Does Industry–Finance Integration Promote Intelligent Manufacturing? Evidence from a Quasi-Natural Experiment of China's Industry–Finance Integration Pilot Program

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Abstract. In the digital economy, intelligent manufacturing has become a pivotal route for manufacturing firms to achieve high-quality development. A persistent challenge is how to channel financial resources toward the long-horizon, high-uncertainty investments required by intelligent manufacturing. From the perspective of finance serving the real economy, this paper exploits China's Industry–Finance Integration Pilot Program as a quasi-natural experiment and evaluates its impact on firms' intelligent manufacturing. Using firm- year observations of A-share listed manufacturing companies from 2010 to 2023, we implement a staggered difference-in-differences design with firm and year fixed effects and firm-level clustered standard errors. The results show that the pilot policy significantly increases firms' intelligent manufacturing index constructed from the MD&A text of annual reports. Mechanism analyses suggest that the policy improves intelligent manufacturing by alleviating financing constraints and fostering technological innovation. Heterogeneity tests indicate stronger effects for firms facing more intense product-market competition, high-tech firms, and firms led by higher-ability managers. Extension analyses further show positive effects on sub-dimensions of intelligent manufacturing (AI, big data, Internet technologies, and value-chain intelligence) and that intelligent manufacturing improves total factor productivity. These findings provide micro-level evidence on how industry–finance integration promotes intelligent manufacturing, offering policy implications for scaling up pilot programs and supporting intelligent transformation and digital upgrading in manufacturing

Keywords: industry–finance integration, pilot policy, intelligent manufacturing, staggered DID, financing constraints, innovation, total factor productivity

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H. Li et al. (eds.), *Proceedings of the 2026 5th International Conference on Big Data Economy and Digital Management (BDEDM 2026)*, Advances in Economics, Business and Management Research 383,
https://doi.org/10.2991/978-94-6239-640-1_28

1 Introduction

The global manufacturing landscape is undergoing a profound transformation driven by Industry 4.0, with intelligent manufacturing emerging as the cornerstone of international competitiveness. Countries such as Germany (Industrie 4.0), the United States (Advanced Manufacturing Partnership), and Japan (Society 5.0) have launched strategic initiatives to integrate digital technologies into manufacturing. For China, the world's largest manufacturing economy, this transformation is particularly significant: the manufac- turing sector contributes approximately 27% of GDP and employs over 100 million workers, making intelligent upgrading essential for sustained economic growth. New-generation information technologies such as artificial intelligence, blockchain, cloud computing, and big data are reshaping economic activities and industrial organization. Intelligent manufacturing, as a key application domain of these technologies, represents a profound transformation of production processes and is widely viewed as a hallmark of new productive forces [30]. Policy initiatives such as Made in China 2025 and the 14th Five-Year Plan underscore China's strategic emphasis on intelligent manufacturing. Whether China can seize this historic opportunity of intelligent manufacturing will directly affect its goal of becoming a manufacturing powerhouse. Promoting intelligent manufacturing requires manufacturing firms to play the leading role, raising the question: how can we accelerate intelligent manufacturing development?

Intelligent manufacturing, as a high-level technological innovation activity, inevitably requires high-quality financial supply [28]. However, there is currently a structural mismatch between financial resource supply and the actual funding needs of intelligent manufacturing [29]. This imbalance severely hinders intelligent manufacturing development. Specifically, since traditional finance tends to be risk-averse, it is difficult to provide stable financial resources for long-cycle, high-risk intelligent manufacturing projects, reducing the capacity of finance to serve the real economy. To fundamentally solve this problem, it is urgent to create an ecosystem of positive interaction between industry and finance.

To strengthen financial support for industry, China launched the Industry–Finance Integration Pilot Program. The first batch of 37 pilot cities was announced on December 29, 2016, and the second batch of 51 cities was announced on December 16, 2020 [19]. The program aims to build an ecosystem where industrial and financial resources interact positively through policy coordination, platform construction, and financial innovation, thereby enhancing financing availability and efficiency for manufacturing upgrading [18].

This paper asks: *Does industry–finance integration promote intelligent manufacturing at the firm level?* Leveraging the pilot policy as a quasi-natural experiment, we estimate its causal impact on listed manufacturing firms' intelligent manufacturing using a staggered difference-in-differences framework [16]. Our study contributes to understanding the relationship between industry–finance integration and intelligent manufacturing, providing useful references for subsequent policy implementation and corporate intelligent manufacturing practices.

2 Institutional Background and Related Literature

2.1 Industry–Finance Integration and Its Economic Effects

The term "industry–finance integration" originates from "industry– finance combination," with both sharing core meanings but subtle distinctions. According to He and Zheng [9], industry–finance inte- gration refers to the deep interaction between industrial capital and financial capital through equity participation, mutual penetration, and cooperation. Existing studies examine its roles in alleviating financing constraints [6], improving investment efficiency [13], and facilitating industrial structure upgrading [23]. However, given the potential for financial risk accumulation if industry–finance combination is driven purely by profit-seeking, existing research shows that industry–finance integration may adversely affect in- vestment efficiency and operating performance. Therefore, in practice, China's industry–finance integration is primarily characterized by the "from industry to finance" model, where enterprises invest in financial institutions to better serve their main business operations.

2.2 Determinants and Measurement of Intelligent Manufacturing

As a new production method, intelligent manufacturing deeply integrates advanced information technologies (including AI, IoT, big data, machine learning, and cloud computing) with manufacturing technologies, covering design, production, sales, logistics, and service [30]. This new production method enables manufacturing firms to possess capabilities such as self-perception, self-learning, self-decision-making, self-execution, and self-adaptation, aiming to improve production efficiency, reduce costs, optimize product quality, and drive industrial structure transformation and upgrading. At the firm level, existing research explores factors influencing intelligent manufacturing from perspectives of capital and human resources [25], information infrastructure [3], and labor and environmental regulations [2, 17]. Following text-based approaches [26], we construct a firm-level intelligent manufacturing index using MD&A disclosures.

2.3 Contributions

Reviewing existing research, studies on the economic effects of industry–finance integration pilot policies remain scarce [11, 24], and no research has yet comprehensively examined the relationship between industry–finance integration and intelligent manufacturing from a micro-enterprise perspective. This study contributes by: (1) providing micro-level evidence on how an industry–finance integration policy shapes intelligent manufacturing; (2) clarifying mechanisms via financing constraints and technological innovation; and (3) examining heterogeneous effects and conducting extension analyses. Our findings verify the empowering effect and pathways of industry–finance integration pilot policies on corporate intelligent manufacturing, providing useful references for subsequent policy implementation and corporate intelligent manufacturing practices.

3 Theoretical Framework and Hypotheses

Firms often face multiple challenges when promoting intelligent manufacturing. First, intelligent manufacturing requires comprehensive transformation covering design, production, logistics, and services, demanding systematic ground-up redesign and restructuring of processes and material resources. To adapt to this transformation, firms must undertake large-scale updates, reorganizations, and rebuilding, which requires enormous capital investment. However, due to financing constraints and technological limitations, firms face a series of adjustment costs that are not only expensive but also require relatively long periods to complete, severely constraining intelligent manufacturing effectiveness [22].

Against this background, the industry–finance integration pilot policy can effectively alleviate corporate financing constraints and enhance firm technological innovation, thereby opening new pathways for intelligent manufacturing. Based on this, we propose the following hypothesis:

Hypothesis 1: Holding other conditions constant, the Industry–Finance Integration Pilot Program improves firms' intelligent manufacturing.

Table 1. Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max
IM	21048	0.073	0.120	0.000	0.683
DID	21048	0.192	0.394	0.000	1.000
Size	21048	22.046	1.174	19.780	26.164
Lev	21048	0.397	0.193	0.051	0.886
ROA	21048	0.045	0.065	−0.220	0.226
Growth	21048	0.172	0.374	−0.566	2.499
BM	21048	0.592	0.236	0.121	1.171
Cashflow	21048	0.049	0.067	−0.167	0.248
Dual	21048	0.309	0.462	0.000	1.000
Indep	21048	0.375	0.054	0.300	0.571
Top10	21048	0.577	0.148	0.230	0.904
Balance	21048	0.371	0.285	0.009	0.996
INST	21048	0.425	0.250	0.004	0.957
Age	21048	2.067	0.800	0.000	3.332
Board	21048	2.114	0.191	1.609	2.708

The pilot policy can achieve this through two main channels. First, the policy enhances cooperation between industrial enterprises and financial institutions, further strengthening financial services for the real economy, alleviating corporate financing pressure, and providing intelligent support [5]. Second, the policy encourages financial institutions to innovate financial products and services, which helps firms accumulate abundant innovation resources and further stimulates technological innovation momentum, ultimately promoting intelligent manufacturing development [27].

4 Research Design

4.1 Sample and Data

We use A-share listed manufacturing firms from 2010 to 2023. Following the original study, we exclude: (i) ST and *ST firms; (ii) insurance and financial firms; (iii) observations with missing data; and (iv) firms with negative equity. To mitigate outliers, continuous variables are winsorized at the 1st and 99th percentiles. The final sample contains 21,048 firm-year observations. Firm-level financial data are sourced from the CSMAR database.

4.2 Measuring Intelligent Manufacturing

The dependent variable is a text-based intelligent manufacturing index (*IM*). Following the original procedure, we crawl annual reports from the Shanghai and Shenzhen stock exchanges, convert the MD&A section into plain text, and build a dictionary-based measure across four dimensions: AI technology (*AI*), big data technology (*DT*), Internet technology (Internet), and value-chain intelligent technology (Value). The index is computed as the proportion of feature words appearing in MD&A, multiplied by 100.

4.3 Treatment Variable: Pilot Policy Exposure

The key explanatory variable is a policy dummy DID defined as the interaction of Treat and Post. Treat equals 1 if a firm's city is selected as an industry–finance integration pilot city, and 0 otherwise. The policy was implemented in two batches: the first batch (37 cities) was announced on December 29, 2016; the second batch (51 cities, including 18 continuing cities) was announced on December 16, 2020. To match the original design, Post is defined case-by-case:

(i) for non-pilot cities, Post=0; (ii) for cities only in the first batch, Post=1 during 2017–2019; (iii) for cities in the first batch and con- tinuing in the second batch, Post=1 for 2017 and subsequent years; and (iv) for cities only in the second batch, Post=1 for 2021 and subsequent years.

4.4 Control Variables

Controls include firm size (*Size*), leverage (*Lev*), return on assets (*ROA*), growth *(Growth)*, book-to-market ratio (*BM)*, cash flow ratio *(Cashflow),* CEO duality *(Dual*), board independence (*Indep)*, top-10 shareholders' ownership *(Top10),* ownership balance (Balance), institutional ownership (*INST*), firm age *(Age)*, and board size (Board).

4.5 Baseline Model

We adopt a staggered difference-in-differences (DID) design for several reasons. First, the pilot policy provides a quasi-natural experiment with exogenous variation in treatment timing across cities, mitigating endogeneity concerns that plague cross-sectional analyses. Second, firm and year fixed effects control for time-invariant firm heterogeneity and common temporal shocks, isolating the policy's incremental effect. Third, firm-level clustering accounts for within-firm serial correlation, yielding conservative inference.

We estimate:

$$IM_{it} = \alpha_0 + \alpha_1 DID_{ct} + \alpha_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where μi and λt denote firm and year fixed effects. Standard errors are clustered at the firm level.

4.6 Descriptive Statistics

Table 1 presents the descriptive statistics for all variables. The mean of IM is 0.073 with a standard deviation of 0.12, while the minimum and maximum values are 0 and 0.683, respectively, indicating substantial heterogeneity in intelligent manufacturing levels among listed manufacturing firms. The mean of DID is 0.192, suggesting that approximately 19.2% of firm-year observations are located in pilot cities during the post-treatment period. The control variables fall within reasonable ranges and are consistent with prior studies.

5 Empirical Results

This section presents our main empirical findings, including baseline results, parallel trends tests, placebo tests, and robustness checks.

5.1 Baseline DID Results

Table 2. Baseline Regression Results

	(1) IM	(2) IM
DID	0.010**	0.009**
	(2.44)	(2.11)
Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Constant	0.071***	−0.307***
	(89.86)	(−4.61)
Observations	21,048	21,048
Adj. $R2$	0.573	0.677

$**p < 0.05$, $***p < 0.01$. t-statistics in parentheses.

The baseline regression examines the impact of the industry–finance integration pilot policy on firms' intelligent manufacturing. Table 2 reports the estimation results. In column (1) without control variables, the coefficient on DID is 0.010, statistically significant at the 5% level. In column (2) with the full set of controls, the coefficient on DID is 0.009, also significant at the 5% level. These results indicate that the pilot policy significantly promotes firms' intelligent manufacturing, supporting Hypothesis 1.

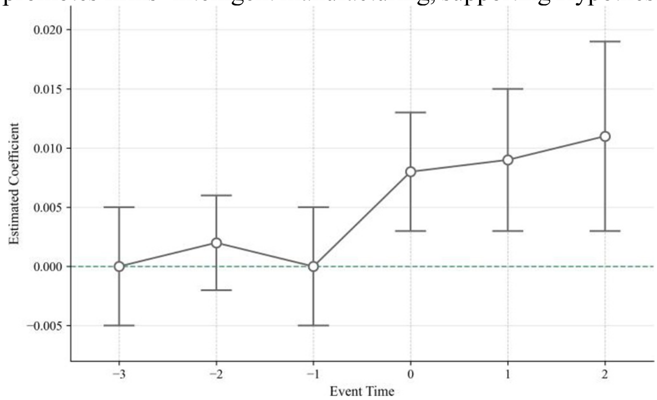

Fig. 1. Parallel trends test (event-study coefficients).

5.2 Parallel Trends and Placebo Tests

The parallel trends assumption is a fundamental prerequisite for valid DID estimation, requiring that treatment and control groups exhibit similar trends before policy implementation. We estimate a dynamic model by interacting year dummies with treatment status. As shown in Figure 1, the coefficients before policy implementation ($DIDk$ for $k < 0$) are statistically insignificant, confirming that the parallel trends assumption holds. After policy implementation, the coefficients become significantly positive, indicating that the pilot policy promotes intelligent manufacturing.

For the placebo test, we randomly assign pseudo-treatment status and re-estimate the baseline model 500 times. Figure 2 shows that most placebo coefficients are distributed around zero with corresponding p-values greater than 0.1, suggesting that the "pseudo-policy dummy" has no significant effect. The solid vertical line represents our true estimate of 0.009, which lies outside the placebo distribution, confirming the robustness of our baseline results.

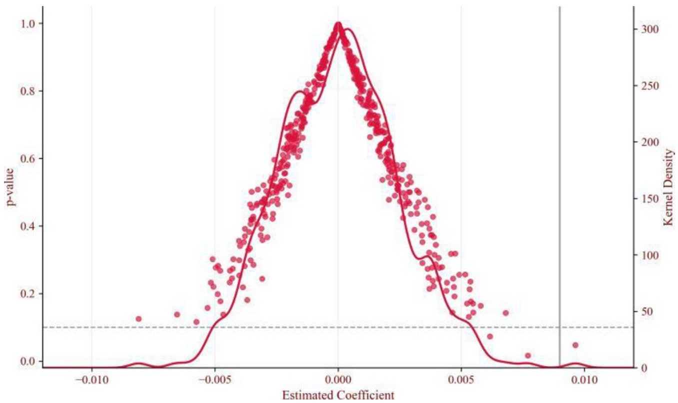

Fig. 2. Placebo test.

Table 3. Robustness via Double Machine Learning

	(1) IM	(2) IM	(3) IM	(4) IM	(5) IM	(6) IM
DID	0.011***	0.011***	0.012***	0.012***	0.013***	0.014***
	(4.03)	(3.82)	(3.80)	(3.19)	(3.49)	(4.27)
Controls (set 1)	Yes	Yes	Yes	Yes	Yes	Yes
Controls (set 2)	No	Yes	Yes	No	Yes	Yes
Controls (set 3)	No	No	Yes	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,048	21,048	21,048	21,048	21,048	21,048

***$p < 0.01$. t-statistics in parentheses.

5.3 Robustness Checks

The two batches of pilot cities cover diverse types including economically developed and commercially prosperous first-tier cities, as well as relatively underdeveloped medium and small cities, providing good preconditions for avoiding sample self-selection issues. However, sample self-selection issues may still exist to some extent. Based on current research, treatment groups may differ in time length and timing of intervention points [15], which may lead to heterogeneous treatment effects and bias in conclusions. Additionally, some first-batch pilot cities that did not continue to the second batch may exhibit policy withdrawal effects. Therefore, we conduct comprehensive robustness checks including PSM/EBM matching, lagged effects, sample exclusions, alternative fixed effects, Goodman–Bacon decomposition for staggered DID [7], Borusyak et al.'s imputation-based event-study estimator [1], and a double/debiased machine learning approach [4]. Table 3 reports the double machine learning results, showing that the coefficients on DID remain significantly positive across all specifications. Figure 3 presents the imputation-based event-study results following Borusyak et al. (2024), which further confirms the parallel trends assumption and significant post-treatment effects.

6 Further Analyses

6.1 Mechanism: Financing Constraints and Technological Innovation

To address the robustness concerns in this study, we adopt the mediation analysis framework [10] to test two channels. First, the pilot policy alleviates financing constraints. Firms currently face enormous capital pressure during intelligent manufacturing promotion. The policy strengthens cooperation between industries and finance, effectively relieves corporate financing difficulties through increased government subsidies, effectively channeling financial resources toward supporting intelligent manufacturing. We measure financing constraints using the SA index [8] and government subsidy intensity *(Lnsubsidy*). Second, the policy enhances technological innovation. Corporate technological innovation is a core driving force for intelligent manufacturing development [14]. Through proactive exploration, adoption, and application of new technologies, new methods, firms can accelerate the intelligent transformation of traditional manufacturing equipment while developing high-efficiency tools and technological support for intelligent production. We measure innovation using patent-based indicators (Patent1–Patent3). Table 4 reports the mechanism test results.

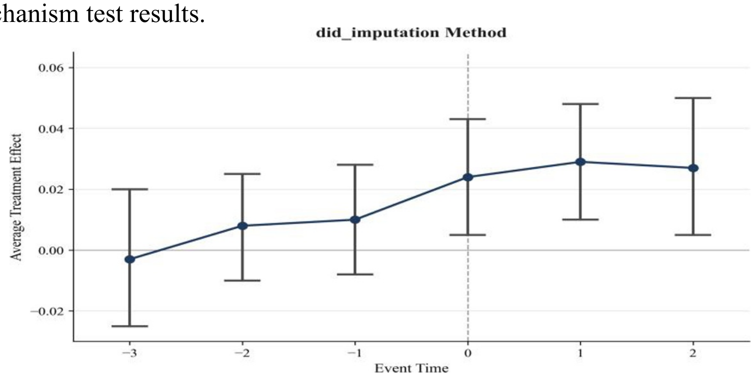

Fig. 3. Imputation-based event-study (Borusyak et al., 2024).

Table 4. Mechanism Tests

	(1) SA	(2) Lnsubsidy	(3) Patent1	(4) Patent2	(5) Patent3
DID	-0.003***	0.212***	0.115***	0.107***	0.130***
	(-2.32)	(3.35)	(2.66)	(2.42)	(3.07)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Constant	3.702***	-5.846***	-1.197***	-2.025***	-1.378***
	(-157.57)	(-3.78)	(-2.86)	(-4.88)	(-3.41)
Obs.	21,076	21,048	21,417	21,417	21,417
Adj.R^2	0.967	0.577	0.312	0.276	0.333

** p <0.05,*** p <0.01.t-stats in parentheses

Table 5. Heterogeneity Tests

	(1) HHI Hi	(2) HHI Lo	(3) Hi-tech	(4) Non-hi	(5) Hi MA	(6) Lo MA
DID	0.020**	−0.002	0.013**	−0.008	0.018***	0.008*
	(2.34)	(−0.37)	(2.13)	(−1.34)	(2.63)	(1.11)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.054	−0.496***	−0.257***	−0.366***	−0.268***	−0.240**
	(−0.45)	(−4.61)	(−2.92)	(−3.11)	(−2.65)	(−2.12)
Obs.	10,229	10,640	16,630	4,403	10,781	9,638
Adj. $R2$	0.702	0.619	0.682	0.635	0.700	0.704

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$. t-stats in parentheses.

Table 6. Effects on Sub-dimensions of IM

	(1) AI	(2) DT	(3) Internet	(4) Value
DID	0.002*	0.001**	0.003***	0.001**
	(1.80)	(2.28)	(3.04)	(2.39)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	-0.156***	-0.052***	-0.041**	-0.008
	(-7.09)	(-6.74)	(-2.41)	(-0.85)
Obs.	21,048	21,048	21,048	21,048
Adj.R^2	0.603	0.476	0.619	0.553

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$. t-stats in paren.

6.2 Heterogeneity

We examine heterogeneous policy effects across three dimensions. First, regarding market competition, firms in more competitive markets face greater pressure to innovate and upgrade, making them more responsive to policy support [21]. Second, high-tech firms possess stronger technological foundations and absorption capabilities, enabling them to better leverage policy benefits for intelligent transformation. Third, firms with higher managerial ability can more effectively utilize policy resources and coordinate internal resources for intelligent manufacturing [12]. Table 5 reports the heterogeneity test results. Results show stronger effects for firms facing intense market competition, high-tech firms, and firms led by higher-ability managers, indicating that the policy's intelligent manufacturing promotion effect is more pronounced for firms with greater transformation needs and capabilities.

7 Extensions and Economic Consequences

This section extends our analysis by examining policy effects on sub-dimensions of intelligent manufacturing and investigating the economic consequences. Specifically, we decompose the intelligent manufacturing index into four sub-dimensions and examine the policy's impact on total factor productivity.

7.1 Sub-dimensions of Intelligent Manufacturing

We further examine policy effects on four sub-dimensions of intelligent manufacturing: AI technology (AI), big data technology (DT), Internet technology (Internet), and value-chain intelligent technology (Value). Table 6 shows that the pilot policy exerts positive and significant effects on all four sub-dimensions. This indicates that the industry–finance integration policy comprehensively promotes AI technology adoption for intelligent production control, big data technology for information processing and decision support, Internet technology for connectivity and digitalization, and value-chain intelligent technology for end-to-end intelligent operations.

Table 7. Economic Consequences: TFP

	(1) TFP_OP	(2) TFP_OP	(3) TFP_LP	(4) TFP_LP
IM	0.102**	0.061*	0.204***	0.156***
	(2.08)	(1.92)	(4.23)	(3.07)
DID		−0.013		−0.016
		(−1.41)		(−1.00)
IM×DID		0.123***		0.144*
		(2.71)		(1.90)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	−1.194***	−1.196***	−2.876***	−2.877***
	(−3.53)	(−8.63)	(−8.19)	(−8.14)
Obs.	20,576	20,576	20,576	20,576
Adj. R^2	0.893	0.893	0.926	0.926

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$. t-stats in paren.

7.2 Economic Consequences: Total Factor Productivity

We next examine whether intelligent manufacturing improves firm productivity. The advancement of intelligent manufacturing helps improve firm total factor productivity by enhancing resource allocation efficiency, reducing production costs, and improving product quality [20]. We measure TFP using OP and LP approaches. As shown in Table 7, in columns (1) and (3), the coefficients on *IM* are0.102 and 0.204, significant at the 5% level, indicating that higher intelligent manufacturing levels improve firm TFP. In columns (2) and (4), the coefficients on the interaction term *IM*×*DID* are 0.123 and 0.144, significant at the 10% level, suggesting that the pilot policy amplifies the positive effects of intelligent manufacturing on TFP.

8 Conclusion and Implications

Using China's Industry–Finance Integration Pilot Program as a quasi-natural experiment and firm-level data from 2010–2023, we find robust evidence that the pilot policy promotes intelligent manufacturing among listed manufacturing firms. Mechanism analyses indicate that the policy works through easing financing constraints and stimulating technological innovation. Effects are stronger for firms under tougher market competition, high-tech firms, and firms with more capable managers—suggesting that policy resources are most effective when directed toward firms with both transformation needs and absorption capacity. Extensions suggest the policy advances multiple sub-dimensions of intelligent manufacturing (AI, big data, Internet, and value-chain technologies) and that intelligent manufacturing improves total factor productivity.

Based on these findings, we offer specific policy recommendations. First, governments should prioritize expanding pilot programs to regions with concentrated high-tech industries and intense market competition, as these environments maximize policy effectiveness. Second, financial institutions should develop tailored products—such as equipment leasing for automation upgrades and supply-chain finance for IoT adoption—to address specific intelligent manufacturing investment needs. Third, enterprises in non- high-tech sectors should strengthen managerial capabilities before engaging with pilot policies to enhance resource utilization efficiency.

This study has limitations that suggest directions for future research. First, our text-based intelligent manufacturing measure captures disclosure rather than actual implementation; future studies could incorporate patent data or survey measures. Second, the analysis focuses on listed firms, which may limit generalizability to SMEs that face distinct financing barriers. Third, while we identify financing constraints and innovation as mechanisms, the specific financial products driving these effects warrant further investigation.

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