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Intelligent Manufacturing, Digital Technology Innovation, and New Quality Productive Forces in the Manufacturing Industry: An Empirical Study Based on Multi-period DID

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Abstract

Intelligent manufacturing has become an important indicator for measuring the core competitiveness of a country's manufacturing industry. Using panel data from A-share listed manufacturing enterprises in China from 2012 to 2023, this paper views the implementation of intelligent manufacturing pilot policies as a quasi-natural experiment, and conducts an empirical analysis employing a mul-ti-period difference-in-differences model to systematically examine the impact of intelligent manufacturing pilot policies on the new quality productive forces of the manufacturing industry and its underlying mechanisms. The empirical results show that intelligent manufacturing pilot policies have a positive effect on promoting new quality productive forces in the manufacturing industry, and this conclusion remains robust after various tests. Mechanism analysis reveals that intelligent manufacturing pilot policies effectively enhance the level of dig-ital technological innovation in manufacturing, thereby assisting in improving new quality productive forces. Group analysis based on enterprise size, owner-ship nature, and geographical location shows that the impact of intelligent man-ufacturing pilot policies on new quality productive forces in manufacturing is heterogeneous, with a greater promoting effect on new quality productive forces in large-scale manufacturing enterprises, non-state-owned enterprises, and northern regions. Therefore, government departments should continue to opti-mize relevant policies and enhance enterprises' digital technological innovation capabilities, ultimately achieving high-quality development of the manufac-tur-ing industry.

Keywords

Intelligent manufacturing; New quality productive forces in the manufacturing industry; Digital technology innovation; Difference-in-differences

1. Introduction

In the current era, marked by the rapid transformation of global manufacturing towards digitalization, networking, and intelligentization, intelligent manufacturing has become a crucial metric for assessing a country's core competitiveness in the manufacturing sector. General Secretary Xi Jinping emphasized in his report to the 20th National Congress of the Communist Party of China that the country should focus on a new generation of artificial intelligence technologies, accelerate the enhancement of the intelligent level of its manufacturing industry, and, based on modern intelligent manufacturing, create new quality productive forces for China's manufacturing sector. This important statement provides strategic direction for the transformation, upgrading, and high-quality development of China's manufacturing industry. As the world's largest manufacturing nation, the Chinese government deeply recognizes the significance of intelligent manufacturing in building a modern industrial system. It has successively introduced a series of industrial policies, providing strong institutional assurance and financial support for the intelligent transformation of manufacturing, further consolidating China's competitive advantage in the global industrial chain.

Since the State Council released the “Made in China 2025” strategic document in 2015, intelligent manufacturing was established for the first time as one of the five major projects for national economic development, marking China's entry into the stage of systematic planning for the development of intelligent manufacturing. Subsequently, the Ministry of Industry and Information Technology issued the “Intelligent Manufacturing Development Plan (2016–2020),” which clarified the development path, key tasks, and safeguarding mechanisms, and promoted a policy toolkit combining pilot demonstrations, standard system construction, and industrial chain collaboration. The report of the 20th National Congress further defined high-end, intelligent, and green development of manufacturing as core elements in establishing a modern industrial system, reflecting the unity of policy continuity and strategic upgrading[1]. Together, these policies have built an industrial policy system driven by intelligent manufacturing, promoting digital empowerment and intelligent transformation of manufacturing enterprises nationwide.

Driven by both policy promotion and technological change, manufacturing enterprises are gradually constructing new productivity systems that are data-driven, algorithm-empowered, and system-coordinated. Research shows that relying on big data analytics, artificial intelligence algorithms, and intelligent sensing devices, intelligent manufacturing systems have achieved cost reduction, quality improvement, and efficiency enhancement in key links such as product design, production scheduling, and process monitoring. Wang et al.[2] pointed out that big data-driven intelligent manufacturing systems possess self-learning, self-optimization, and self-adaptation capabilities, significantly strengthening the manufacturing system's ability to respond to complex environments. Meanwhile, the application of neural networks in predictive maintenance, fault diagnosis, and quality control tasks has become increasingly mature, effectively improving the stability and intelligence of manufacturing processes [3]. Object-oriented software architecture further promotes modularization, flexibilization, and evolvability of manufacturing systems, providing support for intelligent collaboration in complex systems [4][5].

With the combined effect of policy drive and technological empowerment, intelligent manufacturing pilot demonstrations have become an important institution for cultivating new quality productive forces in China's manufacturing industry. However, regarding how intelligent manufacturing pilot policies can substantially realize the leap in new quality productivity for manufacturing enterprises, existing research still lacks systematic empirical analysis. Therefore, this paper will focus on national intelligent manufacturing pilot policies, assessing their mechanisms and effectiveness in promoting technological upgrading and enhancing new quality productive forces in the manufacturing industry, aiming to provide theoretical support and policy recommendations for further improving the intelligent manufacturing policy system and enhancing the high-quality development capacity of the manufacturing industry.

2. Literature Review

As a key driver for promoting high-quality economic development, the new quality productive forces of enterprises mainly manifest as a qualitative leap under the impetus of technological innovation, emphasizing characteristics such as technological disruptiveness, factor synergy, and high-quality development [1]. Its connotation can be specifically divided into three aspects: First, factor reconstruction, including new types of workers, new means of labor, and new labor objects, aims to improve total factor productivity through optimized integration [6]; second, innovation-driven, focusing on disruptive technologies and strategic emerging industries, pushes enterprises towards intelligent and green transformation [7]; third, coordinated development, emphasizing the integration of industry and technology and building efficient industrial ecosystems supported by digital technologies [8]. In terms of indicator system construction, existing research comprehensively evaluates enterprise new quality productive forces from three dimensions: technological, green, and digitalization [9]. The technological dimension mainly covers R&D investment ratio, number of patents, and density of high-tech talents [10]; the green dimension focuses on energy intensity, pollutant emission, and proportion of green patents [7]; the digital dimension measures the degree of digital transformation, the level of digital inclusive finance, and the number of artificial intelligence enterprises [11]. Commonly used methods include the entropy method and principal component analysis, aiming to quantify the comprehensive score of enterprise new quality productive forces [5]. Regarding influencing factors and mechanisms, the external environment—such as institutional openness, free trade zone construction, and digital financial support—significantly enhances enterprise new quality productive forces, with more pronounced effects for non-state-owned enterprises and high-tech industries [12][13]. Regarding internal capacity building, enterprises achieve the improvement of new quality productive forces through three main paths: technological innovation, digital transformation, and green transformation [14]. Furthermore, there are significant regional differences: for instance, the Yellow River Basin exhibits the "Matthew Effect" and "club convergence" phenomena, while digital technology has an obvious spatial spillover effect, promoting the coordinated development of adjacent regions [15]. These mechanisms provide scientific support for policy-making, helping enterprises and regions achieve high-quality economic transformation and upgrading [16].

As a core initiative to promote the intelligent transformation of China’s manufacturing industry, the intelligent manufacturing pilot policy has, since the launch of "Made in China 2025" and the "Intelligent Manufacturing Pilot Demonstration Special Action" in 2015, significantly promoted the deep integration of the new generation of information technology with manufacturing industry [17]. By selecting pilot enterprises, providing fiscal subsidies, and technological demonstrations, this policy promotes the deep integration of new generation information technologies and manufacturing, enhancing enterprises’ micro performance, supply chain collaboration, and innovation capability. Relevant studies mostly adopt quasi-natural experiment methods to reveal the causal effects of the policy [18]. Specifically, the significant optimization in policy has not only improved the efficiency of resource allocation within enterprises, but also reduced cost rigidity, promoted asset adjustments and “machine substitution for labor,” and utilized big data to improve production decision-making [17]; in addition, the policy has a positive effect on enterprises’ ESG performance, especially notable in non-state-owned enterprises and regions with poorer resource and environmental conditions, with significant improvements in environmental performance [19]. The policy also enhances industrial chain integration and innovation investment, improves upstream and downstream cooperation capabilities, and strengthens supply chain resilience, with especially significant effects in high-tech industries and regions with sound intellectual property protection [20]. In terms of innovation, intelligent manufacturing policy promotes both exploratory and exploitative ambidextrous innovation through technological diffusion and human capital upgrading, particularly driving growth in invention patents for strategic emerging industries. However, some enterprises face risks of strategic innovation, which may impact total factor productivity in the short term [21][22]. Regarding regional collaborative innovation, the policy enhances the output of joint patents through digital platforms and industry-university-research cooperation, with more prominent effects in eastern regions [23].

Existing research offers multidimensional discussions around the causal relationship, mechanisms, heterogeneous effects, and policy impacts between intelligent manufacturing and new quality productive forces, showing that intelligent manufacturing upgrades production factors through technological innovation, improves management efficiency of labor, asset operation efficiency, and innovation output efficiency, thereby promoting a leap in the quality of productive forces [24]. Moreover, intelligent manufacturing shifts the production model from standardized mass production to flexible customization, utilizes digital twins and IoT technologies to improve resource allocation efficiency, shortens R&D cycles, and enhances coordination within the industrial chain [25][26]. External policy empowerment and industry ecosystem collaboration are also important drivers for enhancing new quality productive forces—national AI pilot zone policies foster enterprise transformation through digital innovation and market-driven pathways, and pilot intelligent manufacturing enterprises exhibit clear technological spillover effects on non-pilot enterprises within the industry [27][28]. Studies further reveal significant heterogeneity of intelligent manufacturing across different types of enterprises: larger enterprises, labor-intensive firms, and those with abundant data assets benefit more from these policies, and in high-tech industries, service-collaborative intelligent manufacturing outperforms production optimization-type models [23][29]. Regionally, eastern developed areas, due to well-established digital infrastructure and abundant talent reserves, see a stronger role of intelligent manufacturing in propelling new quality productive forces compared to central and western regions [21], and regions with stronger intellectual property protection and policy support display better effects [27].

Overall, the existing literature comprehensively reveals the multidimensional impact mechanisms of intelligent manufacturing pilot policies on enterprises’ new quality productive forces, covering technological innovation, production organization, policy environment, and regional development differences, and employs classical econometric methods combined with machine learning techniques to enhance the rigor and depth of empirical analysis. Nevertheless, there remain several shortcomings: limited research at the macro industrial cluster level, insufficient dynamic and comparative studies of policy tools over the long term, and a need for further investigation into the micro-dynamic process of heterogeneous mechanisms. Based on this, this paper adopts a manufacturing perspective to focus on the impact of intelligent transformation on new quality productive forces in the manufacturing industry, conducts empirical analysis based on the national intelligent manufacturing pilot policy, addresses the lack of existing research which mainly focuses on micro performance and single indicators, and systematically evaluates the overall effect of the policy on new quality productive forces in the manufacturing sector. At the same time, this paper innovatively regards enterprise digital technology innovation as an intermediary mechanism, deeply revealing how intelligent manufacturing promotes the enhancement of new quality productive forces via digital innovation pathways, thus enriching the research on the transmission mechanism of policy effects. By employing a multi-period difference-in-differences model and digital innovation mediation effect analysis, this paper provides more targeted theoretical and empirical support for the optimization of intelligent manufacturing policies, which will help promote the high-quality transformation and upgrading of the manufacturing industry and the continuous improvement of new quality productive forces.

3. Theoretical Basis

As a core initiative by the state to promote high-quality development of the manufacturing industry, the theoretical foundation of the Intelligent Manufacturing Pilot Policy encompasses several dimensions, including the Marxist theory of productive forces, theories of technological innovation, industrial economics, and policy intervention theory. Firstly, based on the Marxist theory of productive forces, intelligent manufacturing systematically restructures the three elements of productive forces—new-quality laborers, new-quality means of labor, and new-quality objects of labor—driving a transformation of production relations towards flatter and more networked configurations, thus achieving the upgrading of elements and intelligent adaptation of production relations [23-25][27]. Secondly, from the perspective of technological innovation theory, pilot policies incentivize internal innovation through fiscal subsidies and tax incentives, promote growth in invention patents, and generate a "lighthouse factory" demonstration effect that drives technological diffusion both within and outside the industry, as well as the construction of innovation ecosystems, thereby facilitating collaborative development among government, industry, academia, research institutions, and finance [28]. Meanwhile, industrial economics theory emphasizes that intelligent manufacturing enhances total factor productivity (TFP) by optimizing production processes and resource allocation through intelligent scheduling, digital twins, and supply chain collaboration, thereby promoting flexible production and the transformation towards servitization, and enhancing market competitiveness. Furthermore, policy intervention theory utilizes quasi-natural experimental methods to identify policy effects, employing multi-period difference-in-differences and robustness checks to ensure scientific validity while stimulating enterprise transformation through signaling effects and resource compensation [29]. From a systems theory perspective, the policy impacts micro-level technological innovation in enterprises, meso-level technological diffusion within industries, and macro-level optimization of economic structures, thereby achieving multi-level coordinated evolution [28]. Empirical research shows that the policy improves new-quality productive forces through three channels: enhancing labor management efficiency, asset operation efficiency, and innovation output efficiency, with the observed policy effects exhibiting heterogeneity according to enterprise scale, regional digital infrastructure, and other factors [21]. In summary, the intelligent manufacturing pilot policy promotes the transformation of the manufacturing industry from traditional factor-driven to innovation-driven modes through element upgrading, technological innovation, institutional incentives, and ecological collaboration, thus achieving a qualitative leap in productive forces and sustainable development. Based on the above, this paper presents the following research hypothesis:

H1: The intelligent manufacturing pilot policy can effectively enhance the new-quality productivity of the manufacturing industry.

The intelligent manufacturing pilot policy systematically enhances enterprises' digital technology innovation capabilities, becoming an important path for accelerating the formation of new-quality productive forces in manufacturing. Digital technologies—represented by big data, artificial intelligence, and the industrial internet—are fundamentally altering the production relations among laborers, means of labor, and objects of labor, driving the intelligentization of production processes, optimization of element allocation, and full-process coordination. Enterprises utilize industrial internet platforms to digitally connect the design, manufacturing, and sales stages, effectively improving R&D efficiency and operational effectiveness [25]; the embedded application of blockchain, cloud computing, and other technologies further strengthens the intelligence of asset management and human resource allocation. At the innovation level, digital technologies enable enterprises to achieve breakthrough technological upgrades, lower R&D risks through virtual simulation and digital twin approaches, and build an enterprise-centered technological innovation network with collaborative participation from industry, academia, and research institutions, thereby stimulating a positive "technology-industry" interaction [24]. Meanwhile, the government reduces the initial input risks of digital transformation for enterprises through fiscal awards, subsidies, and tax reductions, enhancing their motivation for technological innovation. The "technology endorsement" effect of policy pilots also helps enterprises secure additional external capital and strategic cooperation, reinforcing the ability for continuous investment in digital technologies. In addition, the pilot policy generates significant spillover effects [21]. Driven by the “lighthouse effect,” non-pilot enterprises achieve technological catch-up through imitation and learning, promoting the diffusion of digital transformation mechanisms across the entire industry. Under the impetus of policy, building an innovation network centered on enterprises with the collaborative participation of industry, academia, and research institutions becomes imperative, where data resources, knowledge achievements, and technological pathways are jointly shared and constructed, significantly strengthening the systemic innovation capability and element integration efficiency of manufacturing systems. Digital technological innovation has been empirically proven to be closely correlated with new-quality productive forces, as demonstrated by the continuous optimization of enterprise intelligence, greening, human capital structure, and other dimensions [27]. Based on the above, this paper presents the following research hypothesis:

H2: The intelligent manufacturing pilot policy can improve enterprises' digital technology innovation levels, thereby enhancing the new-quality productivity of the manufacturing industry.

4. Research Design

4.1. Model setting

Since the intelligent manufacturing pilot policy was introduced in four phases, this study uses a multi-period difference-in-differences (DID) approach to assess the impact of the intelligent manufacturing pilot policy on new quality productivity in the manufacturing industry. The model is constructed as follows:

$$NPRO_{it} = \alpha_1 + \beta_1 DID_{it} + \theta_1 \sum X_{it} + \lambda_t + \mu_i + \xi_{it} \tag{1}$$

Among them, $NPRO_{it}$ represents the new quality productivity of the manufacturing industry in city i in year t. $DID_{it} = treat_i \times post_t$, where $treat_i$ is the dummy variable for the intelligent manufacturing pilot policy, and $post_t$ is the time dummy variable. In the year the policy begins implementation and the subsequent years, DID_{it} is assigned a value of 1; in all other cases, its value is set to 0. The coefficient β_1 measures the impact of the intelligent manufacturing pilot policy on the new quality productivity of the manufacturing industry, i.e., the core policy effect examined in this paper, used to test research hypothesis 1. X_{it} includes a series of selected control variables; λ_t and μ_i are time and individual fixed effects, respectively; ξ_{it} represents the random disturbance term.

In order to verify Hypothesis 2 proposed in the theoretical analysis, this paper establishes the following mediating effect model using the three-step method to examine its mechanism of action:

$$M_{it} = \alpha_2 + \beta_2 DID_{it} + \theta_2 \sum X_{it} + \lambda_t + \mu_i + \xi_{it} \tag{2}$$

$$NPRO_{it} = \alpha_3 + \beta_3 DID_{it} + \varphi M_{it} + \theta_3 \sum X_{it} + \lambda_t + \mu_i + \xi_{it} \tag{3}$$

The above two formulas, together with formula (1), jointly constitute the mediating effect model. This paper mainly considers the level of digital technology innovation of enterprises as the mediating variable (M).

4.2. Data source

This paper conducts an empirical analysis using panel data of A-share listed manufacturing companies from 2012 to 2023. The financial data of the companies mainly come from the Wind and CSMAR databases, while data on new quality productive forces and enterprise digital technology innovation are obtained by counting relevant keywords through Python programs. In addition, during the research process, this paper excludes samples from the financial and insurance sectors, ST companies, ST* companies, and companies with missing data. For individual missing data, the linear interpolation method is used for completion, and all continuous variables are winsorized at the top and bottom 1% to reduce the impact of outliers. Furthermore, all variables measured by non-percentage indices are processed with logarithmic transformation to reduce the dispersion of the sample data.

4.3. Variable selection

The explained variable is the new quality productive forces of the manufacturing industry. In constructing the indicator system for new quality productive forces, the studies of Song Jia et al.[30] and Zhang Xiue et al.[31] were referenced, and data availability was taken into consideration. Based on the three dimensions of "laborers-labor objects-means of labor," a new quality productive force system was jointly constructed with an inherent linkage and clear hierarchy . In this paper, the entropy method is used to determine the weights of the indicators and to calculate the comprehensive score of new quality productive forces in the manufacturing industry.

Table 1. New Quality Productivity Indicator System.

Primary indicator	Secondary indicators	Tertiary indicator	Indicator description
New-type workers	Staff quality	Proportion of R&D personnel	(Number of R&D personnel / Number of employees)×100
		Proportion of highly educated personnel	(Number of people with a postgraduate degree or above / Number of employees)×100
	Quality of management	Executive Green Cognition	ln (Keyword frequency of green development in annual reports + 1)
		Overseas background of the management team	If there are executives with overseas backgrounds, the value is 1; otherwise, it is 0.
New-type labor objects	Ecological environment	Environmental governance score	The E indicator in the Huazheng ESG rating is assigned values from 1 to 9 for its nine levels.
	Future development	Proportion of fixed assets	(Fixed assets / Total assets)×100
		Capital accumulation rate	(Increase in owners' equity for the year / Beginning owner's equity)×100
Quality of new-type labor	Technology labor materials	Innovation level	ln (Number of granted patents + 1)
	Digital labor materials	Degree of digitalization	ln (Frequency of Digitalization Keywords in Annual Reports + 1)
		Proportion of intangible assets	(Intangible assets / Total assets)×100
	Green labor materials	Green technology level	ln (Number of granted green patents + 1)
		Proportion of green patents	(Number of green patents granted / Number of granted patents)×100

The explanatory variable is the Intelligent Manufacturing Pilot Policy. Based on the list of pilot cities for intelligent manufacturing published on the official website of the Ministry of Industry and Information Technology, this paper regards the implementation of the intelligent manufacturing pilot policy as a quasi-natural experiment. Considering that the intelligent manufacturing pilot policy was introduced during 2015-2018, this study adopts a multi-period Difference-in-Differences (DID) model for analysis. Specifically, the years 2015, 2016, 2017, and 2018 are considered as the years when the four rounds of the pilot policy began to take effect. The values for these four years and subsequent years are set to 1 to reflect the emergence of the policy effect; while the values for years prior to these are set to 0, facilitating the comparison of changes before and after the policy implementation.

Mediating variable. Based on the hypothesis of the theoretical mechanism analysis mentioned earlier, this paper selects the level of digital technological innovation of enterprises (Innovation) as the mediating variable. The specific measurement method refers to the approach of Zheng Panpan et al. [32], constructing an indicator system for digital technological innovation in enterprises from three dimensions: digital product innovation, digital process innovation, and digital business model innovation (Table 2).

Table 2. Enterprise Digital Technology Innovation Index System.

Dimension	Keyword
Digital product innovation	Sensor network, smart home, artificial intelligence, application software, program system, development platform, software system, intelligent terminal, smart hardware, wearable device, mobile healthcare, electronic payment, intelligent security, intelligent service, smart transportation, smart device, smartphone, autonomous driving, smart car, biometric identification, visual recognition, virtual reality, facial recognition, human-computer interaction, unmanned driving, robot, semantic analysis, smart TV, smart city, online education, smart watch, smart community, smart grid, operating system, application system.
Digital Process Innovation	Intelligentization, automation, integration, systematization, data mining, machine learning, neural networks, intelligent algorithms, intelligent technology, virtual simulation, intelligent manufacturing, blockchain, supply chain, information management, information systems, control systems, technology platform, cloud technology, cloud computing, management platform, simulation technology, system management, data management, integration, modularization, autonomy, automatic control, information services, smartization, control system.
Digital Business Model Innovation	Digitalization, electronization, networking, informatization, cloud services, cloud, cloud platform, big data, data resources, information resources, data platform, business intelligence, cloud strategy, cloud application, cloud architecture, cloud construction, cloud migration, cloudification, platformization, service platform, e-commerce, online marketing, Internet Plus, massive data, user profiling, modernization, online platform, triple play, virtualization, business model, online mall, electronic transaction, Internetization, operation platform

Control variables. This paper refers to the approaches of Xi Mingming et al. [23] and Li Xinru et al. [33], selecting the following control variables: the natural logarithm of total assets is used to measure firm size (size); the ratio of total liabilities to total assets is used to measure the asset-liability ratio (lev); the difference between the current year and the year of listing is used to calculate listing age (listage); the proportion of shares held by the largest shareholder is used to measure ownership concentration (top1); the increment of operating income for the current year divided by total operating income of the previous year is used to measure operating income growth rate (growth); fixed assets net value divided by total assets is used to measure the proportion of fixed assets (fixed); net profit as a proportion of ending net assets is used to measure return on equity (roe); and net cash flow from operating activities divided by total assets is used to measure cash flow ratio (cashflow).

4.4. Descriptive statistical analysis

As shown in Table 3, the minimum value of the new quality productivity in the manufacturing industry is 0 and the maximum value is 0.53, indicating a relatively large difference between enterprises. This also highlights the necessity of this study, as the difference may stem from policy dividends. To test for potential multicollinearity in the model, a variance inflation factor (VIF) analysis was conducted for each variable. The results show that all variables have VIF values between 1 and 3.23, with an average VIF of 1.55 and a maximum value of only 3.23, which is significantly below the critical threshold of 10. This indicates that there is no significant multicollinearity problem among the variables selected in this study.

Table 3. Descriptive statistics of each variable.

Variable name	symbol	Observations	Mean	Standard Deviation	Minimum	Median	Maximum	VIF
Manufacturing industry's new quality productive forces	NPRO	11564	0.1336	0.072	0.00	0.12	0.53	-
Intelligent manufacturing pilot policy	DID	11564	0.0150	0.121	0.00	0.00	1.00	1
The level of digital technology innovation in enterprises	Innovation	11564	0.0727	0.086	0.00	0.04	0.49	1.03
Enterprise scale	size	11564	23.319	2.428	19.08	23.27	28.29	3.23
Debt-to-asset ratio	lev	11564	0.5651	0.182	0.06	0.60	0.85	2.11
Listing age	listage	11564	3.3227	0.122	3.04	3.33	3.50	1.44
Equity concentration	top1	11564	0.2057	0.076	0.10	0.22	0.63	1.16
Operating income growth rate	growth	11564	0.2164	0.686	-0.70	0.10	4.73	1.05
Proportion of fixed assets	fixed	11564	0.0669	0.088	0.00	0.02	0.54	1.31
Return on Equity (ROE)	roe	11564	0.0222	0.195	-0.88	0.07	0.23	2.03
Cash Flow Ratio	cashflow	11564	0.0299	0.117	-0.32	0.00	0.66	1.15

5. Empirical Results and Analysis

5.1. Analysis of Benchmark Regression Results

Based on a multi-period difference-in-differences model, the impact of the smart manufacturing pilot policy on new quality productivity in the manufacturing industry was tested. The results in Table 4 show that, whether or not control variables are introduced, the effect of the smart manufacturing pilot policy on new quality productivity in the manufacturing industry is significantly positive, with the level of significance consistently maintained above 1%. This indicates that the smart manufacturing pilot policy can enhance new quality productivity in manufacturing enterprises, thereby confirming Hypothesis 1.

Table 4. The Impact of Smart Manufacturing Pilot Policies on the New Quality Productivity of the Manufacturing Industry.

Variable	(1)	(2)
	NPRO	NPRO
DID	0.0309***	0.0307***
	(3.2197)	(3.1908)
Control variable	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	11564	11564
R-squared	0.1216	0.1221

a. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are t-statistics, the same applies below.

5.2. Parallel trend test

The application of the difference-in-differences model hinges on the treated group and the control group maintaining the same trend in the relevant field prior to policy implementation, thus conforming to the parallel trends assumption. To this end, this paper sets the baseline year for time analysis as the year of implementation of the intelligent manufacturing pilot policy, in order to evaluate the evolutionary trend of new quality productivity in the manufacturing industry before and after the policy implementation. As shown in Figure 1, prior to policy implementation, the evolution of new quality productivity in the manufacturing industry was relatively stable for both the treated and control groups. However, after the implementation of the intelligent manufacturing pilot policy, the new quality productivity in the treated group showed a significantly increasing trend. Therefore, this study satisfies the parallel trends assumption.

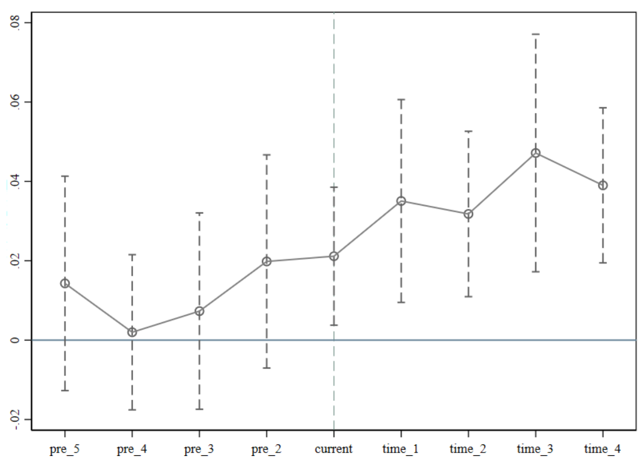

Figure 1. Parallel trend test.

5.3. Placebo test

To ensure that the significant differences in new quality productivity between the treatment group and the control group indeed stem from policy dividends, this paper conducts a placebo test by constructing new treatment and control groups through 1,000 random samples. The results are shown in Figure 2, where it can be observed that the randomly generated coefficients are mostly centered around zero and display a normal distribution, with the significance levels of the vast majority of coefficients above 0.1. Therefore, this paper asserts that unobserved individual characteristics of enterprises do not affect the accuracy of the estimation results, and the DID model on new quality productivity in manufacturing successfully passes the placebo test.

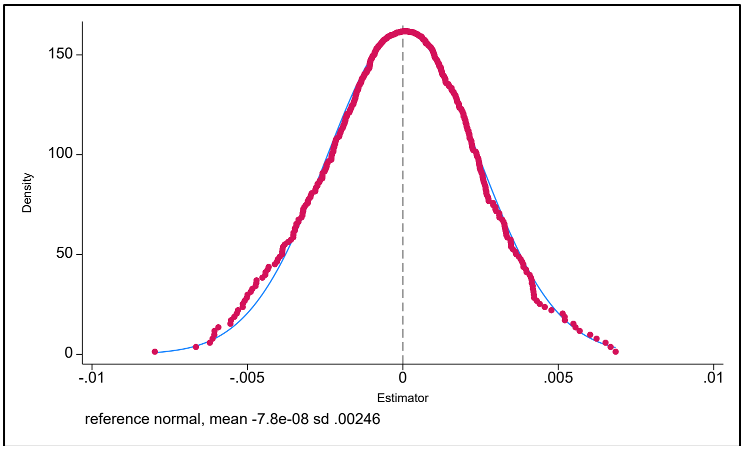

Figure 2. Kernel density distribution of 1000 samples

5.4. Other robustness tests

(1) Replace the core explanatory variable

Excluding the intelligent manufacturing pilot manufacturing enterprises established in 2017 and 2018 from the sample, and replacing the core explanatory variable with the intelligent manufacturing pilot manufacturing enterprises established in 2015 and 2016 for regression analysis. As shown in column (1) of Table 5, the intelligent manufacturing pilot policy still has a positive impact on the new quality productivity of the manufacturing industry at the 5% significance level, which is consistent with the benchmark regression results.

(2) Alternative time window

To prevent the impact of the intelligent manufacturing pilot policy on the new quality productivity of the manufacturing industry from changing over time, this paper shortens the time window to test whether the effect of the intelligent manufacturing pilot policy on the new quality productivity of the manufacturing industry is time-sensitive. Specifically, using the pilot year as the time boundary, sample data from three years before and after the pilot are selected for re-examination. The results in column (2) of Table 5 indicate that when the regression time is changed, the impact of the intelligent manufacturing pilot policy on the new quality productivity of the manufacturing industry remains significantly positive, which further confirms the robustness of the findings of this study.

(3) Replace the clustering method

To ensure the robustness of the research results, this paper adjusts the clustering method by reclustering robust standard errors at the city level. The results are shown in column (3) of Table 5, and the regression results remain significant.

Table 5. Robustness test results.

variable	(1)	(2)	(3)
	NPRO	NPRO	NPRO
DID	0.0218**	0.0293**	0.0402***
	(2.4202)	(2.1693)	(2.8638)
Control variable	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	11564	11564	11564
R-squared	0.1226	0.1602	0.1595

6. Further analysis

6.1. Mechanism analysis

The baseline regression analysis in the previous section preliminarily verified Research Hypothesis 1, namely, that intelligent manufacturing pilot policies can significantly enhance the advanced productive forces in the manufacturing industry. However, through which specific transmission mechanisms does this policy take effect? This still requires more in-depth investigation. Based on the theoretical analysis and research hypotheses discussed earlier, this paper next analyzes the mechanism by which intelligent manufacturing pilot policies improve the advanced productive forces of the manufacturing industry from the perspective of enterprises' digital technological innovation levels. The results are shown in Table 6. The DID coefficients in columns (1) and (2) are both significantly positive, indicating that the intelligent manufacturing pilot policy not only improves the advanced productive forces in the manufacturing industry but is also conducive to enhancing enterprises' digital technological innovation levels. In column (3), the coefficient for enterprises' digital technological innovation level is 0.0373 and is significant at the 5% significance level, indicating that the level of digital technological innovation can effectively improve the advanced productive forces of the manufacturing industry. After introducing the mediating variable "Innovation," the DID coefficient remains significantly positive, signifying that this factor constitutes the mechanism through which the intelligent manufacturing pilot policy exerts its effect on the advanced productive forces of the manufacturing industry. The intelligent manufacturing policy, by providing financial support, technological guidance, and standardized norms, incentivizes enterprises to accelerate the R&D and application of digital technologies, driving digitalization, networking, and intelligent transformation. Driven by digital technological innovation, enterprises realize the reconstruction of production methods, organizational models, and the allocation of factors, thereby significantly enhancing the level of advanced productive forces in the manufacturing industry.

Table 6. Intelligent Manufacturing Pilot Policy, Enterprise Digital Technology Innovation Level, and New Quality Productive Forces in Manufacturing Industry.

variable	(1)	(2)	(3)	(4)
	NPRO	Innovation	NPRO	NPRO
DID	0.0402***	0.0373**		0.0345**
	(2.9298)	(2.1897)		(2.2755)
Innovation			0.1699***	0.1663***
			(9.9637)	(9.5663)
Control variable	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	11564	11564	11564	11564
R-squared	0.1595	0.1820	0.1669	0.1679

6.2. Heterogeneity analysis

(1) Heterogeneity of enterprise scale

Considering that different enterprise sizes affect business decisions and behaviors, this study refers to the research method of Zhou Chen [34] and divides the samples into two categories—large-scale manufacturing enterprises and small- and medium-sized manufacturing enterprises—based on the average size of total assets, then conducts tests separately. The test results are shown in columns (1)-(2) of Table 7. It can be seen that the Intelligent Manufacturing Pilot Policy has a more significant effect on the improvement of new quality productivity in large-scale manufacturing enterprises, while its impact on new quality productivity in small- and medium-sized manufacturing enterprises is relatively small. The main reason is that large-scale manufacturing enterprises have strong resource integration advantages in capital, technology, talent, and management capabilities, allowing them to absorb policy dividends more quickly and accelerate the deployment of digital technologies and intelligent transformation. However, small- and medium-sized manufacturing enterprises generally face multiple challenges, such as insufficient capital investment, relatively weak technological foundations, and a shortage of professional technical talents. As a result, their transformation efficiency under policy support is relatively low, making it difficult to achieve efficient conversion of digital technology into productivity, and thus the policy effect is relatively limited.

(2) Heterogeneity of Property Rights

Different types of enterprises differ in their abilities to acquire resources, access information channels, withstand market risks, and choose operating strategies, and these differences significantly influence their behavioral patterns in decision-making for intelligent manufacturing projects. Therefore, based on the nature of property rights, this paper classifies the sample enterprises into state-owned manufacturing enterprises and non-state-owned manufacturing enterprises, and conducts empirical analysis separately. The analysis results (Table 7, columns (3)-(4)) show that, compared with state-owned manufacturing enterprises, intelligent manufacturing policies have a more significant promoting effect on the new quality productivity of non-state-owned manufacturing enterprises. The possible reasons are as follows: Non-state-owned manufacturing enterprises, facing intense market competition, are more inclined to utilize digitalization and intelligent technologies to improve efficiency and product added value, thereby enhancing competitiveness. At the same time, their internal incentive mechanisms are more flexible, with technological innovation achievements closely tied to enterprise performance and managerial benefits, helping to stimulate the enthusiasm for technological upgrading. In addition, non-state-owned manufacturing enterprises have market-driven advantages in resource allocation, enabling them to quickly adjust strategic priorities according to policy guidance and prioritize resources for intelligent manufacturing. In contrast, although state-owned manufacturing enterprises possess certain advantages in resources and policy support, they have limitations in decision-making efficiency, risk preference, and institutional constraints, resulting in relatively slower responses to policy incentives in improving the new quality production capacity of the manufacturing sector.

(3) Heterogeneity of Geographical Location

China has a vast territory, with significant differences in infrastructure and resource conditions across cities. This paper further examines the impact of the smart manufacturing pilot policy on the new productive forces of the manufacturing industry in different geographic locations. Using the Qinling-Huaihe Line as a boundary, Chinese cities are divided into northern and southern cities [35]. The regression analysis results are shown in columns (5) and (6) of Table 7. It can be seen that the DID coefficient for northern regions is 0.03 and is significant at the 1% level, indicating that the smart manufacturing pilot policy has a significant positive effect on the new productive forces of the manufacturing industry in these regions, while the effect on southern regions is not significant. The main reasons may be: some traditional industries in the north have a heavier foundation, making the manufacturing industry more sensitive to policy support, and the introduction of smart manufacturing policies provides an important opportunity for technological upgrading and efficiency improvement; whereas most manufacturing industries in the south already possess strong market-oriented operations and technological innovation capabilities, relying less on policy-driven effects, resulting in a less obvious marginal effect of smart manufacturing policies and thus a relatively weaker improvement in the new productive forces of the manufacturing industry.

Table 7. Effects of Intelligent Manufacturing Pilot Policies under Different Historical and Cultural Conditions.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Large-scale manufacturing industry	Small and medium-sized manufacturing industries	State-owned manufacturing industry	Non-state-owned manufacturing industry	South	North
DID	0.015**	0.014*	0.005	0.025***	0.011	0.030***
	(2.135)	(1.871)	(0.458)	(3.746)	(1.515)	(3.210)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5863	5996	2207	9652	8772	3087
R-squared	0.077	0.065	0.045	0.057	0.049	0.067

7. Conclusion and Policy Recommendations

7.1. Conclusion

This study utilizes panel data from China's A-share listed manufacturing companies from 2012 to 2023 to systematically examine the intrinsic relationship between intelligent manufacturing pilot policies and new productive forces in the manufacturing industry through a multi-period difference-in-differences (DID) model. The following conclusions are drawn: First, the intelligent manufacturing pilot policy exerts a positive promoting effect on new productive forces in the manufacturing industry, and this conclusion remains valid after placebo tests, replacing core explanatory variables, changing the time window, and utilizing different clustering methods. Second, mechanism analysis shows that the intelligent manufacturing pilot policy can effectively promote the improvement of digital technology innovation in the manufacturing industry, thereby facilitating the enhancement of new productive forces in the sector. Third, the impact of the intelligent manufacturing pilot policy on new productive forces in the manufacturing industry is heterogeneous, with a greater promoting effect on large-scale manufacturing enterprises, non-state-owned manufacturing enterprises, and those located in northern regions.

7.2. Suggestion

First, strengthen policy implementation and optimize mechanisms to promote the widespread and in-depth integration of intelligent manufacturing. Advance and refine the implementation paths and support mechanisms for intelligent manufacturing pilot policies, expand policy coverage, reinforce infrastructure construction, and increase financial and fiscal support for small and medium-sized enterprises to reduce their costs of intelligent transformation. Meanwhile, enhance the integration of policies with local industrial structures and regional development strategies, formulate differentiated support plans tailored to local conditions, and improve policy adaptability and implementation efficiency. Additionally, establish dynamic assessment mechanisms and strengthen performance feedback, select leading intelligent manufacturing enterprises and exemplary cases to play a demonstration role, and build a sound mechanism of "pilot—demonstration—promotion" to accelerate the broad leap in new productive forces within the manufacturing sector.

Second, focus on cultivating enterprises' digital capabilities and improving the technological innovation ecosystem. Increase investment in the research, introduction, and application of digital technologies to promote enterprises' breakthroughs in key core technologies and the construction of digital infrastructure. At the same time, encourage enterprises to establish industry-university-research collaborative innovation mechanisms with higher education institutions and research institutes, build diversified platforms for technological exchange and achievement transformation, and improve the integration and transformation efficiency of digital innovation resources. In addition, efforts should be made to strengthen the cultivation and introduction of digital talent, optimize the application environment for digital technologies, and improve relevant intellectual property protection and incentive mechanisms. This will create an institutional foundation conducive to the continuous emergence of digital innovation, aiming to construct an industrial ecosystem with deep integration of intelligent manufacturing and digital innovation.

Third, focus on categorized policy implementation and tailoring approaches to local conditions to enhance the precision and effectiveness of policies. Specifically, efforts should continue to strengthen the leading role of large-scale manufacturing enterprises, encouraging them to undertake exemplary explorations and technological breakthroughs in intelligent manufacturing, thereby leveraging the "leading goose effect." At the same time, policy support for non-state-owned manufacturing should be increased by optimizing the business environment, expanding financing channels, and providing enhanced technical support to stimulate their intrinsic motivation for digital transformation and technological innovation. Additionally, given the more pronounced policy effects observed in northern regions, it is important to thoroughly summarize their experiences and practices, and explore differentiated implementation paths in southern regions. This should be done in accordance with regional industrial foundations, technological conditions, and resource endowments, to promote deep integration of intelligent manufacturing with local advantageous industries, address shortcomings, enhance overall policy effectiveness, and achieve collaborative regional development and a comprehensive improvement in new quality productive forces.

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