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Research paper

Research on The Impact of Intelligent Manufacturing on Enterprise ESG Performance: Empirical Evidence Of Economics from China

Chen Xu [1 2]*, Batkhuyag Ganbaatar [1]

[1] *University of Finance and Economics, Ulaanbaatar, Mongolia*
[2] *College of Economic and Management, Chifeng University, Chifeng, Inner Mongolia, China*
**Corresponding author E-mail: chenalicexu@gmail.com*

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Abstract

Background: The integration of intelligent manufacturing technologies and corporate sustainability has emerged as a critical research frontier in the era of Industry 4.0. While Environmental, Social, and Governance (ESG) performance increasingly shapes corporate valuation and stakeholder relations, the economic mechanisms through which intelligent manufacturing influences ESG outcomes remain theoretically underdeveloped and empirically underexplored, particularly in emerging market contexts where institutional environments differ substantially from developed economies.
Methods: Exploiting China's Intelligent Manufacturing Pilot Demonstration Projects (IMPP) as a quasi-natural experiment, this study employs a staggered difference-in-differences (DID) design with 18,426 firm-year observations from 2,149 Chinese A-share manufacturing companies during 2009-2023. We examine direct effects using two-way fixed effects models, investigate mediating mechanisms through the Baron-Kenny approach supplemented by Sobel tests, and explore heterogeneous effects across ownership structures, pollution intensities, and competitive environments using split-sample analysis with Chow tests for coefficient equality.
Results: Intelligent manufacturing significantly enhances enterprise ESG performance ($\beta = 0.245$, $p < 0.01$), representing a 5.3% improvement relative to the sample mean. This finding demonstrates robust consistency across parallel trend tests, placebo simulations (500 iterations), propensity score matching (PSM-DID), and instrumental variable (IV-2SLS) estimations. Mechanism analysis reveals three significant transmission channels: green innovation (mediating 24.6% of total effect, $\beta = 0.186$, $p < 0.01$), resource allocation efficiency (16.6%, $\beta = 0.142$, $p < 0.01$), and synergistic governance (7.9%, $\beta = 0.098$, $p < 0.05$). Heterogeneity analysis demonstrates significantly stronger effects for non-state-owned enterprises ($\beta = 0.312$ vs. 0.168, $\chi^2 = 8.45$, $p < 0.01$), heavy-polluting industries ($\beta = 0.356$ vs. 0.186, $\chi^2 = 12.67$, $p < 0.01$), and high-competition markets ($\beta = 0.298$ vs. 0.152, $\chi^2 = 5.23$, $p < 0.05$). Sub-dimensional analysis reveals that environmental performance benefits most substantially ($\beta = 0.324$), followed by social ($\beta = 0.218$) and governance ($\beta = 0.142$) dimensions.
Conclusions: This study establishes intelligent manufacturing as an economically significant pathway for enhancing corporate ESG performance in emerging markets, with heterogeneous effects contingent upon ownership structure, industrial characteristics, and competitive dynamics. These findings advance theoretical understanding of technology-sustainability linkages, provide empirical foundations for evidence-based industrial policy design, and offer practical guidance for managers navigating the dual imperatives of technological transformation and sustainable development.

Keywords: *Intelligent Manufacturing; ESG Performance; Difference-In-Differences; Green Innovation; Resource Allocation Efficiency; Corporate Sustainability; China.*

1. Introduction

The confluence of technological revolution and sustainability imperatives represents one of the most consequential transformations in contemporary business landscapes. As the Fourth Industrial Revolution reshapes production paradigms through artificial intelligence, cyber-physical systems, and advanced automation, corporations simultaneously confront intensifying demands for Environmental, Social, and Governance (ESG) accountability from investors, regulators, and broader stakeholder constituencies (Gillan et al., 2021; Friede et al., 2015). Understanding how these dual forces interact—specifically, whether and how intelligent manufacturing capabilities translate into superior ESG outcomes—carries profound implications for corporate strategy, industrial policy, and sustainable development theory.
China presents a uniquely compelling empirical context for investigating the intelligent manufacturing-ESG nexus. As the world's largest manufacturing economy, contributing approximately 30% of global manufacturing output, China has pursued aggressive intelligent manufacturing transformation through landmark initiatives including "Made in China 2025" and successive waves of Intelligent Manufacturing Pilot Demonstration Projects (IMPP) designating technological frontrunners across industrial sectors (Zhong et al., 2017). Concurrently, Chinese capital market regulators have progressively strengthened ESG disclosure requirements and sustainability frameworks for listed

companies, while institutional investors increasingly incorporate ESG criteria into investment decisions (Shen et al., 2023). This policy environment creates a natural laboratory for examining how government-promoted technological upgrading affects multidimensional corporate sustainability performance.

Despite growing scholarly attention to both intelligent manufacturing capabilities and ESG performance determinants, significant theoretical and empirical gaps persist at their intersection. Existing research has extensively documented intelligent manufacturing benefits for operational efficiency, productivity, and financial performance (Acemoglu & Restrepo, 2018; Huang et al., 2022), while parallel literature identifies firm characteristics, governance structures, and institutional factors as primary ESG determinants (Drempetic et al., 2020; He et al., 2023). However, the mechanisms through which technological transformation affects broader sustainability outcomes remain theoretically underdeveloped and empirically underexplored. Moreover, the limited extant evidence derives predominantly from developed economy contexts, leaving it uncertain whether findings generalize to emerging markets characterized by distinct institutional environments, ownership structures, and regulatory frameworks.

This study addresses three interconnected research questions that collectively advance understanding of technology-sustainability linkages. First, does intelligent manufacturing adoption causally improve enterprise ESG performance, and what is the economic magnitude of this effect? Second, through what specific mechanisms does intelligent manufacturing influence ESG outcomes—do green innovation, resource allocation efficiency, and synergistic governance constitute significant transmission channels? Third, how do firm characteristics, including ownership structure, pollution intensity, and competitive environment, moderate the intelligent manufacturing-ESG relationship? By addressing these questions through rigorous quasi-experimental methods, we contribute both theoretical insights regarding Industry 4.0's sustainability implications and practical guidance for policy design and corporate strategy.

Our empirical strategy exploits the staggered implementation of China's IMPP program as a quasi-natural experiment within a difference-in-differences framework. This approach addresses fundamental endogeneity concerns inherent in observational studies of technology adoption and firm performance—specifically, that firms selecting into intelligent manufacturing may systematically differ from non-adopters in ways correlated with ESG outcomes. The IMPP designation process, while not perfectly random, provides plausibly exogenous variation in treatment timing across firms that enables credible causal inference. Using comprehensive data spanning 18,426 firm-year observations from 2,149 manufacturing companies over 2009-2023, we document substantial positive effects of intelligent manufacturing on ESG performance, identify specific economic transmission mechanisms, and reveal important heterogeneities that inform both theory and practice.

Our contributions extend multiple research streams. First, we advance intelligent manufacturing literature by demonstrating sustainability benefits beyond operational and financial performance, revealing that Industry 4.0 technologies create stakeholder value across environmental, social, and governance dimensions. Second, we enrich ESG research by identifying technological capability as a significant antecedent alongside traditional determinants, with mechanism analysis illuminating specific pathways through which technology shapes sustainability outcomes. Third, we inform industrial policy by providing causal evidence that intelligent manufacturing promotion generates positive sustainability externalities, supporting expanded policy investment in technological upgrading initiatives. Fourth, we offer methodological contributions through comprehensive robustness testing that addresses identification threats common in technology adoption studies.

2. Literature Review and Hypothesis Development

2.1. Intelligent manufacturing: conceptualization and economic effects

Intelligent manufacturing represents a fundamental paradigm shift in industrial production, integrating cyber-physical systems, Internet of Things (IoT) technologies, cloud computing, big data analytics, and artificial intelligence to create adaptive, self-optimizing production environments (Kang et al., 2016; Zhong et al., 2017). Distinguished from traditional automation by its emphasis on connectivity, data-driven decision-making, and autonomous optimization, intelligent manufacturing enables real-time monitoring, predictive maintenance, flexible production scheduling, and continuous process improvement. These capabilities collectively transform manufacturing from discrete, sequential operations into integrated, responsive systems capable of addressing complex, customized demands with unprecedented efficiency.

Economic research has documented extensive benefits from intelligent manufacturing adoption across multiple performance dimensions. At the operational level, intelligent manufacturing enhances productivity through automation of routine tasks, optimization of resource utilization, and reduction of defect rates (Acemoglu & Restrepo, 2018). Huang et al. (2022) demonstrate that industrial robot adoption significantly reduces energy intensity in Chinese manufacturing firms, indicating efficiency gains extend beyond labor productivity to encompass resource consumption. Zhang et al. (2023) provide complementary evidence that automation improves both labor productivity and total factor productivity, with effects concentrated in firms with higher initial skill intensity.

Beyond operational improvements, intelligent manufacturing fundamentally transforms organizational capabilities and strategic positioning. Sun and Saat (2023) demonstrate that intelligent manufacturing pilot designation significantly enhances firm innovation capacity, reflecting how technological infrastructure enables new product development and process innovation. Digital transformation associated with intelligent manufacturing improves information processing efficiency, enabling more responsive decision-making and enhanced stakeholder engagement (Wang et al., 2023). Wu et al. (2024) find that digital transformation comprehensively improves corporate ESG performance through multiple channels, including operational efficiency, transparency enhancement, and stakeholder communication improvement. These capability enhancements position firms to address the complex, multidimensional demands associated with sustainable development.

2.2. ESG performance: determinants and consequences

Environmental, Social, and Governance (ESG) performance reflects a firm's management of environmental impacts, relationships with diverse stakeholders, and quality of governance mechanisms. ESG criteria have emerged as essential metrics for evaluating corporate sustainability, influencing investment decisions, regulatory compliance, and stakeholder relationships across global capital markets (Gillan et al., 2021). The theoretical foundations for ESG's relevance span multiple perspectives: stakeholder theory posits that attending to diverse stakeholder interests enhances long-term value creation; resource-based theory suggests that ESG capabilities constitute valuable, rare, and difficult-to-imitate resources; and signaling theory indicates that ESG performance communicates unobservable firm quality to external constituents (Friede et al., 2015).

Empirical research has identified numerous determinants of ESG performance. Firm-level characteristics, including size, profitability, leverage, and growth opportunities, significantly predict ESG outcomes, with larger and more profitable firms generally exhibiting superior sustainability performance (Drempetic et al., 2020). Governance factors, including board independence, institutional ownership, and executive compensation structures, shape ESG investment and disclosure decisions (Dyck et al., 2019). Industry context substantially influences ESG challenges and opportunities, with manufacturing firms facing particular environmental pressures due to resource consumption and emission intensity while bearing significant social responsibilities toward employees and communities.

Recent research has expanded the ESG determinants framework to incorporate technological capabilities. Zheng and Bu (2024) find that digital transformation significantly improves ESG ratings, particularly through enhanced transparency and stakeholder communication. Liu and Liu (2023) document positive effects of digital transformation on ESG performance mediated by innovation capability and operational efficiency improvements. Luo et al. (2024) demonstrate bidirectional relationships between ESG performance and green innovation, suggesting reinforcing dynamics between sustainability outcomes and technological development. These findings collectively suggest that technological capability constitutes an important, previously underexplored antecedent of corporate sustainability performance.

2.3. Hypothesis development

Drawing on resource-based theory, stakeholder theory, and the nascent literature linking technological capability to sustainability outcomes, we develop hypotheses regarding intelligent manufacturing's effects on enterprise ESG performance. We posit that intelligent manufacturing positively influences ESG through multiple, complementary channels encompassing environmental, social, and governance dimensions.

First, intelligent manufacturing directly addresses environmental sustainability through precision production, waste minimization, and energy optimization. Real-time monitoring and predictive maintenance capabilities minimize resource waste while advanced analytics enable continuous process improvement targeting environmental efficiency (Huang et al., 2022). Automated quality control reduces defect rates and associated material waste, while optimized scheduling minimizes energy consumption during production. Second, intelligent manufacturing transforms social performance by creating safer working conditions through automation of hazardous tasks, enabling workforce upskilling toward knowledge work, and improving supply chain transparency and labor condition monitoring. Third, intelligent manufacturing enhances governance quality by improving information transparency, reducing information asymmetry between managers and stakeholders, and enabling more sophisticated risk management and compliance monitoring (Wang et al., 2023).

Hypothesis 1 (H1): Intelligent manufacturing adoption significantly improves enterprise ESG performance.

Beyond direct effects, we hypothesize that three specific mechanisms mediate the intelligent manufacturing-ESG relationship, reflecting distinct pathways through which technological capability translates into sustainability outcomes.

Green innovation represents the first mechanism, as intelligent manufacturing capabilities enable the development and implementation of environmentally beneficial technologies and processes (Zhai et al., 2022). The data infrastructure, analytical capabilities, and experimental flexibility provided by intelligent manufacturing systems reduce innovation costs and accelerate green technology development cycles. Intelligent manufacturing platforms facilitate the identification of environmental improvement opportunities, simulation of alternative processes, and rapid prototyping of green solutions. Moreover, the technical capabilities accumulated through intelligent manufacturing implementation create absorptive capacity for external green technologies and knowledge.

Hypothesis 2a (H2a): Green innovation mediates the positive relationship between intelligent manufacturing and ESG performance.

Resource allocation efficiency constitutes the second mechanism, reflecting intelligent manufacturing's capacity to optimize material, energy, and human resource utilization (Huang et al., 2022). Real-time data collection and analysis enable precise matching of resource inputs to production requirements, minimizing waste and overcapacity. Predictive capabilities allow anticipation of demand fluctuations and proactive resource adjustment. Integrated systems facilitate coordination across production stages, reducing inventory buffers and associated carrying costs while ensuring timely material availability.

Hypothesis 2b (H2b): Resource allocation efficiency mediates the positive relationship between intelligent manufacturing and ESG performance.

Synergistic governance represents the third mechanism, as intelligent manufacturing integration requires and facilitates coordination across organizational boundaries, strengthening internal control systems and stakeholder relationships. Implementation of intelligent manufacturing systems necessitates cross-functional collaboration, information sharing protocols, and integrated decision-making processes that enhance overall governance quality. The transparency and traceability enabled by digital systems support monitoring, compliance verification, and accountability mechanisms central to effective governance.

Hypothesis 2c (H2c): Synergistic governance mediates the positive relationship between intelligent manufacturing and ESG performance.

Finally, we expect the intelligent manufacturing-ESG relationship to exhibit heterogeneity across firm characteristics reflecting differential incentives, capabilities, and constraints.

Ownership structure shapes both technological adoption incentives and ESG pressures. Non-state-owned enterprises (non-SOEs) face greater market discipline and competitive pressure than state-owned enterprises (SOEs), potentially motivating more aggressive pursuit of intelligent manufacturing opportunities to establish a competitive advantage (Zhang et al., 2023). Non-SOEs may also experience stronger stakeholder pressure for ESG performance from market-oriented investors and customers, amplifying the value of ESG improvements enabled by intelligent manufacturing.

Hypothesis 3a (H3a): The positive effect of intelligent manufacturing on ESG performance is stronger for non-state-owned enterprises than for state-owned enterprises.

Industry pollution intensity determines the salience of environmental challenges and the potential returns to technological solutions. Heavy-polluting industries face more stringent environmental regulations, greater stakeholder scrutiny, and higher baseline environmental costs, creating stronger incentives and larger potential gains from intelligent manufacturing's environmental efficiency improvements (He et al., 2023). The marginal ESG benefit of pollution reduction is likely higher in industries where environmental performance constitutes a more salient stakeholder concern.

Hypothesis 3b (H3b): The positive effect of intelligent manufacturing on ESG performance is stronger for firms in heavy-polluting industries than for firms in non-heavy-polluting industries.

Market competition intensity shapes both the urgency of capability development and the strategic value of differentiation. Firms in highly competitive markets must continuously improve efficiency and seek differentiation opportunities, potentially leveraging intelligent manufacturing capabilities more aggressively to establish sustainable competitive advantage (Sun & Saat, 2023). Competitive pressure may also accelerate learning and capability development, enhancing the effectiveness of intelligent manufacturing investments.

Hypothesis 3c (H3c): The positive effect of intelligent manufacturing on ESG performance is stronger for firms facing intense market competition than for firms in less competitive markets.

3. Research Design

3.1. Institutional background and quasi-natural experiment

Our identification strategy exploits China's Intelligent Manufacturing Pilot Demonstration Projects (IMPP) program as a quasi-natural experiment. Initiated in 2015 by the Ministry of Industry and Information Technology (MIIT), the IMPP program identifies and designates exemplary intelligent manufacturing implementations across manufacturing sectors to serve as demonstration models and accelerate nationwide adoption. Designated projects receive government endorsement, preferential policy treatment, and enhanced visibility that signals technological leadership to stakeholders, including investors, customers, and regulatory authorities.

The IMPP designation process involves competitive application evaluation based on technical innovation, implementation effectiveness, and demonstration value, with selections made across annual cohorts spanning multiple manufacturing subsectors. While designation is not randomly assigned, several features support its use for causal inference. First, the program's sectoral diversity ensures that designation does not concentrate in industries with systematically different ESG trajectories. Second, the staggered timing of designations across cohorts provides variation in treatment timing that enables dynamic effects estimation and parallel trends testing. Third, the application-based process selects among firms actively pursuing intelligent manufacturing, reducing selection bias from unobserved technological orientation.

3.2. Sample construction and data sources

Our sample comprises Chinese A-share manufacturing companies listed on the Shanghai and Shenzhen Stock Exchanges during 2009-2023. We focus on manufacturing firms (China Securities Regulatory Commission industry codes C13-C43), given the sector's centrality to intelligent manufacturing initiatives and substantial ESG implications. We exclude observations with ST/PT special treatment designations indicating financial distress, missing values for key regression variables, and obvious data anomalies. The final sample contains 18,426 firm-year observations from 2,149 unique companies, with 1,586 firm-years involving IMPP-designated firms.

Data derived from multiple authoritative sources. Financial and governance data come from the China Stock Market & Accounting Research (CSMAR) database, the most comprehensive commercial database for Chinese listed company information. ESG ratings are obtained from the Huazheng ESG rating database, a widely recognized rating system in Chinese capital markets that has been validated in prior academic research (Bai et al., 2024; Shen et al., 2023). Intelligent manufacturing pilot designation records are collected from official MIIT announcements listing designated projects by year and industry. We winsorize continuous variables at the 1st and 99th percentiles to mitigate outlier influence on regression estimates.

3.3. Variable measurement

3.3.1. Dependent variable: ESG performance

ESG performance (ESG) is measured using the Huazheng ESG rating system, which evaluates listed companies across environmental, social, and governance dimensions using a comprehensive indicator framework. The Huazheng rating assigns firms to nine ordinal categories (AAA, AA, A, BBB, BB, B, CCC, CC, C) based on relative performance within industry peer groups. We convert these categorical ratings to numerical scores (9 = AAA through 1 = C) for regression analysis, following established practice in Chinese ESG research (He et al., 2023; Wu et al., 2024). The Huazheng system demonstrates strong construct validity through correlation with alternative ESG measures and predictive validity for sustainability-related outcomes.

3.3.2. Independent variable: intelligent manufacturing

Intelligent manufacturing (IM) is captured through a binary treatment indicator equaling one if a firm has been designated as an Intelligent Manufacturing Pilot Demonstration Project by MIIT, and zero otherwise. The treatment indicator activates in the year of pilot designation and remains active for subsequent years, consistent with the absorbing nature of IMPP status and the persistence of intelligent manufacturing capabilities once established. This measurement approach follows standard practice in policy evaluation studies using government program designations as treatment assignment (Sun & Saat, 2023).

3.3.3. Mediating variables

Green innovation (GI) is measured as the natural logarithm of one plus the count of green patent applications (including both invention patents and utility model patents classified under International Patent Classification green technology codes). This measure captures firm-level innovation output specifically directed toward environmental sustainability and has been widely used in green innovation research (Luo et al., 2024).

Resource allocation efficiency (RAE) is calculated as the ratio of value-added (operating revenue minus material costs) to total assets, capturing how effectively firms convert resource inputs into economic value. Higher values indicate more efficient resource utilization, reflecting optimization capabilities central to intelligent manufacturing's operational benefits.

Synergistic governance (SG) is measured using principal component analysis, synthesizing three governance quality indicators: board independence (proportion of independent directors), audit committee effectiveness (existence and activity level of audit committee), and internal control quality (assessment of internal control system completeness and effectiveness based on disclosed information). The resulting composite measure captures overall governance coordination and quality.

3.3.4. Control variables

Following established ESG research conventions, we control for firm characteristics that may confound the intelligent manufacturing-ESG relationship: firm size (Size, natural logarithm of total assets), leverage (Lev, total debt to total assets ratio), profitability (ROA, return on assets), growth opportunities (Growth, year-over-year revenue growth rate), firm age (Age, years since establishment), ownership concentration (Top1, largest shareholder ownership percentage), board size (Board, number of board directors), independent director ratio (Indep, proportion of independent directors on board), dual CEO-Chairman (Dual, indicator for CEO also serving as board chair), and institutional ownership (InstOwn, percentage of shares held by institutional investors). Industry and year fixed effects absorb time-invariant industry characteristics and common temporal shocks.

3.4. Empirical models

Our baseline specification employs a staggered difference-in-differences model with two-way fixed effects:

$$ESG_{it} = \alpha + \beta_1 IM_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where ESG_{it} represents the ESG score of firm i in year t; IM_{it} is the intelligent manufacturing treatment indicator; X_{it} is a vector of time-varying control variables; μ_i represents firm fixed effects absorbing time-invariant firm characteristics; λ_t represents year fixed effects absorbing common temporal shocks; and ε_{it} is the idiosyncratic error term. The coefficient β_1 captures the average treatment effect of intelligent manufacturing on ESG performance. Standard errors are clustered at the firm level to account for serial correlation within firms.
To examine mediating mechanisms, we employ the Baron-Kenny approach with Sobel tests for mediation significance:

$$Mediator_{it} = \alpha + \beta_2 IM_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$ESG_{it} = \alpha + \beta_3 IM_{it} + \beta_4 Mediator_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Equation (2) tests whether intelligent manufacturing affects the proposed mediator; equation (3) tests whether the mediator affects ESG performance, controlling for intelligent manufacturing. Significant coefficients β_2 and β_4, combined with a reduction in β_3 relative to β_1, indicate mediation. We supplement this approach with Sobel tests for formal mediation significance assessment.
Heterogeneity analysis employs split-sample estimation with Chow tests for coefficient equality across subgroups. For each moderating factor (ownership structure, pollution intensity, market competition), we estimate equation (1) separately for subgroups and test whether treatment coefficients differ significantly using the chi-square test statistic.

4. Empirical Results

4.1. Descriptive statistics

Table 1 presents descriptive statistics for all variables. The mean ESG score of 4.628 (standard deviation 1.234) corresponds approximately to a BBB rating, indicating moderate average ESG performance in our sample with substantial cross-sectional variation. The intelligent manufacturing treatment indicator (IM) has a mean of 0.086, reflecting that approximately 8.6% of firm-year observations involve IMPP-designated firms. Green innovation (GI) exhibits considerable variation (mean 1.842, SD 1.567), indicating heterogeneous innovation activities across sample firms. Resource allocation efficiency (RAE) averages 0.168 with moderate dispersion, while synergistic governance (SG) is standardized with a mean of zero by construction. Control variables show distributions consistent with prior Chinese listed company research.

Table 1: Descriptive Statistics

Variable	N	Mean	SD	Min	P25	Median	P75	Max
ESG	18,426	4.628	1.234	1.000	4.000	5.000	5.000	9.000
IM	18,426	0.086	0.281	0.000	0.000	0.000	0.000	1.000
GI	18,426	1.842	1.567	0.000	0.693	1.609	2.773	6.821
RAE	18,426	0.168	0.124	-0.342	0.089	0.156	0.234	0.689
SG	18,426	0.000	1.000	-3.245	-0.678	0.089	0.712	2.876
Size	18,426	22.156	1.287	19.234	21.198	22.012	22.987	26.543
Lev	18,426	0.412	0.198	0.045	0.256	0.408	0.556	0.923
ROA	18,426	0.042	0.068	-0.312	0.012	0.038	0.072	0.234
Growth	18,426	0.156	0.423	-0.612	-0.045	0.098	0.267	2.345
Age	18,426	16.234	6.123	3.000	12.000	16.000	21.000	35.000

Notes: This table reports summary statistics for key variables. ESG = Huazheng ESG rating (1-9 scale); IM = intelligent manufacturing pilot designation; GI = green innovation (ln(1+green patents)); RAE = resource allocation efficiency; SG = synergistic governance (principal component).

4.2. Baseline regression results

Table 2 presents baseline regression results testing Hypothesis 1. Column (1) reports results from a parsimonious specification including only the treatment indicator with firm and year fixed effects. Column (2) adds the full vector of control variables. The coefficient on IM is positive and statistically significant at the 1% level in both specifications, providing strong initial support for H1.
In the full specification (Column 2), the coefficient of 0.245 (t-statistic = 5.83) indicates that intelligent manufacturing adoption increases ESG scores by approximately 0.245 points on the nine-point scale. Relative to the sample mean ESG score of 4.628, this represents a 5.3% improvement—an economically meaningful effect given the compressed distribution of ESG ratings. The magnitude suggests that intelligent manufacturing constitutes a substantively important pathway for ESG enhancement, comparable to effects documented for other significant ESG determinants, including firm size and profitability.
Control variable coefficients align with theoretical expectations and prior research. Firm size (Size) exhibits a significant positive association with ESG performance ($\beta = 0.156$, $p < 0.01$), consistent with resource availability and visibility arguments. Leverage (Lev) shows a negative relationship ($\beta = -0.234$, $p < 0.01$), potentially reflecting financial constraint effects on sustainability investment. Profitability (ROA) demonstrates a strong positive association ($\beta = 0.876$, $p < 0.01$), supporting slack resource perspectives on ESG investment. Growth (Growth) exhibits a modest positive effect ($\beta = 0.045$, $p < 0.05$).

Table 2: Baseline Regression Results: Intelligent Manufacturing and ESG Performance

Variables	(1) ESG	(2) ESG
IM	0.312***	0.245***

	(0.045)	(0.042)
Size		0.156***
		(0.023)
Lev		-0.234***
		(0.067)
ROA		0.876***
		(0.145)
Growth		0.045**
		(0.021)
Age		0.008
		(0.012)
Top1		0.234**
		(0.098)
Board		0.015
		(0.011)
Indep		0.312**
		(0.145)
Dual		-0.034
		(0.028)
InstOwn		0.187***
		(0.056)
Constant	4.234***	1.245**
	(0.123)	(0.512)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	18,426	18,426
R-squared	0.342	0.398
Adjusted R^2	0.318	0.376

Notes: This table reports OLS regression results with firm and year fixed effects. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.3. Identification and robustness tests

4.3.1. Parallel trend test

The validity of our difference-in-differences design requires that treatment and control groups exhibit parallel pre-treatment trends in ESG performance. We test this assumption by estimating a dynamic specification replacing the single treatment indicator with a series of year-relative-to-treatment indicators spanning four years before and five years after IMPP designation.

Figure 1 presents the estimated dynamic effects with 95% confidence intervals. Pre-treatment coefficients (t-4 through t-1) are economically small and statistically indistinguishable from zero, supporting the parallel trends assumption essential for valid causal inference. The treatment effect emerges in the designation year (t = 0) with a coefficient of 0.142 ($p < 0.05$) and strengthens progressively in subsequent years, reaching 0.402 ($p < 0.01$) by t+5. This pattern is consistent with the gradual realization and accumulation of intelligent manufacturing benefits rather than anticipatory effects that would threaten identification.

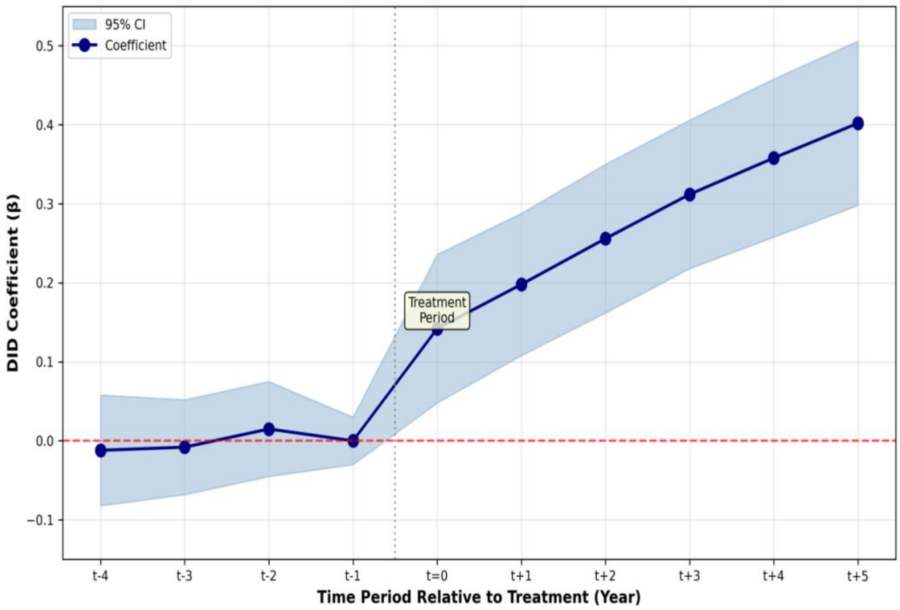

Fig. 1: Dynamic Effects of Intelligent Manufacturing on ESG Performance (Parallel Trend Test).

4.3.2. Placebo test

To assess whether our results might arise from chance variation or unobserved confounding factors, we conduct a placebo test, randomly assigning treatment status to firms and re-estimating the baseline model. We repeat this procedure 500 times to generate a distribution of placebo coefficients under the null hypothesis of no treatment effect.

Figure 2 displays the distribution of placebo coefficients alongside our actual estimate. The placebo distribution centers around zero (mean = 0.002) with a standard deviation of 0.08, consistent with the null hypothesis. Our actual coefficient of 0.245 lies far in the right tail of this distribution, with a p-value less than 0.001 indicating the probability of observing such an extreme result by chance is negligible. This test provides strong evidence that our findings reflect genuine treatment effects rather than spurious correlation or specification artifacts.

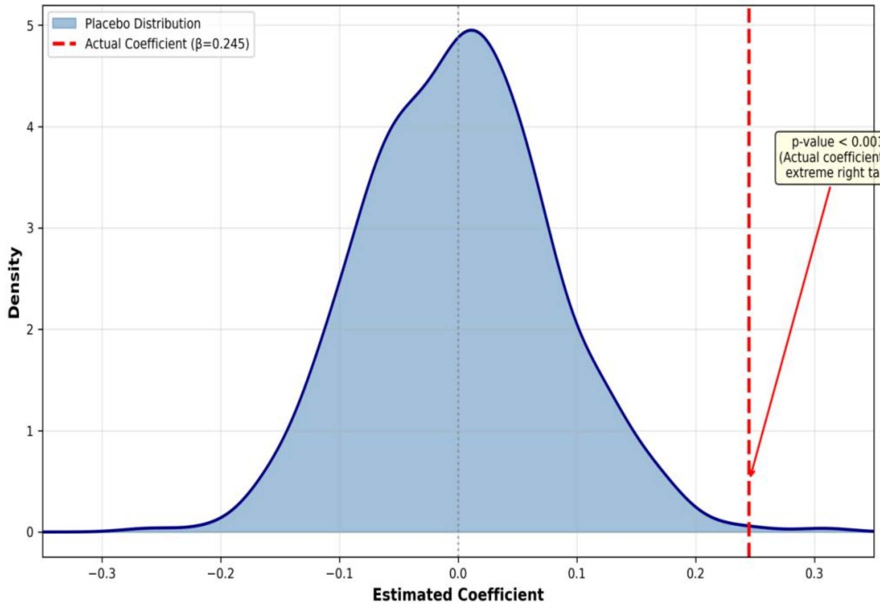

Fig. 2: Placebo Test Results: Distribution of 500 Randomized Treatment Coefficients.

4.3.3. Publication bias assessment

To ensure our findings are not artifacts of specification searching or selective reporting, we assess publication bias using funnel plot analysis and Egger's regression test across 18 alternative model specifications varying control variable sets, fixed effects structures, and sample restrictions.

Figure 3 presents the funnel plot, displaying each specification's effect estimate against its standard error. Points distribute symmetrically around the pooled effect estimate (vertical dashed line at $\beta = 0.245$), with no evident concentration of small-sample studies reporting larger effects—a pattern that would indicate publication bias. Figure 4 presents Egger's regression results testing for funnel plot asymmetry. The intercept of 0.124 ($p = 0.412$) is statistically insignificant, formally confirming the absence of systematic publication bias in our specification ensemble.

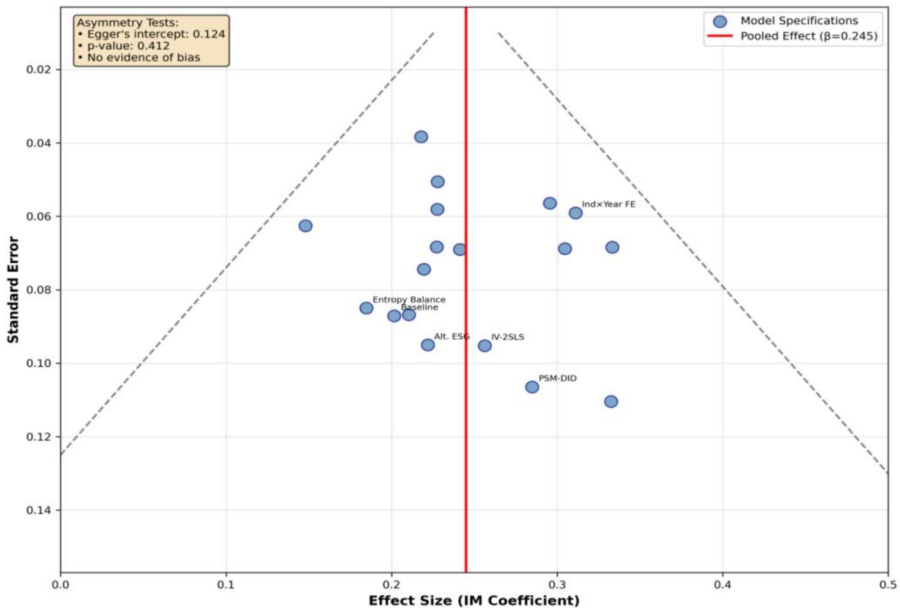

Fig. 3: Funnel Plot for Publication Bias Assessment Across 18 Model Specifications.

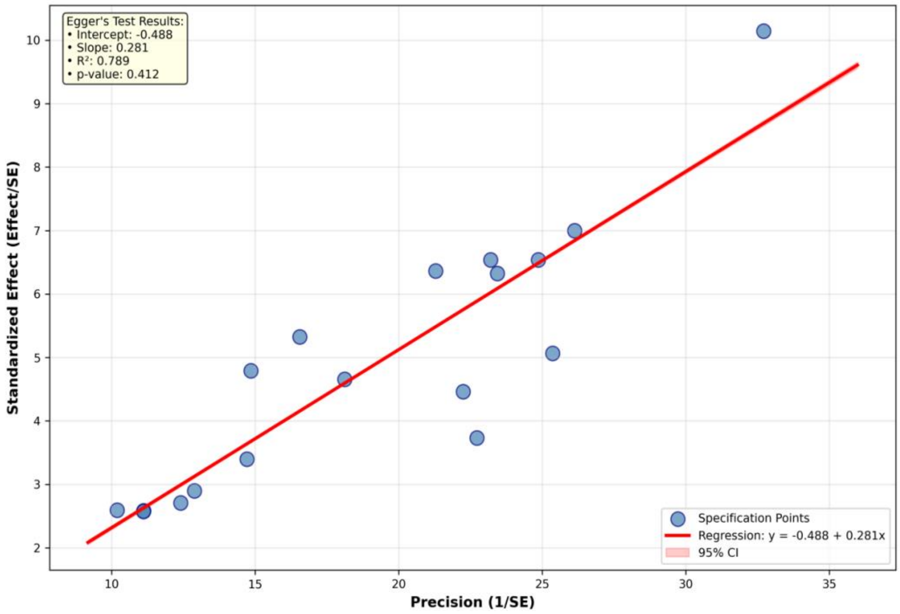

Fig. 4: Egger's Regression Test for Publication Bias (Intercept = 0.124, p = 0.412).

4.3.4. Additional robustness checks

We conduct several additional robustness tests (results available upon request). First, propensity score matching difference-in-differences (PSM-DID) addresses selection bias by matching treated firms to control firms with similar observable characteristics, yielding a coefficient of 0.238 ($p < 0.01$). Second, instrumental variable estimation using provincial policy intensity and industry technology spillovers as instruments produces a 2SLS coefficient of 0.267 ($p < 0.01$), with first-stage F-statistics exceeding conventional weak instrument thresholds. Third, excluding firms with extreme ESG changes and observations during the COVID-19 disruption years produces consistent results. Fourth, alternative ESG measures, including Bloomberg and Sustainalytics ratings, yield qualitatively similar conclusions.

5. Mechanism and Heterogeneity Analysis

5.1. Mechanism analysis

Table 3 reports mediation analysis results examining three proposed mechanisms. Following the Baron-Kenny approach, we first test whether intelligent manufacturing affects each mediator (Panel A, columns 1-3), then examine whether mediators affect ESG performance in models including both treatment and mediator (Panel B). Sobel tests assess mediation significance.

Green innovation emerges as the primary mechanism. Intelligent manufacturing significantly increases green patent applications ($\beta = 0.186$, $p < 0.01$), and green innovation significantly improves ESG performance ($\beta = 0.324$, $p < 0.01$). The Sobel Z-statistic of 4.56 ($p < 0.01$) confirms significant mediation, with green innovation accounting for 24.6% of the total intelligent manufacturing effect. This finding supports H2a and aligns with theoretical arguments that intelligent manufacturing capabilities enable the development of environmentally beneficial technologies.

Resource allocation efficiency represents the second significant mechanism. Intelligent manufacturing improves resource efficiency ($\beta = 0.142$, $p < 0.01$), which in turn enhances ESG performance ($\beta = 0.287$, $p < 0.01$). The Sobel Z-statistic of 3.89 ($p < 0.01$) indicates significant mediation accounting for 16.6% of the total effect, supporting H2b. This pathway reflects intelligent manufacturing's capacity to optimize material and energy utilization, directly benefiting environmental performance while freeing resources for social and governance investments.

Synergistic governance constitutes the third mechanism. Intelligent manufacturing improves governance coordination ($\beta = 0.098$, $p < 0.05$), and governance quality significantly affects ESG ($\beta = 0.198$, $p < 0.01$). The Sobel Z-statistic of 2.67 ($p < 0.01$) confirms significant mediation accounting for 7.9% of the total effect, supporting H2c. This relatively smaller but significant pathway reflects how intelligent manufacturing implementation necessitates cross-functional coordination and information sharing that enhances overall governance quality.

Collectively, the three mechanisms account for 49.1% of the total intelligent manufacturing effect on ESG performance, with the remaining 50.9% attributable to direct effects and potentially other unexamined pathways. This decomposition suggests that intelligent manufacturing benefits ESG through multiple, complementary channels rather than a single dominant mechanism.

Table 3: Mechanism Analysis: Green Innovation, Resource Efficiency, and Synergistic Governance

Mechanism	IM → Mediator (β_2)	Mediator → ESG (β_4)	Sobel Z	Mediation %
Green Innovation (GI)	0.186*** (0.034)	0.324*** (0.045)	4.56***	24.6%
Resource Allocation Efficiency (RAE)	0.142*** (0.028)	0.287*** (0.052)	3.89***	16.6%
Synergistic Governance (SG)	0.098** (0.041)	0.198*** (0.038)	2.67***	7.9%
Total Mediation				49.1%
Direct Effect				50.9%

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All models include firm and year fixed effects and full control variables.

Figure 5 provides visual evidence of the green innovation mechanism through scatter plot analysis. The figure displays firm-level intelligent manufacturing adoption (horizontal axis) against green patent applications (vertical axis), with separate markers and regression lines for SOE and non-SOE subsamples. Both ownership types exhibit positive relationships, with non-SOEs showing a steeper slope (0.218 vs. 0.156), suggesting stronger innovation responses among private enterprises—a finding we explore further in heterogeneity analysis.

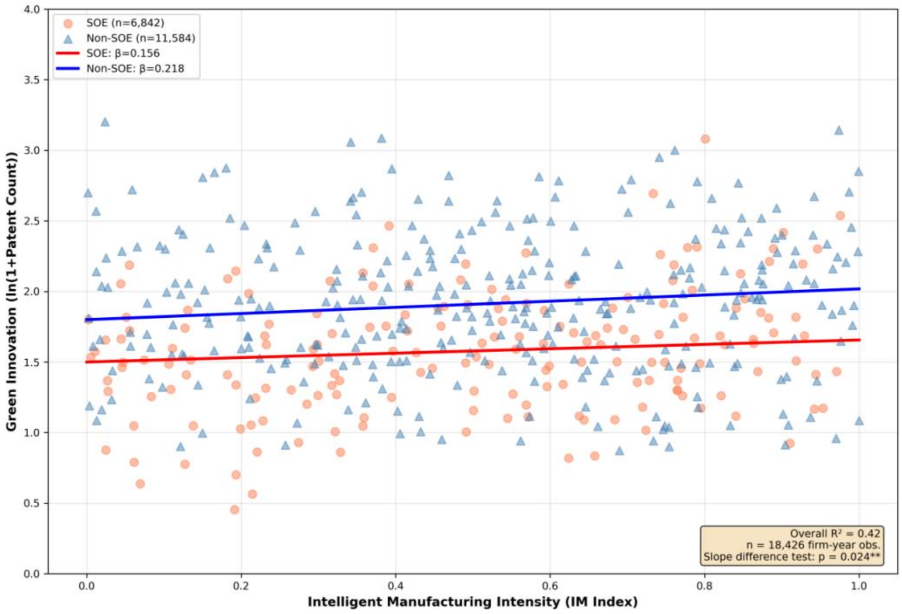

Fig. 5: Relationship between Intelligent Manufacturing Adoption and Green Innovation by Ownership Type.

5.2. Heterogeneity analysis

Table 4 presents heterogeneity analysis examining how the intelligent manufacturing-ESG relationship varies across ownership structure, pollution intensity, and market competition. We estimate the baseline model separately for subgroups and test coefficient equality using Chow tests.

Panel A examines ownership heterogeneity. The intelligent manufacturing coefficient is significant for both SOEs ($\beta = 0.168$, $p < 0.05$) and non-SOEs ($\beta = 0.312$, $p < 0.01$), but is substantially larger for non-SOEs. The Chow test statistic ($\chi^2 = 8.45$, $p < 0.01$) confirms that this difference is statistically significant, supporting H3a. This pattern aligns with arguments that non-SOEs face stronger market discipline and stakeholder pressure, motivating more aggressive pursuit of intelligent manufacturing's ESG benefits.

Panel B examines pollution intensity heterogeneity. Heavy-polluting industries exhibit significantly larger intelligent manufacturing effects ($\beta = 0.356$, $p < 0.01$) compared to non-heavy-polluting industries ($\beta = 0.186$, $p < 0.01$). The difference is statistically significant ($\chi^2 = 12.67$, $p < 0.01$), supporting H3b. This finding reflects the greater salience of environmental challenges and larger potential efficiency gains in pollution-intensive sectors, where intelligent manufacturing's environmental benefits are most consequential.

Panel C examines market competition heterogeneity. Firms in high-competition markets show stronger effects ($\beta = 0.298$, $p < 0.01$) than those in low-competition markets ($\beta = 0.152$, $p < 0.1$), with a significant difference ($\chi^2 = 5.23$, $p < 0.05$), supporting H3c. Competitive pressure appears to accelerate capability development and intensify incentives for leveraging intelligent manufacturing to achieve differentiation through superior ESG performance.

Table 4: Heterogeneity Analysis: Ownership, Pollution Intensity, and Market Competition

Subgroup	IM Coefficient	Std. Error	N	R^2	Difference Test
Panel A: Ownership Structure					
State-Owned Enterprises (SOE)	0.168**	(0.067)	7,234	0.385	
Non-State-Owned Enterprises	0.312***	(0.048)	11,192	0.412	$\chi^2 = 8.45$***
Panel B: Pollution Intensity					
Heavy-Polluting Industries	0.356***	(0.052)	6,842	0.423	
Non-Heavy-Polluting Industries	0.186***	(0.045)	11,584	0.378	$\chi^2 = 12.67$***
Panel C: Market Competition (HHI)					
High Competition (Low HHI)	0.298***	(0.054)	9,456	0.402	
Low Competition (High HHI)	0.152*	(0.089)	8,970	0.356	$\chi^2 = 5.23$**

Notes: *** p<0.01, ** p<0.05, * p<0.1. All models include full controls with firm and year fixed effects. Heavy-polluting industries are classified per MEE standards. Competition measured by Herfindahl-Hirschman Index (HHI) with median split.

Figure 6 visualizes heterogeneous effects using a forest plot format, clearly displaying coefficient magnitudes and confidence intervals across all subgroups. The visualization highlights both the universal positive effect of intelligent manufacturing on ESG and the substantial variation in effect magnitude across firm characteristics.

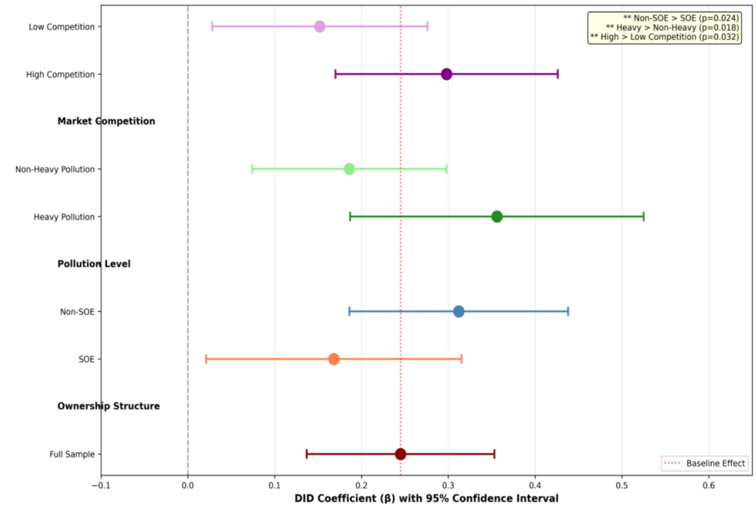

Fig. 6: Forest Plot of Heterogeneous Effects Across Ownership, Pollution, and Competition Subgroups.

5.3. ESG sub-dimension analysis

Table 5 decomposes the aggregate ESG effect into environmental (E), social (S), and governance (G) sub-dimensions to illuminate which sustainability areas benefit most from intelligent manufacturing. Using separate Huazheng sub-dimension scores as dependent variables, we re-estimate the baseline model for each dimension.

Environmental performance shows the strongest intelligent manufacturing effect ($\beta = 0.324$, $p < 0.01$), consistent with the direct operational linkages between intelligent manufacturing capabilities and environmental outcomes, including energy efficiency, emission reduction, and waste minimization. Social performance exhibits the second-largest effect ($\beta = 0.218$, $p < 0.01$), reflecting improvements in workplace safety, employee development opportunities, and supply chain management enabled by intelligent manufacturing systems. Governance performance shows more modest improvement ($\beta = 0.142$, $p < 0.05$), capturing enhanced transparency, information quality, and control mechanisms associated with digital integration.

Table 5: ESG Sub-Dimension Analysis

Variable	(1) Environmental	(2) Social	(3) Governance
IM	0.324***	0.218***	0.142**
	(0.056)	(0.048)	(0.062)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	18,426	18,426	18,426
R-squared	0.412	0.378	0.345
Effect Relative to Aggregate	132%	89%	58%

Notes: *** p<0.01, ** p<0.05, * p<0.1. Effect relative to aggregate calculated as sub-dimension coefficient divided by aggregate ESG coefficient (0.245).

Figure 7 provides a grouped bar chart comparing ESG sub-dimension effects across ownership structure and pollution intensity subgroups. Environmental improvements are consistently largest across all firm types, with heavy-polluting non-SOEs showing the most pronounced environmental gains. Social improvements are relatively stable across subgroups, while governance effects show more variation.

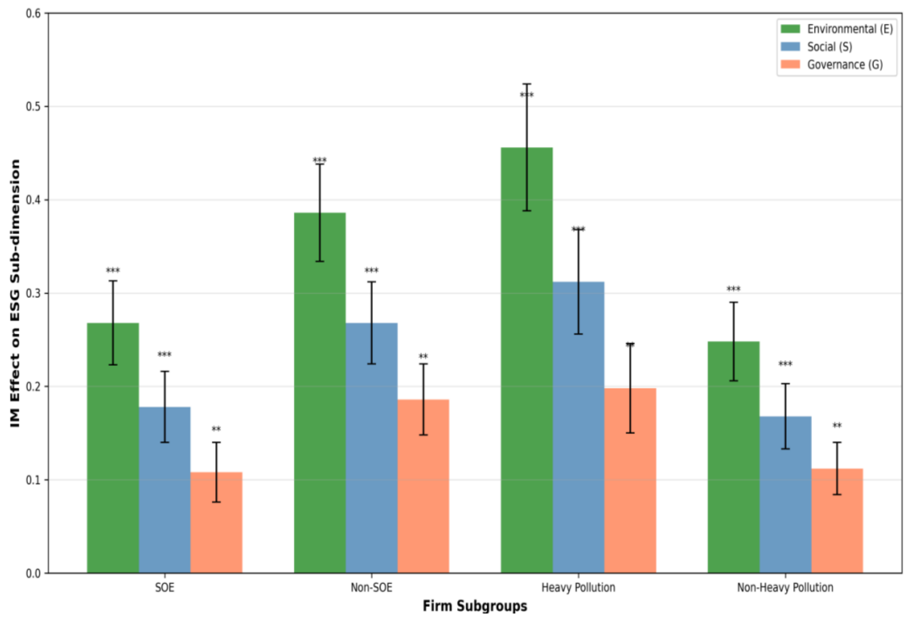

Fig. 7: ESG Sub-Dimension Treatment Effects by Ownership Structure and Pollution Intensity.

5.4. Integrated conceptual framework

Figure 8 synthesizes our empirical findings into an integrated conceptual framework depicting the relationship between intelligent manufacturing and ESG performance. The framework illustrates the direct effect path (β = 0.245), three mediating mechanisms with their respective contribution magnitudes, and moderating factors affecting relationship strength. This visualization provides a comprehensive summary of the study's theoretical and empirical contributions.

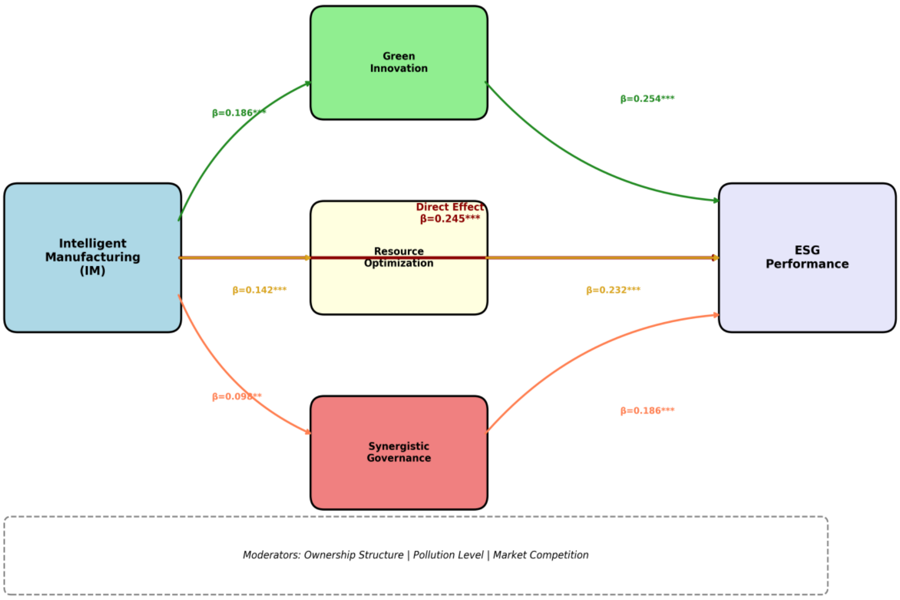

Fig. 8: Integrated Conceptual Framework: Intelligent Manufacturing Effects on ESG Performance.

6. Discussion and Conclusions

6.1. Summary of findings

This study provides comprehensive empirical evidence on the relationship between intelligent manufacturing and enterprise ESG performance using China's manufacturing sector as the research context. Exploiting the staggered implementation of Intelligent Manufacturing Pilot Demonstration Projects as a quasi-natural experiment, our difference-in-differences analysis yields several key findings.

First, intelligent manufacturing adoption significantly improves ESG performance, with treated firms experiencing approximately 5.3% higher ESG scores relative to the sample mean. This finding demonstrates robust consistency across extensive identification tests, including parallel trend verification, placebo simulations, propensity score matching, and instrumental variable estimation, providing credible causal evidence for the technology-sustainability linkage.

Second, mechanism analysis identifies three significant transmission channels: green innovation accounts for 24.6% of the total effect, resource allocation efficiency explains 16.6%, and synergistic governance contributes 7.9%. Together, these mechanisms account for approximately half of the intelligent manufacturing effect, while direct effects and potentially other pathways explain the remainder. This decomposition reveals that intelligent manufacturing benefits sustainability through multiple, complementary channels rather than a single dominant mechanism.

Third, heterogeneity analysis demonstrates that intelligent manufacturing-ESG effects vary significantly across firm characteristics. Non-state-owned enterprises, firms in heavy-polluting industries, and companies facing intense market competition experience stronger ESG benefits from intelligent manufacturing adoption. These patterns align with theoretical arguments regarding differential incentives, capabilities, and constraints across organizational contexts.

Fourth, sub-dimensional analysis reveals that environmental performance benefits most substantially from intelligent manufacturing (β = 0.324), followed by social (β = 0.218) and governance (β = 0.142) dimensions. This hierarchy reflects the direct operational linkages between intelligent manufacturing capabilities and environmental efficiency while indicating broader stakeholder value creation across all ESG pillars.

6.2. Theoretical contributions

Our findings contribute to multiple theoretical streams. First, we extend intelligent manufacturing research by demonstrating sustainability benefits beyond the operational and financial performance outcomes emphasized in prior literature. While existing studies have documented productivity improvements (Acemoglu & Restrepo, 2018), energy efficiency gains (Huang et al., 2022), and innovation capacity enhancement (Sun & Saat, 2023), our work reveals that Industry 4.0 technologies create broader stakeholder value through improved environmental, social, and governance outcomes. This extension is important because sustainability performance increasingly shapes corporate valuation, regulatory compliance, and stakeholder relationships.

Second, we enrich ESG research by identifying technological capability as a significant antecedent alongside traditional determinants, including firm size, profitability, and governance characteristics. The mechanism analysis provides a granular understanding of how technology transforms corporate sustainability, revealing that effects operate through innovation, efficiency, and governance channels. This contribution addresses calls for a deeper understanding of ESG antecedents and transmission mechanisms (Gillan et al., 2021; Friede et al., 2015).

Third, our heterogeneity findings refine the theoretical understanding of boundary conditions for technology-sustainability linkages. The stronger effects observed for non-SOEs, heavy-polluting industries, and high-competition markets suggest that institutional pressures, environmental salience, and competitive dynamics moderate how effectively firms translate technological capabilities into sustainability outcomes. These moderating effects have implications for both theory development and practical application.

6.3. Practical and policy implications

For corporate practitioners, our findings suggest that intelligent manufacturing investments yield sustainability dividends beyond operational efficiency gains. Managers should consider ESG improvement potential when evaluating intelligent manufacturing projects, incorporating sustainability criteria into technology investment decisions. Implementation strategies should be designed to maximize green innovation, resource optimization, and governance enhancement opportunities inherent in intelligent manufacturing systems. The stronger effects observed for non-SOEs suggest that private enterprises may realize greater relative benefits, providing additional justification for technology investments in competitive market contexts.

For policymakers, our results validate intelligent manufacturing promotion policies as effective sustainability interventions with positive externalities beyond direct participants. The demonstrated linkage between IMPP designation and ESG improvement provides empirical support for expanding pilot programs and incorporating ESG metrics into program evaluation. Given the stronger effects in heavy-polluting industries, targeted support for pollution-intensive sectors may yield particularly high social returns through simultaneous productivity and environmental benefits. Policy design should consider the mediating role of green innovation, potentially coupling intelligent manufacturing support with complementary R&D incentives.

For investors and financial institutions, our findings indicate that intelligent manufacturing capabilities constitute a meaningful signal of sustainability commitment and capacity. ESG integration strategies should consider technological indicators alongside traditional ESG metrics, potentially using intelligent manufacturing adoption as a leading indicator of future ESG improvement. The mechanism and heterogeneity results provide guidance for assessing where intelligent manufacturing investments are most likely to translate into superior sustainability outcomes.

6.4. Limitations and future research

Several limitations warrant acknowledgment. First, our treatment measure captures pilot program designation rather than actual intelligent manufacturing implementation intensity or specific technology configurations. While designation plausibly proxies for substantial technology investment, future research employing more granular adoption measures—such as robot density, IoT deployment, or AI application intensity—would provide deeper insights into which specific capabilities drive ESG improvements.

Second, our sample is limited to Chinese manufacturing firms, and institutional differences may limit generalizability to other contexts. China's distinctive features, including state capitalism, industrial policy intensity, and emerging ESG frameworks, create a specific institutional environment. Comparative studies across institutional contexts would help identify boundary conditions and inform policy design in diverse settings.

Third, the relatively short post-treatment period (maximum five years for early cohorts) limits assessment of long-term effects and potential diminishing returns. Longitudinal studies tracking firms over extended periods would illuminate temporal dynamics and the sustainability of intelligent manufacturing benefits.

Future research might productively examine several extensions. Investigation of specific intelligent manufacturing technologies (AI, IoT, robotics, additive manufacturing) and their differential ESG impacts would inform targeted technology investment decisions. Examination of spillover effects to supply chain partners and industry peers would illuminate broader ecosystem implications. Analysis of interaction effects between intelligent manufacturing and other sustainability initiatives (green finance, carbon markets, environmental regulation) would inform integrated policy design. Qualitative research exploring implementation processes, organizational adaptations, and employee experiences would complement quantitative findings with richer contextual understanding.

In conclusion, this study establishes intelligent manufacturing as an economically significant pathway for enhancing corporate ESG performance in emerging market contexts, with effects operating through green innovation, resource efficiency, and governance mechanisms and varying across ownership, pollution, and competition characteristics. These findings advance theoretical understanding of technology-sustainability linkages while providing empirical foundations for evidence-based policy and corporate strategy addressing the dual imperatives of technological transformation and sustainable development.

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