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Intelligent Manufacturing Dynamic Capabilities and Corporate Green Innovation: Empirical Evidence from China

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Abstract

Against the backdrop of accelerating digitalization and intelligent transformation, intelligent manufacturing has emerged as a key driver of green transition in manufacturing. However, evidence on its effects and the mechanisms underlying corporate green innovation remains limited. Using panel data of Chinese A-share manufacturing firms from 2011 to 2023, this study exploits the pilot policy of intelligent manufacturing as a quasi-natural experiment and employs a difference-in-differences (DID) approach. Results indicate that intelligent manufacturing significantly enhances firms' green innovation, with robust evidence across multiple checks. Mechanism analysis shows that this effect operates through an integrated dynamic capability channel, whereby firms strengthen their adaptive capability, absorptive capability for green knowledge and digital technologies, and innovation capability through technological integration, thereby improving green innovation. Moreover, intellectual property protection strengthens this mechanism by increasing innovation returns and enhancing the capability-to-innovation conversion efficiency. Heterogeneity results suggest stronger effects in non-high-tech firms, non–heavily polluting industries, and technology-intensive firms, reflecting differences in digital readiness and resource reconfiguration capacity. Overall, this study provides causal evidence on the green effects of intelligent manufacturing, clarifies internal mechanisms, and highlights institutional and firm-level heterogeneity, with implications for digital-driven green transformation and policy design.

Keywords: intelligent manufacturing; green innovation; dynamic capabilities; intellectual property protection

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1. Introduction

Against the global backdrop of intensifying efforts to address climate change and tightening resource constraints, sustainable development has evolved from a peripheral concern to a global consensus and central agenda. Within this context, China's "dual-carbon" strategy—aimed at achieving carbon peaking and carbon neutrality—has exerted strong regulatory pressure on firms, particularly those in traditional manufacturing industries, creating an urgent need for structural transformation [1]. Green innovation, encompassing technological, product, and managerial innovations that reduce environmental impacts and enhance resource-use efficiency, has emerged as a core strategic driver rather than merely a component of corporate social responsibility.

From a theoretical perspective, green innovation not only has a compliance-driven defensive role but also an offensive role grounded in the Porter Hypothesis [2,3]. The Porter Hypothesis argues that well-designed environmental regulations do not necessarily increase firms' costs; instead, they may stimulate continuous innovation through an "innovation compensation effect," thereby potentially enhancing rather than undermining firm competitiveness. This mechanism operates through a sequential three-channel framework. First, environmental constraints induce firms to reassess and restructure existing production processes, triggering technological upgrading and process optimization under regulatory pressure. Second, these technological adjustments generate learning effects and organizational restructuring, improving resource allocation efficiency and partially or even fully offsetting compliance costs through enhanced operational efficiency. Third, such efficiency gains and technological improvements enable firms to develop greener products and processes, strengthening cost efficiency, enhancing product differentiation, facilitating market expansion, and ultimately transforming environmental pressure into sustained competitive advantage. However, this mechanism critically depends on firms' innovative capacity. Only firms with sustained innovation capabilities can effectively translate environmental constraints into productivity gains through continuous technological upgrading. Otherwise, environmental regulation may fail to trigger innovation compensation and instead lead to higher compliance costs, resource misallocation, and declining competitiveness. Accordingly, the Porter Hypothesis holds conditionally rather than universally, depending on firms' innovation and adaptive capacities.

In response to the latest wave of industrial revolution and the imperative of achieving high-quality manufacturing development, the Chinese government has been actively promoting a digital transformation strategy centered on intelligent manufacturing. Since 2015, a series of policies—from "Made in China 2025" to the "Intelligent Manufacturing Pilot Demonstration Program"—have been systematically implemented to guide firms in leveraging next-generation information technologies to transform the entire production process intelligently, thereby enhancing operational efficiency and manufacturing flexibility. Within the framework of the Porter Hypothesis, intelligent manufacturing policy may function as a technological and institutional mechanism that enables firms to transform environmental regulatory pressure into green innovation incentives. On the one hand, intelligent manufacturing integrates technologies such as the Internet of Things (IoT), Industrial Internet of Things (IIoT), and data-driven systems to facilitate real-time monitoring and intelligent coordination of production processes. These digital technologies reduce information asymmetry and the costs of adopting green technologies while providing digital infrastructure that supports green innovation [4]. On the other hand, intelligent manufacturing generates efficiency gains and improves resource allocation [5], thereby alleviating the financial and resource constraints associated with green R&D activities. In doing so, intelligent manufacturing strengthens the "innovation compensation effect" emphasized by the Porter Hypothesis, enabling firms to convert environmental regulatory pressure into sustained innovation incentives more effectively.

However, the impact of intelligent manufacturing on green innovation is not necessarily positive. Although intelligent manufacturing may reinforce the "innovation compensation effect" emphasized by the Porter Hypothesis, its implementation also requires substantial financial investment, technological upgrading, and organizational restructuring. In practice, firms may prioritize productivity-enhancing digital upgrading and equipment renewal over long-term and high-risk green R&D activities. Under resource constraints, intensive investment in intelligent manufacturing may divert financial resources and managerial attention away from green innovation, thereby generating a potential crowding-out effect. Moreover, efficiency gains derived from intelligent manufacturing do not automatically translate into sustained green innovation outcomes. Without sufficient organizational capability to integrate digital transformation into innovation activities, firms may use productivity gains primarily to support production expansion and short-term performance objectives rather than green technological innovation. In this context, intelligent manufacturing may improve operational efficiency while failing to generate sustained green innovation outcomes. Whether intelligent manufacturing ultimately promotes or constrains green innovation, therefore, remains an open empirical question.

Building on the preceding discussion of intelligent manufacturing and green innovation, this study utilizes data from Chinese A-share listed firms between 2011 and 2023 and links it to relevant intelligent manufacturing policies. A difference-in-differences (DID) model is constructed to systematically examine the impact of these policies on firms' green innovation and the underlying mechanisms. The contributions of this study are threefold. Theoretically, it empirically bridges two major research domains—macro-level industrial policy and micro-level green innovation. While the academic community broadly recognizes the importance of intelligent manufacturing and green development, few studies have examined this relationship from a policy evaluation perspective or provided robust causal evidence on whether government-led intelligent transformation effectively promotes firms' green innovation. By connecting macro-level policy effects with micro-level firm behavior through a rigorous empirical design, this study provides direct evidence for understanding how government-guided technological transformations translate into firms' sustainable performance, thereby enriching the cross-disciplinary literature at the intersection of innovation policy and environmental management. Practically, the findings offer actionable policy and managerial insights. First, by assessing the "green spillover effects" of intelligent manufacturing policies, this study provides empirical guidance for governments seeking to optimize policy design and achieve strategic synergy between intelligent transformation and green development. Second, by elucidating the pathways through which digitalization enables green innovation, it equips managers with knowledge to leverage policy benefits, thereby achieving high-quality development while balancing efficiency improvements and environmental responsibility.

2. Literature Review and Research Hypotheses

2.1. Intelligent Manufacturing and Corporate Green Innovation

The resource-based view (RBV) posits that performance differences among firms fundamentally stem from the heterogeneity and imperfect mobility of the resources they possess [6]. Given this foundation, it is essential to identify which types of resources and capabilities contribute to sustained competitive advantage. Specifically, resources and capabilities that are valuable, rare, inimitable, and non-substitutable (VRIN) serve as the key pillars for establishing and maintaining such advantages, particularly in dynamic environments where the strategic importance of unique resources is amplified [7]. Within the resource-based theoretical framework, digital transformation can be considered a strategic resource. It fundamentally leverages digital technologies to reshape firms' business processes, management practices, and organizational capabilities, which in turn facilitates their transition toward high-quality development [8]. From a resource-based perspective, digital transformation can be conceptualized as a process of integrating resources that are both scarce and inimitable. By leveraging this integration, firms not only enhance their resource allocation efficiency and organizational agility but also, in turn, establish a solid resource foundation for the sustained advancement of green innovation. In the digital era, firms' ability to acquire and efficiently deploy critical resources increasingly depends on the depth and breadth of their digital transformation. By leveraging their resource endowments and developmental needs to embed digital technologies within their business ecosystems, firms enhance strategic responsiveness in complex and dynamic environments, optimize production, marketing, and management processes, and thereby drive the reconstruction and upgrading of value creation mechanisms.

Intelligent manufacturing represents the concrete manifestation of digital transformation in the manufacturing sector. By integrating artificial intelligence, the Internet of Things, big data analytics, and machine learning, it enables smarter, more automated, and more flexible management of production processes. These technological advancements enhance both resource allocation efficiency and environmental performance, thereby laying a robust technical foundation for firms' green innovation. At the firm level, intelligent manufacturing operates through multiple internal channels—including enhanced information flows, the accumulation of human capital, and strengthened financial support—that facilitate the agglomeration and efficient deployment of innovation inputs. Through these pathways, firms not only strengthen their innovation capabilities but also achieve the optimization and upgrading of their overall innovation structures. Compared with traditional manufacturing models, intelligent manufacturing achieves deeper integration between information technologies and production technologies [9]. This integration not only accelerates the digital and intelligent transformation of manufacturing processes but also expands the technological and organizational space required for sustained green innovation. Intelligent manufacturing transforms production systems by enabling automation-based labor substitution through smart technologies [10]. This transformation enhances the flexibility and precision of production processes, thereby reducing resource use and emissions. These improvements in operational efficiency and environmental performance not only lower compliance costs and pollution-related risks but also reinforce firms' incentives to engage in green innovation. On the managerial side, firms integrate big data, the Internet of Things, and artificial intelligence technologies to enable real-time sensing and intelligent processing of massive operational data [11]. By combining historical and real-time information, these capabilities support trend forecasting and operational optimization, thereby providing precise and efficient technical support for decision-making [12]. Through enhanced decision-making, digital technologies facilitate the aggregation and effective deployment of heterogeneous innovation inputs, enhancing their integration with green innovation processes [13]. Consequently, firms strengthen their strategic responsiveness to dynamic environmental conditions and improve their green innovation performance.

Based on this, the study proposes:

Hypothesis 1 (H1). *Intelligent manufacturing policies contribute to enhancing firms' green innovation capabilities.*

2.2. Intelligent Manufacturing, Dynamic Capabilities, and Green Innovation

The enhancement of dynamic capabilities facilitates firms' green innovation. A firm's resources and capabilities are typically interdependent and tightly integrated, forming the basis of its competitive advantage [14]. Dynamic capabilities theory posits that in rapidly changing environments, a firm's existing core competencies may shift from sources of competitive advantage to constraints that hinder its development. Traditional capabilities theory, which primarily emphasizes static resource-based advantages, is therefore insufficient to fully explain how firms form and sustain competitive advantage in dynamic markets. To address these limitations, dynamic capabilities focus on the processes through which firms continuously renew, reconfigure, and integrate their resource base and capability systems in response to external environmental changes, even when constrained by existing path dependencies and market positions [15]. Building on this theoretical foundation, dynamic capabilities are further defined as a firm's ability to integrate, build, and reconfigure both internal and external resources to adapt to dynamic and uncertain environments. Through these processes, firms can continuously respond to evolving conditions and sustain their competitive advantage over time [16]. From the dynamic capabilities perspective, a firm's ability to adapt and innovate in response to external environmental changes is manifested through a set of core processes. First, firms must develop strong environmental sensing capabilities, defined as the sensitivity and foresight to detect and interpret changes in the external environment. Firms with well-developed sensing capabilities can effectively identify green pressures and emerging market opportunities arising from regulations, consumer preferences, and competitor actions. This, in turn, enhances their strategic alertness and their ability to respond innovatively to dynamic environmental changes [17]. Second, firms must be capable of effectively integrating and deploying resources to leverage external opportunities through innovation activities, strategic investments, and market actions. Firms that exhibit higher agility and efficiency in these processes—key manifestations of dynamic capabilities—are better positioned to capitalize on emerging opportunities, thereby enhancing their green innovation performance [18]. Finally, firms need the capability to dynamically adjust and optimize internal resources and organizational structures to enhance overall adaptability and innovation potential. This capability is reflected in effective organizational transformation, which involves breaking free from entrenched routines, institutionalizing sustainable practices, and fundamentally transitioning from traditional operations to environmentally responsible operations. Firms that excel in these processes demonstrate strong internal innovation and reconfiguration abilities, thereby supporting the sustained development of green innovation [19]. The strength of a firm's dynamic capabilities not only affects the extent to which it can leverage the potential of digital technologies but also largely determines its ability to sustain green innovation in uncertain environments. By enabling firms to effectively exploit digital technologies, dynamic capabilities help translate technological potential into continuous green innovation. Green innovation serves as a crucial strategic response for addressing environmental regulations, shifting market demands, and sustainability pressures. Given the inherent uncertainty of this process, firms must continuously adjust their resource allocation and innovation pathways to maintain long-term competitive advantage. With this in mind, dynamic capabilities theory provides a robust analytical framework for understanding these ongoing processes of adaptation and reconfiguration. Based on the above analysis, a firm's dynamic capabilities can be further classified into three key dimensions: innovation capability, absorptive capability, and adaptive capability [20].

Innovation capability forms the foundation for a firm's green innovation. According to Schumpeter's theory, innovation involves the recombination of production factors and the reconfiguration of their allocation, driven by technological progress, which induces fundamental changes in production conditions. Building on this premise, green innovation extends the concept of innovation to target improved environmental performance and sustainable development. Absorptive capability is a critical enabler of a firm's green innovation. Firms with strong absorptive capabilities can accurately collect and process real-time information on internal and external changes, providing essential support for both data-driven analysis and decision-making in green innovation activities [21]. Moreover, this capability allows firms to identify, assimilate, and transform external knowledge into innovation elements with environmental value. Notably, even when some external knowledge initially has negative environmental impacts, it can be recombined to drive green innovation. In this way, absorptive capability not only supports effective use of information but also facilitates the conversion of diverse knowledge into sustainable innovation outcomes. Adaptive capability is a critical driver of a firm's green innovation. Given the long investment payback periods and complex risk structures inherent in green innovation, firms with strong adaptive capabilities can more effectively respond to changes in the external environment by flexibly adjusting their R&D strategies and directions, thereby enhancing the continuity and effectiveness of green innovation activities. Furthermore, such firms are better positioned to collaborate with stakeholders, which further facilitates the development and implementation of sustainable innovations [22].

Intelligent manufacturing enhances firms' dynamic capabilities primarily through the improvement of absorptive capability, innovation capability, and adaptive capability. From the perspective of dynamic capability theory, intelligent manufacturing enables firms to sense external changes, integrate heterogeneous resources, and continuously reconfigure organizational capabilities in response to environmental uncertainty. First, intelligent manufacturing strengthens firms' absorptive capability by improving the acquisition, integration, and utilization of external knowledge. Absorptive capability refers to firms' ability to identify, assimilate, transform, and apply external knowledge to improve innovation performance and resource allocation efficiency [23]. Supported by digital technologies such as big data, industrial internet, and intelligent information systems, firms are better able to identify valuable heterogeneous knowledge and integrate it with existing technological resources [24]. In addition, the strong spillover effects and connectivity of digital technologies facilitate knowledge sharing and collaborative interaction among multiple innovation actors, thereby promoting open innovation and cross-organizational learning [25]. Second, intelligent manufacturing promotes firms' innovation capability by accelerating technological integration and digital innovation processes. Innovation capability refers to firms' ability to integrate internal resources and technological competencies and transform them into market-competitive products and services [26]. Digital transformation driven by intelligent manufacturing reshapes firms' innovation logic, organizational structure, and innovation processes, thereby improving product design, process optimization, and innovation diffusion efficiency [27–30]. Through data-driven decision-making and intelligent production systems, firms can shorten innovation cycles, improve R&D efficiency, and enhance technological upgrading capability. Third, intelligent manufacturing enhances firms' adaptive capability by improving organizational flexibility and environmental responsiveness. Adaptive capability refers to firms' ability to reconfigure internal resources and maintain strategic flexibility under changing external environments. By integrating intelligent technologies and automated management systems into production and operation processes, intelligent manufacturing improves operational coordination, reduces process delays and human errors, and strengthens firms' responsiveness to market and environmental changes [31]. Moreover, digital technologies improve firms' capability to perceive, predict, and manage risks in complex environments, thereby reducing uncertainty and enhancing organizational resilience. Overall, intelligent manufacturing promotes the formation and evolution of dynamic capabilities through the interconnected enhancement of absorptive, innovation, and adaptive capabilities, thereby providing an important capability foundation for firms' green innovation activities.

Based on these, we propose:

Hypothesis 2 (H2). *Intelligent manufacturing policies enhance firms' dynamic capabilities, thereby promoting green innovation.*

2.3. Intelligent Manufacturing, Intellectual Property Protection, and Green Innovation

Green innovation, as a form of knowledge-intensive innovation, is characterized by firm-specificity and scarcity, reflecting the distinctive knowledge bases and technological capabilities embedded within individual firms. Because such innovations often generate environmental and social benefits that exceed the private economic returns firms are able to appropriate, they give rise to substantial positive externalities [32]. In other words, the social value created by green innovation typically surpasses the private benefits captured by innovating firms. However, the knowledge and technological spillovers associated with green innovation may also facilitate imitation and replication by other firms. While these spillovers can lower industry-wide R&D costs and enhance overall social welfare, they may simultaneously erode the expected returns of pioneering firms by limiting their ability to appropriate the full benefits of their innovation investments. Consequently, these dynamics may weaken firms' incentives to sustain long-term technological research and innovation efforts.

In this context, intellectual property (IP) protection serves as a fundamental institutional mechanism that safeguards innovation outcomes and incentivizes firm-level innovation. By granting innovators exclusive rights for a specified period, IP protection enables firms to capture reasonable returns from their innovative efforts, thereby promoting sustained investment in research and development [33,34]. The significance of IP protection is also reflected at the national policy level: the report of the 20th National Congress of the Communist Party of China emphasizes strengthening the legal system for IP rights and improving foundational institutional arrangements that support comprehensive innovation. These measures aim to enhance the efficiency of innovation resource allocation and to reinforce property rights-based incentives for knowledge outcomes. Empirical evidence further underscores the positive role of IP protection in fostering innovation, indicating that stronger protection not only increases firms' expected returns but also acts as a key driver of sustained innovation activities [35].

In the digital era, intellectual property infringement has become increasingly covert, complex, and frequent, posing greater challenges to the protection of innovations and placing higher demands on the efficiency and responsiveness of existing mechanisms. The continuous advancement of information technologies has not only accelerated the iteration of digital innovations and shortened their application and commercialization cycles but also increased the ease of unauthorized replication, as digital information is intangible and highly replicable. Consequently, the costs of patent imitation and infringement have decreased, and rights holders often face difficulties in timely detection and evidence collection. The resulting frequent and widespread infringement cases not only harm the interests of rights holders but also disrupt normal market order, thereby undermining sustained innovation and high-quality industrial development [36].

Effective intellectual property protection limits the replication and imitation of innovations by competitors, ensuring that innovators can capture reasonable returns and thereby strengthening their incentives for sustained research and development. Under the implementation of intelligent manufacturing policies, IP protection and these policies operate in a complementary manner. Intelligent manufacturing facilitates the digitalization and intelligent transformation of firms' technologies, processes, and resources, creating practical pathways for green innovation. Concurrently, IP protection maintains market order and provides institutional incentives, ensuring that the innovations generated through intelligent manufacturing can realize expected returns. Together, these mechanisms reinforce firms' capacity and motivation to engage in sustained green innovation.

Thus, we propose:

Hypothesis 3 (H3). *Enhancing intellectual property protection can effectively reinforce the positive linkage between intelligent manufacturing policies and green innovation.*

The overall theoretical model is illustrated in Figure 1.

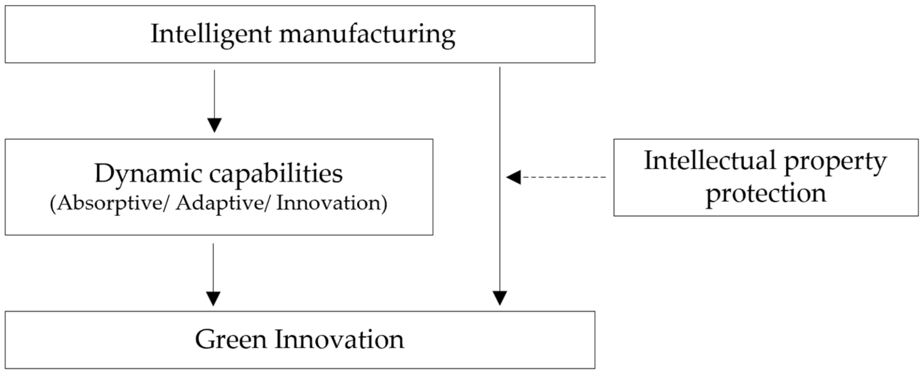


Figure 1. Theoretical framework.

3. Research Design

3.1. Model Specification

To examine the impact of the intelligent manufacturing policy on firms' green innovation, this study constructs the benchmark econometric model shown in Equation (1). As the intelligent manufacturing pilot policy was implemented across manufacturing firms in a staggered manner, it constitutes a quasi-natural experiment. Accordingly, this study employs a multi-period difference-in-differences (*DID*) framework to identify the policy's net effect on firms' green innovation. Specifically, the DID approach captures the differential changes in green innovation between pilot and non-pilot firms before and after policy implementation, while controlling for time-invariant firm heterogeneity and common time shocks.

$$GI_{it} = \alpha_0 + \alpha_1 DID_{it} + \alpha_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

where the subscript i denotes the individual firm and t denotes the year. GI_{it} is the dependent variable representing the firm's green innovation output. DID_{it} is the key independent variable, defined as a dummy equal to 1 if the firm is located in a pilot region in the current year or any subsequent year, and 0 otherwise. X_{it} is a vector of control variables. μ_i captures firm-specific fixed effects, δ_t represents year fixed effects, and ε_{it} is the stochastic error term. In Equation (1), the coefficient of primary interest is α_1, which measures the effect of the intelligent manufacturing policy on firms' green innovation. A significantly positive α_1 would indicate that the intelligent manufacturing policy promotes corporate green innovation.

Meanwhile, to examine the mediating effects of the three dimensions of dynamic capabilities in the relationship between intelligent manufacturing and firms' green innovation, the following mediation effect model is constructed to examine:

$$DC_{it} = \beta_0 + \beta_1 DID_{it} + \beta_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

$$GI_{it} = \gamma_0 + \gamma_1 DID_{it} + \gamma_2 DC_{it} + \gamma_3 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{3}$$

Here, DC_{it} denotes dynamic capabilities, which comprise three dimensions: innovation capability, absorptive capability, and adaptive capability. Equation (2) examines the impact of the intelligent manufacturing policy on firms' dynamic capabilities. Equation (3) extends the baseline model by incorporating dynamic capabilities to test their mediating effect on the policy–green innovation relationship. Firm and year fixed effects are included to ensure robustness.

To examine the moderating effect of intellectual property protection on the relationship between intelligent manufacturing and firms' green innovation, the following model for testing the moderating effect is constructed:

$$GI_{it} = \theta_0 + \theta_1 DID_{it} + \theta_2 IPP_{it} + \theta_3 DID_{it} * IPP_{it} + \theta_4 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (4)$$

Here, IPP_{it} denotes the level of intellectual property protection. Equation (4) examines the moderating effect of intellectual property protection (IPP) on the relationship between the intelligent manufacturing policy and firms' green innovation. The significance of the interaction term $DID_{it} \times IPP_{it}$ captures the moderating effect. Firm and year fixed effects are included to ensure robustness.

3.2. Variables

3.2.1. Green Innovation

$$GI_{it} = \ln(GIP_{it} + 1) \quad (5)$$

Equation (5) is used to explain the definition and measurement of the firm's green innovation variable. In Equation (5), GI_{it} represents the firm's overall level of green innovation, and GIP_{it} denotes the number of green patent applications filed by the firm. Although green innovation encompasses multiple dimensions, including technological and organizational innovations, current research predominantly focuses on green technological innovation [37]. Current approaches to measuring green technological innovation are commonly categorized into input-based, efficiency-based, and output-based methods. Input-based methods primarily focus on innovation inputs, such as R&D expenditure and human capital, but may not fully capture actual innovation outcomes. Efficiency-based methods assess green innovation performance by evaluating the efficiency of transforming innovation inputs into outputs [38], with common approaches including Data Envelopment Analysis and Stochastic Frontier Analysis. In contrast, output-based methods place greater emphasis on the actual outcomes of green technological innovation and typically rely on indicators such as green patents [39]. Accordingly, this study uses the total number of green patent applications filed by firms as the measurement indicator. Patent data are widely recognized as a reliable proxy for firms' innovation output [40], and by leveraging the International Patent Classification (IPC) system, patents related to green technologies can be accurately identified. Compared with granted patents, patent applications offer a more timely indicator of firms' ongoing innovation activities, given the typical one- to two-year lag between application and grant. Moreover, the number of green patent applications is commonly employed in the literature as a measure of green technological innovation output [41].

3.2.2. Intelligent Manufacturing Pilot

The interaction term for the smart manufacturing pilot policy is defined as ($DID_{it} = treat_i \times post_t$). To construct the treatment group, we manually identified listed firms participating in smart manufacturing pilot demonstration projects, based on the lists published by the Ministry of Industry and Information Technology (MIIT) and supplemented by Qichacha data. Firms classified as PT, ST, or *ST, as well as those with severe missing financial data, were excluded to ensure sample quality. The remaining pilot-listed firms constitute the treatment group, while non-pilot firms serve as the control group. Here, $treat_i$ denotes the policy group dummy, taking the value 1 for firms ever included in the smart manufacturing pilot and 0 otherwise. The time dummy, $post_t$ equals 1 for all years from the policy implementation year onward for each treated firm, and 0 for all pre-policy years.

3.2.3. Dynamic Capabilities

Dynamic capabilities embody a set of identifiable key features that display common patterns across organizations [42]. These features can be categorized along multiple dimensions, providing a basis for our dimensional analysis. Moreover, they possess an inherently multidimensional structure, and the identification of these dimensions depends on environmental embeddedness and dynamism [29,43]. We take these environmental contingencies into account. This ensures that our analysis accurately reflects how dynamic capabilities manifest in different organizational contexts. Based on the above discussion of dynamic capabilities, this study analyzes dynamic capabilities from three dimensions. Absorptive capability refers to a firm's ability to effectively identify, acquire, assimilate, transform, and apply external knowledge to improve innovation outcomes and resource efficiency. At its core, it reflects the firm's capacity to recognize external business opportunities and potential risks, as well as to capture key innovation elements [44]. Due to its systemic and multidimensional nature [45], absorptive capability cannot be accurately measured by a single indicator. In this study, we construct a multidimensional indicator system based on firm-level behaviors and use the entropy method to assign objective weights and compute a composite score. Compared with subjective weighting methods, the entropy method captures the informational contribution of each indicator based on data dispersion, thereby reducing bias and enhancing the rigor and accuracy of the measurement. Adaptive capability refers to a firm's ability to maintain a competitive advantage through sustained resource investment in the face of external shocks and environmental uncertainty [46]. It also enables dynamic adjustments in product structures and business models. This capability is reflected not only in the amount of resources a firm possesses but, more importantly, in the flexibility of resource allocation and the speed of response to environmental changes. In strategic management and corporate finance research, firms' adaptation to environmental changes is typically manifested through the dynamic adjustment and reallocation of strategic expenditures, such as R&D investment, capital expenditures, and advertising spending [47,48]. Innovation capability represents a firm's ability to enhance innovation output and organizational performance by integrating innovation elements [49]. It relies on both "hard" inputs, such as R&D intensity, and "soft" supports, such as innovation human capital, which are complementary and equally important [50,51]. Given the differences in scale and numerical range between R&D intensity and human capital, we standardize these indicators before aggregating them into a composite measure to ensure comparability and scientific validity.

Absorptive capacity (*ABC*) is assessed along three dimensions, each capturing a distinct aspect of a firm's ability to acquire, assimilate, and leverage knowledge. Each dimension is first measured individually, and the results are then combined using the entropy method, which leverages objective weighting to derive a comprehensive score. ① Executives' innovation cognition. This dimension constitutes a critical component of top managers' capabilities, which are a key source of an organization's dynamic capabilities. By integrating and optimizing management mechanisms and microfoundations, executives drive the evolution and enhancement of the firm's dynamic capabilities [52]. Given the crucial role of executives' capabilities, their innovation cognition represents a key dimension to be measured. Drawing on the studies of Liu et al. (2025) and Bellstam et al. (2021) [53,54], this study employs a text analysis method to quantify executives' innovation cognition. Specifically, keywords reflecting innovation awareness—such as "innovation," "autonomy," "R&D," "scientific research," "new product," "new technology," "development," "research," and "patent"—are extracted from the firm's annual reports. The total occurrences of these keywords in the board report are counted. The proportion of innovation-related keywords to the total word count of the report is then calculated. This proportion represents the intensity of executives' innovation cognition, capturing the extent to which their cognitive focus on innovation may translate into organizational dynamic capabilities. ② Organizational learning capability. Organizational learning capability is an important aspect of a firm's absorptive capacity, which depends on its prior related knowledge [55]. To measure this dimension, the study uses the proportion of employees with a postgraduate or higher degree. This indicator reflects the overall educational level of employees. Moreover, it captures the firm's ability to identify the value of external information based on its existing knowledge and its capacity to absorb and transform this information into business practice. Thus, it represents the firm's potential for learning and seizing market opportunities. A higher value indicates better human capital quality and, consequently, stronger learning capability. ③ Technology R&D. Absorptive capacity is positively associated with a firm's total R&D expenditure [56]. To operationalize this relationship, this study follows the approach of prior research and uses the ratio of R&D expenditure to revenue to represent the intensity of the firm's R&D investment [57]. This standardized measure allows for comparison across firms and serves as a proxy for the firm's capacity to absorb and leverage external knowledge. Finally, to integrate these dimensions from a multidimensional perspective, the entropy method is applied. By leveraging its advantage of objective weighting, this approach provides a comprehensive measure of a firm's absorptive capacity, reflecting the combined effects of executives' innovation cognition, organizational learning capability, and technology R&D.

Adaptive capability (*ADC*). *ADC* reflects a firm's ability to adapt to changes in the external environment [20]. This study selects three major types of firm expenditures—annual R&D expenditure, capital expenditure, and advertising expenditure. The coefficients of variation of these expenditures (i.e., the ratio of the standard deviation to the mean) are then calculated to capture the firm's flexibility in resource allocation. A lower coefficient of variation indicates that a firm's resource allocation is relatively stable, which generally implies greater resilience and adaptability to external environmental fluctuations. The rationale is twofold. First, substantial fluctuations in strategic expenditures often indicate the absence of stable long-term planning, making firms more vulnerable to strategic instability in the face of external shocks. By contrast, lower expenditure volatility suggests that firms can rely on slack resources and internal buffering mechanisms to sustain core investments and knowledge accumulation under uncertainty [58], thereby reflecting stronger organizational resilience and adaptive capacity. Second, firms with stronger adaptive capabilities typically respond to environmental change through adjustments in resource allocation and improvements in resource utilization efficiency, rather than through large swings in overall investment levels. Consequently, relatively stable resource investment can help cushion external shocks and reflect greater strategic stability and coordination capability. To ensure a positive association with the firm's adaptability in empirical analysis, the negative of the coefficient of variation is taken. In this way, higher values correspond to stronger adaptability, allowing for a consistent interpretation across firms.

Innovation capability (*IC*). *IC* refers to a firm's ability to develop new products by aligning its strategic innovation direction with innovative actions. Based on prior research [59], this study measures innovation capability from two perspectives: R&D investment intensity and human capital. These two indicators are measured in different units; therefore, they are first standardized. A comprehensive measure of innovation capability is then constructed using a weighted sum of the standardized indicators, with equal weights applied, which can be expressed as follows: $\frac{X_{RD} - min_{RD}}{max_{RD} - min_{RD}} + \frac{X_{IT} - min_{IT}}{max_{IT} - min_{IT}}$. This composite indicator captures both the firm's investment in innovation and the quality of its human capital, providing a holistic measure of its capacity to innovate.

3.2.4. Intellectual Property Protection

According to market transaction theory, the core function of intellectual property protection is to incentivize innovators to increase R&D investment by strengthening market regulation and legal enforcement. This, in turn, enhances the quality and efficiency of technological innovation and curbs technology infringement and patent abuse. It also fosters a fair and orderly technology trading environment, thereby promoting the effective functioning of the technology market and the optimal allocation of resources [60].

In 2011, China's National Intellectual Property Administration initiated a national program to select intellectual property (IP) demonstration cities, as part of a regional IP strategy pilot initiative. The first batch of 23 selected cities was officially announced on 27 April 2012. The policy establishes a multi-dimensional evaluation framework that covers the creation, utilization, protection, management, and service of intellectual property. Within this framework, cities undergo a comprehensive assessment process to determine their eligibility for demonstration status. IP demonstration cities are designated at the urban level, which serves as the fundamental spatial unit of policy implementation. Each participating city develops its own implementation plan based on local economic development conditions and industrial structure, and accordingly establishes corresponding IP protection and management systems. To ensure effective policy implementation, a dynamic evaluation and exit mechanism has been introduced, under which cities that fail to meet the required standards are subject to revocation of their demonstration status. This institutional arrangement combines decentralized local implementation with centralized performance evaluation, thereby balancing policy flexibility with regulatory oversight. Overall, the policy is expected to enhance regional awareness of intellectual property protection, facilitate the development of technology trading markets, and strengthen local administrative capacity in intellectual property governance.

Given that the construction cycle of intellectual property demonstration cities is three years, this study includes six batches of cities announced in 2012, 2013, 2015, 2016, 2018, and 2019 as the sample. By 2023, all sampled cities will have been exposed to the policy for more than one full cycle, ensuring sufficient time variation for evaluating its effects. To empirically capture this effect, this study follows Han et al. (2025) and operationalizes the level of IP protection using an interaction term between a city-type dummy variable and a policy implementation-time dummy variable [61]. Specifically, the city-type dummy is assigned a value of 1 if the city is an IP demonstration city and 0 otherwise, while the time dummy is assigned a value of 0 before the policy implementation and 1 afterward. This interaction term effectively reflects the variation in IP protection intensity across cities and over time, thereby aligning the measurement with the theoretical mechanism described above. If a firm's city is designated as a national intellectual property demonstration city in the current year and thereafter, the variable equals 1; otherwise, it equals 0.

3.2.5. Control Variables

In order to more accurately assess the impact of the smart manufacturing policy on firms' green innovation, this study includes a set of control variables in the regression analysis. These variables capture key firm characteristics that may affect green innovation. Following prior studies, heterogeneity analyses are conducted based on firm characteristics, financial conditions [62], and corporate governance [63]. Specifically, the controls include firm size (*Size*), capturing economies of scale; revenue growth rate (*Growth*), reflecting business expansion; operating cash flow (*CF*), indicating financial health; market valuation (*TobinQ*), representing market expectations; proportion of independent directors (*Indir*), reflecting corporate governance quality; and current ratio (*Liquid*), measuring short-term liquidity. By including these controls, the analysis helps isolate the effect of the smart manufacturing policy on green innovation, reducing potential confounding influences from other factors. The selection of control variables follows the principle that they should be related to green innovation, weakly correlated with the policy, and readily available. Key variables such as industry competition and environmental regulation are not included because their effects are partly captured by firm characteristics and fixed effects, and the data for these variables are subject to measurement inconsistencies that could affect the robustness of the estimates.

3.3. Data Description

Considering that the intelligent manufacturing policy was implemented between 2015 and 2018, this study uses Chinese A-share manufacturing firms listed on the Shanghai and Shenzhen stock exchanges over the period 2011–2023 as the sample. This observation window provides sufficient pre- and post-policy observations while minimizing the confounding effects of other concurrent policies that may emerge over a prolonged study period. In addition, due to delays in the updating and verification of 2024 green patent application data and certain corporate governance variables, 2023 is used as the final sample year to ensure data consistency, completeness, and comparability. For the selected sample, data on the number of green patent applications are sourced from the China National Research Data Service Platform (CNRDS), while information on the level of intellectual property protection is obtained from "Intellectual Property Demonstration Cities" released by the National Intellectual Property Administration. Firm-level data are primarily drawn from the China Stock Market & Accounting Research Database (CSMAR) and corporate annual reports. To improve data quality and ensure the reliability of the regression analysis, the collected sample underwent a series of screening procedures. First, ST, SST, and PT listed companies were excluded to avoid potential distortions caused by financial anomalies or unstable operations. Second, firms with missing key research variables or severely incomplete financial data were removed, ensuring data completeness and robustness of the analysis. Meanwhile, to minimize the loss of sample observations, a linear interpolation method was employed to impute a small number of missing values. All empirical analyses in this study are conducted using Stata 18 software.

Table 1 presents the descriptive statistics of the variables. Regarding the dependent variable, corporate green innovation (*GI*) has a mean of 0.4610 and a standard deviation of 0.9251, with values ranging from 0 to 6.8480. This indicates low overall innovation intensity and substantial cross-firm heterogeneity, providing sufficient variation for policy identification. The core explanatory variable, the intelligent manufacturing pilot policy (*DID*), has a mean of 0.0385, implying that 3.85% of observations are treated during the sample period. For the mediating and moderating variables, absorptive capacity (*ABC*), innovation capability (*IC*), and adaptive capability (*ADC*) display marked variation in means and standard deviations, reflecting heterogeneous dynamic capability structures across firms. *ADC* is constructed as the negative of the coefficient of variation; thus, higher values indicate stronger adaptability. The mean *ADC* is −1.0818, suggesting that there is still considerable room for improvement in the adaptive capabilities of Chinese manufacturing firms. Intellectual property protection (IPP) has a mean of 0.5251 and a standard deviation of 0.4994, showing substantial temporal and regional variation suitable for moderation analysis. The number of IPP observations (9693) is smaller due to the exclusion of firms in municipalities directly under the central government and county-level cities during data matching. For control variables, firm size (*Size*) averages 22.3798, indicating a sample dominated by medium- and large-sized firms. Independent directors (*Indir*) account for 37.45% on average, consistent with regulatory requirements. Other financial variables

(*Growth*, *CF*, *TobinQ*, *Liquid*) fall within plausible ranges. All statistics are reported to four decimals except for observation counts.

Table 1. Descriptive statistics of variables.

Variables		Variable Definitions	N	Mean	Standard Deviation	Min	Max
Dependent variable	*GI*	Green Innovation	11,494	0.4610	0.9251	0.0000	6.8480
Independent variable	*DID*	If a firm appears on the pilot list announced by the Ministry of Industry and Information Technology, it takes a value of 1 for that year and all following years; otherwise, it takes a value of 0.	11,494	0.0385	0.1923	0.0000	1.0000
Mediating variable	*ABC*	Absorptive capacity	11,494	0.0538	0.0487	0.0006	0.6263
	IC	Innovation capability	11,494	0.8942	0.4990	0.0000	2.0000
	ADC	Adaptive capability	11,494	−1.0818	0.3163	−1.4142	0.0000
Moderating variable	*IPP*	Intellectual Property Protection	9693	0.5251	0.4994	0.0000	1.0000
Control variables	*Size*	Natural logarithm of total assets at year-end	11,494	22.3798	1.2303	19.5522	26.4523
	Growth	(Current year revenue/Previous year revenue) − 1	11,494	0.1354	0.3173	−0.6735	5.0755
	CF	Net cash flow/total assets	11,494	0.0511	0.0624	−0.2015	0.2669
	TobinQ	Market valuation	11,494	1.9717	1.2018	0.0000	16.6472
	Indir	Proportion of independent directors	11,494	0.3745	0.0538	0.2857	0.6000
	Liquid	Current assets/current liabilities	11,494	2.4884	2.7042	0.2644	29.7633

4. Empirical Results and Analysis

4.1. Baseline Regression Results

Table 2 presents the regression results examining the impact of the smart manufacturing policy on firms' green innovation. Column (1) reports the baseline model, which includes only the policy variable along with firm and year fixed effects. The coefficient of the DID term is significantly positive, providing preliminary evidence that the implementation of the smart manufacturing policy is positively associated with firms' green innovation. Columns (2) to (4) sequentially add control variables, and the estimated coefficients of the DID term remain significantly positive, indicating that the policy effect is robust. Overall, the baseline regression results support Hypothesis 1. Specifically, the DID estimate suggests that, on average, the implementation of the smart manufacturing policy increases green innovation in the treatment group by approximately 17% relative to the control group, showing a statistically significant positive effect.

Table 2. Results of Benchmark Regression.

	(1) *GI*	(2) *GI*	(3) *GI*	(4) *GI*
DID	0.1723 *** (0.0383)	0.1709 *** (0.0383)	0.1711 *** (0.0382)	0.1654 *** (0.0383)
Size		0.0785 *** (0.0136)	0.0826 *** (0.0138)	0.0883 *** (0.0139)
Growth		−0.0376 ** (0.0162)	−0.0369 ** (0.0163)	−0.0331 ** (0.0163)
CF			−0.2280 ** (0.0974)	−0.2474 ** (0.0975)
TobinQ			0.0122 * (0.0064)	0.0139 ** (0.0064)
Indir				0.3161 ** (0.1400)
Liquid				0.0080 *** (0.0026)
_cons	0.3286 *** (0.0171)	−1.3648 *** (0.2941)	−1.4699 *** (0.3016)	−1.7447 *** (0.3124)
Individual Effect	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
R^2	0.7219	0.7229	0.7231	0.7235
N	11,494	11,494	11,494	11,494

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. *t*-values are shown in parentheses.

This economically significant result highlights the effectiveness of "smart manufacturing" as a novel policy instrument. We argue that the observed policy effect operates primarily through two channels: a resource effect and an efficiency effect. Resource effect. Through pilot programs and targeted subsidies, the smart manufacturing policy provides firms with direct resource support, including financial subsidies, tax incentives, and technical assistance. These forms of support substantially reduce the sunk costs and trial-and-error risks associated with green innovation—an activity typically characterized by long investment cycles and high uncertainty. By easing firms' financing constraints, the policy enables them to allocate sufficient resources to green projects that might otherwise have been postponed or abandoned. Efficiency effect. The core objective of the policy is intelligent upgrading, involving the deployment of industrial internet systems, big data platforms, and automated production lines. Such technological upgrading directly enhances production efficiency, generating immediate gains such as lower energy consumption, reduced raw material waste, and more precise control of pollutant emissions (i.e., process greening). The organizational slack created through these improvements—that is, the costs and resources saved—provides a solid internal foundation for firms to further invest in more complex forms of green product innovation.

This study provides new evidence for the "Porter Hypothesis" in the context of the digital economy, thus extending the existing literature. Since smart manufacturing functions both as a policy instrument and a form of digital transformation, understanding its impact on green innovation requires examining policy design and digitalization jointly. First, the findings support the view that "enabling" policies outperform traditional command-and-control regulations. Prior research has shown that regulatory tools such as pollution taxes often produce ambiguous innovation outcomes and increase firms' compliance costs [17]. In contrast, the intelligent manufacturing policy examined in this study generates an average 17% increase in environmentally friendly innovation, indicating that incentive-based policies—by providing positive stimuli such as technological support and resource subsidies rather than imposing penalties—are more effective in activating firms' green innovation. Second, this study clarifies the "goal-oriented" effect of digitalization. Although previous research widely documents that digital transformation promotes green innovation [16,64], such effects vary depending on the nature and motivation of the digital investment. Unlike firms' spontaneous, broadly scoped IT investments, policy-guided digitalization under the smart manufacturing initiative incorporates explicit top-level objectives such as green development and energy conservation. This dual-goal policy signal guides firms' technological upgrading toward integrating intelligence and environmental sustainability from the outset, helping to explain why firms in the treatment group achieve significantly higher levels of green innovation than their counterparts in the control group.

From the estimation results of the control variables, the signs of the coefficients are generally consistent with theoretical expectations in the existing literature, suggesting that the model specification is appropriate and the estimated relationships are broadly in line with prior studies. Specifically, firm size (*Size*) is positively associated with green innovation, indicating that larger firms, with stronger resource bases and greater capacity for R&D investment, are more likely to engage in green innovation activities. In addition, firms with higher growth potential and stronger market valuation—proxied by the growth rate of operating revenue (*Growth*) and Tobin's Q (*TobinQ*), respectively—tend to exhibit higher levels of green innovation. This pattern suggests that firms with optimistic market expectations and stronger development prospects are more inclined to undertake forward-looking and risky innovative investments, including green technologies. Regarding financial conditions, operating cash flow (*CF*) and liquidity ratio (*Liquid*) are also positively related to green innovation, implying that improved internal cash generation and higher liquidity ease financial constraints and thereby enhance firms' ability to sustain innovation inputs. From the perspective of corporate governance, the proportion of independent directors (*Indir*) shows a positive association with green innovation, suggesting that stronger board independence improves monitoring quality and decision-making efficiency, which in turn facilitates more effective allocation of resources toward innovation activities. Overall, these results highlight that both internal resource availability (e.g., firm size and financial capacity) and governance quality constitute key enabling factors for corporate green innovation, while market-based indicators such as growth opportunities and valuation expectations further reinforce firms' willingness to invest in long-term innovative activities.

4.2. Robustness Test

The implementation of smart manufacturing pilot policies has been found to effectively enhance firms' green innovation. However, this conclusion may still be subject to potential omitted variable bias. To assess the robustness of the DID identification strategy, we conducted the following checks.

4.2.1. Parallel Trend Test

Figure 2 presents the dynamic effects of the intelligent manufacturing policy, using 2014 (the year preceding policy implementation) as the baseline period. The point estimates represent regression coefficients relative to the baseline, while the vertical error bars indicate the corresponding 95% confidence intervals, reflecting estimation uncertainty. In the pre-policy period (pre4–pre1), the estimated coefficients hover around zero, and all confidence intervals include zero, suggesting no statistically significant differences in pre-trends of green innovation between the treatment and control groups. This pattern provides evidence supporting the parallel trends assumption required for the difference-in-differences framework. In the post-policy period (post1 and onwards), the coefficients are generally positive, and several periods are statistically significant at conventional significance levels.

The confidence intervals in most post-treatment years do not contain zero, indicating a positive association between the intelligent manufacturing policy and corporate green innovation. Moreover, the post-policy coefficients exhibit an overall upward pattern, suggesting that the policy effect may become more pronounced over time, potentially reflecting dynamic adjustment processes or gradually emerging effects. Overall, the dynamic effect results are consistent with the validity of the parallel trends assumption and indicate a positive post-policy association between the intelligent manufacturing policy and firms' green innovation outcomes.

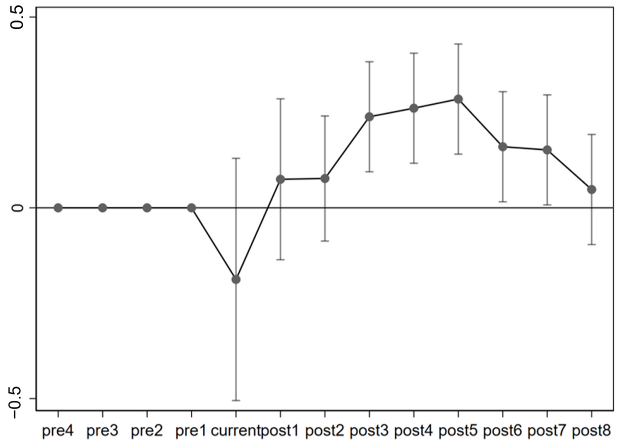


Figure 2. Results of Parallel Trend Test.

The presentation of the parallel trends above is primarily intended to provide an intuitive impression. Building on this, we conduct a more rigorous empirical test of the parallel trends assumption. To implement this approach, drawing on the frameworks of previous studies [65], we employ an event study method. First, we systematically examine whether the parallel trends hold prior to policy implementation. Second, we analyze the dynamic effects of establishing smart manufacturing pilot projects, as well as their potential time-lagged impacts. Specifically, in Equation (1), DID_{it} is replaced with dummy variables representing several years before and after the implementation of the smart manufacturing pilot, while the dependent variable remains unchanged. The equation is then estimated as follows:

$$GI_{it} = \alpha_0 + \prod_{s \geq -1}^{8} \alpha_s D_s + \alpha_3 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (6)$$

In Equation (6), D_0 is a dummy variable indicating the year in which the smart manufacturing policy was first implemented, and S indicates the number of years relative to the policy implementation. Specifically, S is negative in the pre-policy period and positive in the post-policy period. Since the pre-implementation period in the sample is relatively short, we define observations more than two years prior to policy adoption as the baseline group to ensure a stable comparison. α_s denotes the dynamic marginal effect of the intelligent manufacturing pilot policy on firms' green innovation at event time s. It can be interpreted as the heterogeneous impact of the policy shock on firms' innovation efficiency and green productivity across different time horizons. Figure 3 reports the magnitude of the estimated coefficients $\{\alpha_{-2}, \alpha_{-1}, \alpha_0, \ldots, \alpha_6, \alpha_7, \alpha_8\}$ along with their corresponding 90% confidence intervals. As shown in Figure 3, prior to policy implementation, the estimated coefficients are not statistically significant, consistent with the parallel trends assumption. From the year of policy implementation onward, the coefficients become significant at the 10% level, indicating that the policy effects gradually strengthen over time and persist thereafter.

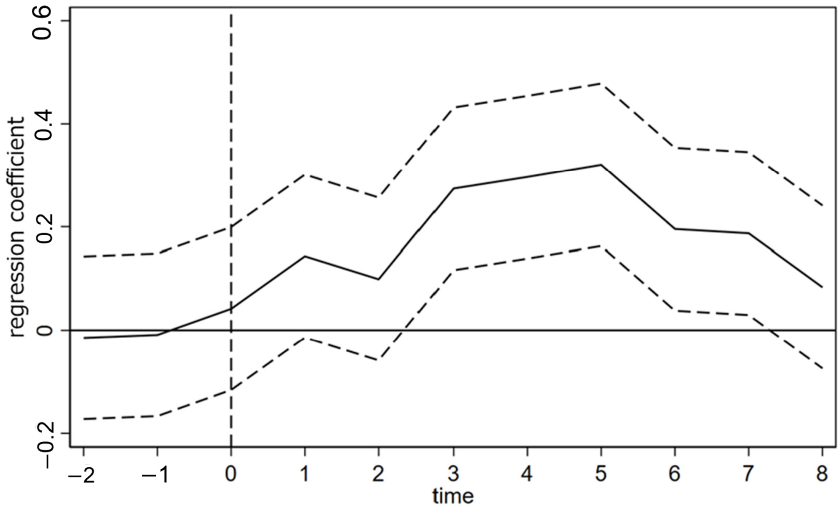


Figure 3. Dynamic effects of the smart manufacturing pilot. Note: ——— Estimated Value – – – – 90% Lower Bound – – – – 90% Upper Bound.

4.2.2. Placebo Test

To verify that the impact of the smart manufacturing policy on firms' green innovation is not merely a coincidental result driven by other external factors or random shocks, we conduct placebo tests by randomly generating pseudo-policy and pseudo-treatment group dummy variables. Specifically, in each of 500 iterations, 60 firms are randomly selected from a sample of 887 firms as the treatment group, and a "policy" year is randomly assigned to each firm. This procedure yields 500 estimated values, allowing us to assess whether the observed policy effects could arise by chance.

As shown in Figure 4, the estimated coefficients from the placebo test are approximately symmetric around zero, with the peak density centered near zero. This indicates that the randomly assigned pseudo-policy shocks do not produce significant effects, consistent with the expectations of the placebo test. Consequently, the significant positive impact of the actual smart manufacturing pilots on green innovation in the treatment group can be considered genuine and not driven by random chance or unobserved omitted variables.

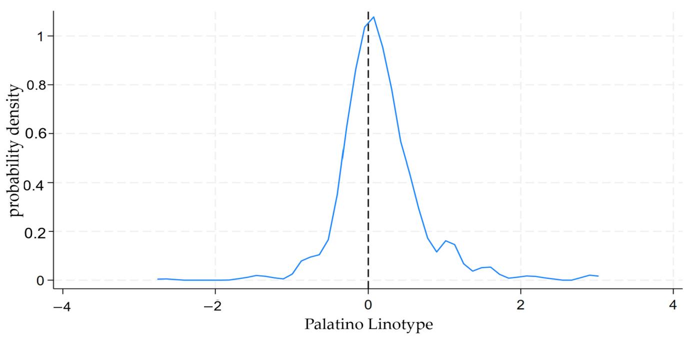


Figure 4. Results of Placebo Test.

4.2.3. PSM-DID Test

To test the robustness of the regression results, this study further employs the propensity score matching–difference-in-differences (PSM-DID) method to analyze the effects of the smart manufacturing pilot policy. Specifically, using the control variables selected above, we first estimate the probability of a firm becoming a smart manufacturing pilot through a Logit regression. Based on these propensity scores, the treatment and control groups are matched using nearest-neighbor, radius, and kernel matching methods, thereby minimizing systematic differences between the groups before policy implementation and reducing potential endogeneity caused by self-selection bias. Subsequently, the DID component is applied to the matched sample to identify the net effect of the smart manufacturing pilots on firms' green innovation. This combined approach leverages the advantages of propensity score matching in controlling for observable covariate biases and those of DID in eliminating the influence of time-invariant and contemporaneously varying unobserved factors, enabling a more precise evaluation of the policy effects.

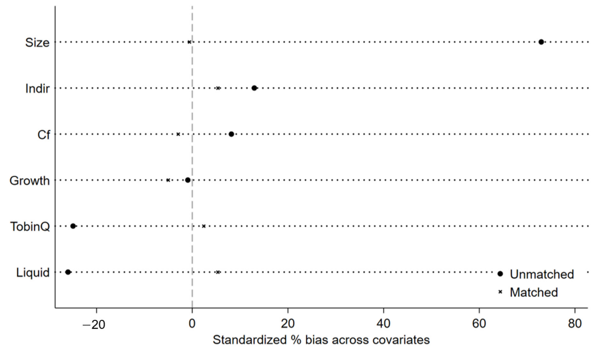
The results presented in Table 3 show that, regardless of whether nearest-neighbor, radius, or kernel matching is used, the estimated coefficients, their signs, and significance levels are consistent with the baseline regression results (Table 1). This indicates that the results across different matching methods do not differ significantly, which in turn confirms that the positive effect of the smart manufacturing pilot policy on firms' green innovation is robust. Figure 5 presents a comparison of variable differences before and after propensity score matching.

Table 3. Results of PSM-DID Test.

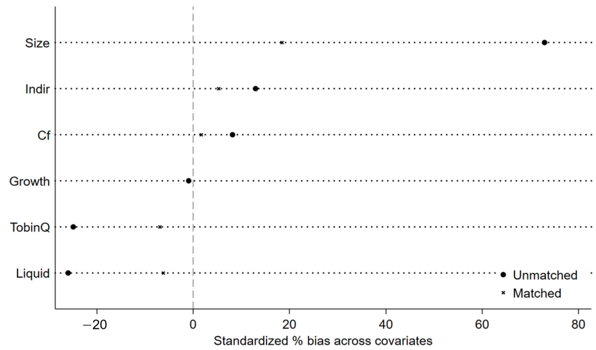
	Radius Matching	**Kernel Matching**	**Nearest-Neighbor Matching**
	GI	***GI***	***GI***
DID	0.1626 ***	0.1654 ***	0.1654 ***
	(0.0386)	(0.0383)	(0.0383)
Size	0.1013 ***	0.0883 ***	0.0883 ***
	(0.0147)	(0.0139)	(0.0139)
Growth	−0.0305 *	−0.0331 **	−0.0331 **
	(0.0170)	(0.0163)	(0.0163)
CF	−0.2797 ***	−0.2474 **	−0.2474 **
	(0.1006)	(0.0975)	(0.0975)
TobinQ	0.0153 **	0.0139 **	0.0139 **
	(0.0073)	(0.0064)	(0.0064)
Indir	0.3224 **	0.3161 **	0.3161 **
	(0.1438)	(0.1400)	(0.1400)
Liquid	0.0084 ***	0.0080 ***	0.0080 ***
	(0.0032)	(0.0026)	(0.0026)
_cons	−2.0370 ***	−1.7447 ***	−1.7447 ***
	(0.3310)	(0.3124)	(0.3124)
Individual Effect	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes
R^2	0.7265	0.7235	0.7235
N	11,119	11,494	11,494

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. *t*-values are shown in parentheses.

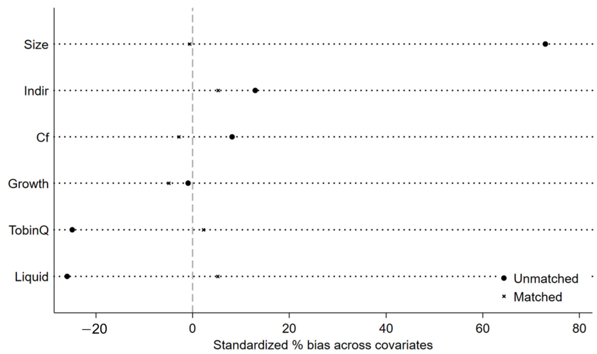
Figure 5 presents the balance test results for different matching methods under the PSM-DID framework. Specifically, panel (a) reports the results of radius matching, panel (b) presents the kernel matching results, and panel (c) shows the nearest-neighbor matching results. Prior to matching, significant differences are observed between the treatment and control groups across several covariates, suggesting the potential existence of sample selection bias. After applying different propensity score matching methods, the standardized biases of all covariates decrease substantially and are generally reduced to below 10%. In particular, the standardized biases after nearest-neighbor matching further decline to within 5%, indicating that the observable differences between the treatment and control groups are effectively mitigated and that sample comparability is significantly improved. Moreover, the graphical distributions show that the standardized biases of the covariates after matching are highly concentrated around zero, suggesting a substantial improvement in covariate balance. These findings indicate that radius matching, kernel matching, and nearest-neighbor matching all effectively reduce the systematic differences in observable characteristics between the treatment and control groups. Therefore, the comparability assumption required for the PSM-DID model is satisfied, providing a reliable basis for the subsequent DID estimations and further supporting the robustness of the benchmark regression results.



(**a**)



(**b**)



(**c**)

Figure 5. Comparison of variable differences before and after matching. (**a**) presents the results of radius matching, (**b**) presents the results of kernel matching, and (**c**) presents the results of nearest-neighbor matching.

4.2.4. Explanatory Variable Lagged by One Period

The results of the parallel trends test show that, although the policy effect remains positive in later periods, it shows a slight downward trend. This observation suggests that the impact of the smart manufacturing policy may diminish over time. To further investigate the persistence of the policy effect, the regression is re-estimated using the core explanatory variable lagged by one period. The empirical results, reported in Column (1) of Table 4, indicate that the coefficient of the lagged policy variable is significantly positive and exhibits a higher significance level than in the baseline model. These findings suggest that the smart manufacturing policy not only has a lagged effect but also remains persistent in promoting firms' green innovation.

Table 4. Results of Robustness Test.

	(1) GI	(2) GI1	(3) GI	(4) GI
DID	0.2146 ***	0.2129 ***	0.1636 ***	0.1859 ***
	(0.0392)	(0.0330)	(0.0403)	(0.0615)
Size	0.0804 ***	0.0999 ***	0.0680 ***	0.0929 ***
	(0.0149)	(0.0120)	(0.0148)	(0.0214)
Growth	−0.0346 **	−0.0405 ***	0.0224	−0.0504 ***
	(0.0168)	(0.0141)	(0.0166)	(0.0169)
CF	−0.2857 ***	−0.2132 **	−0.2027 **	−0.1158
	(0.1020)	(0.0842)	(0.1012)	(0.1109)
TobinQ	0.0136 **	0.0050	0.0194 ***	0.0181 **
	(0.0066)	(0.0056)	(0.0066)	(0.0072)
Indir	0.2938 **	0.3983 ***	0.1438	0.2092
	(0.1467)	(0.1209)	(0.1483)	(0.1622)
Liquid	0.0082 **	0.0043 *	0.0049 *	0.0077 ***
	(0.0032)	(0.0022)	(0.0026)	(0.0024)
_cons	−1.5373 ***	−2.0681 ***	−1.2231 ***	−1.8099 ***
	(0.3356)	(0.2698)	(0.3332)	(0.4776)
Individual Effect	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
R^2	0.7393	0.7220	0.7386	0.7469
N	10,596	11,494	10,596	7955

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. *t*-values are shown in parentheses.

4.2.5. Replace the Dependent Variable

This study uses the number of green patent applications as the baseline dependent variable. To examine whether the empirical results are sensitive to the measure of green innovation, we replace the dependent variable with the number of green patent grants (GI1). To ensure estimation stability and mitigate the impact of excessive variance, the alternative variable is transformed by taking the natural logarithm after adding one, and Model (1) is then re-estimated. The empirical results, reported in Column (2) of Table 4, indicate that replacing the dependent variable does not materially change the core finding: smart manufacturing continues to significantly enhance firms' green innovation.

4.2.6. Control Variables Lagged by One Period

To address potential endogeneity arising from the possibility that the selected control variables may be influenced by the establishment of smart manufacturing pilots, all control variables are lagged by one period, and the regression is re-estimated. The results, reported in Column (3) of Table 4, show that the coefficient signs and significance levels remain largely consistent with those of the baseline regression, providing further support for the robustness of the findings.

4.2.7. Change the Sample Period

The baseline regression in this study is based on the full sample from 2011 to 2023. However, since the smart manufacturing pilot policy was only implemented starting in 2015, including a long pre-policy period may dilute the estimated policy effect and introduce bias. To enhance the robustness of the results and avoid potential confounding effects from the global financial crisis, the sample period is further restricted to 2011–2019, covering four years before and four years after the policy implementation. The regression results based on this restricted sample, reported in Column (4) of Table 4, are largely consistent with the baseline findings, providing additional evidence for the robustness of the study's conclusions.

5. Heterogeneity Analysis

While the baseline regression results confirm the average positive effect of the smart manufacturing policy on firms' green innovation, the strength and mechanisms of this impact may vary across different types of firms. To further investigate the boundary conditions and micro-level transmission mechanisms of the policy, this study conducts heterogeneity analysis along three key dimensions. First, we examine firms' technological attributes. Since smart manufacturing fundamentally relies on technological enablement, high-tech firms with greater knowledge reserves may be better positioned to absorb the policy benefits, whereas non-high-tech firms may face bottlenecks in converting policy support into innovation output. Building on this, we then analyze industry pollution intensity. Firms in heavily polluting industries face stronger "environmental legitimacy" pressures, which could amplify the incentive effect of the smart manufacturing policy in driving "defensive" green innovation. Finally, we consider firms' production patterns, as the realization of the "resource effect" and "efficiency effect" of smart manufacturing depends heavily on firms' production factor structure. For example, asset-intensive firms may be more constrained by the "crowding-out effect" caused by large fixed asset investments. By integrating the insights from these three dimensions, this study aims to provide a comprehensive understanding of the heterogeneous impacts and transmission mechanisms of the smart manufacturing policy on firms' green innovation.

5.1. Technological Attributes of Firms

The effectiveness of the smart manufacturing policy largely depends on firms' technological attributes. In general, high-tech firms, with their greater knowledge reserves, are better positioned to absorb policy benefits, whereas non-high-tech firms may face bottlenecks in converting policy support into innovation output. Therefore, the sample is divided into high-tech and non-high-tech firms for separate regressions. The results, presented in Columns (1) and (2) of Table 5, indicate that the policy has a significantly positive effect on high-tech firms' green innovation, while its effect on non-high-tech firms is significantly negative. This contrast suggests that the policy's impact is contingent on firms' technological capabilities, highlighting the importance of technological readiness in realizing the benefits of smart manufacturing initiatives.

The smart manufacturing policy aims to promote firms' digitalization and intelligent transformation. Firm heterogeneity, particularly technological capability, plays a critical role in shaping the policy's effectiveness. High-tech firms, characterized by intensive R&D and advanced knowledge reserves, naturally align with the cutting-edge technologies emphasized by the policy. This alignment, or "technology–knowledge" coupling effect, allows high-tech firms to efficiently identify, absorb, and apply policy-guided technologies. As a result, they can transform policy incentives into tangible green innovations, including energy-optimized production processes, closed-loop emission reduction designs, and green product development.

Table 5. Results of the Heterogeneity Analysis.

	(1) *GI*	(2) *GI*	(3) *GI*	(4) *GI*	(5) *GI*	(6) *GI*	(7) *GI*
	high-tech	non-high-tech	heavily polluting	non-heavily polluting	technology-intensive	labor-intensive	capital-intensive
DID	0.2345 *** (0.0458)	−0.1032 * (0.0589)	−0.1075 (0.0680)	0.2535 *** (0.0461)	0.2730 *** (0.0518)	−0.0030 (0.0659)	−0.1257 (0.0946)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.7300	0.5256	0.6106	0.7496	0.7599	0.5450	0.6108
N	9045	2448	3470	8023	6694	2442	2319

Note: ***, and * denote significance at the 1%, and 10% levels, respectively. *t*-values are shown in parentheses.

In contrast, non-high-tech enterprises face multiple, interacting constraints in responding to intelligent manufacturing policies. First, they generally lack sufficient technological reserves and digital infrastructure, resulting in poor compatibility between existing production systems and intelligent manufacturing technologies, which limits the efficiency of technology absorption and application and makes it difficult to fully leverage policy incentives. Second, intelligent manufacturing transformation entails substantial costs, including equipment upgrades, system integration, employee training, and process reengineering. With relatively weaker financing capacity and limited resources, non-high-tech enterprises are particularly vulnerable to these pressures. In addition to technical and financial constraints, non-high-tech firms also contend with stronger organizational inertia and path dependence. Traditional production processes and management systems are often slow to adapt to the requirements of intelligent manufacturing, further limiting policy effectiveness. Moreover, intelligent manufacturing transformation is inherently uncertain and long-term, whereas non-high-tech enterprises tend to prioritize short-term performance. Under such resource and time pressures, these firms may allocate funds to compliance or routine operations rather than investing in high-risk, long-term green innovation initiatives. The combined effects of limited technological adaptability, high transformation costs, organizational rigidity, and short-term performance pressures can create a crowding-out effect, potentially weakening green innovation investment and, in the short term, even reducing innovation performance. In summary, high-tech enterprises are able to leverage their strong technological adaptability to translate intelligent manufacturing policies into green innovation gains. In contrast, non-high-tech enterprises, constrained by high transformation costs and limited technological adaptability, tend to fall into a resource allocation dilemma, where the pursuit of intelligent transformation competes with green innovation investment. This also explains why the effects of intelligent manufacturing policies exhibit a clear dual-track pattern, being significantly positive for high-tech firms but significantly negative for non-high-tech firms.

5.2. Industry Pollution Intensity

To examine how technological complexity and cost pressures influence the impact of the smart manufacturing policy across firms with different pollution levels, industries are classified into heavily polluting and non-heavily polluting sectors. Following this classification, group-wise regressions are conducted to assess the policy's differential effects on green innovation. The results, reported in Columns (3) and (4) of Table 5, indicate that the policy significantly promotes sustained green innovation in non-heavily polluting industries, whereas its effect on heavily polluting industries is negative but not statistically significant.

This heterogeneity suggests that the green innovation effects of the smart manufacturing policy do not fully materialize across all industries and are jointly driven by differences in regulatory stringency, resource allocation structures, and technological transition pathways. For firms in heavily polluting industries, long-term exposure to stringent environmental regulation and frequent compliance inspections compels them to allocate substantial resources toward pollution control, environmental equipment upgrades, and emission compliance. Although such compliance-oriented investments reduce the risk of regulatory violations, they also crowd out resources that could otherwise be allocated to green R&D, digital transformation, and frontier technological innovation, thereby generating a pronounced resource crowding-out effect. In addition, heavily polluting industries are typically characterized by capital intensity, complex production processes, and strong technological path dependence, with production systems largely built on traditional energy- and emission-intensive technologies. The adoption of smart manufacturing technologies, therefore, requires large-scale equipment upgrading, system reconfiguration, and deep process digitalization, all of which entail substantial adjustment and coordination costs. In the short run, firms tend to prioritize regulatory compliance over uncertain and long-horizon green innovation activities. As a result, the efficiency gains and production flexibility emphasized by smart manufacturing policies are not readily translated into green innovation performance in these industries, and the policy effect is likely to be dampened by regulatory pressure and transition costs. By contrast, firms in non-heavily polluting industries face relatively weaker environmental regulatory pressure and thus enjoy greater flexibility in resource allocation, allowing them to devote more resources to digital upgrading and green R&D activities. Moreover, production processes in these industries are typically more modular and less energy-intensive, making it easier to embed digital technologies and smart manufacturing systems into existing operations. This facilitates improvements in energy efficiency and resource utilization through data-driven production optimization. In this context, smart manufacturing not only enhances production efficiency but also promotes green innovation by optimizing energy allocation, reducing resource waste, and strengthening process control. Accordingly, for non-heavily polluting firms, smart manufacturing policies are more likely to generate a virtuous cycle of "digital transformation–efficiency improvement–green innovation," thereby significantly improving green innovation outcomes. Overall, these findings indicate that industry pollution intensity plays a critical role in shaping the effectiveness of smart manufacturing policies. Only when firms possess sufficient resource reallocation capacity, lower transformation frictions, and stronger technological adaptability can such policies be effectively translated into sustained green innovation momentum.

5.3. Firms' Production Patterns

Considering the differences in production patterns across firms with varying factor intensities, the impact of the smart manufacturing policy on green transformation likely exhibits heterogeneity. To test this, firms are classified into technology-intensive, labor-intensive, and capital-intensive categories, and separate regressions are conducted for each group. The regression results (Table 5, Columns (5)–(7)) show that the coefficients for green transformation in labor-intensive and capital-intensive firms are not statistically significant. In contrast, the coefficient for technology-intensive firms is significant at the 1% level. Therefore, the smart manufacturing policy has a more pronounced effect on the green transformation of technology-intensive firms, highlighting the importance of production factor structure in shaping policy effectiveness.

This heterogeneity fundamentally reflects structural differences across firms in terms of “digital technology absorption capacity–organizational restructuring capability–green innovation conversion efficiency.” For technology-intensive firms, production processes rely heavily on knowledge, data, and R&D activities, which naturally endow them with stronger compatibility with digital technologies and higher technological absorptive capacity. Under the promotion of the smart manufacturing policy, these firms are able to achieve faster integration of data elements with production processes and accelerate the transformation of green innovation from the R&D stage to the production stage through algorithm-driven decision optimization, modularized R&D organization, and cross-departmental knowledge-sharing mechanisms. In addition, technology-intensive firms typically possess more advanced digital infrastructure and a higher proportion of highly skilled labor, enabling them to embed smart manufacturing systems into key stages such as R&D design, production control, and supply chain management, thereby forming an internal virtuous cycle of “data-driven operations, process optimization, and green innovation.” Furthermore, technology-intensive firms are not only major adopters of smart manufacturing technologies but also important nodes for technological diffusion and standard setting. Supported by industrial internet platforms and digital ecosystems, these firms can not only improve their own energy efficiency and material circulation systems but also disseminate green production practices through technology standard outputs, interface specifications, and supply chain digital coordination. In doing so, they generate significant network spillover effects and contribute to green upgrading along the industrial chain. As a result, smart manufacturing policies are more likely to produce a scale-up effect in technology-intensive firms, evolving from “localized efficiency improvements” to “systematic green transformation.” In contrast, labor-intensive firms rely heavily on low-skilled labor in their production processes and are typically characterized by rigid organizational structures and weak digital foundations, which limit their ability to effectively absorb complex smart manufacturing systems. Even when relevant technologies are introduced, their application is often confined to partial automation rather than comprehensive process restructuring, thereby constraining systematic improvements in green innovation. Although capital-intensive firms benefit from scale advantages, their production systems are typically built on existing heavy asset bases and fixed technological trajectories, with strong path dependence and long equipment replacement cycles, making it difficult to achieve deep compatibility with smart manufacturing systems in the short term. Consequently, their green transformation tends to manifest as marginal improvements rather than structural innovation breakthroughs, which explains the insignificant policy effects. Overall, these findings suggest that the green transformation effects of smart manufacturing policies are not universal but instead critically depend on firms’ factor structure, which determines their technological absorptive capacity and organizational restructuring capability. Only when firms possess strong knowledge intensity and robust digital foundations can policy dividends be effectively translated into sustained green innovation momentum.

6. Mechanism Analysis

6.1. Mediation Analysis

According to the theoretical analysis above, the smart manufacturing policy is expected to promote green innovation primarily by enhancing firms’ absorptive capacity, innovation capacity, and adaptive capacity. To test the above mechanism, this study conducts empirical regression analyses based on Equations (2) and (3) using Stata software. To empirically verify this mechanism, Column (1) of Table 6 reports the baseline regression results, while Columns (2)–(4) incorporate absorptive capacity (*ABC*), innovation capacity (*IC*), and adaptive capacity (*ADC*) as mediating variables. The results show that all three mediators—*ABC*, *IC*, and *ADC*—are significantly positive at the 1% level. Moreover, after including each mediator, the estimated coefficient of the smart manufacturing policy decreases compared with the baseline model, indicating the presence of partial mediation. These findings suggest that the policy indeed enhances firms' absorptive, innovation, and adaptive capabilities, which in turn facilitate their green innovation performance. Thus, the empirical evidence provides strong support for Hypothesis 2.

Table 6. Results of the Mechanism Test.

	(1) ***GI***	**(2)** ***GI***	**(3)** ***GI***	**(4)** ***GI***	**(5)** ***GI***
ABC		0.3761 **			
		(0.1728)			
IC			0.0492 ***		
			(0.0116)		
ADC				0.0786 **	
				(0.0308)	
*DID*IPP*					0.3148 ***
					(0.0809)
DID	0.1654 ***	0.1641 ***	0.1556 ***	0.1648 ***	−0.0395
	(0.0383)	(0.0383)	(0.0383)	(0.0382)	(0.0683)
Size	0.0883 ***	0.0883 ***	0.0907 ***	0.0889 ***	0.0871 ***
	(0.0139)	(0.0139)	(0.0139)	(0.0139)	(0.0151)
Growth	−0.0331 **	−0.0327 **	−0.0261	−0.0329 **	−0.0335 *
	(0.0163)	(0.0163)	(0.0164)	(0.0163)	(0.0181)
CF	−0.2474 **	−0.2333 **	−0.2287 **	−0.2523 ***	−0.2343 **
	(0.0975)	(0.0977)	(0.0975)	(0.0975)	(0.1061)
TobinQ	0.0139 **	0.0136 **	0.0148 **	0.0141 **	0.0124 *
	(0.0064)	(0.0064)	(0.0064)	(0.0064)	(0.0073)
Indir	0.3161 **	0.3106 **	0.3261 **	0.3236 **	0.2291
	(0.1400)	(0.1400)	(0.1399)	(0.1400)	(0.1579)
Liquid	0.0080 ***	0.0077 ***	0.0071 ***	0.0084 ***	0.0067 **
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0030)
_cons	−1.7447 ***	−1.7560 ***	−1.8253 ***	−1.6597 ***	−1.6768 ***
	(0.3124)	(0.3124)	(0.3127)	(0.3141)	(0.3395)
Individual Effect	Yes	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes	Yes
R^2	0.7235	0.7236	0.7239	0.7236	0.7093
N	11,494	11,494	11,494	11,494	9693

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. *t*-values are shown in parentheses.

The identification of this mediating pathway precisely reveals the "black box" of how the smart manufacturing policy indirectly drives firms' green innovation. From an economic perspective, the policy does not directly generate green innovation outcomes; rather, it first reshapes firms' dynamic capabilities, which subsequently facilitate innovation. Specifically, the policy fosters absorptive capacity by promoting the adoption, assimilation, and application of next-generation information technologies. At the same time, tools such as digital twins and big data analytics reduce R&D trial-and-error costs, thereby strengthening firms' innovation potential. Moreover, full-process data transparency in production enables firms to perceive and rapidly respond to changes in the external environment, such as evolving environmental regulations, enhancing their adaptive capacity. Once firms have internalized these capabilities, green innovation emerges as a natural "capability spillover."

Firms can then more agilely capture green technologies, develop green products efficiently, and manage transformation risks robustly. This framework clarifies how the smart manufacturing policy indirectly empowers green innovation through the sequential enhancement of absorptive, innovation, and adaptive capacities, elucidating the mechanisms underlying Hypothesis 2.

This study's findings contribute to the literature in two key ways. First, they validate the universality of the "dynamic capabilities" perspective in the context of the digital economy, highlighting that in rapidly changing environments, firms' capabilities—rather than resources alone—constitute the primary source of competitive advantage. Building on this, the study further unpacks the "black box" of how digital transformation drives green innovation. Specifically, we demonstrate that digitalization does not necessarily lead to greening; it must first be internalized as organizational-level absorptive, innovation, and adaptive capabilities. Digitalization can be effectively channeled toward concrete green innovation objectives only after these capabilities are developed. This mechanism also helps explain why the green performance of digitalization varies significantly across firms, reflecting differences in their capacity to translate digital initiatives into sustainable outcomes.

6.2. Moderation Effect Test

Building on the preceding theoretical analysis, the effect of the smart manufacturing policy on firms' green innovation is expected to be contingent on the level of intellectual property protection. To test the above mechanism, this study conducts empirical regression analyses based on Equation (4) using Stata software. Column (5) of Table 6 reports the moderation test results, showing that the interaction term between the smart manufacturing policy and intellectual property protection is positive and statistically significant. This indicates that stronger intellectual property protection amplifies the positive effect of the smart manufacturing policy on green innovation. In other words, firms with stronger intellectual property protection are better able to translate policy incentives into tangible green innovation outcomes. These findings support Hypothesis 3, demonstrating that intellectual property protection serves as a significant positive moderator of the policy's main effect.

The smart manufacturing policy essentially encourages firms to undertake costly, knowledge-intensive "intelligent" investments. However, the effectiveness of these policy incentives depends critically on the level of intellectual property (IP) protection. When IP protection is weak, firms face severe knowledge spillovers and infringement risks, which dampen their R&D incentives and reduce the policy's impact on green innovation. In contrast, strong IP protection mitigates the risk of imitation, allowing firms to exclusively capture the returns from their intelligent technologies and green innovations. This institutional safeguard enhances firms' responsiveness to the policy and their capacity to absorb and apply new technologies, thereby facilitating the transformation of policy inputs into high-quality green innovation outcomes. In other words, IP protection positively moderates the effect of the smart manufacturing policy on firms' green innovation, amplifying the policy's overall effectiveness.

7. Conclusions and Implications

This study empirically examines the impact of the smart manufacturing policy on firms' green innovation, using data from A-share listed companies on the Shanghai and Shenzhen Stock Exchanges from 2011 to 2023. The results show that the policy significantly enhances firms' green innovation, with intellectual property protection positively moderating this effect. Mechanism analysis further reveals that the policy indirectly promotes green innovation by strengthening firms' adaptive and innovation capabilities, illustrating the internal pathways through which policy incentives translate into green outcomes. Heterogeneity tests indicate that the policy's promoting effect is particularly pronounced in high-tech firms, non-heavily polluting industries, and technology-intensive firms, highlighting the importance of firm and industry characteristics in shaping policy effectiveness. Overall, these findings suggest that the smart manufacturing policy stimulates firms' autonomous and high-quality innovation, thereby supporting the green transformation and sustainable development of the manufacturing sector. Based on these findings, the study provides policy and managerial implications for maximizing the effectiveness of smart manufacturing initiatives.

First, at the government level, policies for intelligent manufacturing should aim to balance economic and environmental objectives, supported by a structured and differentiated policy framework. In selecting and evaluating pilot demonstration projects, attention should shift from solely emphasizing efficiency and production capacity to also incorporating environmental performance indicators, such as reductions in energy consumption and the number of green patent applications, thereby guiding technological upgrades toward the integration of intelligence and sustainability. For non-high-tech and heavily polluting enterprises facing high transformation costs and potential diversion of resources from green innovation, blanket subsidies should be avoided. Instead, a Smart-Green Transformation Fund or long-term, low-interest financing should be established, targeting digital upgrades that enhance energy efficiency and reduce emissions in production processes. Such measures can alleviate internal financing constraints and ensure that investments in green R&D are effectively utilized. Meanwhile, given the positive moderating effect of intellectual property protection, the development of IP demonstration cities should be accelerated, including mechanisms for expedited examination of patents related to digital and green technologies and stronger penalties for infringements, thereby enabling firms to fully realize the returns from their investments in green innovation through intelligent manufacturing.

Second, at the industry level, efforts should prioritize removing technological barriers to the digital-green transition and establishing tiered guidance alongside shared innovation platforms. To address widespread data silos and inadequate technology adaptation in non-high-tech and heavily polluting enterprises, government agencies—including those responsible for industry, information technology, and environmental protection—should collaborate with leading firms in each sector to roll out shared industrial Internet platforms and digital twin systems. These initiatives should offer modular, low-cost, and highly adaptable smart-green solutions, reducing the technological absorption threshold and transformation costs for traditional enterprises. Simultaneously, the green spillover effects of technology-intensive industries should be reinforced. Leveraging their strengths in adopting and implementing intelligent manufacturing technologies, these industries can establish technology diffusion mechanisms led by key chain enterprises, encouraging them to share green digital supply chain standards and transfer critical technologies—such as energy optimization and emissions reduction—to labor- and capital-intensive SMEs along the supply chain. Collectively, these measures promote a systemic upgrade of the entire value chain toward intelligent and green innovation.

Finally, at the firm level, enterprises should reshape their endogenous dynamic capability systems and strengthen strategic orientation toward smart-green integration. Managers need to recognize that digitalization does not automatically translate into greening; instead, external policy incentives should be internalized through systematic enhancements of firms' dynamic capabilities. With respect to absorptive capacity, firms should enhance top management's strategic understanding by explicitly embedding digital and green transformation into corporate strategy, and improve human capital structures by recruiting talent with combined expertise in data analytics and environmental engineering, thereby strengthening firms' ability to identify and assimilate green digital technologies. In terms of innovation and adaptive capabilities, firms can leverage intelligent systems such as MES and IIoT to enable fine-grained monitoring of energy consumption and emissions throughout production processes, while introducing flexible R&D budgeting mechanisms to improve responsiveness to environmental regulations and evolving green market demands. This enables efficiency gains from digitalization to be effectively translated into green innovation outcomes. Moreover, for non-high-tech and heavily polluting firms, caution should be exercised to avoid resource misallocation and crowding-out effects induced by policy mandates. Firms should avoid adopting complex systems that are incompatible with existing energy-saving and emission-reduction frameworks. Instead, they should balance short-term compliance pressures with long-term sustainable innovation objectives by embedding intelligent manufacturing technologies into source-prevention and process-control activities, thereby building sustained green competitive advantages.

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Abbreviations

The following abbreviations are used in this manuscript:

R&D	Research and Development
IP	Intellectual Property
MES	Manufacturing Execution System
IIoT	Industrial Internet of Things

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