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The sustainability payoff of AI: Revisiting TFP in corporate and societal performance

Wenze Jian [a,1], Hang Lu [b,1], Zimo Yang [c,1], Ziqi Zhong [d,*]

[a] Department of Management, London School of Economics and Political Science, London WC2A 2AE, UK
[b] The Bartlett Faculty of the Built Environment, University College London, London WC1E 6BT, UK
[c] Graduate School of International Studies, Sogang University, 35 Baekbeom-ro, Mapo-gu, Seoul 04107, South Korea
[d] Department of Management, London School of Economics and Political Science, London WC2A 2AE, UK

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ABSTRACT

Using data on Chinese A-share listed firms and regions from 2011–2023, this paper employs a difference-in-differences (DID) framework to evaluate the productivity returns to artificial intelligence (AI) application from both firm-level and societal perspectives. The findings are as follows: First, AI intensity significantly increases firms' total factor productivity (TFP). Second, AI intensity significantly increases social TFP. Third, green financial innovation exerts a significant positive mediating effect on the pathway from AI intensity to firm TFP. Fourth, green financial innovation also partially mediates the pathway from AI intensity to social TFP. Substantively, the paper links micro-level firm transformation with macro-level regional performance, providing empirical evidence and policy implications for understanding the transmission mechanism from digitalization to greening to high-quality growth.

1. Introduction

The deep integration of the digital wave and the green transition is reshaping modes of production and resource allocation. As a general-purpose technology, AI is widely viewed as a key engine for boosting TFP (Chen, 2024). As China enters a stage of high-quality development, the simultaneous presence of energy conservation and emission reduction constraints, rising factor costs, and industrial upgrading pressures gives heightened salience to firm-level intelligent transformation and regional-level technology diffusion (Ma, Gao, & Sun, 2022). How to measure the true intensity of AI application, how to assess productivity returns within an identifiable econometric framework, and how to clarify the transmission role of green financial innovation have become shared concerns of academic research and policy discussion.

Existing literature indicates that digital technologies can improve resource allocation efficiency, enhance process management, and increase innovative outputs, yet there remains debate on AI's net effect on productivity (Li, Huang, & Luo, 2025). Micro-level studies often suffer from timing mismatches in adoption, sample selection issues, and measurement error in intensity; macro-level studies face identification challenges due to spillovers and common shocks (Chica, Hernández, & Perc, 2023). More crucially, there is a lack of systematic evidence regarding the interaction between AI and green financial innovation, and the manner in which micro-level firm transformation aggregates into regional-level productivity improvements remains underexplored. Two urgent questions thus arise: first, does AI intensity improve TFP at both the firm and societal levels through testable causal pathways? Second, does green financial innovation play a substantive mediating role in the above pathways?

This paper focuses on four core propositions: the impact of AI intensity on firm TFP; the spillover effects of AI intensity on social TFP; the mediating role of green financial innovation in the "AI intensity – firm productivity" pathway; and the mediating role of green financial innovation in the "AI intensity - social productivity" pathway. The research design extends the existing literature in two respects: first, it establishes a firm–region dual-level framework to test consistency between firm-level and regional-level evidence, thereby identifying technology diffusion and spillovers; second, it incorporates mediation tests of green financial innovation to decompose direct and indirect effects and illuminate the intrinsic mechanisms of productivity returns.

The data span 2011–2023 for Chinese A-share listed firms and matched regional statistical aggregates. Firm TFP is estimated by the

* *Corresponding author.
E-mail addresses: zczqh57@ucl.ac.uk (H. Lu), zyang@sogang.ac.kr (Z. Yang), z.zhong6@lse.ac.uk (Z. Zhong).
[1] Wenze Jian, Hang Lu and Zimo Yang made equal contributions to the manuscript, They are co first authors.

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industry-specific Levinsohn–Petrin method, and social TFP is constructed at the region × industry level using a residual approach and growth accounting to build indices. The econometric approach uses an intensity-based DID and event study, constructing an exposure variable that is zero pre-adoption and varies with intensity post-adoption; regional AI penetration is obtained by intensity-weighted aggregation of firm-level measures, with first-adoption used to identify treatment timing. Green financial innovation is measured by the log-transformed count of green patents, and transmission decomposition is conducted within a two-step mediation framework. Models uniformly include firm fixed effects and year fixed effects (or region fixed effects and year fixed effects), and control for size, age, capital intensity, R&D intensity, financing constraints, profitability, export exposure, and financialization, with standard errors clustered at the firm level.

Empirical results show that AI intensity significantly increases firm TFP, and regional AI penetration significantly increases social TFP; green financial innovation plays a positive mediating role in both pathways. These findings provide empirical evidence for the transmission chain of "digitalization – greening - high-quality growth," offering policy references for advancing AI deployment, improving green finance support systems, and optimizing regional innovation ecosystems. Through multi-level identification from micro to macro and mechanism decomposition, the results provide an operational econometric framework and empirical basis for evaluating AI investment returns and formulating targeted industrial policies.

2. Theoretical analysis and research hypotheses

The use of AI has considerable potential to enhance firm TFP (Sun, Wei, & Wang, 2024). On one hand, AI streamlines production processes, improves resource utilization, and lowers production costs, leading to increased firm productivity (Wang, Yu, & Zhong, 2023). For instance, AI can automate routine tasks, enhance decision-making speed, optimize supply chains, and boost quality control, all of which help minimize waste and improve production efficiency (Feng & Huang, 2024). On the other hand, AI's role in R&D and innovation opens up new growth opportunities, especially in high-tech sectors where it accelerates product development and market responsiveness, further driving productivity (Yang, Wang, Lyu, & Li, 2023). Therefore, as firms invest more in AI, they are expected to realize technological advancements and efficiency gains, ultimately boosting TFP.

Hypothesis 1: An increase in AI intensity will significantly improve firm TFP.

AI intensity not only enhances the productivity of individual firms but also increases TFP at the societal level (Zhao, Wang, & Cheng, 2024). The widespread application of AI promotes technological diffusion across industries—especially through data sharing, knowledge flows, and technology transfer—thereby improving overall economic efficiency (Cao, Wang, Li, Shang, & Zhu, 2025). At the regional level, AI can enhance the efficiency of public services, improve urban infrastructure and resource allocation, and optimize transportation systems and energy consumption (Zhou, Liu, Wang, & Yang, 2022). Additionally, AI can drive industrial upgrading and labor market transformation, reducing imbalances across industries and thereby improving comprehensive regional economic efficiency (Han, Shang, & Li, 2024). As AI becomes more prevalent, productivity improvements at the firm level extend to society through spillover and synergy effects, ultimately raising social TFP.

Hypothesis 2: An increase in AI intensity will significantly improve social TFP.

AI intensity promotes firm TFP in part by enhancing green financial innovation (Deng, Li, & Ren, 2023). With AI's application in green finance—such as environmental data analytics, green project evaluation, and low-carbon technology innovation—firms can use green resources more efficiently, lower environmental costs, and achieve green transformation (Awawdeh, Ananzeh, El-khateeb, & Aljumah, 2022). Meanwhile, AI improves the precision of support for firms' environmental investments, enabling more effective funding and market diffusion for green technologies and projects (Skotnicky, Puccio, & Das, 2025). These green financial innovations not only reduce compliance costs and improve environmental performance but also create new growth opportunities, strengthening market competitiveness and productivity (Wu, 2024). As AI is further applied in green finance, firms can access more innovative capital and technological support, thereby boosting productivity.

Hypothesis 3: AI intensity indirectly promotes firm TFP by enhancing green financial innovation.

Beyond directly driving technological progress, AI intensity improves social TFP indirectly through green financial innovation (Moro-Visconti, Cruz Rambaud, & López Pascual, 2023). As AI is deeply applied in the financial sector, the efficiency of green finance is substantially increased, promoting the growth of environmentally friendly investments and the rational allocation of resources (Rozenstein et al., 2024). Green financial innovation channels funds more efficiently into low-carbon economies, clean energy, and sustainable development, thereby advancing green industrial development and upgrading across society (Dinh, Nguyen, Phan, Do, & Tran, 2025). This not only provides a sustainable driver of economic growth but also improves environmental governance and reduces environmental burdens, which in turn raises productivity at the societal level (Sheng et al., 2022). Through green financial innovation, AI intensity promotes efficient resource utilization and sustainable growth, forming synergies across industries, technologies, and policies, and further increasing social TFP.

Hypothesis 4: AI intensity indirectly promotes social TFP by enhancing green financial innovation.

3. Research design

3.1. Data sources

Firm-level data primarily come from the financial statements of listed companies, as well as from the Wind database, CSMAR database, and companies' annual reports. These sources provide information on financial performance, industry details, capital expenditures, and R&D investments, among other aspects. At the regional level, data are mainly collected from the China Statistical Yearbook, provincial and municipal statistical yearbooks, and macroeconomic data published by the National Bureau of Statistics. This includes regional GDP, industry value added, employment statistics, as well as data on regional energy consumption and carbon emissions. Information on green patents is sourced from companies' annual reports and records of patent commercialization.

3.2. Variable definitions

3.2.1. Dependent variable (firm TFP, TFP_it)

A firm's comprehensive productivity under given inputs, reflecting technological and managerial efficiency. By industry, we estimate TFP using the Levinsohn–Petrin (LP) method, regressing real output on capital, effective labor, and intermediate inputs, taking the productivity term (residual) as $TFP_{\_it}$, which is then log-transformed.

3.2.2. Dependent variable (social TFP, RegionTFP_rt)

The comprehensive productivity level at the region × industry level. We estimate regional (or region × industry) TFP using a residual-based approach: using constant-price GDP value added as output, and capital stock and hours worked as inputs, yielding a regional TFP index (or growth rate).

3.2.3. Independent variable (AI intensity, AI_Intensity)

A continuous measure of the depth and breadth of firms' AI application, ensuring "zero exposure pre-adoption." We standardize and then weight-combine the following into a value in [0,1]: the share of AI positions, the share of AI-related CAPEX/GPU investment, the share of AI patents, and management textual AI semantics. We define an adoption indicator as $1\{\geq 0.5\}$. The first adoption year is defined $\text{First\_year}_i=\min\{t:\text{Adopt}_{it}=1\}$, and we generate $\text{Post}_{it}=1\{t\geq \text{First\_year}_i\}$. The intensity variable used for DID is $\text{AI\_Intensity}_{it}=\text{Score}_{it}\times \text{Post}_{it}$, which guarantees zero exposure pre-adoption and intensity-varying exposure post-adoption. This approach ensures that the effect of AI adoption is properly captured by isolating the impact of increased AI intensity after the initial adoption, mitigating potential biases from pre-adoption influence.

3.2.4. Mediator variable (green financial innovation, GreenInnov)

Firms' innovation outputs targeting energy conservation, emission reduction, and clean technologies. We measure this by green technology R&D efficiency.

3.2.5. Controls variable

Firm size (size), firm age (age), capital intensity (cap), R&D intensity (rd), financing constraints (sa), profitability (roa), export exposure (export), and the degree of financialization (fin).

3.3. Baseline regression specification

To identify the causal effects of AI adoption and deepening AI intensity on productivity and sustainability performance, we construct a staggered-adoption DID framework, characterizing treatment via "intensity exposure." We also provide dynamic event-study analyses, mediation mechanisms, heterogeneity analyses, and regional spillover extensions.

$$\text{TPF\_it}_{it} = \theta_0 + \theta_1 \text{AI\_Intensity}_{it} + \sum \theta_n X_{it} + \text{Frim} + \text{Year} + \varepsilon_{it} \tag{1}$$

$$\text{RegionTFP\_rt}_{it} = \beta_0 + \beta_1 \text{AI\_Intensity}_{it} + \sum \beta_n X_{it} + \text{Frim} + \text{Year} + \varepsilon_{it} \tag{2}$$

3.4. Mediation model specification

To identify the mechanism "AI intensity – green innovation - firm/regional TFP," we employ a two-step mediation model.

$$\text{GreenInnov}_{it} = \varnothing_0 + \varnothing_1 \text{AI\_Intensity}_{it} + \sum \varnothing_n X_{it} + \text{Frim} + \text{Year} + \varepsilon_{it} \tag{3}$$

$$\begin{aligned}\text{TPF\_it}_{it}\left(\text{RegionTFP\_rt}_{it}\right) = {} & \gamma_0 + \gamma_1 \text{AI\_Intensity}_{it} + \gamma_2 \text{GreenInnov}_{itit} \\ & + \sum \gamma_n X_{it} + \text{Frim} + \text{Year} + \varepsilon_{it}\end{aligned} \tag{4}$$

4. Empirical analysis

4.1. Descriptive statistics

Table 1 reports the descriptive statistics. AI intensity (AI_Intensity) has a mean of 0.3643, standard deviation of 0.4812, and ranges from 0 to 1, indicating substantial heterogeneity in firms' AI application. Firm TFP (TFP_it) has a mean of 8.1775 and a standard deviation of 1.0293, indicating sizable productivity dispersion across firms. Social TFP (RegionTFP_rt) has a mean of 5.4743 and a standard deviation of 0.8600, suggesting smaller fluctuations at the regional level. Green financial innovation (GreenInnov) has a mean of 0.5151 and a standard deviation of 0.2193, indicating that most firms have some investment in green financial innovation, though with considerable variation.

4.2. Baseline regression of AI intensity on firm TFP

Table 2 displays the regression results examining the relationship between AI intensity (AI_Intensity) and firm-level TFP (TFP_it). In all model specifications, AI intensity shows a significantly positive effect on firm TFP. In column (1), the coefficient for AI_Intensity is 0.1742, which remains statistically significant after adjusting for standard errors ($t = 23.7828$). Even as additional control variables are included, the positive impact of AI intensity on firm TFP remains consistent, demonstrating that greater AI adoption leads to substantial improvements in productivity. These findings support Hypothesis 1, which posits that an increase in AI intensity significantly enhances firm-level TFP.

4.3. Baseline regression of AI intensity on social TFP

Table 3 presents the baseline regression results for the effect of AI intensity (AI_Intensity) on social TFP (RegionTFP_rt). The regression results indicate that AI intensity has a significantly positive impact on social TFP across all columns. In column (1), the coefficient of AI intensity is 0.1005 and remains statistically significant after controlling for standard errors. With the inclusion of control variables, the impact of AI intensity on social TFP remains significant and stable, with coefficients ranging from 0.0554 to 0.0638. This suggests that the application of AI not only substantially improves productivity at the firm level but also enhances productivity at the societal level through spillover effects. These findings confirm Hypothesis 2, namely, that an increase in AI intensity can significantly raise social TFP.

4.4. Parallel trends analysis

Table 4 presents the parallel-trends tests for firm TFP (TFP_it) and social TFP (RegionTFP_rt). For firm TFP, the pre-treatment period coefficients (pre_4, pre_3, pre_2) are close to zero and insignificant, indicating no significant differential trends prior to treatment. Post-adoption, the coefficients on post_1, post_2, and post_3 increase

Table 1
Descriptive statistics.

VarName	Obs	Mean	SD	Min	Median	Max
AI_Intensity	68,903	0.3643	0.4812	0.0000	0.0000	1.0000
TFP_it	68,903	8.1775	1.0293	3.2768	8.2387	13.1064
RegionTFP_rt	68,903	5.4743	0.8600	0.6012	5.5115	10.7997
GreenInnov	68,903	0.5151	0.2193	0.1333	0.5017	0.9986
size	68,903	22.0676	0.9894	2.9025	21.9791	26.4523
age	68,903	1.8396	0.8613	0.0000	1.9488	3.4340
cap	68,903	2.4200	1.6323	0.3781	2.2072	18.9417
rd	68,903	0.0251	0.0128	0.0001	0.0248	0.0704
sa	68,903	−3.7420	0.2660	−4.5583	−3.7873	−3.0623
roa	68,903	0.0531	0.0581	−0.3730	0.0419	0.2473
export	68,903	0.5498	0.2860	0.0076	0.5009	1.4638
fin	68,903	0.0623	0.0964	0.0000	0.0299	0.7253

Table 2
Baseline results for AI intensity and firm TFP.

Variables	(1)	(2)	(3)	(4)	(5)
	TFP_it				
AI_Intensity	0.1742***	0.1089***	0.0981***	0.1023***	0.1036***
	(23.7828)	(15.2095)	(14.3240)	(14.9597)	(15.1592)
size		0.2631***	0.2673***	0.2624***	0.2603***
		(46.8008)	(48.2052)	(47.3883)	(47.1468)
age		0.0105**	0.0254***	0.0355***	0.0341***
		(2.0226)	(4.9020)	(6.1987)	(5.9432)
cap			−0.1118***	−0.1057***	−0.1037***
			(−47.1330)	(−44.0466)	(−42.9496)
rd			−1.3120***	−1.1916***	−0.5557
			(−3.6344)	(−3.3132)	(−1.3161)
sa				−0.0315	−0.0347
				(−1.2810)	(−1.4174)
roa				1.0158***	1.0438***
				(19.2769)	(19.6294)
export					−0.0421**
					(−2.4651)
fin					−0.3757***
					(−9.5852)
Constant	8.1140***	2.3119***	2.4996***	2.3984***	2.4584***
	(2348.5983)	(19.3470)	(21.3219)	(15.4489)	(15.8700)
N	68,903	68,903	68,903	68,903	68,903
firm fe	YES	YES	YES	YES	YES
year fe	YES	YES	YES	YES	YES
R-squared	0.7243	0.7494	0.7665	0.7686	0.7687

Table 3
Baseline results for AI intensity and social TFP.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	RegionTFP_rt	RegionTFP_rt	RegionTFP_rt	RegionTFP_rt	RegionTFP_rt
AI_Intensity	0.1005***	0.0638***	0.0554***	0.0600***	0.0605***
	(15.8075)	(9.9913)	(9.0431)	(9.8285)	(9.9114)
size		0.1476***	0.1512***	0.1456***	0.1447***
		(33.4118)	(34.7023)	(33.5819)	(33.3903)
age		0.0063	0.0182***	0.0303***	0.0294***
		(1.4996)	(4.3541)	(6.5046)	(6.2961)
cap			−0.0915***	−0.0847***	−0.0839***
			(−41.7491)	(−38.3025)	(−37.7486)
rd			−1.5862***	−1.4605***	−0.9315**
			(−4.8208)	(−4.4518)	(−2.4246)
sa				−0.0254	−0.0276
				(−1.2160)	(−1.3226)
roa				1.1275***	1.1414***
				(21.7181)	(21.8555)
export					−0.0379**
					(−2.4142)
fin					−0.1463***
					(−4.4335)
Constant	5.4377***	2.1828***	2.3448***	2.2701***	2.2963***
	(1811.6776)	(23.2599)	(25.3591)	(17.8343)	(18.0366)
N	68,903	68,903	68,903	68,903	68,903
firm fe	YES	YES	YES	YES	YES
year fe	YES	YES	YES	YES	YES
R-squared	0.6893	0.7014	0.7175	0.7206	0.7207

significantly, indicating that AI intensity significantly boosts firm productivity. For social TFP, pre-treatment coefficients are likewise insignificant, while post-treatment coefficients are significant, indicating that AI increases regional productivity via spillover effects. The results validate the parallel-trends assumption and support the positive impact of AI on productivity.

4.5. *Re-assessment via synthetic control*

Figure 1 shows the synthetic control method (SCM) comparison between treated units and their synthetic controls in firm TFP. The red solid line represents treated units (those adopting AI), and the blue dashed line represents synthetic controls (non-adopters). From 2018 onward, the treated units' productivity significantly diverges upward from the synthetic controls, indicating that AI adoption markedly improves productivity. The figure clearly illustrates the positive impact of AI on productivity and confirms substantial post-treatment gains.

4.6. *Endogeneity analysis*

Table 5 presents the results of the endogeneity test, where the degree of AI development (ai) is used as an instrumental variable. The reason for employing this method is to control for any potential bias caused by reverse causality or omitted variables that could distort the observed relationship between AI intensity and productivity. The coefficient for ai on AI intensity (AI_Intensity) is 0.2749, which is statistically significant,

Table 4
Parallel-trends test results.

VARIABLES	(1)	(2)
	TFP_it	RegionTFP_rt
pre_4	0.1623	0.1214
	(0.6803)	(1.4142)
pre_3	0.1145	0.0697
	(0.6930)	(1.5963)
pre_2	0.1107	0.0711
	(0.6540)	(1.4022)
current	0.1301	0.1010
	(1.2574)	(0.7379)
post_1	0.1012***	0.0673***
	(6.7735)	(4.8303)
post_2	0.0759***	0.0360***
	(5.2749)	(2.7376)
post_3	0.0879***	0.0456***
	(6.5687)	(3.6092)
size	0.2801***	0.1595***
	(49.9771)	(36.3404)
age	0.0347***	0.0297***
	(6.0239)	(6.3519)
cap	−0.1048***	−0.0813***
	(−44.7520)	(−37.7444)
rd	−0.0160	−0.4651
	(−0.0384)	(−1.2290)
sa	−0.0076	−0.0210
	(−0.3175)	(−1.0195)
roa	1.0171***	1.1241***
	(19.3120)	(21.6157)
export	−0.0274	−0.0115
	(−1.6268)	(−0.7445)
fin	−0.3601***	−0.1495***
	(−9.3745)	(−4.6177)
Constant	2.1243***	1.9744***
	(13.7644)	(15.5907)
N	68,903	68,903
firm fe	YES	YES
year fe	YES	YES
R-squared	0.7523	0.7024

confirming the strong relevance of the instrument. After introducing this instrumental variable, AI_Intensity continues to show a significant positive effect on both firm-level TFP (TFP_it) and regional TFP (RegionTFP_rt). Specifically, the coefficients for AI_Intensity on TFP_it and RegionTFP_rt are 0.1560 and 0.1249, respectively, both significant at the 1 % level, indicating that AI improvements substantially boost productivity. This suggests that using ai as an instrumental variable effectively addresses potential endogeneity issues, ensuring the validity of the results.

4.7. *Mediation analysis*

Table 6 presents the mediation analysis of green financial innovation (GreenInnov) in the pathways "AI intensity - firm TFP" and "AI intensity

Table 5
Endogeneity results.

VARIABLES	(1)	(2)	(3)
	AI_Intensity	TFP_it	RegionTFP_rt
ai	0.2749***		
	(215.3797)		
AI_Intensity		0.1560***	0.1249***
		(16.7941)	(13.6497)
size	0.0397***	0.5914***	0.3612***
	(26.9668)	(197.8974)	(122.7534)
age	−0.0401***	0.0146***	0.0157***
	(−19.4240)	(3.4769)	(3.8008)
cap	−0.0055***	−0.1888***	−0.1322***
	(−6.6632)	(−115.1065)	(−81.8511)
rd	3.6120***	0.9524***	1.9910***
	(25.4944)	(3.2791)	(6.9609)
sa	−0.2725***	0.0144	−0.1141***
	(−37.3343)	(0.9542)	(−7.6986)
roa	−0.1888***	0.6839***	0.6891***
	(−6.8292)	(12.3376)	(12.6245)
export	−0.1694***	0.2283***	0.2667***
	(−28.1545)	(18.7985)	(22.3057)
fin	0.2369***	0.0554*	0.2771***
	(16.9434)	(1.9587)	(9.9486)
Constant	−1.6945***	−4.5052***	−2.8049***
	(−39.3006)	(−50.7814)	(−32.1051)
N	68,903	68,903	68,903
firm fe	YES	YES	YES
year fe	YES	YES	YES
LM statistic		2.3e+04	
Wald F statistic		4.6e+04	
R-squared	0.5534	0.5833	0.3786

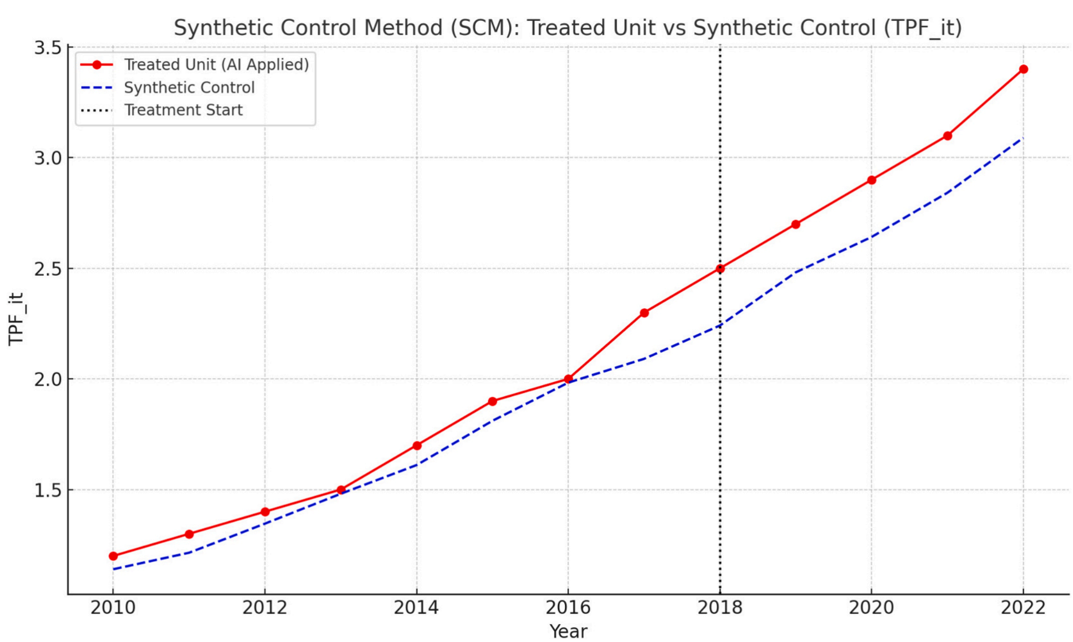

Fig. 1. Synthetic control plot.

Table 6
Mediation results.

VARIABLES	(1)	(2)	(3)
	GreenInnov	TFP_it	RegionTFP_rt
GreenInnov		0.0205***	0.0303*
		(4.2403)	(1.9175)
AI_Intensity	0.0017***	0.1036***	0.0605***
	(3.0278)	(15.1540)	(9.9028)
size	0.0007	0.2603***	0.1447***
	(0.8984)	(47.1449)	(33.3862)
age	−0.0008	0.0341***	0.0295***
	(−1.0758)	(5.9463)	(6.3019)
cap	−0.0001	−0.1037***	−0.0839***
	(−0.2040)	(−42.9503)	(−37.7501)
rd	−0.0293	−0.5551	−0.9306**
	(−0.3744)	(−1.3147)	(−2.4224)
sa	0.0005	−0.0347	−0.0276
	(0.1182)	(−1.4179)	(−1.3233)
roa	−0.0348**	1.0445***	1.1424***
	(−2.5007)	(19.6387)	(21.8675)
export	−0.0006	−0.0421**	−0.0379**
	(−0.1959)	(−2.4643)	(−2.4131)
fin	0.0123*	−0.3759***	−0.1467***
	(1.7366)	(−9.5915)	(−4.4449)
Constant	0.5055***	2.4480***	2.2810***
	(23.6374)	(15.7771)	(17.8746)
N	68,903	68,903	68,903
firm fe	YES	YES	YES
year fe	YES	YES	YES
R-squared	0.7712	0.7684	0.7200

- social TFP." The results show that in column (1), the effect of AI intensity (AI_Intensity) on green financial innovation (GreenInnov) is significant, with a coefficient of 0.0017 for AI_Intensity, indicating that AI intensity promotes green financial innovation. In column (2), the effects of GreenInnov and AI_Intensity on firm TFP are likewise significant, suggesting that green financial innovation indirectly raises firms' productivity by fostering green technological innovation, thereby confirming Hypothesis 3. The regression in column (3) shows that the impacts of AI intensity and green financial innovation on social TFP are also significant. This further indicates that green financial innovation not only affects firm productivity but also enhances social TFP through spillover effects, thereby confirming Hypothesis 4.

5. Conclusion

Using a DID approach with data on Chinese A-share listed firms and regions from 2011–2023, this paper examines the productivity returns to AI application. We find that AI intensity significantly enhances both firm-level TFP and social-level TFP (RegionTFP). Specifically, as firms increase their investment in AI, their production efficiency improves significantly. At the regional level, similar trends emerge, indicating that AI technology not only improves individual firms' productivity but also raises productivity at the societal level through spillovers, thereby enhancing overall economic efficiency. Further analysis shows that green financial innovation plays a significant positive mediating role in the pathways from AI intensity to firm TFP and from AI intensity to social TFP.

Based on these findings, policymakers should encourage firms to accelerate AI adoption and reduce the costs of AI implementation through tax incentives and R&D subsidies. Governments can establish special funds, provide fiscal subsidies, and offer technical support to promote broader investment in AI R&D and application, thereby improving firm productivity and strengthening the economy's competitiveness and efficiency. At the same time, support for green financial innovation should be increased, especially in encouraging green technological R&D and green investment. By providing green financial instruments and policy support, governments can guide capital toward green technologies, further integrating AI with green finance to improve productivity and environmental performance, thereby advancing economic transformation and sustainable development.

In addition, local governments should strengthen interregional cooperation to promote the diffusion of AI technologies, particularly technology transfer and innovation collaboration across industries and regions, fostering coordinated regional development. At the same time, they should enhance the synergy of green financial policies—especially in energy structure optimization and green project investment—to reinforce regions' green competitiveness. Through policy guidance and innovation support, regional economies can be steered toward sustainable high-quality growth.

Data availability

The authors do not have permission to share data.

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