Research on the Impact of Innovative Industrial Clusters on Manufacturing Enterprise Innovation

Nanjin Zhang[1, a], Shiwei Wu [2*]

[1]Graduate student at the School of Economics and Management, Fuzhou University, Fuzhou, 350108, China
[2]Associate Professor, School of Economics and Management, Fuzhou University, Fuzhou, 350108, China

[a]2445933624@qq.com
[*]wushiwei08@126.com

Abstract. Chinese manufacturing enterprises are currently facing challenges such as insufficient demand and even overcapacity, making it imperative to take measures to enhance their innovation capabilities. The innovative industrial cluster policy can promote the agglomeration of enterprises in pilot areas, thereby enabling interrelated industries to collaborate and engage in synergistic innovation. Drawing on theories from regional economics, urban economics, and new economic geography, as well as Schumpeterian innovation hypotheses, this study selects data from 1,818 manufacturing listed enterprises from 2009 to 2023 to construct a multi-period difference-in-differences (DID) model. This model is used to empirically examine the impact of the innovative industrial cluster policy on the innovation of manufacturing enterprises. The research finds that the innovative industrial cluster policy can promote innovation in manufacturing enterprises. Mechanism analysis indicates that this policy enhances manufacturing enterprise innovation by increasing the agglomeration level of skilled personnel and fostering industry-university-research collaboration. Furthermore, the impact of this policy on manufacturing enterprise innovation strengthens with the enhancement of the enterprises' technological absorption capacity.

Keywords: Policy on Innovative Industrial Clusters, Multi-period difference-in-differences (DID) model, Manufacturing, Corporate innovation

1 Introduction

In the context of economic globalization and regionalization of industrial transfer, the rise of global trade protectionism and the increasing fragility and instability of industrial supply chains have become prominent. Policies such as the U.S.-China trade war and the EU's Carbon Border Adjustment Mechanism have distorted global markets, hindering innovation among Chinese enterprises and impeding the effective resolution of overcapacity through free trade. China's manufacturing sector has been significantly affected, facing issues such as insufficient market demand and product stagnation.

H. Dai et al. (eds.), *Proceedings of the 2025 5th International Conference on Business Administration and Data Science (BADS 2025)*, Advances in Computer Science Research 125,
https://doi.org/10.2991/978-94-6463-980-3_23

Many industries are experiencing overcapacity, this predicament is particularly pronounced in certain traditional manufacturing sectors. Taking the steel and cement industries as examples, their capacity utilization rates have remained persistently below internationally recognized reasonable levels for an extended period. This situation leads to thin profit margins for enterprises, leaving insufficient funds for research and development (R&D) and technological upgrading. Concurrently, numerous small and medium-sized manufacturing enterprises (SMEs) face significant "bottlenecks" in their innovation activities. According to data from the China Statistical Yearbook on Science and Technology, although the proportion of R&D expenditure to primary business revenue of China's industrial enterprises above designated size has increased, it remains substantially lower than the levels in developed countries. Furthermore, the majority of R&D activities are concentrated within a limited number of leading firms. Many SMEs, constrained by difficulties in securing financing and a shortage of high-end R&D talent, suffer from a severe lack of independent innovation capacity. This traps them in a vicious cycle of a "low-end lock-in" within the global value chain. Therefore, exploring an effective policy model that can empower the broad spectrum of enterprises, especially SMEs, to innovate is a matter of strong practical urgency.

Addressing overcapacity and stimulating product demand require manufacturing enterprises to phase out outdated production capacities and engage in technological innovation to develop new products that better align with domestic and international demand. However, many manufacturing firms, particularly small and medium-sized enterprises, lack the independent R&D capabilities and talent due to financial constraints. Collaboration and synergistic innovation among enterprises are essential for developing desirable new products. Against this backdrop, fostering enterprise agglomeration and collaborative innovation has become a key solution. Industrial clusters offer a viable approach, as geographically proximate and interconnected firms within a cluster facilitate knowledge exchange, infrastructure sharing, and technological spillovers, thereby promoting innovation and development among cluster members.

The emergence of industrial clusters is not accidental but often guided by policy. The Innovative Industrial Cluster policy is designed to promote enterprise agglomeration and innovation. Since the concept was introduced in 2011, China has conducted multiple rounds of pilot initiatives. In July 2013, the Ministry of Science and Technology issued the "Measures for the Administration of the Pilot Program of Innovative Industrial Clusters", designating the first batch of 10 pilot clusters. Subsequent batches were identified in 2014 and 2017. In April 2020, the Ministry of Science and Technology released the "Guidelines on Further Promoting the High-Quality Development of Innovative Industrial Clusters", aiming to develop 100 national-level Innovative Industrial Clusters. By May 2025, the Ministry of Industry and Information Technology launched a national platform for industry-finance cooperation, providing RMB 540 billion in financing support for advanced manufacturing cluster firms. These measures underscore the importance of the Innovative Industrial Cluster policy and highlight the need for in-depth research into its impact on manufacturing innovation in China.

Given this context, this study utilizes panel data from 1,818 listed manufacturing companies from 2009 to 2023 and employs a multi-period Difference-in-Differences model to empirically examine the impact of the Innovative Industrial Cluster policy on manufacturing firms' innovation.

2 Theoretical analysis

2.1 Literature review

To enhance the sustainable development of industrial clusters and boost national competitiveness, it is imperative for the government to implement relevant policies. Moreover, as innovation plays an increasingly pivotal role in major-power competition, the implementation of Innovative Industrial Cluster policies becomes particularly crucial [1]. The implementation of Innovative Industrial Cluster policies enhances supply chain resilience [2] and economic resilience [3] in pilot regions. It attracts both domestic enterprises [4] and foreign direct investment [5], thereby strengthening agglomeration economies [6]. These policies foster innovation and technological diversification among firms within the clusters [7]. Furthermore, they elevate the overall innovative capacity of the pilot regions [8]. This enhancement in regional innovation contributes to increased total factor productivity [9], promotes the development of new quality productive forces [10], and ultimately advances local green, high-quality development [11]. However, the development of clusters varies significantly across different pilot regions, manifesting as disparities in technical efficiency, scale efficiency, and innovation efficiency [12]. Some pilot areas exhibit over-reliance on policy resources and government guidance, which can undermine the clusters' autonomous development capabilities and long-term competitiveness [13]. Moving forward, it is crucial to enhance the development efficiency of underperforming regions and industries, strike a balance between market operations and scientific research, and foster the healthy and sustainable development of Innovative Industrial Clusters [14].

From an international perspective, developed countries have accumulated substantial experience in promoting innovation within industrial clusters. For instance, Germany's "Cluster of Excellence" initiative emphasizes interdisciplinary and cross-institutional collaboration. Led by top-tier universities and research institutions, it forms a complete cycle from knowledge creation to application. Japan's "Special Zones for Industrial Competitiveness" policy focuses on stimulating corporate innovation vitality in specific regions through regulatory sandboxes and tax incentives. In contrast, China's innovation-oriented industrial cluster policy is characterized by stronger government guidance and top-level design, enabling the rapid deployment of key sectors through national-level pilot programs. This comparative analysis suggests that while leveraging its advantage in concentrating resources on major initiatives, China's policy could potentially draw lessons from Germany's emphasis on integrating basic research with SMEs and Japan's focus on institutional innovation. Such integration could further enhance the policy's sustainability and market adaptability. This international perspective provides a valuable analytical dimension for this study to assess the unique pathway and effectiveness of China's policy.

Existing studies on the effects of Innovative Industrial Cluster policies have primarily relied on macro-level data at the prefectural city level. There remains a scarcity of research examining the impact of these policies from a micro-level firm perspective, and little attention has been paid to how such policies influence specific types of enterprises, such as manufacturing firms. To address this gap, this study selects panel data from 1,818 listed manufacturing enterprises spanning the period from 2009 to 2023. A Difference-in-Differences (DID) model is constructed to empirically examine the impact of the Innovative Industrial Cluster policy on manufacturing firms' innovation outcomes. This approach aims to derive robust and reliable conclusions.

2.2 Theoretical mechanism

Distinct from traditional industrial cluster policies, the Innovative Industrial Cluster policy is characterized by a strong innovation orientation and dynamic adaptability. On one hand, this policy fosters specialized division of labor and collaboration among enterprises, generating economies of scale and reducing production costs. Integrating theories from new economic geography, the core value of industrial clusters lies in knowledge spillovers and collaborative innovation. Such clusters enhance Schumpeterian innovation levels by facilitating the cross-organizational flow of tacit knowledge. Existing research indicates that the implementation of Innovative Industrial Cluster policies is conducive to increasing face-to-face interactions among researchers from different enterprises, thereby stimulating innovation within the relevant firms [15]. On the other hand, the Innovative Industrial Cluster policy helps construct an open innovation ecosystem that reduces transaction costs associated with knowledge transfer, thereby establishing a positive feedback cycle of "innovation-imitation-reinnovation" and providing institutional safeguards for firm innovation [16]. Grounded in Porter's Diamond Model and dynamic capabilities theory, the cluster policy, through strategic guidance, encourages enterprises to engage in knowledge recombination, enabling them to transform spillover knowledge within the agglomeration area into innovative outputs. From a long-term perspective, consistent policy signaling steers firms toward further technological innovation, allowing them to build unique competitive advantages through these technological advancements. Therefore, this article proposes research hypothesis 1:

H1: The implementation of policies for innovative industrial clusters can promote innovation in manufacturing enterprises.

There exists a high degree of correlation between enterprise agglomeration and talent agglomeration [17]. According to theories in urban economics, the geographic concentration of firms induces a corresponding concentration of labor, enabling enterprises to find suitable employees while allowing workers to secure desirable positions [18]. The Innovative Industrial Cluster policy enhances the regional innovation ecosystem and public service platforms, which significantly reduces search costs and the difficulty for firms in attracting high-level talent. Furthermore, the presence of numerous large and growing manufacturing enterprises within a cluster provides highly educated individuals with a broader range of career choices and greater development opportunities, increasing their willingness to remain within the cluster for long-term development. The specific mechanisms are as follows: First, industrial clusters create a "labor pool" effect, which reduces the costs associated with talent search and matching, making it easier for firms to find specialized and scarce talent. Second, frequent technical exchanges and industry conferences within the cluster foster informal knowledge networks, providing valuable career development opportunities and a knowledge-spillover environment for highly skilled professionals, thereby enhancing the region's attractiveness. Finally, the cluster brand effect enhances the reputation of firms within the region in the talent market, giving them a certain advantage in salary negotiations. These factors work together to achieve a positive agglomeration of talent, which in turn promotes innovation among firms within the cluster [19]. Therefore, this article proposes research hypothesis 2:

H2: The policy of innovative industrial clusters can promote innovation in manufacturing enterprises by improving their talent aggregation level.

University-industry-research (U-I-R) collaboration plays a vital role in enhancing enterprise innovation [20]. By engaging in U-I-R cooperation, firms can effectively translate basic research from academic institutions into their knowledge base, thereby improving R&D efficiency. Such partnerships also facilitate valuable exchanges between corporate R&D personnel and academic researchers, while simultaneously mitigating the risks associated with innovation, ultimately leading to a higher level of corporate innovation [21]. The implementation of Innovative Industrial Cluster policies acts as a significant catalyst in this process. These policies create an environment that fosters interaction and collaboration between firms located within the pilot zones and local universities or research institutions. Such collaborations typically manifest in several forms: firstly, "contract-based R&D," where enterprises directly commission universities to solve specific technical challenges; secondly, "co-establishing laboratories or R&D entities," enabling resource sharing, risk mitigation, and outcome sharing; and thirdly, "joint talent cultivation and mobility," such as having industry experts teach at universities and academic researchers taking positions in enterprises, which facilitates the transfer of tacit knowledge. By reducing transaction costs and information asymmetry within these collaborations, policy effectively catalyzes the implementation of these models. Therefore, this article proposes research hypothesis 3:

H3: The implementation of policies for innovative industrial clusters can promote innovation in manufacturing enterprises by facilitating industry university research cooperation.

Cohen and Levinthal were the first to clearly define the concept of technological absorptive capacity, characterizing it as a firm's ability to recognize the value of new external knowledge, assimilate it, and apply it to commercial ends. They further proposed that this technological absorption process could be delineated into three primary stages: recognition, digestion, and application. Initially, a firm identifies and acquires valuable knowledge or technology from the external environment. Subsequently, the firm mobilizes its researchers to study, internalize, and adapt this acquired knowledge, often through sustained investment in related learning and adaptation activities. The ultimate objective is to transform this external knowledge into new internal competencies or technologies. Finally, these newly developed knowledge assets and technologies are effectively deployed into production processes to create economic value [22]. From the perspective of dynamic capabilities, Zahra and George reconceptualized the process of technological absorption into four distinct stages: acquisition, assimilation, transformation, and exploitation. They further defined the first two stages—acquisition and assimilation—as constituting an organization's potential absorptive capacity, while the latter two stages—transformation and exploitation—constitute its realized absorptive capacity [23]. The implementation of the Innovative Industrial Cluster policy co-locates interconnected firms within the same geographic area, where the knowledge and technologies held by individual enterprises are often complementary. This proximity facilitates knowledge spillover effects, enabling R&D personnel from different firms within the cluster to engage in extensive communication and learn advanced technologies from their counterparts. This exposure to external knowledge provides opportunities for firms to integrate and translate acquired insights into their own innovation activities. The extent to which a firm benefits from this process, however, is significantly influenced by its technological absorptive capacity. Firms with stronger absorptive capacity are more adept at assimilating and exploiting the knowledge and technologies available within the cluster, thereby achieving a greater enhancement in their own innovation performance [24]. Therefore, this article proposes research hypothesis 4:

H4: The promotion effect of innovative industrial cluster policies on innovation in manufacturing enterprises will increase with the improvement of their technological absorption capacity.

3 Empirical analysis

3.1 Research Design

3.1.1 Variable Definitions. Explained Variable: Manufacturing Enterprise Innovation (Patent)

The primary indicator for technological innovation includes the number of patent applications, patent grants, and R&D expenditure. Considering data availability, this study uses the number of patent applications from listed manufacturing enterprises to measure the level of manufacturing enterprise innovation.

Core Explanatory Variable: Policy Shock (DID)

This paper matches the headquarters locations of listed manufacturing enterprises with the policy pilot areas. Enterprises headquartered within the designated Innovative Industrial Cluster pilot areas are assigned to the treatment group. The DID variable takes a value of 0 before the policy implementation and 1 for the implementation year and onwards. Enterprises headquartered outside the pilot areas form the control group, for which the DID variable remains 0 throughout the study period.

Control Variables

To isolate the policy's effect, several firm-level characteristics are controlled for, as detailed in the table 1 below.

Table 1. Control Variables

Variable Name	Symbol	Measurement Description
Firm Size	*Size*	Natural logarithm of total assets (in 100 million CNY).

Variable Name	Symbol	Measurement Description
Leverage Ratio	*Lev*	Ratio of total liabilities to total assets.
Return on Assets (ROA)	*ROA*	Ratio of net profit to total assets.
Firm Growth	*Growth*	Growth rate of operating revenue.
Firm Age	*Age*	Number of years since the firm's establishment until the observation year.
Management Incentive	*Mshare*	Proportion of shares held by the management.
Ownership Concentration	*Top1*	Percentage of shares held by the largest shareholder.

3.1.2 Model Construction. The multi-period Difference-in-Differences (DID) method helps mitigate potential biases from concurrent trends that could confound the treatment effect, thereby yielding more precise estimates. It allows for a more accurate capture of the heterogeneous impacts of a policy across different entities and time points, providing more robust and reliable research findings. Consequently, the multi-period DID approach is effective for evaluating the effects of policies implemented at different times. The Innovative Industrial Cluster policy in China was rolled out in three distinct batches, with the pilot initiatives starting in 2013, 2014, and 2017. Given this staggered implementation schedule, this study employs a multi-period DID model to examine the policy's impact on the innovation performance of manufacturing firms:

$$Patent_{it}=\beta_0+\beta_1 DID_{it}+\alpha X_{it}+\gamma_i+\theta_t+\varepsilon_{it} \tag{1}$$

In the model, i denotes a manufacturing firm, t denotes the year, $Patent_{it}$ represents the innovation output of firm i in year t , DID_{it} is the policy dummy variable, X_{it} denotes a set of control variables, γ_i and θ_t represent firm fixed effects and year fixed effects, respectively, and ε_{it} is the error term.

3.1.3 Data source. To ensure the robustness of the empirical findings, this study excludes firms with fewer than six years of observable data and those with data available only from 2017 onward. The final sample consists of 1,818 listed manufacturing firms spanning the period from 2009 to 2023. Patent data are sourced from the Mark Data website, while all other financial and corporate governance data are obtained from the CSMAR database. To mitigate the potential influence of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

3.2 Benchmark regression

The estimation results of the multi-period Difference-in-Differences (DID) model from Equation (1) are presented in Table 2. Column (1) displays the impact of the Innovative Industrial Cluster policy on manufacturing enterprise innovation without including any control variables or fixed effects. It reveals that the coefficient of the core explanatory variable (DID) is positive and statistically significant at the 1% level, providing preliminary evidence that the policy promotes the innovation capability of manufacturing firms. Columns (2) and (3) build upon Column (1) by sequentially incorporating control variables and fixed effects, respectively. The results indicate that the DID coefficient remains positive and significant at the 1% level, reinforcing the finding that the Innovative Industrial Cluster policy has a positive effect on manufacturing innovation. Column (4) presents the full model including all control variables and fixed effects. The coefficient for the DID variable continues to be positive and statistically significant at the 1% level, confirming that the policy significantly stimulates innovation in manufacturing enterprises. In terms of economic significance, the implementation of the policy is associated with an average increase of 19.01 patent applications per manufacturing firm. Consequently, the research hypothesis H1 proposed in this study is supported.

Table 2. Benchmark regression results

	(1)	(2)	(3)	(4)
VARIABLES	Patent	Patent	Patent	Patent
DID	61.96***	27.04***	20.00***	19.01***
	(3.610)	(3.465)	(3.766)	(3.662)
Constant	64.27***	-1295***	3.822	-1088***
	(3.337)	(27.78)	(4.148)	(37.34)
Observations	21785	21785	21785	21785
Controls	NO	YES	NO	YES
Fixed effect	NO	NO	YES	YES
R^2			0.110	0.161

The values in parentheses are robust standard errors. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The same convention applies to the subsequent tables.

3.3 Robustness test

3.3.1 Parallel trend test. To ensure that the observed changes in the treatment group's outcomes are attributable to the policy shock, a parallel trends test is essential for the multi-period Difference-in-Differences (DID) model. Given that the implementation times of the Innovative Industrial Cluster policy varied across different pilot areas, this study employs an event-study approach for the parallel trends test. To avoid perfect multicollinearity, the period immediately preceding the policy implementation (t = -1) is omitted as the benchmark. Furthermore, due to the long time span of the data, all time periods occurring four years or more before the policy implementation are consolidated into a single category labeled "4-or-more periods before treatment". Similarly, all periods seven years or more after the policy implementation are consolidated into a category labeled "7-or-more periods after treatment". The results of this test are presented in Figure 1. This pattern of results suggests that the parallel pre-trend assumption is not violated, thereby supporting the validity of the multi-period DID model constructed in this study.

3.3.2 Placebo test. To ensure the robustness of the estimated causal effect between the Innovative Industrial Cluster policy and the improvement in manufacturing firms' innovation levels, this study adopts a counterfactual test approach for robustness analysis, following the research design of scholars such as Tang Haodan [25]. Specifically, a fictitious treatment group and policy implementation time were artificially created. Through random sampling, 1,000 virtual treatment groups were generated, and the policy effect was re-estimated based on these virtual samples. As shown in Figure 2, the regression coefficients derived from the fictitious samples are close to zero, indicating that the fabricated policy variable has no statistically significant effect on firms' innovation levels. This result stands in sharp contrast to the significant coefficient of 19.01 estimated under the actual policy scenario. Consequently, the falsification test helps rule out potential confounding factors, and the outcome of this counterfactual analysis robustly supports the core conclusion of this study: the implementation of the Innovative Industrial Cluster policy has indeed generated a significant promoting effect on the innovation level of manufacturing enterprises.

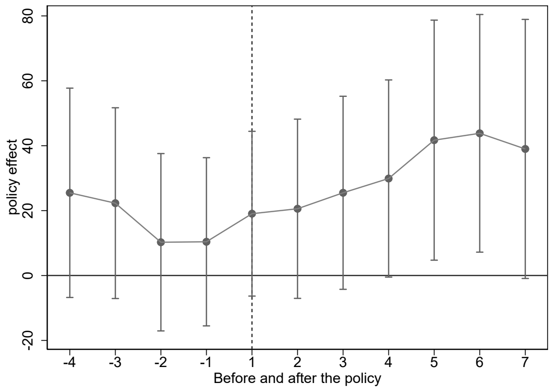

Fig. 1. Parallel Trend Test Chart

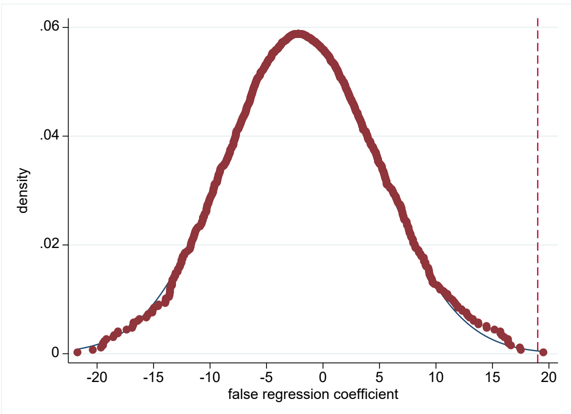

Fig. 2. Placebo test result chart

3.3.3 Other robustness tests. To ensure the robustness of the regression results, this study conducted the following additional tests: (1) replacing the dependent variable with the amount of corporate R&D investment; and (2) excluding the potential influence of major shocks by omitting data from the year 2020 in the regression, following the approach of Chen Lin et al.[26]; and (3) altering the clustering level by clustering the regression standard errors at the city level; (4) employing a PSM-DID approach, matching the treatment and control groups with a 1:1 ratio; and (5) controlling for other policy influences by matching the headquarters locations of the manufacturing listed enterprises with the pilot areas of the "Broadband China" and "Smart City" policies, constructing corresponding policy variables (DID2 and DID3), and including these variables in the regression. The results of these robustness checks, presented in Table 3, show that the estimated coefficients remain statistically significant, indicating that the finding—that the Innovative Industrial Cluster policy promotes the innovation level of manufacturing enterprises—is robust and reliable.

Table 3. Robustness test results

VARIABLES	(1) Replace the explained variable invest	(2) Exclude the impact of major events Paten	(3) Change the clustering hierarchy Patent	(4) PSM-DID Patent	(5) Excluding the impact of other policies Patent
DID	82.41***	17.53***	19.01*	11.51**	22.34***
	(10.78)	(3.713)	(10.45)	(5.496)	(4.064)
DID2					0.0980
					(2.982)
DID3					-12.65***
					(3.685)
Constant	-4377***	-1058***	-1088***	-1316***	-1188***
	(110.0)	(38.00)	(146.2)	(89.41)	(41.64)
Controls	YES	YES	YES	YES	YES
Fixed effect	YES	YES	YES	YES	YES
Observations	21785	20145	21785	5687	19051
R^2	0.259	0.155	0.161	0.198	0.170

3.4 Mechanism test

3.4.1 Talent aggregation level. By providing institutional incentives such as subsidies for research funding, optimizing professional title evaluation mechanisms, and improving lifestyle support services, the Innovative Industrial Cluster policy significantly reduces the mobility costs for talent, thereby facilitating talent agglomeration within the region. Consequently, to examine whether talent agglomeration serves as a mediating mechanism in the impact of the Innovative Industrial Cluster policy on the innovation of manufacturing enterprises, this study, following the approach of Zhang Bo and Ding Jinhong, employs the number of employees with a bachelor's degree or higher within an enterprise to measure the level of talent agglomeration (Talent Agglomeration) [27]. The regression results are presented in columns (1) and (2) of Table 4. Column (1) indicates that the Innovative Industrial Cluster policy significantly promotes talent agglomeration. Column (2) shows that an increase in the level of talent agglomeration facilitates innovation in manufacturing enterprises, with the coefficient of the core explanatory variable being positive and statistically significant at the 1% level. This suggests that talent agglomeration plays a positive mediating role in the impact of the Innovative Industrial Cluster policy on manufacturing firms' innovation.

3.4.2 Industry-university-research collaboration. Through institutional arrangements and targeted fiscal subsidies, the Innovative Industrial Cluster policy can significantly reduce the transaction costs associated with university-enterprise collaboration, thereby increasing the number of industry-university-research (I-U-R) cooperation projects. Furthermore, the number of collaborative patents resulting from I-U-R cooperation is closely related to the dependent variable in this study—the number of patent applications by manufacturing enterprises. Therefore, to investigate the mediating role of I-U-R collaborative patents in the impact of the Innovative Industrial Cluster policy on manufacturing enterprise innovation, this study draws on the methodology of Wang Haiyan et al. and uses a dummy variable (Cooperate) to measure I-U-R collaboration, indicating whether an enterprise collaborated with a university or research institution in a given year [28]. The variable Cooperate is defined as a binary indicator: it takes the value of 1 if a firm engaged in industry-university-research (I-U-R) collaboration in a given year, and 0 otherwise. The regression results are presented in columns (3) and (4) of Table 4. Column (3) shows that the Innovative Industrial Cluster policy significantly promotes the level of I-U-R collaboration. Column (4) indicates that an increase in I-U-R collaboration fosters innovation in manufacturing enterprises, with the coefficient of the core explanatory variable being positive and statistically significant at the 1% level. This suggests that the implementation of the policy significantly increases the frequency of firms' engagement in I-U-R collaboration, which in turn enhances their innovation performance.

3.4.3 Enterprise technology absorption capacity. A firm's technological absorptive capacity plays a vital role in innovation; the stronger this capacity, the more conducive it is for the firm to engage in innovative activities. The implementation of the Innovative Industrial Cluster policy promotes the agglomeration of interconnected firms within the same region. Within these clusters, R&D personnel from different enterprises have opportunities for sufficient interaction, facilitating the mutual absorption of advanced technologies and experiences, which in turn drives innovation across firms. Moreover, enterprises with stronger absorptive capacity can more easily assimilate and utilize knowledge and technologies from other firms to enhance their own innovation levels. Drawing on the methodology of Yang Lin et al., this study uses R&D expenditure intensity to measure technological absorptive capacity (Absorptive Capacity) [29], the R&D expenditure intensity is the ratio of a company's R&D expenditure to its operating revenue. To mitigate the potential influence of extreme values, the continuous variables were winsorized at the 1st and 99th percentiles. The regression results are presented in column (5) of Table 4. The coefficient for the interaction term between the core explanatory variable (DID) and technological absorptive capacity (Absorptive Capacity) is positive and statistically significant at the 1% level. Furthermore, the coefficients for both the core explanatory variable and the absorptive capacity variable are also positive and significant at the 1% level. This indicates that the stronger a firm's technological absorptive capacity, the more it enhances the positive effect of the Innovative Industrial Cluster policy on the firm's innovation level.

Table 4. Mechanism inspection results

VARIABLES	(1) Talent_aggregation	(2) Patent	(3) Cooperate	(4) Patent	(5) Patent
DID	95.93***	15.98***	0.0257***	18.67***	10.93***
	(34.13)	(3.501)	(0.00850)	(3.661)	(4.090)
Talent_aggregation		0.0315***			
		(0.000726)			
Cooperate				13.25***	
				(3.048)	
Absorptive_capacity					138.3***
					(39.28)
DID×Absorptive_capacity					198.6***
					(55.71)
Constant	-17,283***	-543.2***	-0.390***	-1,083***	-1,079***
	(348.0)	(37.84)	(0.0867)	(37.34)	(37.35)
Controls	YES	YES	YES	YES	YES
Fixed effect	YES	YES	YES	YES	YES
Observations	21,785	21,785	21,785	21,785	21,785
R^2	0.249	0.234	0.015	0.162	0.163

4 Conclusions

China's manufacturing enterprises are currently facing the challenge of insufficient effective demand, with some industries experiencing overcapacity. It is imperative to take measures to boost demand for manufacturing products. One reason for this insufficient effective demand lies in the relatively low-end nature of many enterprise products, necessitating continuous innovation to develop new products that better align with domestic and international market needs. The implementation of the Innovative Industrial Cluster policy can facilitate the agglomeration of enterprises within pilot areas. This agglomeration, in turn, promotes cooperation and collaborative innovation among interconnected firms, which is conducive to innovation within manufacturing enterprises.

The Innovative Industrial Cluster policy enhances manufacturing enterprise innovation through mechanisms such as increasing the level of talent agglomeration and fostering industry-university-research collaboration. Furthermore, the positive impact of this policy on manufacturing innovation is strengthened as firms' technological absorptive capacity increases.

Acknowledgments

This work was supported by the Special Project of the Department of Finance of Fujian Province, "Research on the Digital Economy Leading the High-Quality Development of Fujian's Economy" (Min Cai Zhi [2023] No. 834).

References

1. Liu X, Zhang A, Xie Y. **2023**. Industrial policy and cluster development: a literature review[J]. International Journal of Technology, Policy and Management, 23(2): 187-215.
2. Huang H B, Zhang Y Y, Li Y Y. **2024**. Can the pilot policy of innovative industrial clusters enhance supply chain resilience? [J]. Science Research Management, 45(9): 39-60.
3. Xu S L, Min Z, Yan W. **2024**. "Can innovative industrial clusters enhance urban economic resilience? A quasi-natural experiment based on an innovative pilot policy." Energy Economics 134: 107544.
4. Song D Y, Liang Y Y, Lin X S. **2025**. Impact of innovative industrial cluster policies on urban new firm entry. Urban Problems, (4): 19-33.
5. Jing G W. **2023**. Has the pilot policy of innovative industrial clusters promoted FDI inflows?—Also on its impact on high-quality economic development. West Forum, 33(3): 82-93.
6. Li R, Zhang J X. **2021**. Impact of innovative industrial clusters on the agglomeration effect of national high-tech zones. Technical Economy and Management Research, (8): 114-118.
7. Fu X W, Xie J Z. **2025**. Government-guided funds, technological diversification, and enterprise ambidextrous innovation: Also on the moderating role of innovative industrial clusters. Collected Essays on Finance and Economics, (8): 17-27.
8. Li J Q, Zhang B J, Li N N. **2024**. How do innovative industrial clusters enhance regional innovation capability?—A configurational analysis based on network architecture. Enterprise Economy, 43(8): 63-73.
9. Liu J, Guo L H, Zhang W K. **2024**. Research on the impact of innovative industrial clusters on urban total factor productivity. Science Research Management, 45(5): 105-113.
10. Zhang M Y, Ma X Y. **2025**. How do digital infrastructure and innovative industrial promotion policies drive the development of new quality productive forces?—Policy effects of "Broadband China" demonstration city construction and innovative industrial cluster pilot programs. West Forum, 35(1): 1-21.
11. Jing G W. **2023**. Innovative industrial clusters and green high-quality development. Journal of Yunnan University of Finance and Economics, 39(7): 1-15.
12. Sha D C, Hu X H, Zhao C P. **2021**. Research on the innovation efficiency of China's innovative industrial clusters. Technology Economics, 40(2): 18-27.
13. Guo X T, Tan Y Q. **2021**. Research on the relationship between innovative industrial clusters and policy resource dependence. Science and Technology Progress and Policy, 38(21): 53-62.
14. Wang X M, Hu H H. **2022**. Evaluation and decomposition of innovative industrial cluster efficiency: From the perspective of chain structure. Science and Technology Management Research, 42(24): 61-68.
15. Shi L, Yang Z, Qian G M. **2025**. Digital industrial cluster policy and breakthrough innovation in key core technologies. China Industrial Economics, (1): 100-117.
16. Li H L, Wang F B. **2025**. Research on corporate fission entrepreneurship: A review based on the ladder of theoretical maturity. Management World, 41(5): 198-222.
17. Cao X F, Huo P, Yu L L. **2017**. Research on the interactive relationship between high-tech talent agglomeration and high-tech industry agglomeration. Science Research Management, 35(11): 1631-1638.
18. An H S. **2022**. Some theoretical issues in urban economics. Journal of Hebei University of Economics and Business, 43(4): 54-64.

19. Sun H J, Zhang L N, Wang S G. **2019**. Agglomeration of scientific and technological talents, spatial spillover, and regional technological innovation: A partial differential method based on the spatial Durbin model. Science of Science and Management of S.& T., 40(12): 58-69.
20. Ni H F, Peng S Y, Zhong D C. **2025**. Driving factors of industry-university-research collaborative innovation from the perspective of strategic initiative. China Industrial Economics, (8): 159-177.
21. Jin H, Niu Z H, Yue Z G. **2025**. Public data openness, industry-university-research collaboration, and key digital technology breakthrough. Collected Essays on Finance and Economics, 1-13.
22. Cohen W M, Levinthal D A. **1990**. Absorptive capacity: A new perspective on learning and innovation[J]. Administrative science quarterly, 35(1): 128-152.
23. Zahra S A, George G. **2002**. Absorptive capacity: A review, reconceptualization, and extension[J]. Academy of management review, 27(2): 185-203.
24. Liu W G, Zhou L Y, Li J. **2020**. Service quality of production inputs and enterprise innovation: An analysis based on the production outsourcing model. China Industrial Economics, (8): 61-79.
25. Tang H D, Fang S H, Jiang D C. **2022**. Market performance of digital transformation: Can digital M&A enhance the market power of manufacturing enterprises? Journal of Quantitative & Technological Economics, 39(12): 90-110.
26. Chen L, Gao Y P, Yu L H. **2024**. How does artificial intelligence change enterprises' demand for labor?—An analysis based on big data from recruitment platforms. Management World, 40(6): 74-93.
27. Zhang B, Ding J H. **2022**. Impact of China's talent ecological environment on the agglomeration effect of highly educated talents. Science Research Management, 43(12): 24-33.
28. Wang H Y, Li C H, Gao L Y, et al. **2025**. Bridging with data: The impact of digital technology application on industry-university-research collaboration [J/OL]. Science and Technology Progress and Policy, 1-10.
29. Yang L, He X, Gu H F. **2020**. TMT experience, dynamic capabilities and strategic mutation: The moderating effect of managerial discretion. Management World, 36(6): 168-188+201+252.