# Research on the Influence of The Identification of "Green Factory" on Enterprise Intelligent Manufacturing

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**Abstract.** This study investigates whether voluntary environmental regulation, exemplified by China's Green Factory Certification (GFC), can stimulate the development of intelligent manufacturing. Leveraging a panel dataset of A-share listed firms from 2007 to 2020 and employing a staggered difference-in-differences (DID) framework, we identify the causal effect of GFC certification on smart manufacturing capabilities. Results reveal a significant positive effect, particularly in firms with strong internal governance. Mechanism analysis shows GFC alleviates financing constraints and boosts R&D investment. Further, GFC-induced smart manufacturing contributes to total factor productivity (TFP) growth, validating the Porter Hypothesis. These findings offer empirical insights into the synergy between green industrial policies and technological upgrading.

**Keywords:** Intelligent manufacturing; Green factory; Overlapping difference-in-differences model; Green industry policy.

## 1. Introduction

Amid the Fourth Industrial Revolution, smart manufacturing has become a critical driver of global industrial transformation.[1]. Grounded in technologies such as IoT, AI, and big data, it reshapes production through digitization, connectivity, and intelligence across the manufacturing lifecycle . Studies show smart manufacturing enhances efficiency, reduces costs, and improves resource allocation and total factor productivity (TFP) through data-driven innovation[2]. Consequently, nations worldwide are accelerating strategic deployments in smart manufacturing—exemplified by Germany's "Industry 4.0" and the U.S. "Advanced Manufacturing Partnership"—to harness technological empowerment for global industrial competitiveness[3]. For China, the world's largest manufacturing economy, advancing smart manufacturing is not only critical to its "dual circulation" strategy but also an imperative response to diminishing demographic dividends and tightening environmental constraints. These plans integrate innovation, sustainability, and digitalization to address demographic pressures and environmental constraints. The 20th National Congress reaffirmed breakthroughs in smart manufacturing and digital infrastructure as national priorities[4].

At the enterprise level, firms are pivotal in advancing smart manufacturing. Evidence confirms it reduces marginal costs[5], stimulates innovation[6], improves capacity utilization, and drives TFP growth[7]. Identifying its determinants is therefore vital. Environmental regulation—a key government tool—has a significant influence.Policies like "Industrial Internet+ Green Manufacturing" embed green compliance into the smart manufacturing framework[8], making environmental performance a condition for financial incentives.

Regulatory tools fall into three categories: command-and-control, market-based, and voluntary. While command-and-control may spur compliance-driven innovation[9] or crowd out R&D[10], market-based incentives like subsidies help ease financing constraints[11] but risk inefficiencies[12]. Voluntary approaches, such as Green Factory Certification (GFC), reduce information asymmetries and enhance governance, motivating firms to engage in sustainable innovation.

GFC, introduced by MIIT in 2016, certifies firms with strong environmental practices and grants access to green finance and tax incentives. However, its impact on smart manufacturing adoption and productivity growth remains understudied[13].

Existing gaps include limited research on GFC's technological effects[14], ongoing debates over the efficacy of industrial policies, and methodological challenges in evaluating staggered interventions. This study leverages firm-level panel data and high-dimensional DID models, including LASSO-DID, to rigorously identify GFC's impact on smart manufacturing. Results indicate that GFC enhances smart manufacturing by alleviating financing constraints and boosting R&D, especially in private and well-governed firms. It also improves TFP through both efficiency and technological channels.

Our contributions are threefold: (1) extending green policy literature to include smart manufacturing dynamics; (2) applying machine learning-enhanced identification strategies, and (3) quantifying long-term productivity gains, offering evidence-based policy implications aligned with China's Dual Carbon Goals.

## 2. Theoretical Analysis and Research Hypotheses

### 2.1. Green Factory Certification Enhances Smart Manufacturing

China's Green Factory Evaluation Standard (GB/T 36132-2018) defines green factories as entities minimizing resource use and environmental impacts through sustainable practices[15]. Green Factory Certification (GFC) drives smart manufacturing via technological upgrades and resource optimization.

First, GFC mandates industry benchmarks in energy efficiency and intelligent equipment adoption, compelling firms to deploy technologies like industrial robots and digital systems. This reduces energy consumption per output and material waste, fostering innovation. GFC also requires periodic disclosure of technical roadmaps, enabling industry-wide knowledge spillovers.

Second, GFC signals "green credibility" to capital markets, alleviating information asymmetry and improving resource allocation. This addresses challenges like high sunk costs and insufficient market incentives during technological transitions[16]. Thus:

H1: GFC significantly enhances smart manufacturing.

### 2.2. Heterogeneous Effects of GFC

#### 2.2.1. SOE Heterogeneity

SOEs face dual pressures: institutional advantages ease early-stage investment constraints[17], but organizational inertia and rigid management weaken transformation incentives. Non-SOEs, driven by market competition, may prioritize smart upgrades more actively. Competing hypotheses emerge:

H2a: GFC's effect is stronger in SOEs.

H2b: GFC's effect is stronger in non-SOEs.

#### 2.2.2. Corporate Governance Heterogeneity

Strong governance enhances policy responsiveness and long-term investment capacity. Cross-departmental collaboration under governance mechanisms accelerates green-tech integration[18].

H3: GFC's positive impact is greater in firms with stronger governance.

### 2.3. Mechanisms: How GFC Drives Smart Manufacturing

Aligned with the Porter Hypothesis, GFC incentivizes innovation despite compliance costs.

#### 2.3.1. Financing Constraints Channel

GFC unlocks green financing, easing liquidity constraints for smart technology adoption[19].

H4a: GFC promotes smart manufacturing via financing alleviation.

#### 2.3.2. R&D Investment Channel

Smart manufacturing requires heavy R&D. GFC improves access to government grants and external funding, boosting R&D commitment.

H4b: GFC promotes smart manufacturing via amplified R&D investment.

# 3. Research Design

## 3.1. Sample Selection

This study utilizes 2007－2020 Shanghai and Shenzhen A-share listed data, excluding special treatment(ST) or particular transfer(PT) status, financial firms, and missing values, yielding 19,477 firm-year observations. All data are sourced from the CSMAR database and the China Listed Firms Patent Details Database.

## 3.2. Variable Definitions

1. Dependent Variable

*Smart Manufacturing Intensity* (Im): Measured via keyword frequency in annual reports using a domain-specific lexicon[20]. The lexicon, developed through deep learning (seed: “smart manufacturing”) and expert validation (57 keywords across 5 dimensions), aggregates frequencies to capture strategic emphasis.

2. Key Independent Variables

*Green Factory Certification (Treatment)*: Dummy variable (1 if certified in year *t*, else 0).

*Post-Policy Period (Post)*: Time dummy (1 post-MIIT certification policy implementation).

*DID Estimator (Treatment×Post)*: Interaction term isolating certification’s causal effect.

3. Control Variables

Controls include:

*Financial Structure*: Liability ratio (Tl), tangibility (*Tang*), liquidity (*Cr*), cash (*Cash*), investment (*Invt*).

*Firm Characteristics*: Firm size (*Insale, logarithm of sales*), listing age (*Inage*), and return on equity (*Roe*).

**Table 1.** Variable Definitions

| Variable Name | Variable Symbol | Variable Description |
|---|---|---|
| Intelligent Manufacturing Ratio (%) | Im | Measured via textual analysis of annual reports, counting smart manufacturing keyword frequency to capture corporate disclosure emphasis. |
| Green Factory Enterprise | Treatment | Assigned a value of 1 if the firm is certified as a green factory, and 0 otherwise. |
| Policy Implementation Timing | Post | A time dummy variable equal to 1 after the firm is certified as a green factory, and 0 otherwise. |
| Total Asset-Liability Ratio | Tl | Total liabilities divided by total assets |
| Asset Structure | Tang | (Net fixed assets + net inventory) divided by total assets |
| Current Ratio | Cr | Current assets divided by current liabilities |
| Cash Holdings | Cash | (Monetary funds + trading financial assets) divided by total assets |
| Investment Expenditure Ratio | Invt | Cash paid for the purchase/construction of fixed assets, intangible assets, and other long-term assets divided by total assets. |
| Firm Size | Insale | Natural logarithm of operating revenue |
| Listing Age | Inage | Natural logarithm of (current year － year of listing) |
| Return on Equity | Roe | (Net profit / average shareholders’ equity) × 100% |

### 3.3. Empirical Model Specification

The difference-in-differences (DID) method evaluates policy impacts by comparing outcome changes between treatment (GFC-certified firms) and control (non-certified) groups. We employ a staggered DID framework, with the baseline model:

$$\text{Im}_{i,t} = \alpha_0 + \alpha_1 \text{Post}_{\text{i,t}} + \alpha_2 \text{Treatment}_{\text{i,t}} + \alpha_3 \text{Post}_{\text{i,t}} \times \text{Treatment}_{\text{i,t}} + \sum \text{Control}_{\text{i,t}} + \varepsilon_{\text{i,t}} \tag{1}$$

Where:
$\text{Im}_{\text{it}}$: Smart manufacturing intensity of firm *i* in year *t*.
Treatmenti: Dummy (1 if GFC-certified; 0 otherwise)..
Postt: Time dummy (1 post-policy; 0 otherwise).
$\text{Xi}_{\text{t}}$: Controls (financial structure, firm traits).
$\mu_{\text{i}}$: Firm FE (time-invariant heterogeneity).
$\lambda_{\text{t}}$: Year FE (macroeconomic shocks).
$\epsilon_{\text{it}}$: SE clustered by firm.

## 4. Empirical Results

### 4.1. Descriptive Statistics of Key Variables

Table 2 reports descriptive statistics: smart manufacturing intensity (*Im*) has a mean of 0.142 (range 0 – 3.003), indicating significant cross-firm heterogeneity. The low standard deviation (0.218) suggests stable industry trends and high data reliability.

**Table 2.** Descriptive Statistics of Variables

| Variable Name | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Im | 0.142 | 0.215 | 0 | 3.003 |
| DID | 0.0499 | 0.218 | 0 | 1 |
| Tl | 0.450 | 0.202 | 0.00708 | 1.280 |
| Tang | 0.408 | 0.173 | 0.000319 | 0.971 |
| Cr | 0.547 | 0.204 | 0.0143 | 0.999 |
| Cash | 0.170 | 0.118 | 0.000479 | 0.915 |
| Invt | 0.0512 | 0.0488 | 0 | 0.642 |
| ROE | 0.0345 | 0.798 | -50.08 | 2.324 |
| lnSale | 21.62 | 1.461 | 13.54 | 28.72 |
| lnage | 2.262 | 0.626 | 1.099 | 3.401 |

Note: Data are sourced from the CSMAR (China Stock Market & Accounting Research) database.

### 4.2. Parallel Trends Test

To validate our staggered DID design, we test the parallel trends assumption—essential for causal inference—using an event study framework. Restricting the sample to an eight-year window around certification (four years pre/post), with firm/year fixed effects.

$$\text{Im}_{it} = \alpha + \sum_{T=-4}^{4} \beta_T \bullet TimetoTreat_{iT} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

Figure 1 shows statistically insignificant pre-certification coefficients (＜0), consistent with parallel trends, while post-certification coefficients (＞0) exhibit monotonically increasing and statistically significant magnitudes, indicating sustained improvements in smart manufacturing intensity driven by GFC adoption. These results validate the staggered DID design's causal identification.

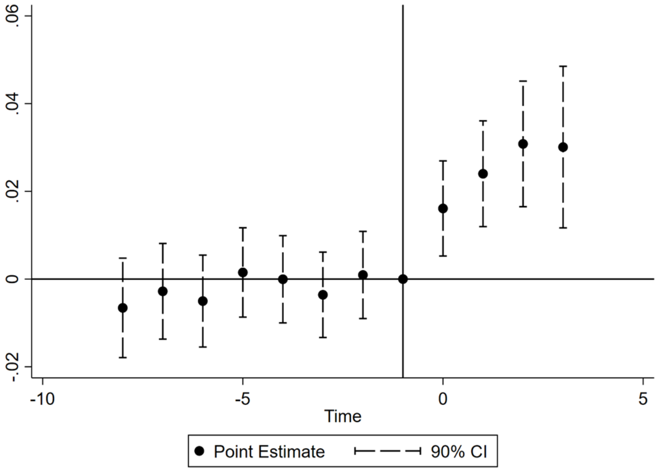

**Figure 1.** Parallel Trends Test

### 4.3. Analysis of DID Model Empirical Results

Table 3 presents the net policy effects of Green Factory Certification (GFC) on corporate smart manufacturing, with a focus on the coefficient of the interaction term Treatment×Post (denoted as DID). After controlling for two-way fixed effects (firm and year), the coefficient of Treatment×Post is 0.0785, statistically significant at the 1% level, indicating that GFC certification significantly enhances firms' smart manufacturing development.

**Table 3.** The Impact of Green Factory Certification on Firms' Intelligent Manufacturing

| Variable | Im |
|---|---|
| DID | 0.0785***<br>(0.016) |
| Tl | 0.0541***<br>(0.019) |
| lnSale | 0.0273***<br>(0.005) |
| lnage | 0.0476***<br>(0.011) |
| ROE | 0.0006<br>(0.001) |
| Invt | 0.1113***<br>(0.030) |
| Cash | -0.0656***<br>(0.021) |
| Cr | -0.0163<br>(0.023) |
| Tang | -0.0729***<br>(0.020) |
| Constant Term | -0.5283***<br>(0.103) |
| Sample Size | 15,310 |
| $R^2$ | 0.008 |

Note: ***p<0.01, **p<0.05, *p<0.1, Robust standard errors (heteroskedasticity-consistent) are reported in parentheses; the same applies to the following tables.

Government policy incentives critically shape corporate behavior. By providing GFC-certified firms with fiscal subsidies, tax incentives, and green credit, policymakers directly and indirectly accelerate smart manufacturing transitions. These measures compel firms to upgrade technologies and optimize production models, embedding intelligent monitoring across product design, manufacturing, and logistics. Through big data analytics, IoT, and AI, certified firms reduce energy waste, improve product qualification rates, and achieve green-intelligent upgrades throughout product lifecycles.

Simultaneously, GFC certification signals sustainability commitments to capital markets, enhancing firms' reputational capital and financing conditions. Improved access to low-cost funding enables higher R&D investments in smart manufacturing, creating a virtuous cycle of innovation and competitiveness. This aligns with the signaling theory, wherein credible certifications reduce information asymmetry and attract ESG-focused investors, further amplifying resource allocation efficiency.

## 4.4. Robustness Tests

1. Winsorization

To mitigate outlier bias, we winsorize key variables at 1%/99% percentiles[21]. Re-estimating the DID model, the Treatment×Post coefficient remains significant ($p<0.01$) with nearly identical magnitude (0.0768 vs. 0.0785), confirming GFC's robust positive effect on smart manufacturing (Table 4).

**Table 4.** Regression Results with Winsorized Data

| Variable | (1) |
|---|---|
| | Im |
| DID | 0.0171**<br>(0.008) |
| Constant Term | 0.5402***<br>(0.111) |
| Sample Size | 12,106 |
| $R^2$ | 0.818 |

2. Lagged Control Variables

To address endogeneity, we lag controls by one period. The DID coefficient remains significant ($p<0.01$) in Table 5, confirming GFC's persistent positive effect. This suggests long-term impacts from government incentives and reputational gains that continually reshape firms' production models.

**Table 5.** Regression Results with Lagged Control Variables (One Period)

| Variable | (1) |
|---|---|
| | Im |
| fx | 0.0234**<br>(0.010) |
| Constant Term | -0.4756***<br>(0.114) |
| Sample Size | 12,911 |
| $R^2$ | 0.836 |

3. Altering the Time Window

To address time window sensitivity, we restrict the sample to 2009-2019. Table 6 shows the DID coefficient remains significant ($p<0.05$), confirming GFC's persistent positive effect on smart manufacturing across periods. This robustness indicates a structural relationship between green certification and technological upgrading, unaffected by temporal boundaries.

**Table 6.** Regression Results after Changing the Window Period

| Variable | (1) |
|---|---|
| | Im |
| DID | 0.0200**<br>(0.008) |
| Constant Term | -0.4722***<br>(0.119) |
| Sample Size | 11,247 |
| $R^2$ | 0.839 |

4. Robustness Test with LASSO-DID

To address potential multicollinearity among controls (e.g., liability/current ratios, cash holdings), we apply LASSO-DID[22] with L1 regularization for variable selection. Table 7 shows the DID coefficient remains significant ($p<0.05$), confirming GFC's robust positive effect and mitigating multicollinearity concerns.

**Table 7.** LASSO-DID Regression Results

| Variable | (1) |
|---|---|
| | Im |
| DID | 0.0270**<br>(0.013) |
| Constant Term | 0.1272**<br>(0.063) |
| Sample Size | 11,575 |

5. Placebo Test

In policy evaluation research, aside from the “Green Factory” certification, other unobservable factors may affect the adoption of intelligent manufacturing by firms, thereby influencing the accuracy of regression estimates. To ensure the robustness of the research conclusions, this study further employs the spatial placebo test method. This approach involves randomly reallocating treatment groups to construct a hypothetical “Green Factory” certification group, allowing us to examine the distribution of DID estimates in the absence of actual policy intervention. The placebo test results are then compared with the actual DID estimates. The core idea behind this method is as follows: if the effect of “Green Factory” certification on intelligent manufacturing is genuine, then in the case of random assignment of treatment groups, the DID estimates should follow a normal distribution and be close to zero. Conversely, if the randomly assigned DID estimates are still significantly positive, it suggests that the regression results may be influenced by other factors, raising concerns about the identification of the policy effect.

Figure 2 illustrates the distribution of placebo regression coefficients for the randomly assigned treatment groups. The coefficients exhibit a normal distribution overall, and are randomly distributed around zero, aligning with the characteristics of random error. This distribution significantly differs from the benchmark estimate of this study (0.0785), indicating that the observed impact of the "Green Factory" certification on firms' intelligent manufacturing adoption is not incidental, but rather robust.

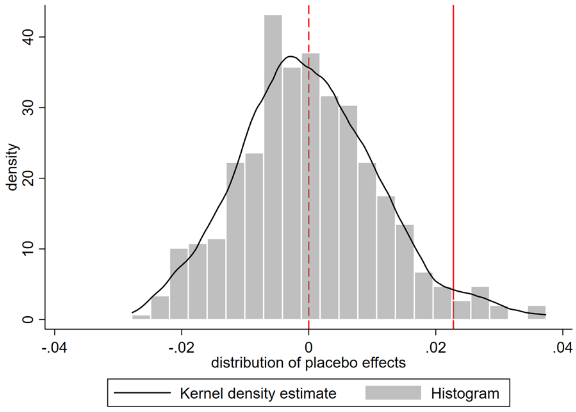

**Figure 2.** Mixed Placebo Test for Standard DID

6. Changing Fixed Effects

To validate the robustness of the Difference-in-Differences (DID) estimates, this study performs regressions on the DID variable under multiple fixed effect specifications and analyzes the results within a 95% confidence interval. Figure 3 presents the coefficient estimates of the DID variable under five model specifications (a-e). The results show that the coefficient estimates are positive across all five models and significantly non-zero at the 95% confidence level, demonstrating that the effect of "Green Factory" certification on the development of firms' intelligent manufacturing is stable and statistically significant.

Specifically, different fixed effect specifications effectively control for potential heterogeneity, thereby enhancing the reliability of the estimates. Among these models, the industry-year interaction fixed effect model (d) produces the highest coefficient estimate, indicating that after considering the interaction effects between industries and years, the "Green Factory" certification still exerts a positive impact on the development of intelligent manufacturing. This result further confirms that the model's robustness is strengthened under stricter fixed effect controls. Notably, even after controlling for potential unobserved factors at different time points and industry levels, the results consistently show a positive relationship.

Overall, the estimates of the DID variable remain consistent across different fixed effect specifications, suggesting that the conclusions of this study are robust. This further enhances the reliability of the research and the broad applicability of its conclusions.

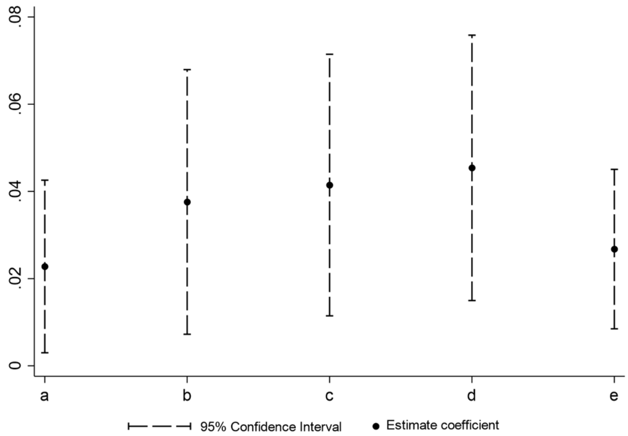

**Figure 3.** Fixed effects analysis

7. Changing the Clustering Level

This study conducts robustness checks by applying four different clustering specifications at the 95% confidence interval: standard errors without clustering, standard errors clustered at the city level, standard errors clustered by firm size, and two-way clustering of standard errors by firm size and listing year. The results indicate that the estimated coefficients of the DID variable remain positive and relatively stable across all clustering settings, ranging from 0.0193 to 0.0201. This suggests that the "Green Factory" certification has a significant effect on firms' intelligent manufacturing development, and that the direction and magnitude of the policy impact are robust. These findings imply that the estimated treatment effects are not substantially influenced by the choice of clustering level.

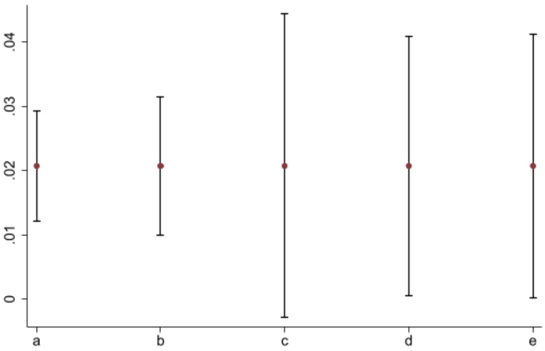

**Figure 4.** Changing the Clustering Level

### 4.5. Heterogeneity Analysis

1. Heterogeneity analysis of state-owned enterprises

To explore heterogeneous effects of Green Factory Certification (GFC) across firm types, we partition the sample into government-linked enterprises (SOEs) and non-government-linked enterprises (non-SOEs) for subgroup regression analyses. As shown in Table 7, the coefficient of the DID variable *(Treatment×Post)* is statistically insignificant, indicating no material divergence in smart manufacturing outcomes between SOEs and non-SOEs. This finding suggests that under China's national strategy to prioritize smart manufacturing development, both SOEs and non-SOEs benefit from universal policy incentives and non-discriminatory subsidies, narrowing historical disparities in their technological trajectories.

The theoretical and contextual interpretation are as follows. First is Policy Homogenization. The "Made in China 2025" initiative and subsequent sectoral guidelines have established a unified policy framework, reducing institutional advantages traditionally enjoyed by SOEs. Fiscal subsidies, tax rebates, and green credit programs are increasingly accessible to all qualified firms, regardless of ownership structure. Second is Technological Convergence. As smart manufacturing evolves into an emerging "blue ocean" industry, standardized technological pathways diminish first-mover advantages. Intensified market competition compels both SOEs and non-SOEs to adopt similar innovation strategies to maintain competitiveness. Third is Erosion of SOE Privileges. SOEs' historical reliance on policy-driven monopolies and preferential financing has weakened in technology-intensive sectors, where agility and R&D efficiency dominate competitive dynamics.

2. Heterogeneity analysis of corporate governance

To assess the effectiveness of corporate resource allocation, we utilize the Internal Control Index from the CSMAR database to measure governance quality, where higher index values indicate stronger internal governance systems. As shown in Table 8, the impact of Green Factory Certification (GFC) on smart manufacturing exhibits stark heterogeneity across governance levels: firms with high internal governance efficiency demonstrate a statistically significant positive effect, , whereas those with low governance efficiency show a marginally negative effect. This divergence suggests that GFC's efficacy in driving smart manufacturing is contingent on firms' internal governance capabilities.

The theoretical mechanism are as follows. First is about Resource Mobilization Efficiency. Smart manufacturing hinges on large-scale R&D investments and advanced technological integration. High governance efficiency enhances capital deployment precision and reduces agency costs, enabling firms to allocate resources strategically toward smart technology adoption. Second is about Information Transparency: Robust internal controls mitigate information asymmetry between managers and shareholders, improving access to external financing and lowering capital costs. Transparent governance structures also attract ESG-aligned investors, amplifying funding channels for smart manufacturing. Third is about Dynamic Capabilities. Firms with strong governance exhibit superior adaptability in reconfiguring resources to align with smart manufacturing requirements.

**Table 8.** Heterogeneity analysis of state-owned enterprises and corporate governance

| Variable | IM | | |
|---|---|---|---|
| | State-owned enterprises | corporate governance | |
| | | High | Low |
| DID | 0.0153 | 0.0197** | -0.0253 |
| | (0.016) | (0.011) | (0.053) |
| Constant Term | -0.2865 | -0.5596*** | 0.4251 |
| | (0.207) | (0.106) | (0.185) |
| Sample Size | 11,247 | 13,562 | 1,480 |
| $R^2$ | 0.839 | 0.8364 | 0.8193 |

# 5. Mechanism and Economic Consequence Tests

## 5.1. Mechanism Tests

To explore the underlying mechanisms through which the “Green Factory” certification influences firms' intelligent manufacturing, as well as its economic value, this study conducts a mechanism analysis along two main pathways: the alleviation of financing constraints and the enhancement of R&D investment. Furthermore, we evaluate the long-term impact of the policy on total factor productivity (TFP).

1.Financing Constraints Channel

As shown in Table 9, the mechanism test results indicate that the Green Factory certification promotes intelligent manufacturing through both channels. First, in the financing constraint pathway, the DID coefficient is significantly negative at the 1% level, suggesting that the policy reduces firms’ financing risk premium by providing a green credit endorsement, thereby enhancing their access to external capital. Intelligent manufacturing, being capital-intensive, depends heavily on large-scale fixed asset investments and technological upgrades. The alleviation of financing constraints thus provides crucial funding support for technology advancement[23].

Second, in the R&D investment pathway, the DID coefficient is significantly positive at the 5% level, indicating that the policy incentivizes firms to increase R&D expenditures. Certified Green Factory enterprises, benefiting from tax incentives and innovation subsidies, accelerate in-house development of core technologies such as artificial intelligence and big data analytics, thereby creating technological barriers to strengthen their market competitiveness[24]. The synergy between these two pathways demonstrates that the policy not only optimizes access to external resources but also strengthens internal innovation capabilities, jointly promoting the integration of intelligent manufacturing systems.

Further evaluation of economic consequences (Table 10) shows that the Green Factory certification leads to an average annual increase of 0.89% in firms’ TFP, of which 63% is attributed to technological progress and 37% to efficiency improvements. This decomposition validates the “dual-engine” effect of intelligent manufacturing—simultaneous advancements in technological breakthroughs and process optimization. Such developments not only align with the emission reduction targets under China’s dual-carbon goals but also reshape firms’ competitive advantages through high value-added production.

Importantly, TFP gains exhibit persistence, with a sustained annual growth rate of 0.72% even three years after policy implementation. This suggests that Green Factory certification not only triggers short-term technology catch-up but also fosters long-term growth momentum through knowledge accumulation and supply chain coordination.

The findings offer dual implications for policy design: on the one hand, it is essential to strengthen the synergy between green finance instruments and R&D incentives to alleviate capital bottlenecks in technology-intensive transformations; on the other hand, the establishment of platforms for intelligent manufacturing technology diffusion is crucial for facilitating spillover effects and amplifying the multiplier effect of TFP improvements.

## 5.2. Economic consequences test

To empirically evaluate the real economic impact of policy implementation at the firm level, this study further investigates the effect of “Green Factory” certification on firms’ total factor productivity (TFP). As presented in Column (1) of Table 10, the certification significantly increases firms’ TFP at the 1% confidence level, suggesting that the policy delivers tangible economic benefits beyond its environmental goals. By enhancing production efficiency and optimizing resource allocation, firms are able to improve the utilization of labor and capital, thereby achieving greater overall productivity. These findings confirm that the recognition as a Green Factory contributes not only to environmental transformation but also to measurable gains in operational efficiency.

TFP can be further decomposed into two distinct components: technical efficiency (TECH) and technological progress (TECCH) [25]. The former captures improvements in the allocation and management of existing resources, while the latter reflects advancements in production technology and innovation. According to Column (2) of Table 10, the DID coefficient for technological progress is significantly positive at the 1% level, indicating that the Green Factory policy facilitates TFP growth primarily through technological advancement. This effect likely stems from firms' increased investment in green and intelligent manufacturing technologies following certification. Such investments enable more efficient production processes, allowing firms to achieve higher output with fewer resource inputs.

Moreover, the impact of technological progress may extend beyond internal innovation. By promoting vertical integration and technological coordination across supply chains, certified firms can foster knowledge spillovers and enhance industry-wide innovation capacity. In this regard, Green Factory certification may serve as a catalyst for systemic technological upgrading, strengthening both firm-level and sectoral productivity.

In sum, the empirical evidence indicates that Green Factory recognition exerts a meaningful economic effect on firms by improving their total factor productivity. The observed gains arise not only from enhanced production efficiency but also from accelerated technological progress, suggesting that environmental policy can play a dual role in advancing both sustainability and industrial competitiveness.

**Table 9.** Mechanism Tests and Economic consequences Tests

| Variable | Mechanism Tests | | Economic consequences Tests | | |
|---|---|---|---|---|---|
| | FC_index | RD | TEPCH | TECH | TECCH |
| DID | -0.0283*** | 0.3550** | 0.0030*** | -0.0003 | 0.0024*** |
| | (0.006) | (0.141) | (0.001) | (0.001) | (0.000) |
| Constant Term | 2.6170*** | 36.8069*** | 0.9536*** | 0.9822*** | 0.9912*** |
| | (0.090) | (6.154) | (0.016) | (0.018) | (0.012) |
| Sample Size | 20,137 | 14,534 | 20,239 | 20,295 | 20,137 |
| $R^2$ | 0.096 | 0.743 | 0.857 | 0.649 | 0.796 |

# 6. Research Conclusions and Policy Implications

## 6.1. Research Conclusions

As a key driver of China's manufacturing transformation, intelligent manufacturing is crucial to achieving the synergistic integration of green and smart manufacturing under the “dual carbon” targets. Whether this integration can be effectively supported by green industrial policies—exemplified by the “Green Factory” certification—remains a pressing empirical question. This study takes the “Green Factory” certification policy, introduced by China’s Ministry of Industry and Information Technology in 2016, as a quasi-natural experiment. Utilizing panel data from A-share listed firms on the Shanghai and Shenzhen stock exchanges, the analysis applies difference-in-differences (DID) and LASSO-DID methodologies to assess the policy's impact on intelligent manufacturing development and its underlying mechanisms. The findings are as follows:

(1) Overall, the implementation of the “Green Factory” policy significantly alleviates firms' financial constraints and increases their R&D investment, thereby promoting the adoption and advancement of intelligent manufacturing technologies;

(2) The heterogeneity analysis by ownership structure reveals that the effect of the policy does not differ significantly between state-owned and non-state-owned enterprises. However, heterogeneity based on corporate governance indicates that firms with stronger internal controls respond more positively to the policy, exhibiting greater advancement in intelligent manufacturing;

(3) In terms of economic consequences, the “Green Factory” certification demonstrates tangible economic benefits for firms, notably through improvements in efficiency and technological advancement, ultimately contributing to the growth of total factor productivity (TFP).

## 6.2. Policy Recommendations

Against the backdrop of China’s “dual carbon” strategy and under the guidance of its new development philosophy, this study offers several policy suggestions grounded in its theoretical framework and empirical findings, aligned with the country’s path toward green and intelligent industrial development.

First, t leverage green industrial policies like China's "Green Factory" initiative to accelerate smart manufacturing adoption. As a key driver of total factor productivity (TFP) growth and industrial upgrading, empirical evidence confirms GFC's significant positive impact on firms' smart manufacturing capabilities, warranting broader policy implementation.

Second, enhance support for certified firms through targeted incentives and resource allocation. Encouraging greater investment in smart technologies maximizes their demonstration effect, while diversified financial instruments can alleviate funding constraints and boost R&D for faster transformation.

Third, the diversity and multi-layered structure of green industrial policy should be further enriched. Drawing on the framework of New Structural Economics, national-level green policies like the “Green Factory” initiative promote transformation through the dual mechanisms of regulatory standards and market-based incentives, thereby advancing intelligent manufacturing. This synergy illustrates the feasibility of green-smart integration. Hence, it is essential to build upon the experiences of existing policies, systematically synthesize successful practices, and expand the application of complementary green policy instruments to broaden the impact across a wider range of manufacturing firms engaged in industrial upgrading.

# References

[1] Zhang, Y., & Song, J. (2021). Intelligent manufacturing in the Industry 4.0 era. China Industry & Information Technology, (9), 32-34. (in Chinese)

[2] SOORI M, AREZOO B, DASTRES R. Digital twin for smart manufacturing, A review [J]. Sustainable Manufacturing and Service Economics, 2023, 2: 100017.

[3] Zhou, J. (2015). Intelligent manufacturing: The main direction of "Made in China 2025". China Mechanical Engineering, 26(17), 2273-2284. (in Chinese).

[4] Liao, G., Jiang, M., & Wang, W. (2022). Green credit policy, debt financing and corporate innovation: DID test based on "two high" industries. Friends of Accounting, (17), 54-60. (in Chinese)

[5] Han, L., Tu, Y., & Zhuang, Q. (2024). Intelligent manufacturing pilot and corporate innovation: Quasi-natural experiment based on "Intelligent Manufacturing Pilot Demonstration Special Action". Forum on Science and Technology in China, (6), 77-86. (in Chinese)

[6] Huang, Z., Tao, Y., Liu, Z., et al. (2024). How intelligent manufacturing improves corporate capacity utilization: From the perspective of prosumption integration. Management World, 40(5), 40-59. (in Chinese)

[7] Wang, Q., & Sun, G. (2024). The "de-mismatch" effect of intelligentization and total factor productivity growth. Management Review, 36(4), 39-48. (in Chinese)

[8] Wu, L., Jia, X., Wu, C., et al. (2020). The impact of heterogeneous environmental regulations on China's green total factor productivity. China Population, Resources and Environment, 30(10), 82-92. (in Chinese)

[9] Li, X., Zhang, Y., & Jiang, F. (2019). Green industrial policy: Theoretical evolution and China's practice. Journal of Finance and Economics, 45(8), 4-27. (in Chinese)

[10] CHAO Z, LINGYUN H, HONGYIN L. Environmental regulations and green innovation of enterprises: quasi-experimental evidence from China [J]. Environmental science and pollution research international, 2023, 30(21): 60590-606.

[11] Chen, G., Ding, S., & Zhao, X. (2021). China's green finance policy, financing costs and corporate green transformation: From the perspective of central bank collateral policy. Journal of Financial Research, 498(12), 75-95. (in Chinese)

[12] Wang, Z., & Sun, H. (2022). The impact of market-based environmental regulation on corporate green technology innovation and its mechanism. Science and Technology Management Research, 42(8), 208-215. (in Chinese)

[13] Wang, M., Ye, T., & Kong, D. (2024). Green manufacturing and corporate environmental information disclosure: Policy experiment based on China's green factory creation. Economic Research Journal, 59(2), 116-134. (in Chinese).

[14] LIN J, CHANG H J. Should Industrial Policy in developing countries conform to comparative advantage or defy it? A debate between Justin Lin and Ha-Joon Chang [J]. Development policy review, 2009, 27(5): 483-502.

[15] MIIT. (2018). General rules for green factory evaluation (GB/T 36132-2018). Standards Press of China. (in Chinese)

[16] Liu, J., Liu, J., & Chao, Y. (2024). Green credit and low-carbon transition: Capital integration or technological innovation? Evidence from quasi-natural experiments. The Journal of Quantitative & Technical Economics, 41(6), 151-171. (in Chinese)

[17] YU Y, ZHANG N. Environmental regulation and innovation: Evidence from China [J]. Global Environmental Change, 2022, 76: 102587.

[18] ECCLES R G, IOANNOU I, SERAFEIM G. The impact of corporate sustainability on organizational processes and performance [J]. Management science, 2014, 60(11): 2835-57.

[19] BENTO N, FONTES M. The construction of a new technological innovation system in a follower country: Wind energy in Portugal [J]. Technological Forecasting and Social Change, 2015, 99: 197-210.

[20] Guo, L., He, F., & Li, J. (2020). Analysis of China's intelligent manufacturing development trends: Based on text data from annual reports of manufacturing listed companies. Innovation Science and Technology, 20(2), 61-71. (in Chinese)

[21] WILCOX R R, ERCEG-HURN D M. Comparing two dependent groups via quantiles [J]. Journal of Applied Statistics, 2012, 39(12): 2655-64.

[22] Jiang, T. (2022). Mediating effects and moderating effects in causal inference empirical research. China Industrial Economics, (5), 100-120. (in Chinese)

[23] MYERS S C, MAJLUF N S. Corporate financing and investment decisions when firms have information that investors do not have [J]. Journal of financial economics, 1984, 13(2): 187-221.

[24] AGHION P, BLUNDELL R, GRIFFITH R, et al. The effects of entry on incumbent innovation and productivity [J]. The review of economics and statistics, 2009, 91(1): 20-32.

[25] Wang, D., & Zhu, Y. (2009). Research on dynamic decomposition and evaluation of total factor productivity changes in China's high-tech industry. Science & Technology Progress and Policy, 26(18), 104-107. (in Chinese).