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Impact of Industrial Robot Adoption on Trade Credit Financing in Manufacturing Firms

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Abstract: *With the global pursuit of artificial intelligence as a key strategic objective, the in-depth development of industrial robots becomes crucial for fostering high-quality economic and social progress. This paper delves into the influence of industrial robot utilization on commercial credit financing, exploring the perspectives of corporate financing behavior. An empirical investigation is conducted using a research sample consisting of Chinese A-listed manufacturing companies spanning the years 2011-2019. The study reveals that the incorporation of industrial robots enhances the level of corporate commercial credit financing. Notably, attenuation is observed in firms that have higher textual similarity in their annual reports. By extending the examination of micro-firm effects caused by industrial robot use through a financing behavioral lens, this article aims to provide empirical evidence and targeted recommendations for the ongoing advancement of industrial robotics in China, fostering a conducive external financing environment for firms.*

Keywords: *Robots Adoption, Trade Credit Financing, Financing Constraints*

1. Introduction

Industrial robots, often regarded as the "crown jewel" of manufacturing, are a pivotal force for enterprises to sustain long-term competitive advantages and propel regional economic growth. They also serve as a benchmark for measuring a nation's manufacturing development. Since 2012, developed countries such as the United States and Japan have articulated strategic plans that encompass artificial intelligence technologies, particularly robotics, as focal points for national development. In 2022, the Ministry of Science and Technology, along with six other departments, issued the "Guiding Opinions on Accelerating Scene Innovation and Promoting High-quality Economic Development with High-level Application of Artificial Intelligence." This document further detailed the integration of artificial intelligence and the real economy, exploring application scenarios like robot-assisted manufacturing and logistics sorting.

Propelled by a series of policies, China has witnessed remarkable achievements in industrial automation (Liu et al., 2020)[1]. Notably, statistics indicate that China's industrial robot production in 2021 reached 366,000 units, marking a tenfold increase since 2015 and positioning China as the world's leading industrial robot market.

The global prevalence of industrial robots is evident, with prior studies predominantly exploring their macro-level impact on national or regional scales. These investigations have considered dimensions such as export, employment, and the qualitative aspects of economic development, including industrial structure upgrades, green technology innovation, and common prosperity (Acemoglu & Restrepo, 2020; Alguacil et al., 2022; Deng et al., 2021; Graetz & Michaels, 2018;Lee et al., 2022; Xu et al., 2022)[2][3][4][5][6][7]. However, micro-level research focusing on the impact of industrial robots at the enterprise level is relatively scant, primarily concentrating on business decision-making aspects such as labor employment and technological innovation (Dixon et al., 2021)[8]. Unfortunately, there is a lack of exploration into the influence of industrial robot utilization on corporate financing behavior.

Among the various financing behaviors of enterprises, informal financing mechanisms like commercial credit play a pivotal role (D'Melo & Toscano, 2020)[9]. For instance, among A-share non-financial listed companies in China from 2000 to 2021, credit support from suppliers, including accounts

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receivable, constituted a substantial 12.16% of total assets. This pattern is also observed in other countries (Rajan and Zingales, 1995)[10]. Not only does it alleviate financing constraints (McGuinness et al., 2018)[11], but it also enhances corporate performance and equity returns (Molina & Preve, 2009)[12].

Motivated by these observations, this paper aims to explore the impact and boundary conditions of industrial robot use on corporate financing behavior and the conditions under which it occurs, especially when it comes to commercial credit financing. Empirical testing was conducted using a sample of 1346 A-share manufacturing companies spanning the years 2011 to 2019. The findings indicate that industrial robot utilization enhances the level of commercial credit financing for enterprises. Moreover, the effects are more pronounced in companies with higher increments of textual information. Further research reveals that customer concentration and the degree of financing constraints are key pathways through which industrial robots enhance commercial credit financing.

The innovation of this paper lies in two main aspects: (1) It expands existing research on industrial robot use by shifting the focus from micro-firm productivity behavior to financing behavior. (2) The paper enriches research on the antecedents influencing commercial credit financing behavior by exploring the internal technical behavior of enterprises, specifically examining the impact of industrial robots. (3) The third aspect of the innovation lies in identifying the key pathways through which industrial robots enhance commercial credit financing.

2. Research Design

2.1 Sample Selection and Data Sources

Considering that the installation and ownership of industrial robots in China exhibited a significant upward trend only after 2010, with their predominant use in manufacturing enterprises (Wang & Dong, 2020)[13], this study focuses on a sample of 1346 Chinese A-share manufacturing listed companies spanning the period from 2011 to 2019. Samples with missing key data are systematically excluded, resulting in a final dataset comprising 9565 "company-year" observation values. The data on industrial robots is sourced from the International Federation of Robotics (IFR), currently recognized as the most authoritative global repository for robot statistics. Additional data is sourced from the CSMAR database and the Wind database.

2.2 Variable Measurement

2.2.1 Industrial Robot Use (Robots).

Considering that the industrial robot data released by IFR is statistically aggregated to the industry level, drawing on previous studies (Acemoglu & Restrepo, 2020; Wang & Dong, 2020)[1][13], this paper uses the TBartik variable method to construct the robot penetration index at the level of Chinese manufacturing enterprises, as shown in Equation (1).

$$Robots_{i,t} = \frac{Staff_{i,t=2011}}{Median(Staff_{j,t=2011})} * \frac{IFR_{j,t}}{Labor_{j,t=2010}} * \frac{1}{1000} \tag{1}$$

Among them, the number of industrial robots in China's J industry t year is the number of employment in China's J industry in 2010 (base period), and the ratio of the two is the industrial robot penetration rate index at the industry level. Next, this paper breaks down the industry-level penetration rate to the enterprise level through weight indicators. It is the ratio of the number of employees in the production department of enterprise i in 2011 and the median ratio of the number of employees in the production department of all enterprises in the J industry in 2011, and the ratio of the two is the decomposition weight index $IFR_{j,t}Labor_{j,t=2010}Staff_{i,t=2011}Median(Staff_{j,t=2011})$. Finally, by multiplying the indicators, it can be obtained, $Robots_{i,t}$that is, the degree of use of industrial robots in T years.

2.2.2 Business Credit Financing (Credit).

Drawing on previous studies (Lu et al., 2022)[14], this paper measures the commercial credit financing level of enterprises by the ratio of accounts payable to total assets. The larger the indicator, the higher the level of commercial credit financing.

2.2.3 Annual Report Text Similarity (SIM).

Drawing on previous studies (Song et al., 2022)[15], the stammering word segmentation module is first used to process the text of the annual report of listed companies in the calculation process of this

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indicator, and non-text information such as Arabic numerals, punctuation marks, and picture tables is removed from the word segmentation process. Next, the cosine similarity calculation method is used to calculate the similarity between the "management discussion and analysis" in the annual report and the text of the previous year. The larger the indicator, the higher the similarity of the text of the annual report.

2.2.4 Controls

Drawing on previous research (D'Mello & Toscano, 2020; Lu et al., 2022; Pan et al., 2022)[9][14][16], selected enterprise size (*Size*), asset-liability ratio (*Lev*), return on assets (*ROA*).), cash flow ratio (*CF*), fixed asset ratio (*Fixed*) and other basic financial indicators, enterprise age (*Age*), ownership nature (*SOE*) and other corporate characteristic indicators,, the number of board of directors (*Board*), the proportion of independent directors (*Ind*), whether the chairman concurrently serves as the general manager (*Dual*) and other governance indicators were put into the model as control variables, and annual fixed effect and enterprise fixed effect were added. The main variables are shown in Table 1 below.

2.3 Empirical Models

To empirical test the impact of industrial robot adoption on trade credit financing, the following regression models are constructed (Equation 2 and Equation 3), respectively.

$$Credit_{i,t} = \alpha_0 + \alpha_1 Robots_{i,t} + \alpha_{2-12} Controls_{i,t} + \sum Year + \sum Firm + \varepsilon \tag{2}$$

$$\begin{aligned} Credit_{i,t} = \beta_0 + \beta_1 Robots_{i,t} + \beta_2 Sim_{i,t-1} + \beta_3 Robots_{i,t} * Sim_{i,t-1} + \alpha_{4-14} Controls_{i,t} \\ + \sum Year + \sum Firm + \varepsilon \end{aligned} \tag{3}$$

In equation (2), this paper focuses on the coefficientsα_1, which are expected to be significantly positive, and in equation (3), the coefficientsβ_3 are expected to be significantly negative. It should be pointed out that due to the delay in the release period of annual reports, for example, 2021 annual reports often need to be released around March 2022. Therefore, when exploring the moderating effect of textual similarity in annual reports, this paper changes the lag period to T-1 period. In addition, all the regressions in this article containing industry dummy variables categorize manufacturing by category and category, and other industries by category. To avoid the influence of heteroscedasticity, all regression analyses in this paper are tested under clustered robust standard errors.

3. Analysis of Empirical Results

3.1 Analysis of Basic Empirical Results

Table 1 is the basic empirical results of this paper, where column (1) is without control variables, column (2) adds control variables based on column (1), and column (3) adds annual and firm fixed effects. It can be seen that regardless of whether control variables are added, the coefficient of the use of industrial robots is significantly positive at the 1% level, which indicates that the use of industrial robots will improve the commercial credit financing level of enterprises. In column (4), it can be seen that the coefficient of *Robots*Sim* is significantly negative at the level of 5%, which indicates that the positive impact of the use of industrial robots on the commercial credit financing of the enterprise is significantly suppressed when the text of the annual report is more similar.

Table 1: Basic empirical results

Credit	(1)	(2)	(3)	(4)
Robots	0.2276***	0.1980***	0.0457***	0.2926**
	(16.9971)	(17.0875)	(4.1565)	(2.3886)
Sim				0.0002**
				(1.9834)
*Robots*Sim*				-0.0026**
				(-2.0501)
Size		-0.0045***	-0.0012	-0.0013
		(-6.8981)	(-0.7823)	(-0.8384)
Lev		0.1520***	0.0999***	0.1001***
		(36.3625)	(17.4509)	(17.4919)
ROA		0.0569***	0.0279***	0.0280***
		(5.1499)	(3.2782)	(3.2838)

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Cashflow		0.0341***	0.0251***	0.0253***
		(3.1165)	(3.2639)	(3.2884)
Fixed		-0.0726***	0.0062	0.0060
		(-15.9999)	(0.9141)	(0.8779)
Board		-0.0062	0.0057	0.0057
		(-1.5924)	(1.4261)	(1.4101)
Ind		-0.0397***	0.0027	0.0024
		(-3.2255)	(0.2301)	(0.2059)
Age		-0.0128***	-0.0122*	-0.0118*
		(-7.5025)	(-1.8304)	(-1.7784)
SOE		0.0200***	0.0098***	0.0100***
		(13.9512)	(3.0781)	(3.1793)
Dual		-0.0027**	-0.0017	-0.0016
		(-2.1201)	(-1.3468)	(-1.2862)
Constant	0.0868***	0.1877***	0.0900**	0.0724*
	(117.9907)	(11.9328)	(2.3569)	(1.8269)
Observations	9,593	9,593	9,565	9,565
Firm	NO	NO	ANDES	ANDES
Year	NO	NO	ANDES	ANDES
R^2	0.0556	0.2778	0.1047	0.1053

*, **, and *** represent significance levels of 10%, 5%, and 1%, respectively, with the t-value in parentheses.

3.2 Robustness Test

3.2.1 Change the Dependent Variable Measurement Method

Drawing on previous studies (Pan et al., 2022)[16], this paper uses the ratio of the sum of accounts payable, notes payable and advance receivables to total assets as a proxy variable for the level of business credit financing of enterprises (Credit2). The test results are shown in column (1) of Table 2, and the coefficient before the use of industrial robots is still significantly positive at the 5% level, and the research conclusion has not changed. This shows that the measurement validity of the dependent variable in this paper is more accurate, and does not challenge the conclusion of this paper.

3.2.2 Tail Shrinking Treatment

In order to exclude the influence of outliers, this paper shrinks the extreme outliers of all non-log-continuous variables at the 1% and 99% levels year by year. The test results are shown in column (2) of Table 2, the pre-use coefficient of industrial robots is significantly positive at the 1% level, and the research conclusion is still valid. This indicates that the interference caused by outliers is less problematic and does not affect the conclusions of this paper.

3.2.3 Lag the Independent Variable by One Period

Considering the possibility of reverse causation to a certain extent, that is, companies with higher levels of commercial credit financing have more abundant cash flow and are more likely to provide a material basis for the development of industrial automation. To this end, drawing on previous studies (Lu et al., 2022)[14], this paper will use the independent variable industrial robot (Robots) lag for one period to rule out the reverse causal problem. The test results are shown in column (3) of Table 2, and the pre-use coefficient of industrial robots is still significantly positive at the 1% level, which means that the impact of industrial robot use on commercial credit financing does exist, and the reverse causal problem will not affect the research conclusions of this paper.

3.2.4 Add Control Variables

Considering that environmental factors such as the level of rule of law in different regions can also affect the level of commercial credit financing (Pan et al., 2022)[16], it is necessary to draw on previous studies (Bai, 2009)[17]. This paper adds the interactive fixed effect of province and year, which can control the impact of time-varying factors such as GDP and rule of law level on the level of commercial credit financing. The test results are shown in column (4) of Table 2, and the coefficient before the use of industrial robots is still significantly positive at the 1% level. This shows that the conclusions of this paper still hold true after considering the time-varying factors at the regional level.

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3.2.5 Change the Sample Time

Affected by the 2015 stock market crash, the financial indicators of listed companies will be abnormal. Drawing on previous studies (Song et al., 2022)[15], this paper excludes the 2015 sample for retesting. The test results are shown in column (5) of Table 2, and the pre-use coefficient of industrial robots is still significantly positive at the 1% level. This suggests that the conclusions of this study were not challenged after excluding the effect of abnormal years.

Table 2: Robustness test

	(1)	(2)	(3)	(4)	(5)
variable	Credit2	Credit	Credit	Credit	Credit
$Robots_{i,t}$	0.0363**	0.0497***		0.0428***	0.0454***
	(1.9792)	(4.7833)		(3.8139)	(4.0712)
$Robots_{i,t-1}$			0.0427***		
			(2.9769)		
$Size_{i,t}$	-0.0055**	-0.0024*	-0.0019	-0.0016	-0.0008
	(-2.1861)	(-1.7469)	(-0.9189)	(-1.0208)	(-0.4882)
$Lev_{i,t}$	0.2077***	0.1025***	0.1003***	0.1021***	0.0990***
	(21.6630)	(20.6886)	(15.2694)	(17.5889)	(16.0403)
$ROA_{i,t}$	0.0715***	0.0243***	0.0211**	0.0316***	0.0259***
	(5.1276)	(2.8355)	(2.2701)	(3.6991)	(3.0126)
$Cashflow_{i,t}$	0.1070***	0.0206***	0.0325***	0.0232***	0.0231***
	(8.8443)	(2.8571)	(3.6937)	(2.9913)	(2.9595)
$Fixed_{i,t}$	-0.0441***	0.0075	0.0051	0.0047	0.0046
	(-3.9698)	(1.1952)	(0.6155)	(0.6791)	(0.6499)
$Board_{i,t}$	0.0143**	0.0056	-0.0009	0.0057	0.0058
	(2.1210)	(1.4459)	(-0.1904)	(1.3672)	(1.3387)
$Ind_{i,t}$	0.0296	-0.0013	-0.0050	0.0028	0.0048
	(1.5790)	(-0.1175)	(-0.3829)	(0.2257)	(0.3849)
$Age_{i,t}$	-0.0468***	-0.0128**	-0.0183*	-0.0111	-0.0132**
	(-3.9962)	(-1.9734)	(-1.9485)	(-1.6101)	(-1.9687)
$SOE_{i,t}$	0.0173***	0.0095***	0.0095***	0.0112***	0.0105***
	(3.1380)	(2.9990)	(2.6178)	(3.4568)	(3.1820)
$Top1_{i,t}$	0.0095	0.0104	0.0047	0.0105	0.0118
	(0.7326)	(1.3799)	(0.4617)	(1.3013)	(1.4344)
$Dual_{i,t}$	-0.0024	-0.0014	-0.0009	-0.0017	-0.0017
	(-1.1223)	(-1.2061)	(-0.6257)	(-1.3219)	(-1.2181)
Constant	0.0363**	0.1189***	0.1421***	0.0702*	0.0839**
	(1.9792)	(3.3859)	(2.9022)	(1.7501)	(2.0926)
Observations	8,530	9,565	7,636	9,565	8,562
Firm	ANDES	ANDES	ANDES	ANDES	ANDES
Year	ANDES	ANDES	ANDES	ANDES	ANDES
*Year*Province*	NO	NO	NO	ANDES	NO
R^2	0.1650	0.1129	0.1000	0.1076	0.1031

*, **, and *** represent significance levels of 10%, 5%, and 1%, respectively, with the t-value in parentheses.

4. Conclusion

This study adopts artificial intelligence technology as a research perspective to investigate the potential impact of industrial robot usage on the financing capacity of Chinese enterprises. The aim is to provide valuable policy insights for China's "14th Five-Year Plan" on robotics and overall economic and social development. The research findings reveal that the adoption of industrial robots significantly enhances the level of commercial credit financing for enterprises. However, it is noteworthy that the positive impact of industrial robot use on commercial credit financing is significantly restrained in enterprises with higher similarity in annual report texts.

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