Intelligent Manufacturing Leads the Green Trend: An Empirical Exploration of Manufacturing Companies Listed on China's Shanghai and Shenzhen A-Share Markets

Received: June 02, 2024
Revised: June 21, 2024
Accepted: June 22, 2024

*Linrong Wu Jianmin Sun
International School of Management, Rattana Bundit University, Thailand
*wulinrong@glc.edu.cn

Abstract

In the transformative era of industry driven by intelligent manufacturing, its capacity to shape corporate environmental responsibility stands as a critical concern. This study draws upon a decade of data from manufacturing firms listed on China's Shanghai and Shenzhen A-share markets, encompassing the years 2010 to 2022. Employing a two-way fixed-effects model, an empirical examination is conducted to assess the influence of intelligent manufacturing on investments in corporate environmental governance. The results reveal a significant and positive impact of intelligent manufacturing on the enhancement of corporate environmental governance investment, with the key driver being the increased investment in technological innovation by corporations. To substantiate the robustness of these findings, a series of rigorous checks were applied, encompassing two-stage least squares (2SLS) estimation, propensity score matching (PSM), the lagging of independent variables, and the system generalized method of moments (System GMM). Even amidst these exacting evaluations, the conclusions of the study have proven to be consistently robust. The implications of this research are dual-fold: it offers empirical evidence to guide corporate strategies in the domain of intelligent manufacturing and provides policymakers with a theoretical framework to advocate for industry greening and the formulation of sustainable environmental policies. This study, therefore, contributes to both the corporate strategy discourse and the policy-making arena by providing insights grounded in evidence of the pivotal role intelligent manufacturing plays in advancing environmental stewardship.

Keywords: Intelligent Manufacturing; Corporate Environmental Investment; Technological Innovation

1. Introduction

In the crucible of the 21st-century industrial revolution, intelligent manufacturing has emerged as a key driver, redirecting the course of the global manufacturing sector. Embracing the core tenets of digitalization, networking, and intelligence, these technologies are setting the stage for the industry's future, as insightfully discussed by Zhong et al. (2017), Zhou et al. (2018), and Nakandala et al. (2023). The rise of intelligent manufacturing is not just a technological milestone; it is the new battleground in the arena of international technological competition, with far-reaching effects on a nation's industrial edge and the engine for robust economic progress, as underscored by Zhong et al. (2017) and Zhou et al. (2018). Intelligent manufacturing, akin to a master artisan, is sculpting a manufacturing landscape that is smarter and more eco-conscious, steering production towards greater efficiency, precision, and innovation, resonating with the views of Evans and Annunziata (2012) and Zhou et al. (2018).

Yet, the luminescence of intelligent manufacturing casts a long shadow that reflects the environmental challenges our planet faces, as noted by Lodeiro et al. (2021). The industry's swift ascent has come at the cost of resource exhaustion and environmental decay, as documented by Osei Opoku and Aluko (2021), Aluko et al. (2021), and Li et al. (2019). The billowing smoke from factory chimneys, the fumes from vehicle exhausts, and the outflow of industrial wastewater—all serve as stark reminders of the seemingly irreconcilable conflict between industrial development and environmental preservation. This tension poses a critical question: Can intelligent manufacturing serve as a novel solution to environmental issues? Does it hold the key to enhancing economic efficiency while fulfilling environmental responsibilities? The answers are vital for corporate longevity and have profound implications for societal welfare and our planet's sustainability.

Despite the vast potential of intelligent manufacturing, scholarly work on its environmental implications is sparse. Studies have concentrated on its macroeconomic implications for economic growth, as discussed by Li (2018), and its role in industrial upgrading, as examined by Zou and Xiong (2022). There is also a micro-level focus on corporate innovation capabilities, as explored by Ying et al. (2022), Yang et al. (2020), and Lyu et al. (2023), as well as labor productivity, and operational efficiency, as studied by Zhu et al. (2024), Yang et al. (2020), Ying et al. (2022), Lu et al. (2023), and Xi et al. (2024). However, the specific influence of intelligent manufacturing on environmental governance, especially its impact on corporate environmental governance investment, has yet to be clearly illuminated by current research.

This study aims to fill this scholarly gap by examining the influence of intelligent manufacturing on corporate environmental governance investment. We propose an intrinsic connection between intelligent manufacturing and environmental governance. From a theoretical standpoint, intelligent manufacturing can offer innovative solutions to corporate environmental governance by increasing production efficiency, optimizing resource allocation, and minimizing energy use, as suggested by Zheng et al. (2018) and Zhou et al. (2018). Furthermore, intelligent manufacturing can enhance a company's ability to identify, manage environmental risks, and improve the effectiveness of environmental governance through real-time monitoring and data analytics, as indicated by Cui et al. (2020).

Our research contributes in several significant ways. Firstly, it expands on the environmental governance impacts of intelligent manufacturing technology, presenting a fresh perspective on its potential to catalyze corporate green initiatives. Secondly, by analyzing the motivational factors for environmental governance from a strategic corporate standpoint, the study uncovers how intelligent manufacturing can encourage companies to adopt proactive environmental governance measures through improved resource efficiency and technological innovation. Additionally, the research delves into the specific mechanisms by which intelligent manufacturing influences corporate environmental performance, offering empirical support for the integration of environmental responsibility in the manufacturing industry.

The structure of the paper is as follows: the second section provides a literature review to establish a theoretical foundation; the third section postulates research hypotheses; the fourth section explains the methodology; the fifth section conducts the empirical analysis; and the sixth section concludes with a discussion of the findings and the extraction of practical implications.

2. Literature Review

2.1 Conceptualization of Intelligent Manufacturing

In the realm of industrial evolution, the advent of intelligent manufacturing, first conceptualized by American scholars Wright and Bourne, has marked a significant paradigm shift. In their foundational work "Intelligent Manufacturing," it was initially described as the employment of knowledge engineering, manufacturing software systems, and robotic vision to empower intelligent robots to undertake small-batch production autonomously. As the tide of digital and intelligent technology continues to surge, intelligent manufacturing has evolved beyond automation and unstaffed production. It has integrated production and consumption mechanisms, propelling a transition from mass production to customized production, thereby enhancing production efficiency and optimizing resource allocation. Pioneering studies predominantly concentrated on the architecture and implementation strategies of intelligent manufacturing systems. Zhou et al. (2018) emphasize that these systems should encompass cloud systems and the industrial internet to facilitate the operation of their functional components. Li et al. (2019) dissect the intelligent manufacturing system from a technology-enabled process perspective, delineating it into a technological integration framework comprising the resource layer, network layer, platform layer, and application layer. The implementation trajectory of intelligent manufacturing is driven by the propelling roles of intelligent technologies such as the Internet of Things (IoT) (Tao et al., 2014), artificial intelligence (AI) (Karabegovic et al., 2018), and big data (Zhong et al., 2017), along with the synergistic effects of these technologies in actualizing intelligent manufacturing functions. Giret et al. (2016) devised an engineering framework that converges multiple technologies to aid developers in managing and operating service-oriented intelligent manufacturing systems.

Despite the absence of a one-size-fits-all definition of intelligent manufacturing, the United States' National Institute of Standards and Technology posits it as an intelligent, integrated, collaborative system that empowers companies to fully engage in production collaboration and meet production demands in real time (Kusiak, 2018). The manufacturing execution systems within intelligent manufacturing are capable of automatically harvesting data from equipment sensors, offering real-time information to bolster enterprise resource planning. This supports managers in making informed decisions grounded in a comprehensive and precise status of the production system, achieving efficient integrated collaboration (Frank et al., 2019; Tao et al., 2018). Zhou et al. (2018) contend that intelligent manufacturing is a dynamically evolving system, distinguishable into phases such as digital manufacturing, digital networked manufacturing, and the new generation of intelligent manufacturing. The latter represents a profound integration of artificial intelligence technology with advanced manufacturing technology. The evolution from the nascent stages of computer-aided manufacturing, through the digitization, networking, and intellectualization of manufacturing processes, to the Japanese government's "New Robotics Strategy," mirrors the transformative impact of information technology on manufacturing. Artificial intelligence, as the vanguard of the new generation of information technology, converges with advanced manufacturing technology to form the core technology underpinning the new industrial revolution. This article, referencing the "Intelligent Manufacturing Development Plan (2016–2020)," encapsulates intelligent manufacturing as "a novel production paradigm founded on the deep integration of new-generation information and communication technology with advanced manufacturing technology. This encompasses all facets of manufacturing activities, including design, production, management, and services, endowed with capabilities for self-perception, self-learning, self-decision-making, self-execution, and self-adaptation" (Zhong et al., 2017; Li, 2018)..

2.2 Measurement of Intelligent Manufacturing Indicators

In the realm of quantifying intelligent manufacturing, a variety of approaches have been posited by academicians, with three prevalent methods highlighted below. Firstly, the installation density or penetration rate of industrial robots serves as a surrogate metric to gauge the levels of automation, digitalization, and intelligence inherent in the "Second Machine Revolution" (Li et al., 2024). This metric is a tangible reflection of the integration and pervasiveness of advanced technologies within the manufacturing sector. Secondly, the implementation of intelligent manufacturing by enterprises is often operationalized as a binary variable, drawing on the pilot demonstration projects publicized by the Ministry of Industry and Information Technology. This dummy variable delineates between firms that have embraced intelligent manufacturing initiatives and those that have yet to do so (Jiang et al., 2019; Zhu et al., 2024; Wei et al., 2024), offering a clear-cut distinction for comparative analysis. Lastly, the innovative application of text mining techniques has emerged as a valuable tool for crafting indicators of intelligent manufacturing. By analyzing keyword frequency, these methods encapsulate the critical technological dimensions across the value chain, such as artificial intelligence, the Internet, big data, and intelligent manufacturing, which refers to the integration of advanced information technology with manufacturing processes to achieve greater automation, data-driven decision-making, and intelligent optimization (Lu et al., 2023; Ying et al., 2022; Zhuo and Chen, 2023). This approach provides a nuanced understanding of the multifaceted nature of intelligent manufacturing, capturing the essence of technological advancements within the industry.

2.3 Intelligent Manufacturing and Environmental Governance

Intelligent manufacturing, the linchpin of Industry 4.0, serves as a dual catalyst, propelling not only the enhancement of production efficiency but also forging new pathways for corporate green transformation, as discussed by Zhou et al. (2018). The nexus between intelligent manufacturing and the greening of corporate production and development has been a focal point of extensive scholarly inquiry and debate, particularly in the context of industrial robots, as noted by Chen et al. (2024) and Zhang et al. (2022). Industrial robots, the cornerstone of intelligent manufacturing, are increasingly emerging as a pivotal driver of green production and governance. Through automation and precision control, these robots significantly curtail energy consumption and waste generation within the production process, thereby effectively fostering resource conservation and environmental protection, as articulated by Liu (2023). The extant research suggests that industrial robots, while elevating production efficiency, also bolster corporate green innovation. This is achieved by refining product design and manufacturing processes, which in turn mitigates their adverse environmental footprint, echoing the findings of Kumar and Rodrigues (2020). As Industry 4.0 progresses, the convergence of industrial robots with technologies such as the Internet of Things and big data analysis is set to further augment corporate capabilities in environmental monitoring and management. This integration is on track to realize more intelligent and sustainable production paradigms, as posited by Lee et al. (2015).

However, despite the existing discourse on the relationship between intelligent manufacturing and green production, there remains a relative dearth of research exploring the interplay between intelligent manufacturing and corporate environmental governance. Within the current academic landscape, Wei et al. (2024), in their research, propose that intelligent manufacturing not only streamlines production processes but also markedly ameliorates corporate environmental performance. This assertion underscores the need for further investigation into how intelligent manufacturing can be leveraged to enhance environmental governance practices within corporations.

3. Research Hypotheses and Conceptual Framework

3.1 Intelligent Manufacturing and Corporate Environmental Governance

Intelligent manufacturing, a convergence of digital technology and industrial processes, stands at the vanguard of technological progress, offering novel perspectives and tools for the realm of corporate environmental governance. From the resource-based view articulated by Barney (1991), a firm's competitive edge is derived from its unique bundle of resources and capabilities. Intelligent manufacturing, as a strategic resource, engenders a dual benefit for enterprises—enhancing environmental sustainability and economic viability by increasing resource efficiency and curtailing production costs. In tandem, transaction cost theory, as posited by Coase (1937), implies that firms can mitigate transaction costs through the internalization of transactions. Intelligent manufacturing streamlines production processes and bolsters information processing, thus reducing the costs associated with resource allocation and market transactions.

The influence of intelligent manufacturing on corporate environmental governance is channeled through a suite of internal mechanisms. Initially, by refining production processes and boosting machine efficiency, it diminishes the reliance on tangible production factors, thereby lowering labor and energy costs (Brynjolfsson & Hitt, 2000; Zhou et al., 2018). This heightened efficiency precipitates greater labor output and fortifies green total factor productivity (Kumar & Rodrigues, 2020), which is instrumental in resource conservation and environmental safeguarding. Subsequently, intelligent manufacturing harnesses data analytics and optimization algorithms, markedly improving information processing capabilities (Zhong et al., 2017; Sarbu, 2022). This empowerment enables firms to assess production capacity more precisely, forecast market demand more reliably, and achieve intelligent scheduling along with the optimal allocation of resources, thereby curtailing resource wastage and environmental strain. Moreover, intelligent manufacturing amalgamates avant-garde technologies such as the Internet of Things, big data, and cloud computing, which are adept at real-time data collection and analysis during production (Sarbu, 2022). This technological synthesis not only underpins decision-making but also erects an early warning system, enabling enterprises to swiftly detect and tackle environmental concerns, thus mitigating environmental risks. Furthermore, intelligent manufacturing nurtures green innovation, spurring enterprises to innovate environmentally benign products and processes. Artificial intelligence technologies offer a simulation platform for green technological innovation, allowing firms to leverage intelligent devices and cloud computing platforms for research and development (Wang et al., 2024). By scrutinizing historical data from trials and errors, enterprises can refine and optimize their future trajectories of green innovation. Against this backdrop, we proffer Research Hypothesis 1:

Hypothesis 1: Intelligent manufacturing exerts a positive influence on advancing corporate environmental governance.

3.2 Intelligent Manufacturing, Technological Innovation, and Corporate Environmental Governance

As a pivotal trend in modern industrial evolution, intelligent manufacturing wields both direct and indirect influences on bolstering the capacity for corporate environmental governance. The direct impact is evident in the deployment of intelligent manufacturing technologies, which streamline production processes, curtail energy usage, and enhance the efficiency of energy utilization, thus catalyzing conservation efforts and the reduction of emissions (Zheng et al., 2018; Zhou et al., 2018; Machado et al., 2020). The indirect impact, however, stems from the impetus it provides to technological innovation, fortifying the investment and engagement of corporations in environmental preservation practices. The theory of technological spillovers underpins this study with robust theoretical grounding (Jaffe et al., 1993; Keller, 2002). It sheds light on the phenomenon where novel technologies extend beyond their immediate fields of application, permeating into other sectors and regions, and invigorating widespread economic and societal gains. Within the intelligent manufacturing paradigm, the spillover of technology not only catalyzes internal innovation within firms but also forges a cross-industry green technology network. This network, forged through technological exchanges and collaborations among businesses in the supply chain, diminishes the costs associated with environmental governance and amplifies the collective impact of such efforts (Li et al., 2012). Furthermore, the integration of cutting-edge technologies such as artificial intelligence and intelligent control within intelligent manufacturing accelerates the acquisition of new knowledge and skills by enterprises through information technology (Brynjolfsson and Mitchell, 2017). This acceleration not only fosters green technological innovation and the manufacture of eco-friendly products but also propels companies towards sustainable development. The spillover effects of intelligent manufacturing technologies, facilitated by interconnected information platforms, enhance inter-enterprise information exchange, curtail the costs of information dissemination, and stimulate regional knowledge and technological innovation, thereby accelerating the pace of innovation. Against this analytical backdrop, we propose Research Hypothesis 2:

Hypothesis 2: Intelligent manufacturing acts as a catalyst for corporate environmental governance by elevating the capabilities for technological innovation.

4. Research Design

4.1 Sample Selection and Data Sources

In this research, we have chosen manufacturing firms listed on China's Shanghai and Shenzhen A-share markets, encompassing the period from 2010 to 2022. Following the initial compilation of our sample database, a rigorous series of filters were applied to ensure the precision and integrity of the data. Firstly, we excluded companies that received the Special Treatment (ST) designation or were suspended from trading (PT) at any point during the research timeframe, in accordance with the criteria established by Chen et al. (2020) and Xu et al. (2021). This exclusion was critical to maintain the financial health and trading continuity of the sample cohort. Secondly, we eliminated samples with incomplete data for key variables, as these omissions would compromise the robustness of our analysis. Subsequently, we conducted a thorough review to exclude firms with financial indicators that deviated significantly from the norm, thus precluding any potential skewing of our analytical outcomes due to outlier values. Post these methodical refinements, our study culminated in a curated dataset comprising 20,277 firm-year observations. To bolster the reliability of our data even further, we applied a 1% winsorization treatment to all continuous variables. This statistical technique is instrumental in muting the influence of extreme values, thereby ensuring a more representative and accurate dataset. The primary sources of our data are the China Stock Market & Accounting Research (CSMAR), a reputable repository known for its comprehensive and reliable financial data, and the annual financial reports published by the listed companies themselves, which offer a trove of publicly disclosed information.

4.2 Sample Selection and Data Sources

4.2.1 Dependent Variable

In delineating the construct of Corporate Environmental Governance Investment, colloquially denoted as 'Green' investments, this study draws upon the analytical techniques established by Zhang et al. (2019) and Fu et al. (2024). Our methodology involves a meticulous manual collection and qualitative synthesis of data extracted from the annual reports of the listed enterprises under scrutiny. To particularize, the investigation encompasses a comprehensive review of the annual reports' construction work annex tables, where we meticulously identify and catalog the financial outlays earmarked for environmental governance and green production initiatives. This includes, but is not limited to, expenditures on desulfurization and denitrification processes, wastewater management, waste gas and slag treatment, and the promotion of clean production practices. These discrete investment items are then consolidated to form a composite figure, which serves as a holistic representation of the company's fiscal commitment to environmental stewardship. To normalize this figure and render it reflective of the company's relative investment intensity in environmental governance, we divide it by the company's year-end total assets.

4.2.1 Independent Variable

Intelligent Manufacturing (IM). In this study, we leverage the scholarly insights of Yu et a1. (2020), Lu et al. (2023), Ying et al. (2022), and Zhuo and Chen (2023), employing text mining techniques to develop a suite of indicators that quantify the sophistication of intelligent manufacturing. This quantification is achieved by scrutinizing the frequency distribution of pertinent keywords. The strategic selection of keywords is paramount for the precise measurement of intelligent manufacturing's developmental status. This paper's approach to keyword selection spans three dimensions: academic literature, policy documentation, and the annual reports of listed companies. As intelligent manufacturing represents an innovative production paradigm that amalgamates cutting-edge technologies such as big data, the Internet, and artificial intelligence, our keyword selection encompasses a spectrum of elements including artificial intelligence, Internet, big data, and manufacturing technologies within the value chain. In our review of academic literature, we draw upon the research conducted by Yu et al. (2020) to initially identify specific keywords associated with the aforementioned technologies. For policy documents and research reports, we augment our keyword repository with terms related to intelligent manufacturing technology, informed by strategic initiatives such as "Made in China 2025," the "Intelligent Manufacturing Development Plan (2016-2020)," and recent "Government Work Reports." In analyzing the annual reports of listed companies, we undertook a multi-step process to expand our keyword lexicon. Initially, we utilized the Python programming language to scrape annual reports from the CNINFO website, focusing on the "Management Discussion and Analysis (MD&A)" sections. Subsequently, we extracted intelligence-related vocabulary from pertinent policy documents and authoritative texts, creating a bespoke dictionary that was integrated into the jieba word segmentation library to perform segmentation on the MD&A texts. Ultimately, employing the word2vec word bag model, we extracted related words from the segmented texts. This automated extraction was complemented by a manual review process to refine the selection of keywords that are intimately connected to artificial intelligence, Internet, big data, and manufacturing technologies within the value chain. The culmination of these efforts resulted in a refined keyword library that is intrinsically linked to intelligent manufacturing technology, the specifics of which are elaborated in Table 1.

Table 1

Compilation of Structured Feature Vocabulary for Intelligent Manufacturing

Index	Measuring dimensions	feature words
Intelligent manufacturing	Artificial Intelligence technology	Artificial Intelligence, Intelligent Manufacturing, Intelligent Manufacturing, Active Manufacturing, Intelligent Transformation, Business Intelligence, Image Understanding, Intelligent Data Analytics, Intelligent Robotics, Manufacturing Execution System, Intelligent Manufacturing, Machine Learning, Deep Learning, Integration, Unmanned, Human-Computer Interaction, Biometrics, Face Recognition, Intelligent Terminal, Voice Recognition
	Internet technology	Industrial Internet, Mobile Internet, E-commerce, Mobile Payment, Cloud Computing, Billion Level Concurrency, Internet of Things, Information Physical Systems, Cyber Physical Systems, EB Scale Storage, Cloud Manufacturing
	Big data technology	Big Data, data mining, data visualization, virtual reality, industrial digitization, data-driven, heterogeneous data, data twins, text mining, mixed reality
	Value Chain Intelligence Technology	Planning and Scheduling, Production Execution, Equipment Operation and Maintenance, Intelligent Warehousing, Intelligent Distribution, Network Collaboration, Intelligent Marketing, Intelligent Customer Service, Intelligent Home, Intelligent Wear, Intelligent Agriculture, Intelligent Medicine

Considering the differences in the length of the "Management Discussion and Analysis (MD&A)" section in the annual reports of various listed companies, we propose a method to quantify the level of intelligent manufacturing. This method includes the following three steps: first, calculate the ratio of the frequency of selected keyword combinations to the total number of words for the sample companies; second, compare this ratio with the total ratio of other sample companies in the same industry and year; finally, multiply this ratio by 100 to reflect the level of intelligent manufacturing of the sample companies in percentage form. If the selected keywords do not appear in a company's annual report, the intelligent manufacturing level of the company for that year is assigned a value of 0.

4.2.3 Control Variables

In this research, we adhere to the academic convention by selecting fundamental information and financial data from manufacturing companies listed on the stock exchange. We have identified a comprehensive set of control variables that encapsulate various dimensions, including the nature of the enterprise, profitability, solvency, and corporate governance. To mitigate the potential bias that may arise from individual firm characteristics and temporal trends in the estimation results, we have incorporated both individual fixed effects (i.e., entity-specific dummy variables) and temporal fixed effects (i.e., year-specific dummy variables) into our model. This methodological approach is designed to isolate the effects of our variables of interest from confounding factors that are invariant across observations within the same entity or time period. By controlling for these individual and time-specific effects, we ensure a more precise estimation of the relationships under investigation, thereby enhancing the accuracy and reliability of our analytical outcomes.

Table 2

Variable Definition Table

Variable Type	Variable	Variable Symbol	Variable Definition
Explained Variable	Environmental Governance	Green	Environmental governance inputs
Explanatory Variable	Intelligent Manufacturing	IM	as mentioned above
Control Variables	Return on Assets	ROA	Net Profit / Total Assets
	Revenue Growth Rate	Growth	Operating income growth/previous year's operating income
	State-owned Enterprise	SOE	State-owned enterprises are coded as 1, otherwise coded as 0
	Equity Balance	Balance	Sum of holdings of the second to fifth shareholders / Holding of the largest shareholder
	Duality	Dual	1 if CEO and Chairman are the same person, 0 otherwise
	Asset liability ratio	Lev	Total Liabilities / Total Assets
	Tobin Q Value	TobinQ	Company Market Value / Asset Book Value
	Enterprise Age	Age	Ln(Year - Foundation Year)
	Board Size	Board	Ln(Total Number of Board Members + 1)
	Enterprise Size	Size	Ln(Total Assets)
	Individual Fixed Effects	Firm	
	Time Fixed Effects	Year	

4.3 Model Construction

This study, aiming to investigate the impact of intelligent manufacturing on corporate environmental governance performance, employs a two-way fixed-effects model for empirical analysis. The model is articulated as follows:

$$Green_{i,t} = \beta_0 + \beta_1 IM_{i,t} + \text{Control} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (1)$$

In this model, the independent variable is denoted as Intelligent Manufacturing (IM), and the dependent variable is Corporate Environmental Governance Investment (Green). The subscripts i and t represent individual firms and time series, respectively, a convention that will persist throughout the paper. The crux of this paper is the regression coefficient β_1; if its estimated value is significantly positive, it implies that the adoption of intelligent manufacturing may foster corporate investment in environmental governance. The suite of control variables (Control) includes a variety of factors that could influence corporate environmental governance investment, thereby accounting for other underlying confounding effects. Individual fixed effects (μ_i) and time fixed effects (γ_t) are utilized to control for unobservable heterogeneity at the firm and temporal levels, respectively. The stochastic disturbance term ($\varepsilon_{i,t}$) captures the random error in the model that remains unexplained. To mitigate potential issues of serial correlation and heterogeneity, this paper primarily utilizes clustered robust standard errors at the firm level, thereby enhancing the precision and reliability of the estimation results.

$$RD_{i,t} = \beta_0 + \beta_1 IM_{i,t} + \text{Control} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (2)$$

$$Green_{i,t} = \beta_0 + \beta_1 IM_{i,t} + \beta_2 RD_{i,t} + \text{Control} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (3)$$

To probe whether technological innovation acts as a mediator between intelligent manufacturing and corporate environmental governance investment, Models (2) and (3) are constructed based on the pre-existing Model (1). Model (2) concentrates on the influence of intelligent manufacturing (IM) on corporate technological innovation (RD), with IM as the independent variable and corporate technological innovation as the dependent variable. Subsequently, Model (3) incorporates technological innovation as a mediating variable on the right side of Model (1) to scrutinize its potential influence on the nexus between intelligent manufacturing and corporate environmental governance investment. According to mediating effect theory, if the independent variable intelligent manufacturing in Model (1) significantly affects corporate environmental governance investment, and IM in Model (2) significantly impacts technological innovation, with the mediating variable technological innovation in Model (3) also notably influencing corporate environmental governance investment, then a mediating effect can be preliminarily inferred. Moreover, if the regression coefficient of intelligent manufacturing in Model (3) remains significant, this suggests that technological innovation plays a partial mediating role in the process of intelligent manufacturing's impact on corporate environmental governance investment; if the coefficient of intelligent manufacturing becomes insignificant, it may suggest a full mediating effect.

5. Empirical Analysis

5.1 Descriptive Statistics

Table 3 presents a comprehensive descriptive statistical analysis of the key variables under investigation. The data reveal a notable degree of variability in corporate investment in environmental governance, denoted as 'Green,' with values spanning a range from 0.0165 to

1.2840. This variation underscores the diverse investment approaches toward environmental governance demonstrated by the sample companies throughout the research period. Intelligent manufacturing (IM) also exhibits a spectrum of application levels, with a mean score of 2.8750 and a standard deviation of 1.2898. This dispersion highlights the variability in the adoption and utilization of intelligent manufacturing technologies across different companies, indicative of a broad distribution. Among the control variables, the state-owned enterprise (SOE) indicator has a mean of 0.2644 and a standard deviation of 0.4410, with values ranging from 0 to 1. This statistic suggests that, within the sample, state-owned enterprises constitute roughly 26.44% of the companies, a finding that resonates with previous research (Kang and Kim, 2012). The debt ratio (Lev), a measure of financial leverage, has a mean of 0.3936 and a standard deviation of 0.1918, with the minimum and maximum values recorded at 0.0555 and 0.9073, respectively. These figures indicate a range in the reliance on debt across the sample companies, with an average debt level that is somewhat elevated, as suggested by the mean value approaching 0.4 (Iqbal et al., 2022). The standard deviation adds further nuance to this picture by showcasing the variability in the financial structures of the companies.

Table 3

Descriptive Statistical Results

Variable	Obs	Mean	Std.dev.	Min	Max
Green	20277	0.1665	0.1285	0.0165	1.2840
IM	20277	2.8750	1.2898	0	5.8289
ROA	20277	0.0392	0.0678	-0.3559	0.2188
Growth	20277	0.1817	0.4217	-0.6575	3.4567
SOE	20277	0.2644	0.4410	0	1
Balance	20277	0.7554	0.5923	0.0318	2.8353
Dual	20277	0.3243	0.4681	0	1
Lev	20277	0.3936	0.1918	0.0555	0.9073
Tobin Q	20277	2.1362	1.3370	0.8384	8.8879
Age	20277	2.0520	0.7752	0.6931	3.3673
Board	20277	2.2248	0.1691	1.7918	2.7726
Size	20277	22.0386	1.1514	19.8793	26.2430

5.2 Correlation Analysis

Table 4 meticulously presents the Pearson correlation coefficient matrix among the variables under investigation. The analysis indicates a statistically significant positive correlation between Intelligent Manufacturing (IM) and Corporate Environmental Governance (CEG), with a correlation coefficient of 0.022 that passes the significance test at the 1% confidence level. This result underscores a pronounced positive association between the two constructs. Moreover, the majority of the other pairwise correlations within the correlation matrix have attained statistical significance, providing preliminary evidence for further regression analysis. To delve deeper into the potential issue of multicollinearity among variables, this study conducted a Variance Inflation Factor (VIF) analysis, the outcomes of which are consolidated in Table 5. According to the criterion for VIF analysis, a value exceeding 5 suggests the presence of substantial multicollinearity among variables. However, in this study, the average VIF value is 1.34, significantly below the threshold of 5. This indicates the absence of severe multicollinearity among the variables in the research model, thereby ensuring the reliability of the regression analysis outcomes.

Table 4

Correlation Coefficient Matrix

Variable	Green	IM	ROA	Growth	SOE	Balance
Green	1					
IM	0.022***	1				
ROA	-0.257***	-0.049***	1			
Growth	-0.122***	0.021***	0.232***	1		
SOE	-0.072***	-0.077***	-0.074***	-0.038***	1	
Balance	0.058***	0.054***	-0.017**	0.032***	-0.194***	1
Dual	0.047***	0.058***	0.022***	0.019***	-0.288***	0.038***
Lev	-0.193***	0.046***	-0.374***	0.054***	0.258***	-0.095***
Tobin Q	0.235***	-0.001	0.174***	0.058***	-0.075***	0.025***
Age	-0.076***	-0.047***	-0.169***	-0.060***	0.460***	-0.161***
Board	-0.077***	-0.066***	0.023***	0.002	0.269***	0.005
Size	-0.320***	0.061***	0.054***	0.076***	0.307***	-0.082***
Variable	Green	IM	ROA	Growth	SOE	Balance
Dual	1					
Lev	-0.103***	1				
Tobin Q	0.037***	-0.217***	1			
Age	-0.244***	0.352***	-0.013*	1		
Board	-0.178***	0.131***	-0.088***	0.169***	1	
Size	-0.142***	0.451***	-0.293***	0.445***	0.232***	1

Note: ***, **, * respectively indicate passing the significance tests at the 1%, 5%, and 10% levels.

Table 5

Variance Inflation Factor Analysis

Variable	VIF	1/VIF
Size	1.85	0.54
Lev	1.64	0.61
Age	1.63	0.61
SOE	1.44	0.69
ROA	1.44	0.70
Tobin Q	1.19	0.84
Board	1.14	0.88
Dual	1.13	0.89
Growth	1.1	0.91
IM	1.09	0.91
Balance	1.07	0.94
Mean VIF	1.34	

5.3 Baseline Regression Analysis

5.3.1 Intelligent Manufacturing and Corporate Environmental Governance

The inaugural column of Table 6 delineates the regression outcomes pertaining to the influence of intelligent manufacturing on corporate environmental governance investment. A discernible positive regression coefficient for intelligent manufacturing (IM) of 0.0059 emerges, attaining significance at the 1% level. This result points to a constructive impact of intelligent manufacturing on the investment enterprises make towards environmental governance, corroborating our initial hypothesis. The implication is that the adoption of intelligent manufacturing practices could stimulate greater corporate investment in environmental stewardship, a notion that aligns with existing scholarly discourse on the subject of technological progress enhancing corporate environmental performance (Bloom et al., 2010; Shapiro and Walker, 2018).

Regarding the control variables, the return on assets (ROA) exhibits a negative coefficient (-0.4583), which is in concordance with literature that proposes a trade-off between corporate financial performance and environmental investment (Orlitzky et al., 2003). This suggests a potential corporate strategy of prioritizing financial success over environmental expenditure. The growth rate of operating income (Growth; -0.0258) also presents a negative coefficient, echoing findings that firms in swift growth phases might incline towards allocating resources to expansion rather than environmental governance (Aragón-Correa and Sharma, 2003). The debt ratio (Lev; -0.0416) shows a negative coefficient, indicating that companies with elevated financial leverage might curtail their environmental governance investments, a phenomenon that resonates with the theory of financial constraints (Fazzari et al., 1988). This theory suggests that companies with higher debt levels might face limitations in funding for environmental governance due to their capital structure (Klassen and McLaughlin, 1996). Conversely, the positive coefficient of Tobin's Q (Tobin Q; 0.0074) implies that firms with higher market valuations could be inclined to augment their environmental governance investment. This may signify the market's favorable reception to corporate social responsibility and a predisposition towards evaluating companies on the merit of their long-term value and commitment to sustainable development (Orlitzky et al., 2003). The coefficients for firm age (Age) and board size (Board) are statistically significant but economically modest, suggesting a nuanced impact of company maturity and board dimensions on environmental governance investment. Lastly, the negative coefficient of firm size (Size; -0.0259) indicates that larger firms might be inclined to invest more in environmental governance, a finding that is congruent with the resource-based theory. This theory posits that larger firms possess greater resources to bolster their environmental governance endeavors.

5.3.2 The Mediating Role of Technological Innovation

Having established the affirmative influence of intelligent manufacturing on corporate environmental governance, our investigation delves into the underlying mechanisms that drive this relationship. The mediating effect analysis, detailed in the subsequent Table 6, uncovers the potential intermediary role of technological innovation (RD) in this dynamic. Building upon the prior analysis that substantiated the significantly positive impact of intelligent manufacturing (IM) on corporate environmental governance (Green), the second and third columns of Table 6 shed further light on the mediating influence of RD. Specifically, Model (2) in Table 6 affirms the positive influence of IM on technological innovation, with a regression coefficient of 0.0010, attaining significance at the 5% level. This suggests that the deployment of intelligent manufacturing technologies not only fosters corporate environmental governance directly but may also enhance environmental governance indirectly through the advancement of technological innovation. In Model (3), when accounting for the effects of both IM and RD on corporate environmental governance, the regression coefficient for RD is 1.1542, significant at the 1% level. This finding reinforces the mediating role of RD between IM and corporate environmental governance. It is noteworthy that the incorporation of RD as a mediating variable attenuates the direct impact of IM on corporate environmental governance. Nonetheless, the regression coefficient remains significant, indicating that the mediating effect of RD is partial. This suggests that IM might influence corporate environmental governance investment through a variety of mechanisms, with technological innovation being one, among others. These findings resonate with existing scholarly discourse that identifies technological innovation as a pivotal catalyst for corporate environmental performance (e.g., Ahuja and Lampert, 2001; Rothaermel and Deeds, 2004). Concurrently, they underscore the multifaceted role of intelligent manufacturing in propelling corporate sustainable development. Intelligent manufacturing contributes not solely by bolstering production efficiency and resource utilization but also by spurring innovative activities, thereby indirectly fostering environmental governance.

Table 6

Regression Results of Intelligent Manufacturing, Technological Innovation, and Corporate Environmental Governance Investment

Variable	(1) Green	(2) RD	(3) Green
RD			1.1542*** (12.34)
IM	0.0059*** (4.31)	0.0010** (2.53)	0.0048*** (3.71)
ROA	-0.4583*** (-14.98)	-0.0778*** (-11.87)	-0.3685*** (-13.21)
Growth	-0.0258*** (-9.73)	-0.0054*** (-9.79)	-0.0196*** (-7.92)
SOE	0.0036 (0.56)	-0.0013 (-0.59)	0.0051 (0.78)
Balance	0.0037 (0.98)	0.0011 (1.08)	0.0024 (0.72)
Dual	-0.0029 (-1.04)	-0.0008 (-1.08)	-0.0020 (-0.74)
Lev	-0.0416*** (-2.66)	-0.0203*** (-6.19)	-0.0182 (-1.21)
Tobin Q	0.0074*** (4.87)	-0.0003 (-1.12)	0.0078*** (5.22)
Age	-0.0131*** (-2.93)	-0.0039*** (-3.31)	-0.0086** (-2.02)
Board	-0.0112 (-1.01)	0.0050** (1.98)	-0.0169 (-1.61)
Size	-0.0259*** (-7.00)	0.0028*** (2.58)	-0.0291*** (-8.23)
Constant	0.7811*** (9.65)	-0.0221 (-0.95)	0.8066*** (10.65)
Observations	20,277	20,277	20,277
R-squared	0.286	0.144	0.349

Note: ***, **, * respectively indicate passing the significance tests at the 1%, 5%, and 10% levels, with the values in parentheses representing t-values, the same below.

5.4 Robustness Test and Endogeneity Issue Explanation

To affirm the robustness of the baseline regression findings, this study undertook a series of supplementary tests:

5.4.1 Two-Stage Least Squares (2SLS) Instrumental Variable Estimation

Acknowledging the potential endogeneity between intelligent manufacturing (IM) and corporate environmental governance, we resorted to an instrumental variable approach for a more rigorous analysis. We designated the annual-industry mean of intelligent manufacturing as the instrumental variable, leveraging its direct relevance to IM while ensuring its exogeneity, meaning this variable does not independently influence corporate environmental governance. The initial two columns of Table 7 exhibit the instrumental variable method's estimation outcomes. In the first column, the regression coefficient for the instrumental variable (intelligent manufacturing annual-industry mean) is 0.6010, significant at the 1% level, indicating a substantial correlation with the independent variable. The second column reveals a regression coefficient for intelligent manufacturing of 0.0448, also significant at the 1% level, substantiating the exogeneity assumption and aligning with the baseline regression findings. This outcome underscores that the positive influence of intelligent manufacturing on corporate environmental governance is resilient and significant, even when accounting for potential endogeneity.

5.4.2 Propensity Score Matching (PSM)

To address the potential impact of sample selection bias on the study's conclusions, we employed the Propensity Score Matching (PSM) technique for robustness checks. The essence of PSM lies in balancing key covariates between the treatment group—companies that have adopted intelligent manufacturing—and the control group—companies that have not, by matching on propensity scores. The procedure is as follows: Initially, the likelihood of a company adopting intelligent manufacturing technology, its propensity score, is determined through a Logit regression model, factoring in a suite of covariates that might influence the adoption decision. This model forecasts the probability of a company being in the treatment or control group. Subsequently, using the calculated propensity scores, the nearest neighbor matching method (1:1 nearest neighbor matching with replacement) is applied to select the most analogous unmatched samples from the control group. Post-matching, regression analysis on the matched samples was performed to evaluate the precise impact of intelligent manufacturing on corporate environmental governance investment. The third column of Table 7 shows that the impact coefficient of intelligent manufacturing (IM) on corporate environmental governance investment (Green) is 0.0062, and this effect is statistically significant ($p < 0.001$). This finding is in concordance with the baseline regression analysis, corroborating that intelligent manufacturing significantly and positively influences corporate environmental governance investment, an effect that endures even after considering potential sample selection bias.

5.4.3 Lagged Effect Analysis of the Independent Variable

Acknowledging the possible time lag in the influence of intelligent manufacturing on corporate environmental governance investment, this study incorporates a one-period lagged intelligent manufacturing variable into the regression analysis. This modification is designed to capture any potential delayed impacts of intelligent manufacturing. The fourth column of Table 5 displays the regression outcomes for the lagged effect. Even when accounting for potential lagged effects, the regression coefficient for intelligent manufacturing (L.IM) is 0.0028, significant at the 10% level, thereby providing further evidence that the positive effect of intelligent manufacturing on corporate environmental governance investment is robust.

5.4.4 System Generalized Method of Moments Estimation (SYS-GMM)

To address the dynamic panel data model and counteract the potential influence of prior environmental governance on the current period, this study employs the System Generalized Method of Moments (SYS-GMM). SYS-GMM, introduced by Blundell and Bond (1998), permits the inclusion of lagged dependent variables, effectively mitigating endogeneity concerns that traditional Ordinary Least Squares (OLS) regression may not surmount. The SYS-GMM of Arellano and Bover (1995) circumvents biases associated with small sample sizes and weak instruments, augmenting the precision and reliability of the estimation. Wintoki et al. (2012) have noted that SYS-GMM offers more robust estimations for dynamic panel data compared to OLS. The fifth column of Table 7 illustrates the SYS-GMM estimation results. The Arellano-Bover autocorrelation test indicates no second-order serial correlation in the difference equation residuals (p-value > 0.1), suggesting that the model passes the autocorrelation test. Concurrently, the Hansen test validates the instrumental variables (p-value > 0.1), indicating their statistical soundness. Adhering to Roodman's (2009) recommendations, the number of instrumental variables is capped at 45 to ensure their validity. These findings indicate that our model estimation fulfills the criteria for generalized moment estimation, demonstrating a high level of consistency and reliability. The SYS-GMM estimation reveals that the impact coefficient of intelligent manufacturing (IM) on corporate environmental governance investment (Green) is 0.0681, statistically significant ($p < 0.01$). This finding aligns with the baseline regression results, further corroborating that intelligent manufacturing significantly and positively affects corporate environmental governance, an effect that persists even after considering endogeneity.

Table 7

Robustness Test (Below)

	(1) Instrumental Variable Method	(2)	(3) PSM	(4) Lagged Independent Variable by One Period	(5) System GMM
Variable	IM	Green	Green	Green	Green
IV	0.6010*** (13.21)				
IM		0.0448*** (4.76)	0.0062*** (4.05)		0.0681* (1.75)
L.IM				0.0028* (1.78)	
L.Green					0.5373*** (7.32)
ROA	0.1513 (1.33)	-0.4635*** (-14.98)	-0.4470*** (-14.22)	-0.4578*** (-14.78)	-0.0217 (-0.09)
Growth	0.0133 (0.94)	-0.0265*** (-9.64)	-0.0260*** (-9.30)	-0.0259*** (-9.60)	-0.0747*** (-3.39)
SOE	-0.1002* (-1.88)	0.0077 (1.09)	0.0020 (0.30)	0.0035 (0.50)	0.1745** (2.28)
Balance	0.0395 (1.50)	0.0019 (0.50)	0.0032 (0.77)	0.0042 (1.07)	-0.0104 (-0.65)
Dual	0.0333 (1.52)	-0.0044 (-1.52)	-0.0031 (-1.01)	-0.0028 (-0.94)	0.0014 (0.12)
Lev	-0.2053** (-2.38)	-0.0335** (-2.03)	-0.0409** (-2.36)	-0.0448*** (-2.75)	0.0019 (0.03)
TobinQ	-0.0019 (-0.27)	0.0074*** (4.93)	0.0080*** (4.80)	0.0068*** (4.25)	-0.0124*** (-2.85)
Age	0.0494 (1.38)	-0.0148*** (-3.14)	-0.0172*** (-3.47)	-0.0161*** (-3.35)	0.0264 (1.61)
Board	0.0885 (1.20)	-0.0147 (-1.31)	-0.0109 (-0.90)	-0.0139 (-1.17)	0.2585 (1.07)
Size	0.2472*** (9.79)	-0.0358*** (-7.32)	-0.0268*** (-6.45)	-0.0257*** (-6.52)	-0.0896*** (-3.25)
Constant	-4.5747*** (-8.42)	0.9242*** (9.67)	0.8000*** (8.77)	0.7999*** (9.13)	1.2279** (2.36)
Firm	Control	Control	Control	Control	Control
Year	Control	Control	Control	Control	Control
AR(1)					0.00
AR(2)					0.65
Hansen test p-value					0.15
Number of instruments					45
Observations	20,277	20,277	17,153	19,061	18,969
R-squared	0.469	0.216	0.299	0.287	

6. Results and Discussion

6.1 Research Findings

This study investigates the influence of intelligent manufacturing on corporate environmental governance and the mechanisms underpinning this relationship. The results demonstrate a significant positive impact of intelligent manufacturing on the advancement of corporate environmental governance, predominantly through the enhancement of technological innovation capabilities. This outcome is in harmony with existing literature that highlights the role of technological innovation in fostering corporate environmental performance, thereby emphasizing the critical function of technological progress in the sustainable development trajectory of corporations (Bloom et al., 2010; Shapiro and Walker, 2018). Following a comprehensive suite of robustness tests, including Two-Stage Least Squares (2SLS), Propensity Score Matching (PSM), analysis with a one-period lagged independent variable, and the System Generalized Method of Moments (SYS-GMM) approach, our findings have proven to be highly robust. These methodologies have not only mitigated potential endogeneity concerns but have also taken into account temporal lag effects and the intrinsic characteristics of dynamic panel data. This multifaceted approach has fortified the statistical validation of the research conclusions. Moreover, this study echoes the Porter Hypothesis, which suggests that stringent environmental regulations can act as a catalyst for corporate innovation, leading to concurrent environmental and economic advantages (Porter and Van der Linde, 1995). The study's findings extend this hypothesis, illustrating that intelligent manufacturing, as an emergent production paradigm, offers the dual benefit of enhancing production efficiency and fostering corporate environmental governance through the agency of technological innovation.

6.2 Practical Implications

The findings of this study carry substantial practical implications for both the corporate sector and policymakers. Initially, for corporate decision-makers, this research underscores the critical role of intelligent manufacturing technology in bolstering the efficacy of corporate environmental governance. It is imperative for businesses to regard intelligent manufacturing as a vital instrument in the pursuit of sustainable development goals. This involves formulating long-term strategies that leverage intelligent systems for optimized resource allocation, mitigating environmental risks, and bolstering corporate competitiveness in green markets. Subsequently, the study illuminates the mediating function of technological innovation in the nexus between intelligent manufacturing and investment in environmental governance. This revelation offers businesses a definitive developmental trajectory. Companies are encouraged to dedicate resources to technological innovation, particularly in the research and development of intelligent manufacturing solutions, to nurture the implementation and proliferation of eco-friendly technologies. For policymakers, this study provides empirical evidence that can inform the creation and refinement of industrial policies. Governments can stimulate the adoption of intelligent manufacturing technologies by businesses through incentives such as tax relief, financial assistance, and green financing mechanisms. These measures can propel the industry towards a more environmentally conscious and sustainable trajectory. Furthermore, this study holds instructive value for industry associations and non-governmental organizations. These entities can harness the insights from this research to craft and execute pertinent training initiatives and promotional campaigns. By doing so, they can aid enterprises in gaining a deeper comprehension of intelligent manufacturing technologies and facilitate their utilization in achieving environmental governance objectives.

6.3 Management Inspiration

This study imparts a spectrum of policy implications that are crucial for both regulators and corporate entities. Firstly, it is imperative for policymakers to acknowledge the transformative potential of intelligent manufacturing technology in enhancing corporate environmental governance. Secondly, corporate management should accord significant value to the intermediary role that technological innovation plays in the dynamic interplay between intelligent manufacturing and environmental governance. Businesses are encouraged to amplify their research and development (R&D) expenditures, with a particular focus on technological domains that are conducive to environmental sustainability. Moreover, companies ought to adopt a long-term investment perspective when assessing their commitments to environmental governance. It is essential to regard environmental governance not as a mere short-term expenditure but as a strategic long-term investment. Such an investment is poised to yield enduring benefits for the corporation by enhancing its reputation, mitigating potential environmental risks, and curtailing compliance costs.

6.4 Limitations and Future Prospects

This study has indeed advanced our comprehension of how intelligent manufacturing influences corporate investment in environmental governance, but it also recognizes its inherent limitations and suggests opportunities for future inquiry. Initially, the study's focus on Chinese manufacturing firms listed in Shanghai and Shenzhen presents a starting point for research expansion. Future studies should consider a more expansive and varied sample, encompassing companies across diverse geographies and industries to enhance the generalizability and comparative scope of the findings. Building upon the multidimensional nature of intelligent manufacturing, this study has primarily examined its aspects related to artificial intelligence, the Internet, big data, and value chain technologies. Future research is encouraged to delve deeper into less explored facets of intelligent manufacturing, such as supply chain management and customer relationship management, to uncover their distinct influences on environmental governance. This approach will add layers to our understanding of intelligent manufacturing's comprehensive impact. Moreover, while this study has illuminated the immediate effects of intelligent manufacturing on corporate environmental investments, it also paves the way for investigations into the enduring consequences and broader benefits of these investments. Longitudinal studies could reveal how a company's ongoing dedication to environmental governance influences its financial health, market standing, and societal influence over time. Lastly, although technological innovation has been considered as a mediating variable in this study, the complex interplay between intelligent manufacturing and environmental governance likely involves additional mechanisms. Future research should aim to incorporate a wider array of potential mediators, such as organizational culture, leadership behaviors, and employee engagement, to shed light on the intricate pathways through which intelligent manufacturing shapes corporate environmental governance.

References

Ahuja, G., & Lampert, C. M. (2001). Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal, 22*(6-7), 267-294. https://doi.org/10.1002/smj.176

Aluko, O. A., Opoku, E. E. O., & Ibrahim, M. (2021). Investigating the environmental effect of globalization: Insights from selected industrialized countries. *Journal of Environmental Management, 281*, 111892. https://doi.org/10.1016/j.jenvman.2020.111892

Aragón-Correa, J. A., & Sharma, S. (2003). A Contingent Resource-Based View of Proactive Corporate Environmental Strategy. *Academy of Management Review, 28*(1), 71-88. https://doi.org/10.5465/amr.2003.8925233

Arellano, M., & Bover, O. (1995). Another Look at the Instrumental Variable Estimation of Error-Components Models. *Journal of Econometrics, 68*(1), 277-297. https://doi.org/10.1016/0304-4076(94)01642-D

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

Bloom, N., Genakos, C., Martin, R., & Sadun, R. (2010). Modern Management: Good for the Environment or Just Hot Air? *The Research Online Documents on Economics* (120), 551-572. https://doi.org/10.1111/j.1468-0297.2010.02351.x

Blundell, R., & Bond, S. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics, 87*, 115-143. https://doi.org/10.1016/S0304-4076(98)00009-8

Brynjolfsson, E., & Hitt, L. M. (2000). Beyond Computation: Information Technology, Organizational Transformation and Business Performance. *Journal of Economic Perspectives, 14*(4), 23-48. https://doi.org/10.1257/jep.14.4.23

Chen, H., Yang, D., Zhang, J. H., & Zhou, H. (2020). Internal controls, risk management, and cash holdings. *Journal of Corporate Finance, 64*, 101695. https://doi.org/10.1016/j.jcorpfin.2020.101695

Coase, R. H. (1937). The Nature of the Firm. *Economica, 4*(16), 386-405. https://doi.org/10.1111/j.1468-0335.1937.tb00002.x

Cui, Y., Kara, S., & Chan, K. C. (2020). Manufacturing big data ecosystem: A systematic literature review. *Robotics and Computer-Integrated Manufacturing, 62*, 101861. https://doi.org/10.1016/j.rcim.2019.101861

Evans, P. C., & Annunziata, M. (2012). Industrial Internet: Pushing the boundaries of minds and machines. Boston: General Electric.

Fazzari, S. M., Hubbard, R. G., & Petersen, B. C. (1988). Financing Constraints and Corporate Investment. *Brookings Papers on Economic Activity, (1)*, 141-195. https://doi.org/10.3386/w2387

Fu, H., Jiang, Q., Cifuentes-Faura, J., & Chen, Q. (2024). Corporate environmental governance and firm value: Beyond greenwashing for sustainable development. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-023-04375-7

Giret, A., Garcia, E., & Botti, V. (2016). An engineering framework for service-oriented intelligent manufacturing systems. *Computers in Industry, 81*(2), 116-127. https://doi.org/10.1016/j.compind.2016.02.002

Iqbal, N., Xu, J. F., Fareed, Z., Wan, G., & Ma, L. (2022). Financial leverage and corporate innovation in Chinese public-listed firms. *European Journal of Innovation Management, 25*(1), 299-323. https://doi.org/10.1108/EJIM-07-2020-0304

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic Localization of Knowledge

Spillovers as Evidenced by Patent Citations. *The Quarterly Journal of Economics, 108*(3), 577-598. https://doi.org/10.2307/2118401

Jiang, J. X., Wang, L. Y., & Wang, K. P. (2019). Big N auditors and audit quality: new evidence from quasi-experiments. *The Accounting Review, 94*(1), 205-227. https://doi.org/10.2308/accr-52106

Kang, Y.-S., & Kim, B.-Y. (2012). Ownership structure and firm performance: Evidence from the Chinese corporate reform. *China Economic Review, 23*(2), 471-481. https://doi.org/10.1016/j.chieco.2012.03.006

Karabegovic, I., & Husak, E. (2018). The fourth industrial revolution and the role of industrial robots with focus on china. *Journal of Engineering and Architecture, 6*(1), 67-75. https://api.semanticscholar.org/CorpusID:208233986

Keller, W. (2002). Geographic Localization of International Technology Diffusion. *American Economic Review, 92*(1), 120-142. https://doi.org/10.1257/000282802760015630

Klassen, R. D., & McLaughlin, C. P. (1996). The impact of environmental management on firm performance. *Management Science, 42*(8), 1199-1214. https://doi.org/10.1016/j.jclepro.2021.126057

Kumar, M., & Rodrigues, V. S. (2020). Synergetic effect of lean and green on innovation: A resource-based perspective. International Journal of Production Economics, 219, 469-479. https://doi.org/10.1016/j.ijpe.2018.04.007

Lee, J., Bagheri, B., & Kao, H. A. (2015). A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems. *Manufacturing Letters, 3*(1), 8-13. https://doi.org/10.1016/j.mfglet.2014.12.001

Li, J., Wu, Z., Yu, K., & Zhao, W. (2024). The effect of industrial robot adoption on firm value: Evidence from China. *Finance Research Letters, 60*, 104907. https://doi.org/10.1016/j.frl.2023.104907

Li, L. (2018). China's Manufacturing Locus in 2025: With a Comparison of "Made-in-China 2025" and "Industry 4.0". *Technological Forecasting and Social Change, 135*, 66-74. https://doi.org/10.1016/j.techfore.2017.05.028

Li, L. S., Shi, X. A., & Liu, J. (2019). 40 Years of Manufacturing in China: Intelligentization Process and Outlook. *China Soft Science*, (1), 1-9+30. (in Chinese)

Liu, Y. (2023). Impact of industrial robots on environmental pollution: evidence from China. *Scientific Reports*, 13, 20769. https://doi.org/10.1038/s41598-023-47380-6

Lu, N., Zhou, W., & Dou, Z. W. (2023). Can intelligent manufacturing empower manufacturing? – An empirical study considering ambidextrous capabilities. *Industrial Management & Data Systems, 123*(1), 188-203. https://doi.org/10.1108/IMDS-11-2021-0718

Lyu, W., Wang, T., Hou, R., & Liu, J. (2023). Going green and profitable: The impact of smart manufacturing on Chinese enterprises. *Computers & Industrial Engineering*, 181, 109324. https://doi.org/10.1016/j.cie.2023.109324

Machado, C. G., Winroth, M. P., & Ribeiro Da Silva, E. H. D. (2020). Sustainable Manufacturing in Industry 4.0: *An Emerging Research Agenda. International Journal of Production Research, 58*(5), 1462-1484. https://doi.org/10.1080/00207543.2019.1652777

Nakandala, D., Yang, R., Lau, H., & Weerabahu, S. (2023). Industry 4.0 technology capabilities, resilience and incremental innovation in Australian manufacturing firms: a serial mediation model. *Supply Chain Management, 28*(4), 760-772. https://doi.org/10.1108/SCM-08-2022-0325

Orlitzky, M., Schmidt, F. L., & Rynes, S. L. (2003). Corporate Social and Financial Performance: A Meta-Analysis. *Organization Studies, 24*(3), 403-441. https://doi.org/10.1177/0170840603024003910

Osei Opoku, E. E., & Aluko, O. A. (2021). Heterogeneous effects of industrialization on the environment: Evidence from panel quantile regression. *Structural Change and Economic Dynamics, 59*, 174-184. https://doi.org/10.1016/j.strueco.2021.08.015

Porter, M. E., & Van der Linde, C. (1995). Toward a New Conception of the Environment-Competitiveness Relationship. *Journal of Economic Perspectives, 9*(4), 97-118. https://doi.org/10.1257/jep.9.4.97

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics, 71*(1), 135-158. https://doi.org/10.1111/j.1468-0084.2008.00542.x

Rothaermel, T., & Deeds, L. (2004). Exploration and Exploitation Alliances in Biotechnology: A System of New Product Development. Strategic Management Journal, 25(3), 201-221. https://doi.org/10.1002/smj.376

Sarbu, M. (2022). The impact of industry 4.0 on innovation performance: Insights from German manufacturing and service firms. *Technovation, 113*, 102415.

Shapiro, J. S., & Walker, R. (2018). Why is Pollution from U.S. Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade. *American Economic Review, 108*(12), 3814-3854. https://doi.org/10.1257/aer.20151272

Tao, F., Zuo, Y., Xu, L. D., et al. (2014). IoT-based intelligent perception and access of manufacturing resource toward cloud manufacturing. *IEEE Transactions on Industrial Informatics, 10*(2), 1547-1557. https://doi.org/10.1109/TII.2014.2306397

Wang, Z., Zhang, T., Ren, X., & Shi, Y. (2024). AI adoption rate and corporate green innovation efficiency: Evidence from Chinese energy companies. *Energy Economics, 132,* 107499. https://doi.org/10.1016/j.eneco.2024.107499

Wei, X., Jiang, F., Chen, Y., & Hua, W. (2024). Towards green development: The role of intelligent manufacturing in promoting corporate environmental performance. *Energy Economics, 131*, 107375. https://doi.org/10.1016/j.eneco.2024.107375

Wintoki, M. B., Linck, J. S., & Netter, J. M. (2012). Endogeneity and the Dynamics of Internal Corporate Governance. Journal of Financial Economics, 105, 581-606. https://doi.org/10.1016/j.jfineco.2012.03.005

Yu, F., Wang, L., Li, X. (2020). The effects of government subsidies on new energy vehicle enterprises: The moderating role of intelligent transformation. *Energy Policy,* 141. https://doi.org/10.1016/j.enpol.2020.111463

Zhang, Q., Zhang, F., Mai, Q. (2022). Robot adoption and green productivity: Curse or Boon. *Sustainable Production and Consumption, 34*, 1-11. https://doi.org/10.1016/j.spc.2022.08.025

Zheng, P., Wang, H., Sang, Z., Zhong, R. Y., Liu, Y., Liu, C., et al. (2018). Smart manufacturing systems for Industry 4.0: conceptual framework, scenarios, and future perspectives. *Frontiers in Mechanical Engineering, 13*, 137-150. https://doi.org/10.1007/s11465-018-0499-5

Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent manufacturing in the context of industry 4.0: *a review. Engineering, 3*(5), 616-630.

resolution/the_international_comparative_legal_guide_to_enforcement_of_foreign_judgments_2018.pdf?sfvrsn=d6d53a47_2

Standing International Forum of Commercial Courts. (2020). *2nd Edition of the SIFoCC Multilateral Memorandum on Enforcement of Commercial Judgments for Money*. https://www.judiciary.uk/wp-content/uploads/2020/12/Memorandum-on-Enforcement-2nd-Edition.pdf

The Supreme People's Court of the People's Republic of China. (2019). *Opinions of the Supreme People's Court on Further Providing Judicial Services and Guarantees by the People's Court for the Belt and Road Initiative[(2019)Fafa No.29]*. https://english.court.gov.cn/2021-10/23/c_761783.htm

The Supreme People's Court of the People's Republic of China. (2022). *Minutes of the National Symposium on the Foreign-related Commercial and Maritime Trial Work of Courts* [CLI.3.5114710(EN)]. https://pkulaw.com/en_law/bffd20e9aee35db2bdfb.html

Zhang, W. L. (2014). *Recognition and Enforcement of Foreign Judgments in China:rule, practice and strategies*. Alphen aan den Rijn, The Netherlands: Kluwer Law International.

张先春. (2021). "一带一路"背景下外国民商事判决承认和执行中推定互惠原则的适用. *People's Judicature Application*, Vol.912, 63. https://kns.cnki.net/kcms2/article/abstract?v=RkYMyaebi8VANtEld9beLAAI2LRTUkc9ZszKYO4dkEQbZ1gWj7wihN3wBeadLCYxIndQdEaI0B_sBLNOOR-Bxs7KLFTt5NkmqpGlodm9B501zEaIsCpdjflXETUyqirevYKlk6sQNAU=&uniplatform=NZKPT&flag=copy