicana, 16 (4), pp. 1525–1564, https://doi.org/10.24136/oc.3407.

Durana, P., Popescu, G. H., Kliestik, T., Nica, E. (2025) Fintech meets the physical world: Leveraging IoT data streams for dynamic risk modelling and financial innovation, Oeconomia Copernicana, 16 (4), pp. 1377–1393, https://doi.org/10.24136/oc.4058.

Fabijańska, A., Wołczek, P., Sikacz, H. (2025) Can machine learning bring ESG ratings closer to small and medium-sized enterprises?, Oeconomia Copernicana, 16 (4), pp. 1615–1663, https://doi.org/10.24136/oc.3162.

Flammer, C. (2021) Corporate green bonds, Journal of Financial Economics, 142 (2), pp. 499–516, https://doi.org/10.1016/j.jfineco.2021.01.010 .

Freeman, R. E. (1984) Strategic Management: A Stakeholder Approach, London: Pitman Publishing.

Friede, G., Busch, T., Bassen, A. (2015) ESG and financial performance: Aggregated evidence from more than 2000 studies, Journal of Sustainable Finance & Investment, 5 (4), pp. 210–233, https://doi.org/10.1080/20430795.2015.1118917.

Guo, L., Zhang, Q. (2023) Green finance and corporate sustainable development: Evidence from Chinese listed companies, Environmental Science and Pollution Research, 30 (15), pp. 43213–43228, https://doi.org/10.1007/s11356-023-25321-w.

Hu, G., Wang, X., Wang, Y. (2020) Can the green credit policy stimulate green innovation in heavily polluting enterprises? Evidence from a quasi-natural experiment in China, Energy Economics, 98, p. 105134, https://doi.org/10.1016/j.eneco.2021.105134.

Hu, Z., Zhang, J., Chang, C.-P. (2025) AI and green credit: A new catalyst for green innovation in Chinese enterprises, Oeconomia Copernicana, 16 (4), pp. 1447–1489, https://doi.org/10.24136/oc.3020.

IPCC (2023) Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Geneva: IPCC.

Khan, M., Serafeim, G., Yoon, A. (2016) Corporate sustainability: First evidence on materiality, The Accounting Review, 91 (6), pp. 1697–1724, https://doi.org/10.2308/accr-51383.

Lăzăroiu, G., Gedeon, T., Fernando, X., Herciu, M., Grecu, G., Chiru, C., Nădăban, C. (2025) The algorithmic management of job loss and creation in the enterprise generative, multimodal, and agentic artificial intelligence economy, Oeconomia Copernicana, 16 (4), pp. 1491–1524, https://doi.org/10.24136/oc.3994.

Porter, M. E., van der Linde, C. (1995) Toward a new conception of the environment–competitiveness relationship, Journal of Economic Perspectives, 9 (4), pp. 97–118, https://doi.org/10.1257/jep.9.4.97.

Taghizadeh-Hesary, F., Yoshino, N. (2019) The way to induce private participation in green finance and investment, Finance Research Letters, 31, pp. 98–103, https://doi.org/10.1016/j.frl.2019.04.016.

Tang, D. Y., Zhang, Y. (2020) Do shareholders benefit from green bonds?, Journal of Corporate Finance, 61, 101427, https://doi.org/10.1016/j.jcorpfin.2018.12.001.

Teng, Y.-M., Wu, K.-S. (2025) Integrating green transformational leadership, green HRM, and green innovation to enhance sustainable performance in hotels, Oeconomia Copernicana, 16 (4), pp. 1565–1614, https://doi.org/10.24136/oc.3797.

Tornatzky, L. G., Fleischer, M. (1990) The Processes of Technological Innovation, Lexington: Lexington Books.

Wang, H., Li, Y., Lin, W., Wei, W. (2024) Digital transformation, green technology innovation and enterprise ESG performance, International Review of Financial Analysis, 92, p. 103085, https://doi.org/10.1016/j.irfa.2024.103085.

Yavuz, H. B., Aytun, C., Cengiz, O. (2025) Energy efficiency, human development, and renewables as drivers of the load capacity factor, Oeconomia Copernicana, 16 (4), pp. 1725–1767, https://doi.org/10.24136/oc.3880.

Yu, G., Qi, Y. (2025) Does AI application make enterprises productivity greener? Evidence from China, Oeconomia Copernicana, 16 (1), https://doi.org/10.24136/oc.3215.

Zhang, D., Cao, H., Zou, P. (2021) Exuberance in China's renewable energy investment: Rationality, capital structure and implications with firm-level evidence, Energy Policy, 95, pp. 468–478, https://doi.org/10.1016/j.enpol.2016.05.024.

Umjetna inteligencija i zelena transformacija: unapređenje ljudskog kapitala, zelene financije i ESG procjena kao pokretači održive produktivnosti

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Sažetak: U radu se ispituje kako su usvajanje umjetne inteligencije (AI), zeleno financiranje i uspješnost u području okolišnih, društvenih i upravljačkih čimbenika (ESG) zajednički povezani s održivom produktivnošću kineskih uvrštenih poduzeća. Koristeći stvarne panelne podatke na razini poduzeća koji obuhvaćaju 1.000 uvrštenih poduzeća u razdoblju od 2012. Do 2024. Godine, odnosno ukupno 13.000 opažanja poduzeće-godina prikupljenih iz baze podataka CSMAR, korporativnih objava i priznatih pružatelja ESG ocjena, studija primjenjuje objedinjene OLS i modele s fiksnim učincima, pristup razlika-u-razlikama (DiD) te testove medijacije kako bi odgovorila na nedostatke u razumijevanju mehanizama održive transformacije. Rezultati pokazuju da je usvajanje umjetne inteligencije pozitivno povezano s održivom produktivnošću ($\beta = 0{,}115$, $p < 0{,}01$), kao i intenzitet zelenog financiranja ($\beta = 11{,}16$, $p < 0{,}05$ u modelima s fiksnim učincima). Međutim, učinci ESG-a čini se da više odražavaju međupoduzećnu selekciju nego poboljšanja unutar samih poduzeća tijekom vremena. Analiza medijacije sugerira da zeleno financiranje i ESG zajedno prenose približno 18 % ukupne povezanosti umjetne inteligencije s održivom produktivnošću (5,9 % i 12,0 %), dok se preostalih 82 % ostvaruje putem izravnih operativnih kanala. Smjernice za zeleno kreditiranje iz 2012. Godine povezane su s relativnim padom mjerene produktivnosti u industrijama koje zagađuju okoliš (DiD: −16,48, $p < 0{,}01$), što je u skladu s pretpostavkom da je politika ograničila sektore s visokom potrošnjom energije i visokim razinama onečišćenja („Two-High“ sektore). Analiza heterogenosti pokazuje da mala poduzeća ostvaruju razmjerno veće koristi od usvajanja umjetne inteligencije ($\beta = 0{,}131$ naspram $\beta = 0{,}112$ za velika poduzeća), čime se dovode u pitanje uobičajene pretpostavke o prednostima velikih organizacija u usvajanju novih tehnologija. Glavna ograničenja istraživanja uključuju moguću endogenost, oslanjanje na pokazatelje temeljene na tekstualnoj analizi i ESG ocjenama te činjenicu da je istraživanje provedeno u samo jednoj zemlji. Buduća istraživanja trebala bi primijeniti strategije instrumentalnih varijabli, alternativne mjere i međudržavne usporedbe. Studija doprinosi razumijevanju održive transformacije kao sinergijskog procesa koji integrira tehnološke, financijske i upravljačke dimenzije.

Ključne riječi: umjetna inteligencija, zeleno financiranje, ESG uspješnost, održiva produktivnost, analiza panelnih podataka, analiza medijacije, kineska uvrštena poduzeća
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