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The Impact of High-Level Smart Factory Recognition on Supply Chain Stability: Evidence from a Quasi-Natural Experiment among Chinese A-Share Manufacturing Firms

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Abstract

With the development of smart manufacturing, smart factory recognition becomes a key policy for the transformation and upgrading of the manufacturing industry. This work takes China's A-share manufacturing listed companies from 2019 to 2025 as a sample, and takes the firms selected into the list of excellent level and leading level smart factories in 2024-2025 as a treatment group, and uses the difference-in-differences method to examine the impact of smart factory recognition on the stability of the firms' supply chain. The research results show that high-level smart factories have been identified as reducing the stability of the supply chain in the sense of measurement in the short term, but this does not mean that their supply chain capacity will decline immediately, but that firms have carried out stronger supply chain restructuring in the short term. After adopting different sample processing methods and recognition tests, the conclusion is still robust.

Keywords

High-level Smart Factory Recognition; Supply Chain Stability; Supply Chain Restructuring; Difference-in-Differences; Smart Manufacturing.

1. Introduction

With the continuous advancement of smart manufacturing, smart factories have become an important path for the transformation and upgrading of the manufacturing industry, and the stability of the supply chain has increasingly become an important dimension for measuring the stability of firms. Industrial Internet, artificial intelligence and other technologies are increasingly being used to improve production efficiency, strengthen quality control and enhance production flexibility. This process is strongly supported by industrial policies in China. The officially recognized excellent level and leading level smart factories are aimed at identifying firms with relatively advanced digital infrastructure and intelligent production systems. Therefore, this kind of recognition is not only an honorary label, but also may affect the subsequent strategic and operational decisions of the firm.

Supply chain relationship is one of the important aspects, but the impact of research is relatively insufficient. Manufacturing firms rely on relatively stable customer and supplier networks in terms of production planning, product delivery and cash flow management. And smart manufacturing can strengthen these relationships by improving information sharing and coordination. However, recognized firms may also use upgraded capabilities to enter new markets, adjust customer portfolios, or reorganise supplier relationships. Therefore, while it is recognized that it may improve the long-term adaptability of firms, it will also lead to relatively large changes in customer concentration and supplier concentration in the short term.

This study examines whether the recognition of high-level smart factories will affect the stability of the supply chain of Chinese A-share manufacturing firms. Based on the list of firms

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selected for excellent level and leading level smart factories in 2024 and 2025, this paper constructs the firm-year panel data from 2019 to 2025 and adopts a difference-in- differences model for analysis. Supply chain stability is measured by annual changes in customer concentration and supplier concentration. Further research found that this impact is mainly driven by customer-side adjustment, concentrated in large firms, and has a greater impact on low-leverage firms.

The contribution of this article is mainly reflected in three aspects. First, this article adopts official recognition events with clear time nodes and processing boundaries, thus surpassing the broad measurement of digital transformation in the past. Second, this article will shift the research focus from supply chain resilience to the changes in customer relationship and supplier relationship. Third, this article provides relevant evidence that smart factory recognition may first trigger short-term restructuring, rather than immediate stability improvement. In this sense, this study links smart manufacturing policies with the external supply chain adjustment of firms.

2. Literature Review

2.1. Smart Manufacturing and Supply Chain Stability

Smart factories integrate cyber physical systems, real-time communication and flexible production, and are widely regarded as a key form of Industry 4.0[1,2]. Research evidence in China shows that intelligent upgrading can improve productivity and operational efficiency[3,4]. Relevant literature also links network structure and information sharing to supply chain stability[5,6]. More recent studies have found that digital transformation and smart manufacturing can enhance the stability or resilience of the supply chain by improving coordination and information integration[7-10].

However, the existing research mainly adopts a broader digital transformation measurement index, or focusses on supply chain resilience and performance. The existing research still lacks a full understanding of whether the official smart factory determines whether it will change the customer relationship and supplier relationship of the firm in the short term. This article regards this recognition as a policy-related event with a clear time node, and examines its impact on the annual adjustment of the supply chain, so as to make up for this research gap.

2.2. Hypothesis Development

High-level smart factory recognition may improve the production flexibility, information processing ability and coordination ability of the firm. These capabilities help to achieve more accurate delivery and strengthen cooperation between firms and supply chain partners. However, the recognition may also allow firms to reorganise the existing supply chain relationship. Recognized firms may enter new customer networks, reduce dependence on major partners, or adjust suppliers to meet upgraded production requirements. In the short term, these changes may increase the annual fluctuations of customer concentration and supplier concentration, thus reducing the measured stability of the supply chain.

H1. High-level smart factory recognition is associated with stronger short-term supply chain restructuring, leading to a decline in measured supply chain stability.

There may be differences in the adjustment at both ends of the supply chain. When firms gain stronger production flexibility or market access, the customer portfolio can usually change faster. In contrast, supplier relationships often rely on technical standards, quality certification and long-term coordination. Therefore, the forecast will have a more obvious short-term impact on the customer side.

H2. The impact of high-level smart factory recognition on the stability of the measured supply chain is mainly reflected in customer-side adjustment, not the supplier-side adjustment.

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The degree of supply chain restructuring may also be affected by the characteristics of the firm. Large firms usually have a wider supply chain network, stronger bargaining power, and more resources for restructuring external relations, so they may make greater adjustments after being recognized. Financial flexibility also affects supply chain restructuring to some extent, because supply chain restructuring may require additional investment and management resources. Low-leverage firms face weak debt constraints, so they are more capable of supporting these changes.

H3a. The negative effect of high-level smart factory recognition on measured supply chain stability is more pronounced among large firms than among small firms.

H3b. The supply chain restructuring effect of high-level smart factory recognition is more pronounced among low-leverage firms than among high-leverage firms.

3. Method

3.1. Sample and Data

This study takes China's A-share listed manufacturing firms as a sample to examine the impact of high-level smart factory recognition on the stability of the supply chain. The initial data covers 2018-2025, and the regression sample period is 2019-2025. The treatment group includes firms that are included in the list of excellent level or leading level smart factories in 2024 and 2025. The manufacturing firms that are not included in the above list during the sample period constitute the control group.

The recognized list includes both listed companies and non-listed entities. Therefore, according to the firm name, stock code, equity relationship and name change record, this work will manually match the recognized factory with the A-share listed company. Samples with unclear parent-child relationships or uncertain matching results shall be eliminated. Firm-level supply chain, financial and corporate governance data mainly come from the CSMAR database.

This paper further limits the sample to manufacturing firms, and eliminates ST and *ST firms, as well as the missing observations of key variables. Although the data collection began in 2018, the observations in 2018 are only used to calculate the lag changes in customer concentration and supplier concentration required for supply chain stability indicators in 2019. The final data is unbalanced panel data, and the complete benchmark regression model contains 19,051 annual observations of firms.

3.2. Variable Definition and Measurement

3.2.1. Supply Chain Stability.

The dependent variable is supply chain stability, denoted by SCS. It is measured using annual changes in customer and supplier concentration. Larger changes indicate stronger restructuring, while smaller changes suggest more stable supply chain relationships.

$$SCS_{it} = -(|CustomerCon_{it} - CustomerCon_{it-1}| + |SupplierCon_{it} - SupplierCon_{it-1}|)$$

where $CustomerCon_{it}$ and $SupplierCon_{it}$ represent the customer and supplier concentration of firm i in year t. The negative sign ensures that a higher value of SCS indicates greater stability. A lower value therefore reflects stronger year-to-year adjustment in customer or supplier structure.

3.2.2. High-level Smart Factory Recognition.

The core explanatory variable of the work is the DID interaction term:

$$DID_{it} = Treat_i \times Post_{it}$$

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For firms that are recognized as excellent level or leading level smart factories in 2024 or 2025, the value of $Treat_i$ is 1, otherwise the value is 0. $Post_{it}$ equals 1 in the recognition year and subsequent years, and 0 before recognition. The coefficient of DID_{it} reflects the changes in the stability of the supply chain of recognized firms compared with those that have not been recognized.

This article uses the official recognition list. Compared with the broader degree of digital transformation or smart manufacturing intensity indicators, the officially released list can provide a clearer treatment group boundary and recognition time.

3.2.3. Control Variables.

The model includes several firm-level controls. Size is the natural logarithm of total assets; Lev is total liabilities divided by total assets; ROA measures profitability; Growth is the annual revenue growth rate; Cashflow is operating cash flow scaled by total assets; and Top1 is the shareholding percentage of the largest shareholder. These variables control for differences in firm scale, financial condition, operating performance and ownership structure.

3.3. Model Specification

To estimate the effect of high-level smart factory recognition on supply chain stability, this study applies a difference-in-differences model:

$$SCS_{it} = \alpha + \beta\, DID_{it} + \gamma\, X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where SCS_{it} is the supply chain stability of firm i in year t, and DID_{it} is the interaction between the treatment and post-recognition indicators. X_{it} denotes the set of firm-level control variables. Firm fixed effects, μ_i, absorb time-invariant differences across firms, while year fixed effects, λ_t, control for common macroeconomic and policy shocks. ε_{it} is the error term.

The core coefficient that this work focusses on is β. The positive coefficient indicates that the stability of the supply chain measured by the firm has improved after being recognized; the negative coefficient indicates that the customer concentration or supplier concentration has been adjusted more in the short term. Given the construction method of SCS, the negative estimation results should be interpreted as a stronger supply chain restructuring, and should not be directly understood as an automatic decline in supply chain capacity.

Standard errors are clustered at the firm level. This paper also adopts an event research model and carries out robustness testing, customer-side and supplier-side decomposition analysis, and subgroup analysis based on firm scale and leverage level.

4. Results

4.1. Descriptive Statistics

Table 1. Variable definitions and descriptive statistics.

Variable	Definition	N	Mean	SD
SCS	Negative sum of the absolute annual changes in customer and supplier concentration	19,489	−10.891	9.502
DID	Indicator equal to one for recognized firms in and after the recognition year	19,489	0.016	0.126
Size	Natural logarithm of total assets	19,489	22.177	1.226
Lev	Total liabilities divided by total assets	19,489	0.388	0.191
ROA	Return on assets	19,489	0.034	0.077
Growth	Annual revenue growth rate	19,489	0.239	3.756
Cashflow	Operating cash flow divided by total assets	19,489	0.054	0.070
Top1	Shareholding percentage of the largest shareholder	19,207	32.051	14.177

Note: SCS is defined as the negative sum of the absolute annual changes in customer and supplier concentration. A higher value indicates greater supply chain stability.

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Table 1 reports the descriptive statistics. The mean of SCS is −10.891 and the standard deviation is 9.502, indicating that there is a large difference in annual customer and supplier concentration changes. The low mean of DID reflects the relatively limited number of recognized firms. Growth displays the greatest dispersion among the controls, supporting the use of winsorization in the robustness analysis.

4.2. Baseline Regression Results

Table 2 reports the results of the DID estimates. Column (1) includes the fixed effect of the firm and the fixed effect of the year, and column (2) further adds the full set of the control variables at the firm level. Under the two model settings, the coefficient of DID is negative and statistically significant, indicating that the result is not affected by whether to add control variables.

Table 2. Baseline DID regression results.

Variables	(1)	(2)
	SCS	SCS
DID	−1.491***	−1.626***
	(0.557)	(0.570)
Size		−0.445
		(0.436)
Lev		−4.407***
		(1.225)
ROA		−1.830
		(1.804)
Growth		−0.081*
		(0.041)
Cashflow		2.366
		(1.480)
Top1		0.009
		(0.024)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	19,342	19,051
Adjusted R^2	0.241	0.246

Note: The dependent variable is supply chain stability (SCS). Column (1) includes the fixed effect of the firm and the fixed effect of the year, and column (2) further adds all control variables. The report in parentheses is the standard error after clustering adjustment at the firm level. *, ** and *** indicate significance at the levels of 10%, 5% and 1% respectively.

In the full model, the coefficient of DID is -1.626, which is significant at the level of 1%. According to the construction of SCS, this estimate shows that after the firm is recognized, there is a greater adjustment in customer and supplier relationships, thus supporting the hypothesis H1. Leverage is also significantly negative, while the remaining controls are generally insignificant.

4.3. Parallel Trend Test

Figure 1 shows insignificant pre-treatment coefficients, supporting the parallel trend assumption. The coefficients become negative in the recognition year and thereafter, indicating that the change occurs after recognition rather than reflecting a prior trend.

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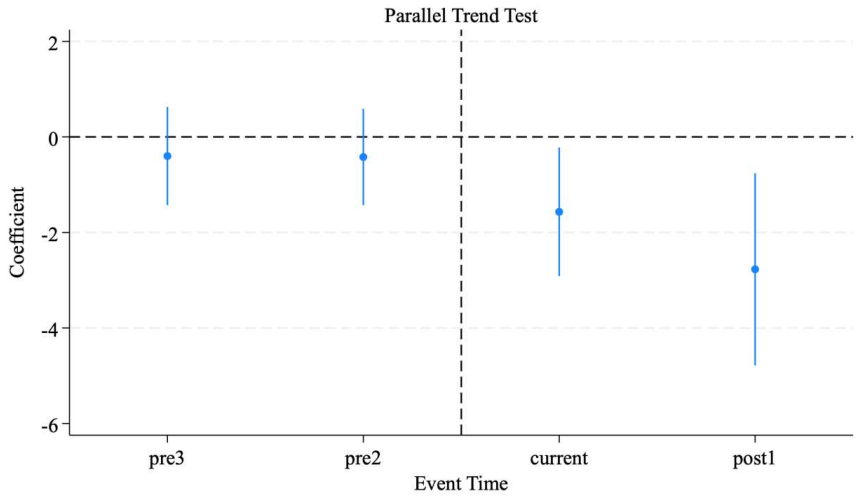


Figure 1. Parallel trend test.

4.4. Robustness Tests

Table 3 shows that the negative estimated results of DID are still significant after winsorization, PSM matching and the exclusion of firms first recognized in 2025. In contrast, the coefficients in the placebo test are not significant. These results further support the hypothesis H1 and reduce the possible impact of extreme values, observable selection deviations and pre-treatment effects.

Table 3. Robustness tests.

Variables	(1) Winsorized	(2) PSM-DID	(3) 2024 cohort only	(4) Placebo
DID	−1.428***	−1.306**	−1.640***	
	(0.527)	(0.610)	(0.584)	
Placebo DID				−0.703
				(0.454)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	19,051	3,859	18,415	19,051
Adjusted R^2	0.261	0.246	0.249	0.245

Note: Column (1) winsorizes continuous variables at the 1st and 99th percentiles. Column (2) reports the PSM-DID estimation results based on 1:3 nearest neighbour matching. Column (3) excludes the firms that were recognized for the first time in 2025. Column (4) moves the recognition year one year earlier. All regressions include the full set of controls, firm fixed effects and year fixed effects. The report in parentheses is the standard error after cluster adjustment at the firm level. *, ** and *** indicates that significance at the level of 10%, 5% and 1% respectively.

4.5. Customer- and Supplier-side Decomposition

Table 4 shows that the DID coefficient corresponding to the change of customer concentration is positive and significant, while the estimated results on the supplier side are not significant. Therefore, the decline of SCS is mainly driven by customer-side adjustment, which is consistent with the H2. Customer portfolios may respond more quickly to greater production flexibility, whereas supplier ties often depend on certification and long-term coordination.

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Table 4. Customer- and supplier-side decomposition.

Variables	(1) Customer change	(2) Supplier change
DID	1.388***	0.238
	(0.448)	(0.296)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	19,051	19,051
Adjusted R^2	0.208	0.203

Note: Column (1) uses the absolute annual change in customer concentration as the dependent variable, while column (2) uses the absolute annual change in supplier concentration. All regressions include the full set of controls, firm fixed effects and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

4.6. Heterogeneity Analysis

Table 5 examines whether the effect of smart factory recognition differs by firm size and leverage. The sample is divided at the median of each characteristic.

Table 5. Heterogeneity analysis.

Variables	(1) Small firms	(2) Large firms	(3) Low leverage	(4) High leverage
DID	3.026*	−1.641***	−4.606***	−0.908*
(1.566)	(0.606)	(1.739)	(0.542)	
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	9,256	9,494	9,226	9,270
Adjusted R^2	0.237	0.260	0.248	0.259

Note: Columns (1) and (2) divide the sample at the median of firm size. Columns (3) and (4) divide the sample at the median of leverage. All regressions include the full set of controls, firm fixed effects and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

For firm size, the DID coefficient is negative and significant for large firms, but positive and only weakly significant for small firms. This shows that the measured decline in supply chain stability is mainly concentrated in large firms. Large firms usually have a wider supply chain network and stronger adjustment capacity, so they may be more active in reorganizing customer and supplier relationships after being recognized.

For leverage, the DID coefficient is negative in both groups, but its magnitude is substantially among low leverage firms. Firms with lower debt pressure may have greater financial flexibility, which can support the adjustment of production systems and business relationships. Relevant evidence shows that supply chain restructuring is more obvious in firms with more complex supply chain structures or stronger financial capabilities. These results are consistent with H3a and H3b. However, since these group differences come from separate regression rather than a formal coefficient difference test, they should be explained carefully.

5. Conclusion

This study examines how high-level smart factory recognition affects the stability of the supply chain of Chinese A-share manufacturing firms. Based on the recognition list in 2024 and 2025,

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this paper adopts a difference-in-differences design. The results show that the stability of the measured supply chain of the recognized firms has decreased significantly. Since SCS reflects the annual changes in customer concentration and supplier concentration, this result shows that firms carry out stronger supply chain restructuring in the short term, rather than a simple decline in their supply chain capacity.

The results of the decomposition analysis show that this impact is mainly driven by customer-side adjustments, while the supplier-side changes are relatively limited. This shows that the recognition may improve the production flexibility and market expansion ability of the firm, so that it can adjust the customer portfolio faster. The negative supply chain restructuring effect is mainly concentrated in large firms and has a greater impact on low-leverage firms.

These findings extend smart manufacturing research beyond internal efficiency and show that intelligent upgrading can also reshape firms' external supply chain networks. For policymakers, short-term instability should not be directly regarded as evidence of policy failure. For firms, the key challenge is how to maintain the continuity of important supply chain relationships while adjusting the customer portfolio.

The limitation of this study is that the observation period after recognition is relatively short. Therefore, the relevant estimates only reflect the initial adjustment stage of the firm, and it is not certain whether the supply chain restructuring will further bring stronger long-term stability. Future research should adopt a longer observation window to examine the continuity of these changes and their long-term impact.

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