The Impact of Intelligent Manufacturing on Company Investment Efficiency

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Abstract. Manufacturing technological advancements have had a significant impact on corporate operations and development in today's highly digital economy. This paper develops a double difference model using sample data from all A-share listed companies in China from 2010 to 2019, as well as a quasi-natural experiment on the promotion of intelligent manufacturing demonstration projects in China, to investigate the impact that implementing intelligent manufacturing policies can have on the efficiency of corporate investment. According to the report, implementing intelligent manufacturing can boost firm investment efficiency. Through effective corporate internal control, the mechanism analysis discovered that intelligent manufacturing can play a negative buffering role in enhancing corporate investment efficiency.

Keywords: Intelligent Manufacturing; Investment Efficiency; Double Differencing; Manufacturing Technology Upgrading.

1. Introduction

Intelligent manufacturing is based on the deep integration of advanced manufacturing technology and a new generation of information technology, throughout the whole life cycle of products such as design, production, management and service, with self-awareness, self-decision, self-execution, self-adaptation, self-learning and other characteristics, aimed at improving the quality, efficiency and effectiveness of manufacturing and flexible advanced production methods. (The definition of intelligent manufacturing is derived from the "14th Five-Year Plan" for the development of intelligent manufacturing.) At the historical intersection of global technological revolution and industrial change and China's accelerated high-quality development, China has issued the "14th Five-Year Plan" for the development of intelligent manufacturing, "National Intelligent Manufacturing Standard System Construction Guide" and other related documents, indicating that intelligent manufacturing is the main direction of China's manufacturing power.

Intelligent manufacturing will have a positive impact on the operations of enterprises in terms of operating costs, productivity and financing constraints. Intelligent manufacturing can reduce the operating costs of enterprises in general by reducing risk losses and energy consumption costs, thus improving enterprise performance (Zhang Shushan et al., 2021). Intelligent manufacturing facilitates productivity improvement by promoting firms to invest more in R&D (Bronwyn H H, 1995). Intelligent manufacturing companies can also obtain government subsidies through policies to make up for the shortage of resources thus serving to alleviate financing constraints (Yang et al., 2017).

The transformation and upgrading of manufacturing industries may face the risk of reduced investment efficiency. Investment efficiency in manufacturing is mainly affected by externalities, economies of scale and technological spillover effects (Xu, S. Yang et al., 2020). Some studies have found that during the transformation and upgrading of the manufacturing industry, the investment efficiency of China's manufacturing industry is affected by the gap between technical efficiency and scale efficiency, leading to a decrease in the efficiency of manufacturing investment (Zhang Zhonghua et al., 2017). Thus, whether the intelligent manufacturing policy can effectively improve the investment efficiency of enterprises has become a question worth considering in the evaluation of the implementation of this policy.

This paper mainly studies and addresses the question of how intelligent manufacturing effect on firm investment efficiency. The research contributions are mainly in the following three aspects: First, this paper enriches the research on intelligent manufacturing investment efficiency. Secondly, this paper explores the buffering effect of intelligent manufacturing from the perspective of internal control of enterprises. Thirdly, this paper places the practical effect test of intelligent manufacturing in the internal operation of enterprises, providing reference for the government to promote intelligent manufacturing and enterprises to transform and upgrade.

2. Theoretical Analysis and Research Hypothesis

2.1 The Relationship between Manufacturing Change and Investment Efficiency

At present, less literature has studied the impact of intelligent manufacturing on the investment efficiency of enterprises. The existing literature mainly focuses on: Firstly, the increase in the level of intelligence and intelligence helps to improve the efficiency of enterprise investment (Zeng Lingling et al., 2022); Secondly, as a kind of industrial policy it plays an enhancing role on investment efficiency. Some scholars believe that enterprises supported by industrial policies are more likely to receive bank loans and improve the level of credit financing, thus increasing investment efficiency (He Xiqiong et al., 2016). At the same time higher market competition can more greatly enhance the role of industrial policy in improving the efficiency of enterprise investment. This paper argues that the implementation of intelligent manufacturing reduces the agency costs of enterprises and plays an effective role in improving the investment efficiency of enterprises in terms of both moral hazard and compliance costs. In terms of moral hazard, the implementation of intelligent manufacturing can reduce the conflict of interest between shareholders and management through government incentives or subsidies, thereby reducing moral hazard and enabling management to make effective investments and reduce over-investment or under-investment, thus improving the efficiency of corporate investment. In terms of compliance, in order to implement intelligent manufacturing, enterprises need to continuously improve the quality of their own internal controls, resulting in higher compliance costs, reduced operating cash flow, reduced risky behavior of management, and lower risk of non-compliance, thus improving the efficiency of enterprise investment. Accordingly, this paper proposes the first hypothesis:

H1: The implementation of intelligent manufacturing can significantly improve the efficiency of a company's investment.

2.2 Intelligent Manufacturing, Internal Control and Investment Efficiency

1. Intelligent manufacturing and Internal Control

Intelligent manufacturing will have an impact on internal control through organizational structure, control activities and information communication. On the one hand, in the context of intelligence, digital interconnection drives the organizational structure of enterprises towards flattening, decentralizing management authority and reducing decision-making control processes, which helps to improve organizational internal control (Qi, 2020). On the other hand, most scholars believe that on one hand, enterprises can collect and analyze market demand through big data, make good demand forecasts and improve their awareness of risk prevention (Zhao Can, 2017; Zhao Zhen,); on the other hand, they can use intelligent platforms to share information and allocate resources to various parts of the supply chain (Zhang Yongshen et al., 2021) to reduce their operating costs and thus improve their internal control . At the same time, the implementation of intelligent manufacturing can break the phenomenon of "information silos", improve the transparency of enterprise information, and enhance the ability of enterprises to access and process information, thus improving the level of internal control of enterprises (Zhang Xinyu, 2022).

2. Internal controls and investment efficiency

Internal control will improve the efficiency of corporate investment by reducing information asymmetry and alleviating principal-agent problems. On the one hand good internal control can reduce information asymmetry and thus improve the efficiency of corporate investment. Better internal control helps to improve the quality of financial reporting (Chao Zhang et al., 2015), which in turn allows investors to have a more realistic understanding of the company's operations, thereby reducing the financing constraints caused by adverse selection and thus reducing the likelihood of generating underinvestment. On the other hand, good internal control can alleviate the principal-agent problem and thus improve the efficiency of corporate investment (Pu, Linxia, 2011). Internal control can reduce the phenomenon of underinvestment brought about by corporate managers due to risk aversion and laziness, as well as prevent the consequences of underinvestment brought about by the transfer of benefits from controlling shareholders through the supervision of management and the monitoring of connected transactions. Based on the above analysis, this paper proposes a second hypothesis:

H2: Internal controls play a buffering role in the implementation of intelligent manufacturing to improve the efficiency of business investment.

3. Study Design

3.1 Sample Selection and Data Sources

This paper uses all A-share listed companies in China from 2010-2019 as the research sample to study the impact of intelligent manufacturing on the investment efficiency of enterprises using the CEM-DID method. According to the Circular of the Ministry of Industry and Information Technology on the Announcement of the List of Intelligent Manufacturing Pilot Demonstration Projects issued by the State Ministry of Industry and Information Technology, the list of listed companies that implemented intelligent manufacturing projects was manually compiled. The initial sample data were all obtained from the CSMAR database. To ensure the stability and validity of the findings, the following treatments were applied to the initial sample: (1) eliminating samples with missing data and obvious outliers in the variables; (2) the so-called treatment of continuous variables at the 1% and 99% levels; (3) eliminating the financial sector and enterprises marked as ST and *ST.

3.2 Variable Definitions

1. Explained variables

Investment efficiency ($Residuals\ Q_{i,t}$):This paper uses Richardson (2006) and constructs the following model (1): first calculate the expected capital investment of the firm in year t, and then subtract the expected capital investment from the actual capital investment of the firm, and the difference is the unanticipated investment of the firm. The regression residuals of this model$\varepsilon_{i,t}$ represents the firm's inefficient investment. Where$\varepsilon_{i,t} > 0$ represents over-investment by the firm and$\varepsilon_{i,t} < 0$ represents under-investment by firms. For ease of understanding, in the regression analysis the $\varepsilon_{i,t} < 0$ the sample is taken as an absolute value to measure the degree of underinvestment by firms.

$$\begin{aligned} Residuals\ Q_{i,t} = \beta_0 + \beta_1 TobinQ_{i,t-1} + \beta_2 Lev_{i,t-1} + \beta_3 Cash_{i,t-1} + \beta_4 Roa_{i,t-1} + \beta_5 Age_{i,t-1} + \beta_6 Size_{i,t-1} \\ + \beta_7 Ret_{i,t-1} + \beta_8 Inv_{i,t-1} + \sum Year + \sum Industry + \varepsilon_{i,t} \end{aligned} \quad (1)$$

$Residuals\ Q_{i,t}$ represents the company's investment level in year t and is the ratio of cash paid for the acquisition of fixed assets, intangible assets and other long-term investments to total assets at the beginning of the period. $TobinQ_{i,t-1}$, $Lev_{i,t-1}$, $Cash_{i,t-1}$, $Roa_{i,t-1}$, $Age_{i,t-1}$, $Size_{i,t-1}$, $Ret_{i,t-1}$ and $Inv_{i.t-1}$ denote the firm's growth capacity, gearing ratio, cash holding ratio, operate capacity, years on the market, firm size, stock return, and investment level in $period_{t-1}$, respectively. $Year$ and $Industry$ are dummy variables for year and industry, respectively.

2. Explanatory variables

The interaction term between the time variable and the intelligent manufacturing variable ($period_{i,t} \times emanu_{i,t}$): $period_{i,t}$ is the time dummy variable; $emanu_{i,t}$ is the intelligent manufacturing dummy variable, which takes the value of 0 for the sample firms in the control group and 1 for the sample firms in the experimental group. if the firm implements intelligent manufacturing in the current year, then $period_{i,t} \times emanu_{i,t}$ If a company implements intelligent manufacturing in the current year, it takes the value of 1 in the current year and subsequent years, otherwise it takes the value of 0.

3. Control variables

Drawing on existing literature (Liu, Hs. et al., 2013; Zhang, Shushan et al., 2021), this paper treats total asset value added, firm size, the shareholding ratio of the largest shareholder, and financing constraints as control variables in the model, and defines each control variable as shown in Table.

Table 1. Defines each control variable

Nature of variables	Variable name	Variable symbols	Variable definitions
Explained variables	Investment efficiency	$Residuals\ Q_{i,t}$	Calculated from model (1)
Explained variables	Policy dummy variables	$emanu_{i,t}$	For the experimental group implementing s intelligent manufacturing, the value is 1; otherwise the value is 0
	Time dummy variables	$period_{i,t}$	The value is 0 until 2015 and 1 in 2015 and beyond
Control variables	Total asset appreciation rate	$TAAT$	Net profit/total assets
	Size of business	$Size$	Natural logarithm of the total assets of the business
	Percentage of shareholding of the largest shareholder	$owncon1$	Shareholdings of the largest shareholders of listed companies at the end of the year
	Financing constraints	FC	Ratio of interest expense to fixed assets

3.3 Model Construction

In order to study the impact of intelligent manufacturing on the investment efficiency of enterprises, this paper uses the promotion of intelligent manufacturing demonstration projects in China as a quasi-natural experiment to analyze the impact mechanism of this policy on the investment efficiency of enterprises by comparing the experimental and control groups before and after the implementation of intelligent manufacturing, and constructs the following benchmark regression equation by applying the double split (DID) model:

$$ResidualQ = \alpha_0 + \alpha_1\left(period_{i,t} \times emanu_{i,t}\right) + \beta_1 TAAT + \beta_2 Size + \beta_3 owncon1 + \beta_4 FC + \varepsilon_1 \quad (2)$$

In equation (2), the subscripts i, t denote firm and year respectively. Interaction term $period_{i,t} \times emanu_{i,t}$ is the explanatory variable in the model, and its coefficient α_1 captures the difference in investment efficiency between firms in the experimental and control groups before and after the implementation of intelligent manufacturing. If the coefficient is positive, it means that intelligent manufacturing will increase the investment efficiency of enterprises; if the coefficient is negative, it means that intelligent manufacturing will decrease the investment efficiency of enterprises.

4. Empirical Analysis and Results

4.1 Descriptive Statistics

Table shows the results of descriptive statistics for the main variables in this paper. The mean value of Emanu is 0.08, implying that 8% of all observations belong to the experimental group sample. The mean value of investment efficiency is 0.03 and the standard deviation is 0.04, with a minimum value of 0 and a maximum value of 0.95, indicating that there is some variation in the investment efficiency of different sample enterprises, and therefore it is meaningful to explore the role of intelligent manufacturing on investment efficiency. The mean value of total asset value added is 0.1, with a standard deviation of 0.22, fluctuating between the ranges of -0.31 to 8.44; the mean value of enterprise size is 22.50, with a standard deviation of 0.980, fluctuating between the ranges of 19.15 to 27.77; the mean value of the shareholding ratio of the first shareholder is 33.66%, with a standard deviation of 12.41%, fluctuating between the ranges of 4.08% to 85.23% The mean value of financing constraint was 0.05, with a standard deviation of 0.06, fluctuating between -0.54 and 0.97.

Table 2. The results of descriptive statistics for the main variables in this paper

variable	N	mean	min	p25	p50	p75	max	sd
$emanu_{i,t}$	4140	0.120	0	0	0	0	1	0.330
$period_{i,t}$	4140	0.0800	0	0	0	0	1	0.260
$Residuals\ Q_{i,t}$	4140	0.0300	0	0.0100	0.0200	0.0400	0.950	0.0400
$TAAT$	4140	0.100	-0.310	0.0200	0.0700	0.150	8.440	0.220
$Size$	4140	22.50	19.15	21.87	22.36	23	27.77	0.980
$owncon1$	4140	32.66	4.080	23.77	31.29	41.18	85.23	12.41
FC	4140	0.0500	-0.540	0.0100	0.0300	0.0700	0.970	0.0600

4.2 Baseline Regression Analysis

Table presents the results of the double-difference estimation of the impact of intelligent manufacturing on the efficiency of business investment. Where column (1) does not include control variables, the interaction term $period_{i,t} \times emanu_{i,t}$ of the regression coefficient is negative and significant at the 10% level, indicating that the investment efficiency of firms that implement intelligent manufacturing is significantly reduced. In column (2) of Table, the relevant control variables are added to the regression model, and the coefficient of the interaction term $period_{i,t} \times emanu_{i,t}$ The coefficient of the regression model is still negative at -0.005 and is still significant at the 5% level, indicating that the investment efficiency of companies implementing intelligent manufacturing has increased compared to companies not implementing intelligent manufacturing. In summary, the results of the benchmark regression demonstrate that the implementation of intelligent manufacturing helps to improve the efficiency of enterprise investment. This finding validates hypothesis H1 proposed in this paper.

Table 3. The results of the double-difference estimation of the impact of intelligent manufacturing on the efficiency of business investment

	(1)	(2)
VARIABLES	$Residuals\ Q_{i,t}$	$Residuals\ Q_{i,t}$
$period_{i,t} \times emanu_{i,t}$	-0.004*	-0.005**
	(-1.73)	(-2.00)
$TAAT$		0.052***
		(3.32)
$Size$		-0.002
		(-1.35)
$owncon1$		-0.000
		(-0.38)
FC		-0.029
		(-0.76)
$Constant$	0.033***	0.075**
	(109.40)	(2.36)
$Observations$	2,178	2,178
$R-squared$	0.192	0.215

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3 Robustness Tests

1.Placebo test

To further test the robustness of the study findings, this paper conducted a placebo test by randomly selecting samples to generate a new experimental group. In this paper, 500 experimental groups were randomly generated and the same double difference regression method was used to test the impact of intelligent manufacturing implementation on the investment efficiency of enterprises, and the test results are shown in the figure. The results show that the coefficients fitted to the randomly selected 500 experimental groups lie roughly in the range of -0.01-0.01, with a coefficient distribution significantly different from that of the benchmark regression of -0.005, and the absolute value of the fitted coefficients is lower than that of the benchmark regression results, proving that the coefficients obtained from the above regression are reliable and not chance events, and pass the placebo test.

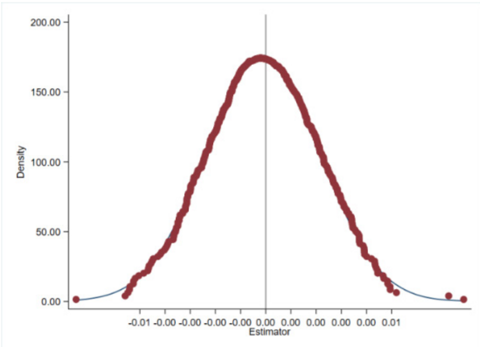

Fig 1. The test results

2.Excluding the influence of distracting factors.

To further test the robustness of the study findings, this paper performs a regression analysis by excluding the sample data affected by the domestic stock market crash (2015). The results show that after excluding the part of the sample data affected by the stock market crash, the $period_{i,t} \times emanu_{i,t}$ the estimated coefficients are still significantly negative at the 1% level, verifying the robustness of the core findings of this paper.

Table 4. Regression analysis of sample data affected by the domestic stock market crash (2015) is excluded

VARIABLES	(1) $Residuals\ Q_{i,t}$
$period_{i,t} \times emanu_{i,t}$	-0.010***
	(-2.68)
$TAAT$	0.114***
	(3.19)
$Size$	-0.001
	(-0.50)
$owncon1$	-0.000
	(-0.93)
FC	-0.030
	(-1.46)
$Constant$	0.055
	(1.22)
$Observations$	3,764
$R-squared$	0.237

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3. Substitution of explanatory variables

In order to exclude the above results from being affected by the measure of investment efficiency, the regression test was conducted again by referring to the measure of (Wang Shanping, 2011) and using the growth rate of operating income as a measure of the firm's growth level and re-measuring the investment efficiency according to the previous method. The results show that after replacing the measure of the explanatory variable $period_{i,t} \times emanu_{i,t}$ the estimated coefficients are still significantly negative at the 1% level, verifying the robustness of the core findings of this paper.

Table 5. The growth rate of operating income is used as the regression test of the growth level of enterprises

VARIABLES	(1) $Residuals\ Q_{i,t}$
$period_{i,t} \times emanu_{i,t}$	-0.011***
	(-3.06)
$TAAT$	0.127***
	(4.29)
$Size$	-0.002
	(-1.10)
$owncon1$	-0.000
	(-0.94)
FC	-0.044*
	(-1.90)
$Constant$	0.077*
	(1.94)
$Observations$	4,135
$R-squared$	0.249

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.4 Regulation Mechanism Test

Table 6. Internal control index regression results

	(1)	(2)
VARIABLES	$Residuals\ Q_{i,t}$	$Residuals\ Q_{i,t}$
$period_{i,t} \times emanu_{i,t} \times internal$		-0.000***
		(-3.05)
$period_{i,t} \times emanu_{i,t}$	-0.011***	
	(-3.14)	
$TAAT$	0.128***	0.128***
	(4.35)	(4.35)
$Size$	-0.001	-0.001
	(-0.85)	(-0.83)
$owncon1$	-0.000	-0.000
	(-0.95)	(-0.96)
FC	-0.046**	-0.046**
	(-2.05)	(-2.05)
$Constant$	0.065*	0.065*
	(1.70)	(1.68)
$Observations$	4,137	4,137
$R-squared$	0.254	0.254

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In this paper, internal control is selected as a buffer variable. Based on the existing literature, good internal control helps to improve the quality of financial reporting (Doyle et al., 2007a), reduces information asymmetry or mitigates principal-agent problems, and effectively discourages underinvestment or overinvestment, thereby improving investment efficiency. In this paper, we explore the role played by internal control indices in the relationship between intelligent manufacturing implementation and corporate investment efficiency. The regression results are shown in the table. The study shows that internal control buffers the effect of intelligent manufacturing on investment efficiency, verifying the hypothesis H2 of this paper. the implementation of intelligent manufacturing will prompt enterprises to improve their own management quality, improve internal governance, improve the quality of internal control, and thus improve their investment efficiency.

5. Research Findings and Policy Recommendations

This paper explores the mechanism of the impact of intelligent manufacturing implementation on firms' investment efficiency by constructing a double difference model using the promotion of intelligent manufacturing demonstration projects in China as a quasi-natural experiment and all A-share listed companies in China from 2010 to 2019 as the research sample. It is found that (1) intelligent manufacturing implementation can enhance corporate investment efficiency and the effect still holds after passing a series of robustness tests such as placebo test and replacement of explanatory variables. (2) Internal control plays a negative buffering role in the relationship between intelligent manufacturing and improved investment efficiency. Enterprises with better quality of internal control do not have a significant effect on the improvement of investment efficiency after implementing intelligent manufacturing, while enterprises with poor quality of internal control have a significant improvement of investment efficiency after implementing intelligent manufacturing.

Based on the above findings, this paper puts forward the following policy recommendations: First, the government should support and promote the implementation of intelligent manufacturing policies at multiple levels and in all aspects. At present, the government's promotion of the implementation of intelligent manufacturing is mainly based on policy incentives and support. In the future, it is also necessary to strengthen support and guidance in terms of technological upgrading and technological change, so as to make the implementation of intelligent manufacturing more popular and give full play to the role of intelligent manufacturing in improving the efficiency of investment. Secondly, enterprises with poor internal control quality should make full use of intelligent manufacturing policies to improve internal control efficiency, reduce principal-agent conflicts, standardize corporate information disclosure and improve information transparency and symmetry, so as to better utilize the role of intelligent manufacturing implementation in improving corporate investment efficiency and promoting high-quality corporate development.

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