Competing with Robots: Product Market Competition and Robot Adoption in Chinese Manufacturing

Manman Tu[1]; Xueling Yan[2]; Leyang Wang[3]; Shule Yu[4]†; Jialin Huang[5]

[1] School of Economics & Management, South China Normal University, No. 55 Zhongshan West Avenue, Guangzhou, 510631, P.R. China

E-mail: tumm@m.scnu.edu.cn

[2] School of Economics, Sichuan University, 24 Yihuan South Road, Chengdu 610065, PR China

E-mail: yxl@scu.edu.cn

[3] School of Economics & Management, South China Normal University, No. 55 Zhongshan West Avenue, Guangzhou, 510631, P.R. China

E-mail: wangleyang@m.scnu.edu.cn

[4] School of Economics & Management, East China Normal University, No. 3663 Zhongshan North Road, Putuo District, Shanghai, 200062, P.R. China

E-mail: slyu@sem.ecnu.edu.cn

[5] School of Economics & Management, South China Normal University, No. 55 Zhongshan West Avenue, Guangzhou, 510631, P.R. China

E-mail huangjialin@m.scnu.edu.cn

†Correspondence to: Shule Yu (slyu@sem.ecnu.edu.cn)

The authors have no conflicts of interest to declare. All co-authors have reviewed and approved the contents of the manuscript, and there are no financial interests to disclose. We certify that the submitted work is original and is not currently under consideration by any other publication.

Manman Tu gratefully acknowledges financial support from the Postdoctoral Fellowship Program of CPSF under Grant (Number: 2025M783686). Xueling Yan gratefully acknowledges financial support from the National Natural Science Foundation of China (Grant Number: 72573114). All errors are our own.

Competing with Robots: Product Market Competition and Robot Adoption in Chinese Manufacturing

ABSTRACT

Robot adoption is often viewed as a response to rising labor costs. Using Chinese listed manufacturing firms from 2011 to 2019 and employing text-analysis methods to construct firm-level product market competition, this paper shows that intensified competition significantly promotes robot adoption. Further analysis suggests that robot adoption is not merely a cost-saving response, but also a strategic choice that enhances product innovation and expands market share. This effect is stronger among firms with lower financing constraints and more stable supply chains. These findings provide a new perspective on the determinants of robot adoption by shifting attention from internal labor cost-saving motives to external competitive market pressures, and highlight the strategic role of industrial robots in firm survival and growth.

Keywords:

Product market competition; Robot adoption; Strategic response; Product innovation

1. Introduction

With the rise of industrial robots and artificial intelligence (AI), manufacturing production has undergone significant technological changes (Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017; Acemoglu and Restrepo, 2020; Aghion et al., 2021). A growing body of literature has examined the driving factors behind firms' adoption of industrial robot, highlighting the roles of labor scarcity (Wang & Dong, 2020; Acemoglu & Restrepo, 2021; Yu et al., 2024), wage growth (Fan et al., 2021), and policy support (Howell, 2017; Wang et al., 2025; Yan et al., 2025). However, this line of research tends to view industrial robot mainly as a labor-replacing technology, paying less attention to its broader strategic value in modern manufacturing. In practice, recent survey evidence from Manufacturing Today[1] shows that AI and robotics are reshaping manufacturing systems by increasing production flexibility and optimizing efficiency through predictive maintenance, and quality control, digital twins. Similarly, Deloitte's 2025 survey of 600 large U.S. manufacturing firms[2] indicates that 92% of executives view smart manufacturing as a key driver of product competitiveness. These observations suggest that firms may adopt industrial robot not only to economize on internal labor cost, but also to enhance external product competitiveness. Yet, existing research has paid far less attention to this product-market channel.

This study constructs a firm-level measure of product market competition (PMC) using text analysis and links it to robot adoption data for Chinese listed manufacturing firms to examine how external market competition drives firms' adoption of industrial robots. China provides an ideal setting for studying the relationship between the PMC and the adoption of robots. On the hand, China's product market differs from that of many developed economies in both scale and competitive intensity. In the automobile sector, for example, McKinsey's 2024 survey of 2,449 consumers in 19 major Chinese cities reports that more than 40 new EV models were launched in the RMB 200,000-plus segment in 2023, most of them featuring similar configurations such as smart cockpits, autonomous-driving functions, and ultra-fast charging. This suggests that China's product market is characterized not only by large scale, but also by intense price-based rivalry and a high degree of product homogeneity[3] (Chen,

[1] https://manufacturing-today.com/news/ai-and-robotics-are-redefining-the-factory-floor/
[2] https://www.deloitte.com/us/en/insights/industry/manufacturing-industrial-products/2025-smart-manufacturing-survey.html
[3] Mckinsey. (2024). Mckinsey China Auto Consumer Insights 2024. Available at: https://www.mckinsey.com/~/media/mckinsey/industries/automotive%20and%20assembly/our%20insights/mckinsey%20china%20auto%20consumer%20insights%202024/mckinsey-china-auto-consumer-insights-2024-evolution-not-involution.pdf

2004; Choi and Nailer, 2005). At the meanwhile, Globally, the industrial robot adoption in China is the most remarkable (Cheng et al., 2019). According to the International Federation of Robotics (IFR), Chinese firms installed 290,258 new robots in 2022, over 50% of the world total, with a ten-year compound annual growth rate of 32.55%, far surpassing other economies (see Figure 1).

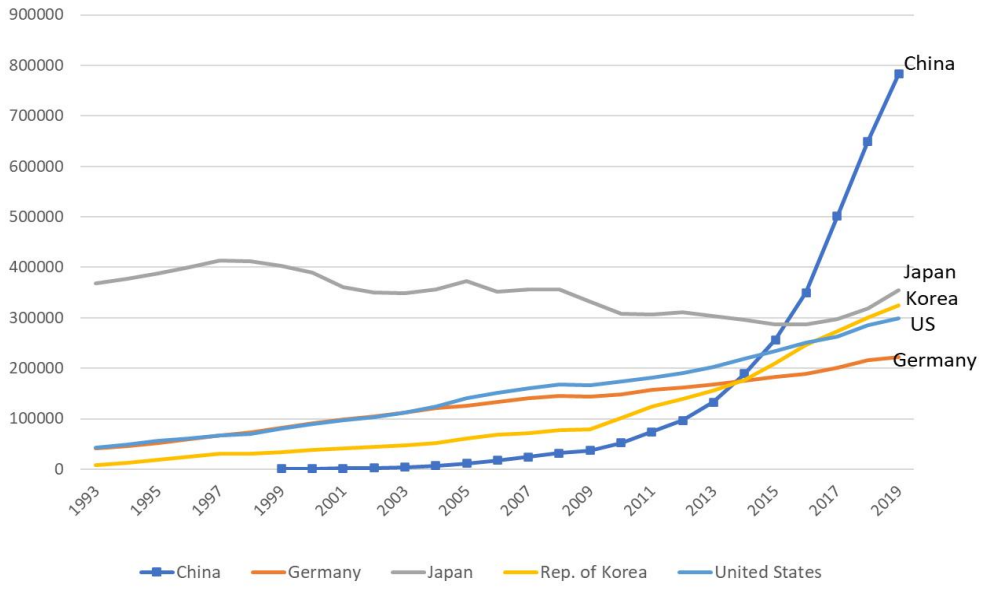


Figure 1 Operational stock of industrial robots (Data from IFR)

Notes: This figure presents the trend of operational stock of industrial robots in five countries. We obtained global industrial robot stock data through 2019 from the International Federation of Robotics (IFR) and selected the five countries with the highest inventories in 2019 (China, Japan, South Korea, the United States, and Germany) for analysis. These five countries held a combined total of 1,982,904 robots in 2019, accounting for approximately 72.6% of the global market. We then plotted the historical annual stock trends for each of these countries.

Against the backdrop of the rapid adoption of industrial robots in China's manufacturing sector, the intense price competition and widespread product homogeneity observed in highly competitive product markets have made flexible and differentiated production increasingly critical for firm survival. This raises our central research question: To what extent, and through what channels, does product market competition drive firms to adopt industrial robots?

To answer this question, we first construct firm-level measures of both product market competition and robot adoption. Rather than relying on conventional industry-level indicators of competition, we follow Hoberg and Phillips (2016) and use textual analysis to measure

product market competition at the firm level, calculating the cosine similarity between a firm's product descriptions and those of its peers. To capture firms' exposure to industrial robots, we combine China's industrial robot stock data from the International Federation of Robotics (IFR) up to 2019 with a Bartik-style measure that maps industry-level robot exposure into firm-level.

Based on these measures, we estimate the effect of product market competition on firms' adoption of industrial robots. The baseline results show that stronger product market competition significantly increases robot adoption. Specifically, for each one-unit increase in competition intensity, firms' degree of robot adoption rises by 0.65 units. This finding remains robust to a variety of specification checks, including alternative variable constructions and different fixed-effects settings. To further address potential endogeneity concerns, we construct two instrumental variables based on the Catalogue of Foreign-Invested Industries and the Hurun Brand List, following the logic of Babar and Habib (2020) and Xu and Ni (2024). The instrumental-variable estimates continue to support our main conclusion.

Having established this relationship, we next examine the mechanisms through which product market competition promotes robot adoption. We focus on two channels: product innovation and market share expansion. The first channel highlights the role of robots as a strategic tool for product differentiation. Our evidence shows that robot adoption significantly improves firms' product innovation, and that this positive effect is stronger under more intense product market competition. This suggests that firms facing greater competitive pressure are more likely to adopt robots to enhance innovation capacity and build differentiated product advantages. The second channel shows that robot adoption also increases firms' market share, and again, this effect is amplified when product market competition is stronger.

Finally, we investigate the boundary conditions of this effect. The impact of product market competition on robot adoption is more pronounced among firms with lower financing constraints and more stable supply chains. This implies that although competitive pressure creates strong incentives for intelligent transformation, firms' ability to implement such transformation still depends on the availability of financial resources and the reliability of upstream and downstream production networks.

This paper makes several contributions to existing literature. First and foremost, our

research contributes to the literature evaluating the firms' automation adoption decision. Early work (Acemoglu et al., 2020, 2025; Aghion et al., 2025; Di Giacomo and Lerch, 2022; Tambe, 2025) focus on the economic consequences of robots' adoption, especially on the labor market. More recently, from the perspective of labor markets' characteristics, Acemoglu (2010) and Acemoglu and Restrepo (2022) finds that demographic change is associated with greater adoption of robots and other automation technologies. Our work differs from these papers since, on the one hand, rather than the implications of automation, we focus on its determinants. On the other hand, we focus on the product market, rather than labor market.

Second, our study adds to the literature on the economic consequences of PMC. A growing literature emphasizes the corporate governance effect of PMC, lending to higher growth of corporate performance (e.g. Nickell, 1996; Giroud and Mueller, 2010, 2011; Dasgupta et al., 2018). Besides, several studies have examined the coping strategies when firms face higher product market competition, including changing proclivity to undertake foreign direct investment (Loncan, 2023), corporate Relocation (Chen et al., 2023), CSR strategy (Dupire and M' Zali, 2018; Ryou et al., 2022) and debt choice (Boubaker, 2018). We differ from this stand of literature by focusing on corporates' technical change decision, specifically the automation technology, which leads to higher product innovation and higher product market share.

2. Literature Review and Hypothesis

2.1 Economic Consequences of Product Market Competition

Product market competition is a core external market mechanism shaping corporate behavior and performance, and existing literature has confirmed that it exhibits dual economic consequences. First, intense market competition may compress firms' profit margins by triggering price wars or increasing marketing costs (Islam et al., 2008), elevating operational risks and even pushing some firms into distress. Furthermore, severe short-term competitive pressure may induce managerial myopia, and firms may tend to cut long-term investments such as R&D and technological upgrading to maintain current cash flow, hindering sustainable development (Giroud & Mueller, 2011). At the same time, fierce competition increases the likelihood of product-related disputes, such as quality complaints and intellectual property infringement lawsuits, exacerbating firms' reputational risks (Karpoff et

al., 2008).

However, product market competition can also serve as an external governance mechanism to mitigate agency problems. In market competition, firms with poor performance are more likely to be eliminated by competitors. Therefore, product market competition can constrain managerial slack by raising the cost of inefficient operations (Bertrand & Mullainathan, 2003). Meanwhile, moderate competition can stimulate corporate innovation (Bena & Simintzi, 2025), as firms seek differentiated advantages to break through homogeneous competition. Aghion et al. (2005) also propose an inverted U-shaped relationship between the two: moderate competition promotes innovation, but excessive competition inhibits it due to resource constraints. Moreover, competition enhances resource allocation efficiency by directing production factors to more efficient firms (Hsieh & Klenow, 2009).

2.2 **Driving Factors of industrial robot adoption**

At the macro level, national industrial policies such as Made in China 2025[4] and technological infrastructure such as 5G and cloud computing are key drivers. For instance, Xuan & Xu (2022) and Yan et al. (2025) find that smart manufacturing subsidies can alleviate firms' financing constraints, accelerating technology deployment and industrial robot adoption.

At the industry level, industry characteristics play important roles. For instance, labor-intensive industries such as electronic assembly are more inclined to replace labor with industrial robots (Acemoglu & Restrepo, 2020); industries with low concentration are more likely to benefit from industrial agglomeration effects, thereby promoting their technological progress (Joshua et al., 2012); enterprises facing supply chain pressure tend to enhance production flexibility through intelligence when confronted with supply chain fluctuations. Liu et al. (2023) argue that supply chain digitization can effectively improve enterprises' ex-ante prevention capabilities and ex-post resolution capabilities against crisis risks, enhance the stability of enterprise performance under risk shocks, and achieve resilient growth.

At the micro level, firms' internal resources such as high R&D investment provide material support for industrial robot adoption, making firms more capable of implementing it. Managerial digital literacy and risk preference (Yang & Tang, 2025) as well as the relational

[4] https://www.gov.cn/zhengce/content/2015-05/19/content_9784.htm

networks of core management teams (Feng & Wang, 2020) also determine the willingness to embrace new technologies. In addition, labor cost pressure is the direct driving force for firms to replace manual labor with intelligent equipment (Wang & Dong, 2020).

2.3 **Theoretical Analysis and Research Hypotheses**

Higher product competition usually implies greater product-market overlap and, in turn, more severe product homogenization (Hoberg et al., 2014; Chen et al., 2016; Hoberg and Phillips, 2016; Breitung and Muller, 2025; Pellegrino, 2025). To cope with such fierce rivalry, firms have much incentive to strategic maneuvers such as initiating price wars to secure market share[5] or undertaking foreign direct investment (FDI) to capture overseas markets (Loncan, 2023). In addition, consistent with the "escape competition" effect, intense market pressure can also stimulate innovation, often reflected in increased patenting activity, as firms seek to break away from homogeneous competition (Aghion et al., 2005; Xia et al., 2026; Dai et al., 2026).

Yet, while the innovation effect of competition has been well documented, the operational mechanism through which firms translate competitive pressure into innovation remains less explored. To fill this gap, our study focuses on the adoption of industrial robots as a concrete strategic response. Although robots are traditionally viewed as labor-substituting technologies adopted mainly to reduce labor costs (Acemoglu, 2010; Acemoglu and Restrepo, 2022; Chen et al., 2026) , this perspective is incomplete in highly competitive markets characterized by severe homogenization, where price-cutting alone compresses profit margins and undermines long-run growth (Miura, 2025).

More importantly, industrial robots provide technological support for differentiation strategies by improving both production flexibility and quality consistency. Their programmability and adaptability reduce the marginal cost of customized production and enable firms to respond more quickly to heterogeneous demand (ßmann et al., 2015). At the same time, the precision and continuity of automated systems reduce human error and improve product reliability, helping firms maintain customer trust and market share under competitive pressure (Xiang et al., 2025; Puttero et al., 2025). Based on these arguments, we

---

5 https://www.reuters.com/business/retail-consumer/chinas-e-commerce-companies-are-getting-singed-by-price-war-2025-09-08/

hypothesize that:

H1: ***Firms facing more intense product market competition exhibit a higher degree of industrial robot adoption.***

While intensified competition strengthens firms' incentives to adopt industrial robots, actual adoption also depends on whether firms possess the necessary capabilities. we furthermore investigate the boundary conditions of this driving effect from the perspective of financial constraints and supply chain conditions.

Firms facing lower financial constraints are significantly more likely to actively adopt industrial robots. Although the direct purchase price of industrial robots may not be prohibitive, their practical deployment typically necessitates substantial complementary investments, including production line reconfiguration and labor resource reallocation (Benmelech and Zator, 2022). Consequently, financially constrained firms exhibit heightened sensitivity to the cost risks associated with robot adoption . Koch et al. (2021) also finds that larger and more productive firms and exporters are more likely to adopt robots. Besides, industrial robots are highly specific assets whose value is closely tied to particular production processes and becomes difficult to redeploy once installed, implying greater investment irreversibility and risk for firms (Kulatilaka, 1984; Sachs et al., 2015). Therefore, firms with relaxed financial constraints possess a distinct advantage in absorbing these strategic investment risks, making them substantially more likely to adopt industrial robots on a larger scale.

Firms with greater supply chain stability are significantly more likely to actively adopt industrial robots. Faced with intense product market competition, firms adopt industrial robots to achieve differentiated product innovation and capture a larger market share. however, this effect highly depends on the reliability of their supply chains. A fragile supply chain, like upstream supply shortages or downstream logistical disruptions, severely undermines a firm's fulfillment reliability (Chopra and Sodhi, 2004; Elliott et al., 2022). Consequently, technology-driven customized or innovative products fail to be delivered to customers on schedule, precluding any potential gains in market share. Furthermore, Wu et al. (2006) find that internal technological advantages, when coupled with a highly coordinated external supply chain, translate into greater firm value. Given these arguments, we hypothesize that:

H2: ***The positive impact of product market competition on industrial robot adoption is***

more pronounced among firms facing lower financial constraints or exhibiting greater supply chain stability.

3. Statistical Analysis and Identification Strategy

3.1 Data

We construct our sample based on all publicly listed A-share manufacturing firms in China from 2011 to 2019. The selection of this sample period is motivated by the rapid surge in industrial robot adoption in China post-2010 (Cheng et al., 2019). Data on industrial robots are sourced from the International Federation of Robotics (IFR), which provides publicly available statistics up to 2019. Firm-level financial and operational data are primarily obtained from the China Stock Market & Accounting Research (CSMAR) and Wind databases. Specifically, data regarding employee composition and corporate operations are extracted from Wind, while textual data from the Management Discussion and Analysis (MD&A) sections are manually collected from the annual and semi-annual reports of each listed firm. To enhance the robustness of regression results, we exclude samples of ST，ST*, and PT firms, as well as those firms with assets less than liabilities. We also winsorize all the continuous variables at the 1st and 99th percentiles to reduce the influence of outliers.

3.1.1 Product Market Competition

The core independent variable is the product market competition (PMC) of listed firms. Hoberg and Phillips (2016) argued that the fundamental connotation of competition lies in product similarity, which is that higher product similarity indicates a more intense level of competition. Their empirical research revealed that competition measures based on product similarity can accurately and dynamically assess the product competitive environment of listed companies, helping to overcome the limitations of previous approaches that measured market competition using static industry concentration. Drawing on their methodology, we use text analysis methods to characterize product similarity between firms based on product description information in the annual reports of listed companies. According to Clarkson et al. (1994), we extract the Management Discussion and Analysis (MD&A) sections from companies' annual and semi-annual reports during 2008–2022 to construct the PMC. The specific steps are as follows:

Step 1. Construct the product lexicon.

The construction of our product lexicon refers to Hoberg and Phillips (2016)and draws on three main sources: product names extracted from the Main Business Composition - Item Name (by Product) section of annual reports of all A-share listed companies, which are sourced from the iFinD Database; 28 Alibaba industry dictionaries compiled by Sogou Input Method; and an e-commerce-specific dictionary, also compiled by Sogou Input Method. Product terms from these three sources are cleaned and integrated to form the baseline product lexicon..

Step 2. Feature representation of annual report texts.

First, we convert each MD&A section into a term sequence and perform keyword matching on all companies' MD&A texts using the product lexicon to identify firm-specific product terms for each company in a given year. Then, following the approach of Hoberg and Phillips (2016), we adopt the Term Frequency-Inverse Document Frequency (TF-IDF) method from the bag-of-words model to convert these firm-specific product terms into a high-dimensional word vectors. Finally, we calculate the cosine similarity to measures the product similarity between two companies based on the angle between their product term vectors. A higher cosine value indicates greater similarity in the product businesses of the two companies.

Step3. Define product market competition.

for the i company in a given industry and year, the product market competition it faces is defined as the average similarity between the company and the remaining companies in the same industry. The specific formula is as follows:

$$PMC_{i,t} = \sum_{q=1}^{Q} Sim_{i,q}/N$$

Where i denotes the target company; q denotes other companies in the same industry as company i based on clustering results; N denotes the total number of companies in the industry minus 1 (based on clustering results); t denotes the year; $PMC_{i,t}$ is the product market competition faced by the listed company in each year. A higher value of this indicator indicates greater similarity between the target company and peer firms in the same year, which corresponds to more intense the product market competition faced by the firm.

Figure 2 illustrates the evolutionary trend of product market competition (PMC) faced by Chinese A-share listed manufacturing firms from 2008 to 2022. First, the time-series of the

median PMC exhibits a volatile upward trend, indicating an overall intensification of competitive pressure within the manufacturing industry (a supplementary analysis using annual means shows consistent results). Second, the competitive environment exhibits a pronounced structural divergence. The interquartile range (the height of the box), which captures the middle 50% of the sample, widens significantly over time. Specifically, firms in the upper quartile (the top 25%) experience a sharp acceleration in their PMC indices, reflecting intense competitive rivalry. In contrast, for firms in the lower quartile (the bottom 25%), although the competitive pressure also rises, the magnitude of the increase is substantially milder.

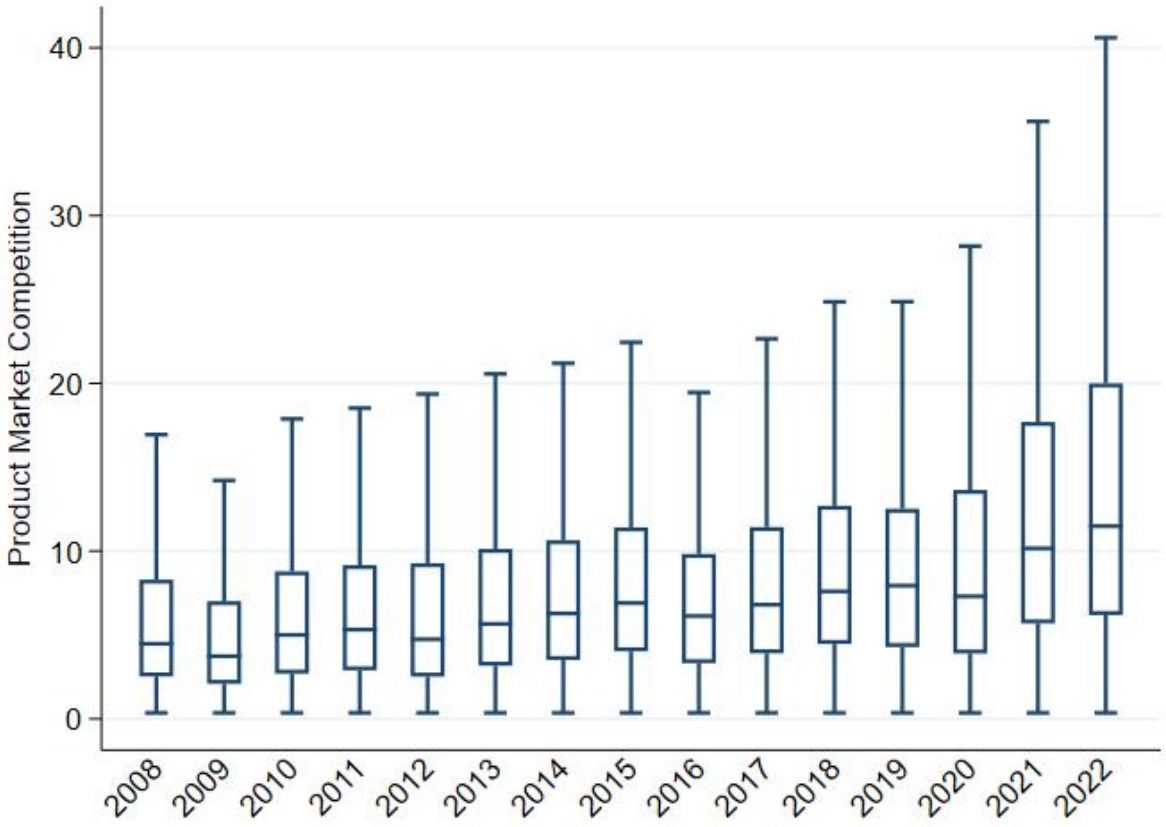


Figure 2 Annual distribution and evolutionary trend of product market competition (2008–2022)

Notes: This figure illustrates the annual distribution of product market competition (PMC) for Chinese listed manufacturing firms from 2008 to 2022. The firm-level PMC index is constructed utilizing advanced text-analysis techniques. In each annual box plot, the horizontal line within the box represents the median PMC value, while the lower and upper bounds of the box correspond to the 25th and 75th percentiles, respectively, capturing the interquartile range (IQR) of the middle 50% of the sample. The whiskers extend to the upper and lower adjacent values. Extreme outliers have been omitted for graphical clarity.

3.1.2 Adoption of industrial robots

The data on the stock of robots by industry, country, and year are sourced from the

International Federation of Robotics (IFR), a professional organization of robot suppliers established in 1987 to promote the robotics industry worldwide. These data are based on yearly surveys of robot suppliers and contain information for 70 countries, covering more than 90 percent of the industrial robot market. This dataset has been employed by Acemoglu & Restrepo (2020) for the US, Dauth et al. (2019) for Germany, Giuntella et al. (2019) for China, Anelli et al. (2019) for Europe, and by Graetz & Michaels (2018) in a cross-country analysis. The IFR data provide the operational stock of "industrial robots", which are defined as "automatically controlled, reprogrammable, and multipurpose [machines]". Basically, industrial robots are fully autonomous machines that are automatically controlled, do not need a human operator and can be programmed to perform several tasks such as welding, painting, assembling, carrying materials, or packaging. This paper constructs an firm-level exposure to robots based on Chinese manufacturing data, with the specific measurement method as follows:

Step 1. Calculate the industry-level exposure to robots, denoted as $PR_{i,t}$.

$$PR_{i,t} = \frac{MR_{i,t}}{LB_{i,t=2010}}$$

Where $MR_{i,t}$ represents the stock of industrial robots in China's industry i in year t, $LB_{i,t=2010}$ denotes the number of employees in China's industry i in 2010 (the base period), and $PR_{i,t}$ is the calculated exposure to robots in China's industry i in year t.

Step 2. Construct the enterprise-level exposure to robots.

$$exposure\ to\ robots_{i,f,t} = \frac{PWP_{i,f,t=2011}}{MedianPWP_{t=2011}} \times \frac{MR_{i,t}}{LB_{i,t=2010}}$$

This indicator measures the industrial exposure to robots of firm f in industry i in year t, with the unit being units per 10,000 people. Where $PWP_{i,f,t=2011}/MedianPWP_{t=2011}$ represents the ratio of the proportion of employees in the production department of firm f in industry i (in 2011) to the median proportion of employees in the production department of all manufacturing firms (in 2011). The Exposure indicator is generated by taking the natural logarithm of $exposure\ to\ robots_{i,f,t}$.

3.2 Empirical Strategy

To examine the baseline relationship between product market competition and firms' exposure to industrial robots, we estimate the following model:

$$Robot_{i,t} = \beta_0 + \beta_1 PMC_{i,t} + \beta_2 Controls_{i,t} + Year_t + firm_i + \epsilon_{i,t}$$

where i denotes the firm and t denotes the year. The dependent variable $Robot_{i,t}$ measures firms' exposure to industrial robots, while the key explanatory variable, $PMC_{i,t}$ captures the intensity of product market competition faced by firms. Our primary interest lies in the coefficient β_1, which reflects the association between product market competition and firms' adoption of industrial robots. Consistent with our hypothesis, we expect β_1 to be significantly positive. Following the existing literature, we further include a set of firm-level control variables that may affect firms' adoption of industrial robots, including firm size (*Size*), firm leverage ratio (*Lev*), return on assets (*ROA*), capital expenditure (*Invest*), tangible asset ratio (*PPE*). In addition, the model further includes year fixed effects $Year_t$ and firm fixed effects $firm_i$ to account for time-specific shocks and time-invariant firm heterogeneity. $\epsilon_{i,t}$ denotes the error term.

Table 1 reports the summary statistics for the variables used in this study. The mean value of Exposure is 32.3517, whereas the median is 6.8902, indicating a right-skewed distribution. To ensure that the empirical results are not driven by the scaling of the dependent variable, we follow the per-thousand-units convention adopted in related studies (Yu et al., 2024) and use this alternative measure in the robustness tests. For PMC, the mean is 8.0994 and the median is 6.3656, suggesting a relatively balanced distribution. The summary statistics of the remaining control variables are broadly consistent with those reported in the existing literature. Detailed definitions of all variables are provided in Appendix A.

Table 1 Summary Statistics

Var	Obs	Mean	SD	P10	Median	P90
Robot	11083	32.3517	65.1272	0.5731	6.8902	92.7808
PMC	11083	8.0994	6.5040	1.9168	6.3656	16.7863
Size	11083	22.0612	1.1579	20.6905	21.9209	23.6615
ROA	11083	0.0339	0.0630	-0.0102	0.0334	0.0976
Lev	11083	0.4088	0.1990	0.1463	0.4007	0.6746
PPE	11083	0.2391	0.1398	0.0802	0.2129	0.4444
Invest	11083	0.0500	0.0473	0.0060	0.0370	0.1154

Table 2 presents the Pearson correlation coefficients of the main variables. The core explanatory variable, *PMC* exhibits a statistically significant positive correlation with *Robot* at the 1% significance level, which preliminarily reflects the positive association between product market competition and the extent of firms' industrial robot adoption. The absolute values of the correlation coefficients among variables are generally low, indicating no

evidence of severe multicollinearity.

Table 2 Correlation Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Robot	1						
(2) PMC	0.176***	1					
(3) Size	0.188***	0.154***	1				
(4) ROA	-0.101***	0.0140	0.036***	1			
(5) Lev	0.121***	0.046***	0.477***	-0.367***	1		
(6) PPE	-0.089***	-0.049***	0.127***	-0.154***	0.191***	1	
(7) Invest	-0.129***	-0.027***	-0.023**	0.149***	-0.075***	0.178***	1

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In addition, before conducting the firm-level empirical analysis, we provide preliminary graphical evidence on the relationship between product market competition (PMC) and robot adoption at the industry level. As shown in Figure 3, we plot the industry-average firm-level PMC against the natural logarithm of raw robot installations obtained from the IFR. The scatter plot reveals a striking positive correlation between the two variables. Generally, the figure indicates that intensified market competition is strongly associated with greater deployment of industrial robots across industries, which is consistent with the hypothesis 1.

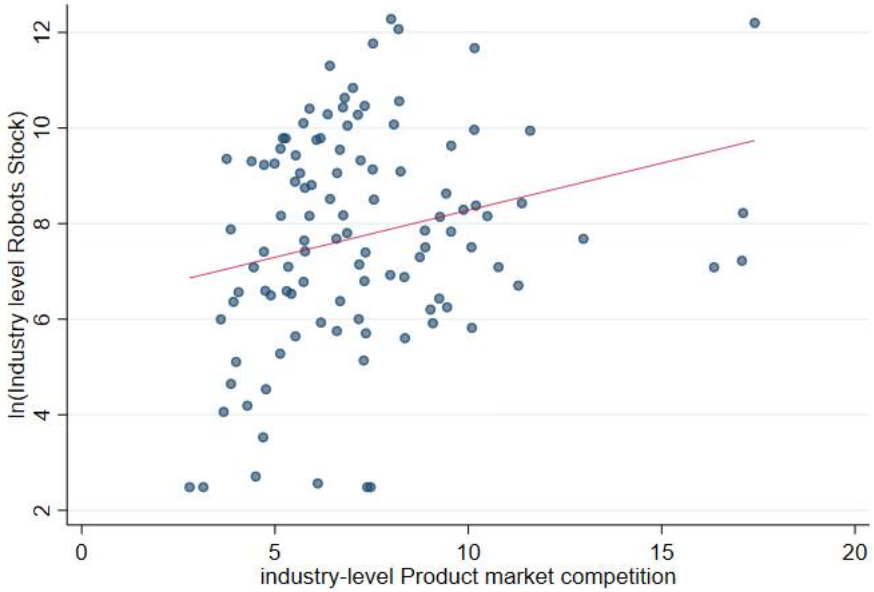


Figure 3 Relationship between the PMC and industry adoption

Notes: This figure illustrates the macroscopic relationship between product market competition (PMC) and robot adoption strictly at the industry level. To construct this scatter plot, we aggregate the firm-level data by calculating the annual industry-average PMC (horizontal axis). The vertical axis represents the natural logarithm of industry-level industrial robot

installations, sourced directly from the International Federation of Robotics (IFR). The solid line represents the linear fit, demonstrating a pronounced positive correlation between market competition and robot adoption across manufacturing industries.

4. Main Results

4.1 Baseline

Table 3 reports the baseline regression results on the relationship between product market competition and firms' adoption of industrial robots. Column (1) includes only the core explanatory variable together with firm and year fixed effects. Column (2) further adds a full set of firm-level control variable. The results show that the coefficient on *PMC* is positive and statistically significant at the 1% level across both columns. Specifically, the estimated coefficient is 0.6506 in Column (1) and 0.6530 in Column (2), indicating a high degree of stability after the inclusion of additional controls. This finding suggests that when firms face more intense competition from product-similar rivals, they are more likely to accelerate automation and intelligent upgrading.

This finding is consistent with the theoretical argument developed above. In highly competitive product markets, firms are often confronted with severe product homogeneity and intensified price pressure. Under such conditions, relying solely on conventional price-cutting strategies may compress profit margins and weaken long-term competitiveness. By contrast, industrial robots can help firms improve production flexibility, enhance quality consistency, and support product differentiation. Therefore, stronger product market competition increases firms' incentives to adopt industrial robots not merely as a labor-saving technology, but also as a strategic tool to strengthen market competitiveness.

Table 3 The effect of product market competition on firm's robots adoption

	(1)	(2)
	Robot	Robot
PMC	**0.6506*** **	**0.6530*** **
	(0.1740)	**(0.1740)**
Size		-2.3678
		(2.5872)
ROA		-17.0305
		(11.0993)
Lev		8.0214
		(8.1185)
PPE		1.1700
		(8.4946)

Invest		9.6242
		(14.3909)
_cons	27.0824***	75.8372
	(1.4094)	(55.1957)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	11083	11083
Adjusted R^2	0.691	0.691

This table reports firm-level panel regressions of robots adoption on product market competition. The dependent variable is *Robots*, which is a Bartik-style measure (Bartik, 1991) to capture firm-level exposure to robots using data from IFR. The main independent variable is *PMC*, which is product market competition measured by the cosine similarity between a firm's product vocabulary and those by other firms within the K-means cluster group. Control variables include Size, Lev, ROA, Invest, PPE. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.2 Robustness Tests

4.2.1 Instrumental Variable Regressions

A potential concern with the baseline estimates is that product market competition may be endogenous. On the one hand, unobserved firm characteristics may simultaneously affect both the intensity of competition and firms' robot adoption decisions. On the other hand, reverse causality may arise if robot adoption itself changes firms' product positioning and thus affects the competitive environment they face. To address these concerns, we employ two instrumental-variable strategies.

To overcome potential endogeneity, we used the IV and apply the two-stage least square (2SLS) method. The first- and second-stage equations in our identification can be expressed as follows:

$$PMC_{i,t} = \beta_0 + \beta_1 IV_{i,t} + \beta_2 Controls_{i,t} + Year_t + firm_i + \epsilon_{i,t} \quad (2)$$

$$Robot_{i,t} = \beta_0 + \beta_1 \widehat{PMC_{i,t}} + \beta_2 Controls_{i,t} + Year_t + firm_i + \epsilon_{i,t} \quad (3)$$

Where we choose two IVs, the first one is constructed based on the opening-up of restricted industries in the Catalogue for the Guidance of Industries for Foreign Investment promulgated in 2011 and 2015 (Lu et al., 2017; Loncan, 2023), and the second one is the "Hurun Most Valuable China Brand"[6] as an instrumental variable for PMC.

Panel A of Table 4 reports the two-stage least squares (2SLS) results using an instrument

[6] The "Hurun Most Valuable China Brands" list, published annually by the Hurun Research Institute, is a widely recognized ranking that comprehensively evaluates the brand value and market influence of leading enterprises operating within the Chinese market. For further methodological details, see: https://hurun.net/en-us/rank/hsrankdetails?num=V7ME9EXB.

constructed from the opening-up of restricted industries in the Catalogue for the Guidance of Industries for Foreign Investment promulgated in 2011 and 2015, following Babar and Habib (2020). Specifically, we define industries that were newly opened to foreign investment in 2015 relative to 2011 as industries subject to stronger external competitive pressure, and construct a corresponding dummy variable. We then interact this dummy with the post-2015 policy period to form the instrumental variable. The intuition is that the relaxation of foreign investment restrictions intensifies product market competition through an external policy shock, while it is unlikely to affect firms' robot adoption except through the change in competitive pressure.

Panel B presents the results using the Hurun Brand List as an alternative instrument for PMC, following Xu and Ni (2024). Specifically, we construct a dummy variable indicating whether any of the top 30 rivals with the highest product similarity to a focal firm have ever appeared on the Hurun Brand List. The presence of such strong brand competitors is expected to increase competitive pressure in the focal firm's product market, while being plausibly exogenous to the firm's own robot adoption decisions. This instrument therefore captures variation in product market competition stemming from the external brand environment of closely related rivals.

The results of the instrumental variable (IV) estimation are presented in Table 4. The coefficients of both IVs are positive and statistically significant at the 1 % level, suggesting that they have substantial explanatory power for product market competition. The Cragg-Donald Wald F-statistics of the first-stage regressions are 24.629 and 26.344, both of which are higher than the 10% critical value of 16.38 for the Stock-Yogo weak instrument test. More importantly, the second-stage results continue to show a significantly positive effect of PMC on firms' adoption of industrial robots. These findings indicate that the baseline relationship is unlikely to be solely driven by reverse causality or omitted-variable bias.

Table 4 Robustness Tests –2SLS regression

Panel A: Using Foreign Investment Catalogue as Instrument Variable

	(1)	(2)
	PMC	Robot
IV-investment	2.0407***	
	(0.4112)	
$\overline{PMC}$		30.1128***
		(6.1740)
Control variable	Yes	Yes

Firm FE	Yes		Yes
Year FE	Yes		Yes
F-statistic		24.629	
N	11083		11083
Adjusted R^2	0.652		-9.777
Panel B: Using Hurun Brand List as Instrument Variable			
	(1)		(2)
	PMC		Robot
IV-hurun	0.7705***		
	(0.1501)		
$\overline{PMC}$			5.6069***
			(2.1018)
Control variable	Yes		Yes
Firm FE	Yes		Yes
Year FE	Yes		Yes
F-statistic		26.344	
N	9894		9894
Adjusted R^2	0.657		-0.276

This table presents two-stage least squares (2SLS) regression results. Panel A uses the policy-based instrument derived from the Catalogue for the Guidance of Foreign-Invested Industries. Panel B uses the Hurun Brand List instrument. The dependent variable is *Robots*, which is a Bartik-style measure (Bartik, 1991) to capture firm-level exposure to robots using data from IFR. The main independent variable is *PMC*, which is product market competition measured by the cosine similarity between a firm's product vocabulary and those by other firms within the K-means cluster group. PMC is treated as endogenous. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. First-stage F-statistics are reported to assess instrument strength. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.2.2 Additional Robustness Checks

Beyond endogeneity, another concern is whether the baseline findings are sensitive to the way key variables are measured or to the specific empirical specification adopted. To address this issue, we conduct a series of additional robustness tests reported in Table 5.

First, we replace the measure of the key explanatory variable. On the one hand, we use the Herfindahl-Hirschman Index (HHI), a conventional indicator widely adopted in the literature, as an alternative proxy for product market competition. On the other hand, we also use the average similarity between each firm and the top 50 firms with the highest product market similarity to it to measure the product market competition faced by the firm. The results, reported in Panel A of Table 5, remain statistically significant, indicating that our findings do not depend on a specific construction of the competition measure.

Second, we construct a firm-level indicator of robot adoption based on the construction-in-progress and R&D outlays from the financial reports. Firms typically

implement industrial intelligence technologies through one of two channels: externally acquiring the necessary software and hardware, or internally developing them in-house. Because production lines centered on intelligent equipment including industrial robots are complex, system-level engineering projects that demand detailed design, construction, and commissioning, the associated expenditures appear in firms' financial statements as construction-in-progress and R&D outlays. In China, listed firms disclose line-item details for both construction-in-progress and R&D expenditures in their annual reports. By parsing the project descriptions, we can thus quantify each firm's total investment in industrial-intelligence application projects.

We firstly identify a set of industrial-intelligence keywords based on national policy reports, academic literature, including terms such as "robotics and intelligent applications," "automated welding robots," "green smart factories," and "robotic grinding systems" (see Appendix B). By matching project descriptions in construction-in-progress and R&D expenditures with these keywords, we compute the investment in automation-related projects transferred to fixed assets or recognized as intangible assets. We construct variable *LnAutomation* as the natural logarithm of those expenditures plus one, capturing the scale of industrial intelligence intensity. As is shown in column (1) of Panel B, the coefficient of PMC is positive and statistically significant at the 10% level, indicting that a greater PMC leads to higher robots adoption.

Besides, we consider the robots adoption of the firm in year t+1, t+2, and t+3 in our baseline regression. The results of this analysis are presented in column (2)-(4) of Panel B, which also show the positive relationship between PMC and robots adoption of the firm for the next few years. This suggests that the promoting effect of product market competition on robot adoption is not only robust to alternative operationalizations, but also exhibits a degree of dynamic persistence.

Third, we adopt alternative fixed-effects specifications to further account for potentially omitted time-varying heterogeneity. Specifically, we include industry × year fixed effects to control for industry-specific shocks that evolve over time, and province × year fixed effects to account for time-varying regional heterogeneity. The results, reported in Panel C of Table 5, remain statistically significant at conventional levels. This further alleviates concerns that the baseline findings are driven by unobserved industry-level or region-level shocks correlated

with both competition and robot adoption.

Table 5 Other Robustness Tests

Panel A: Alternative measures of independent variables

	(1) Robot	(2) Robot
HHI	-0.0156*	
	(0.0089)	
SimiTop50		2.2398*
		(1.3090)
Controls	Yes	Yes
_cons	73.1101	71.0794
	(57.3586)	(55.6569)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	10799	10799
Adjusted R^2	0.700	0.699

Panel B: Alternative measures of dependent variable

	(1) LnAutomation	(2) F1.Robot	(3) F2.Robot	(4) F3.Robot
PMC	**0.0283***	**0.3814****	**0.3556****	**0.8693*****
	(0.0166)	**(0.1724)**	**(0.1674)**	**(0.1787)**
Controls	Yes	Yes	Yes	Yes
_cons	3.2782***	60.1455	53.7140	64.0138
	(0.1354)	(59.4496)	(58.4067)	(60.3667)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	10799	9531	8253	6975
Adjusted R^2	0.373	0.746	0.789	0.837

Panel C: Alternative Fixed Effects

	(1) Robot	(2) Robot	(3) Robot	(4) Robot
PMC	**0.5797*****	**0.6044*****	**0.6254*****	**0.6259*****
	(0.1499)	**(0.1500)**	**(0.1733)**	**(0.1738)**
Controls	NO	YES	NO	YES
_cons	27.6562***	102.7861**	27.2867***	60.1668
	(1.2140)	(47.6984)	(1.4035)	(55.3359)
Firm FE	Yes	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	NO	NO

Province*Year FE	NO	NO	Yes	Yes
N	11083	11083	11083	11083
Adjusted R^2	0.788	0.789	0.695	0.695

This table reports robustness tests using alternative measures of product market competition and firm-level robots adoption. Panel A uses alternative PMC measures, including the industry-level HHI index, where a higher HHI value indicates a higher degree of industry monopoly and thus lower intensity of product market competition. Besides, we use SimiTop50 as an alternative independent variable, which is the mean of cosine similarity between a firm's product vocabulary and that of the top 50 firms with the highest product market similarity to it. Panel B uses alternative dependent variables, including the natural logarithm of one plus industrial intelligence-related investments (LnIntelligence), which are identified from financial statements of construction-in-progress and R&D outlays. In addition, we use one-, two-, and three-period-ahead robot adoption (F1.Robot, F2.Robot, F3.Robot) to examine the long-term effects of the PMC. Panel C adds industry×year and province×year fixed effects. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.3 Mechanisms

4.3.1 product innovation

A first channel through which product market competition may promote robot adoption is product innovation. Existing research suggests that manufacturing firms' innovation activities can be broadly divided into product innovation and service transformation (Visnjic Kastalli & Van Looy, 2013). Among these, product innovation is particularly important because it directly reflects firms' ability to improve the novelty, quality, and technological content of their products, thereby enhancing market differentiation and long-run competitiveness.

In this paper, we argue that industrial robots can support product innovation in at least two ways. First, robot adoption improves the flexibility and precision of the production process, allowing firms to experiment with new product designs, upgrade existing products, and respond more effectively to differentiated market demand. Second, automated production systems help reduce human error and improve quality consistency, thereby providing a more reliable technological foundation for product upgrading. In this sense, industrial robots are not only production tools, but also an enabling technology for innovation. This mechanism becomes particularly relevant in highly competitive product markets. When firms face intense product homogeneity and price pressure, competing solely through price cuts is often unsustainable because it compresses profit margins and weakens long-term growth prospects. Under such conditions, firms have stronger incentives to "escape competition" by upgrading products and creating differentiated advantages. Product innovation therefore becomes a key

strategic response to external competitive pressure. Since industrial robots can facilitate such innovation, firms facing stronger product market competition are more likely to adopt robots in order to improve their innovation capability and reinforce their market position. Put differently, product market competition enhances firms' robot adoption through the channel of product innovation.

To operationalize this mechanism, we use firms' invention patent applications as a proxy for product innovation. Patents are commonly divided into invention patents and non-invention patents. Invention patents refer to new technical solutions for products or methods and require substantive novelty and significant technological progress relative to existing knowledge (Fang et al., 2017). Compared with other patent types, invention patents are generally more technology-intensive, more valuable, and more indicative of a firm's genuine innovation capability and core competitiveness. For this reason, we use the number of invention patent applications to measure the level of firms' product innovation.

In Fig. 4, we find that relative to the overall sample mean, robots adoption has a significant positive effect on firms' product innovation levels. More notably, the impact of robot adoption on product innovation is substantially stronger among firms with higher PMC. This suggests that, while the adoption of industrial robots in production processes helps improve firms' product innovation levels across the board, firms facing higher PMC benefit more significantly from the increase in product innovation driven by robot adoption. More detailed explanation is shown in the Appendix C.

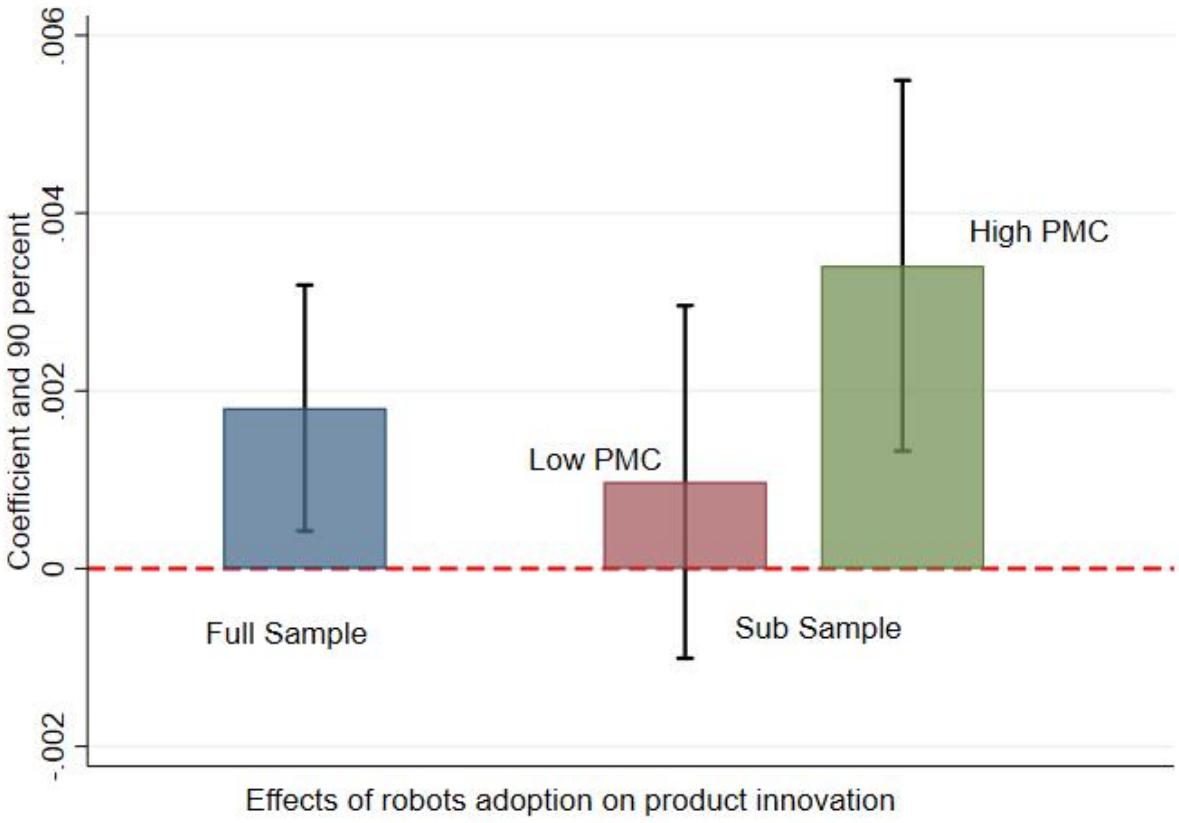


Figure 4 Effects of robot adoption on product innovation of the firm varying different PMC

Notes: Based on the calculated PMC index, we categorize firms into two groups using the median of each year as the cutoff: those facing higher PMC and those facing lower PMC.

4.3.2 product market share

Market size effect constitutes one of the core drivers of firms' technological upgrading (Acemoglu, 2002). From the perspective of marginal cost, manufacturing firms' adoption of industrial robots enables them to accomplish the same tasks at lower costs, which can reduce the relative market prices of related products and thereby expand firms' market share (Graetz & Michaels, 2018). Thus, this study argues that by increasing the adoption rate of industrial robots, firms can significantly expand their product market share while enhancing their core competitiveness. Similarly, the effect of this mechanism is more pronounced when firms face a more intense PMC environment. Specifically, when confronting fiercer external PMC, firms

tend to enhance their competitiveness by expanding their product market scale to cope with such competitive pressure. Therefore, PMC increases firm-level exposure to robots through the indirect channel of product market share.

We adopt the formula a firm's operating income in the current year divided by the total operating income of all firms in the same industry for the same year to construct the firm-level market share indicator (Giroud & Mueller, 2010), and use the growth rate of this indicator in empirical regressions. A higher growth rate indicates that the firm captures a larger market share in each period, and similarly implies stronger product market competitiveness for the firm.

In Fig. 5, we find that relative to the overall sample mean, robots adoption has a significant positive effect on firms' product sales growth. More notably, the impact of robot adoption on firms' product sales growth is substantially stronger among firms with higher PMC. This suggests that, while the adoption of industrial robots in production processes helps improve the growth rate of firms' product market share across the board, firms facing higher PMC benefit more significantly from the increase in product market share driven by robot adoption. More detailed explanation is shown in the Appendix D.

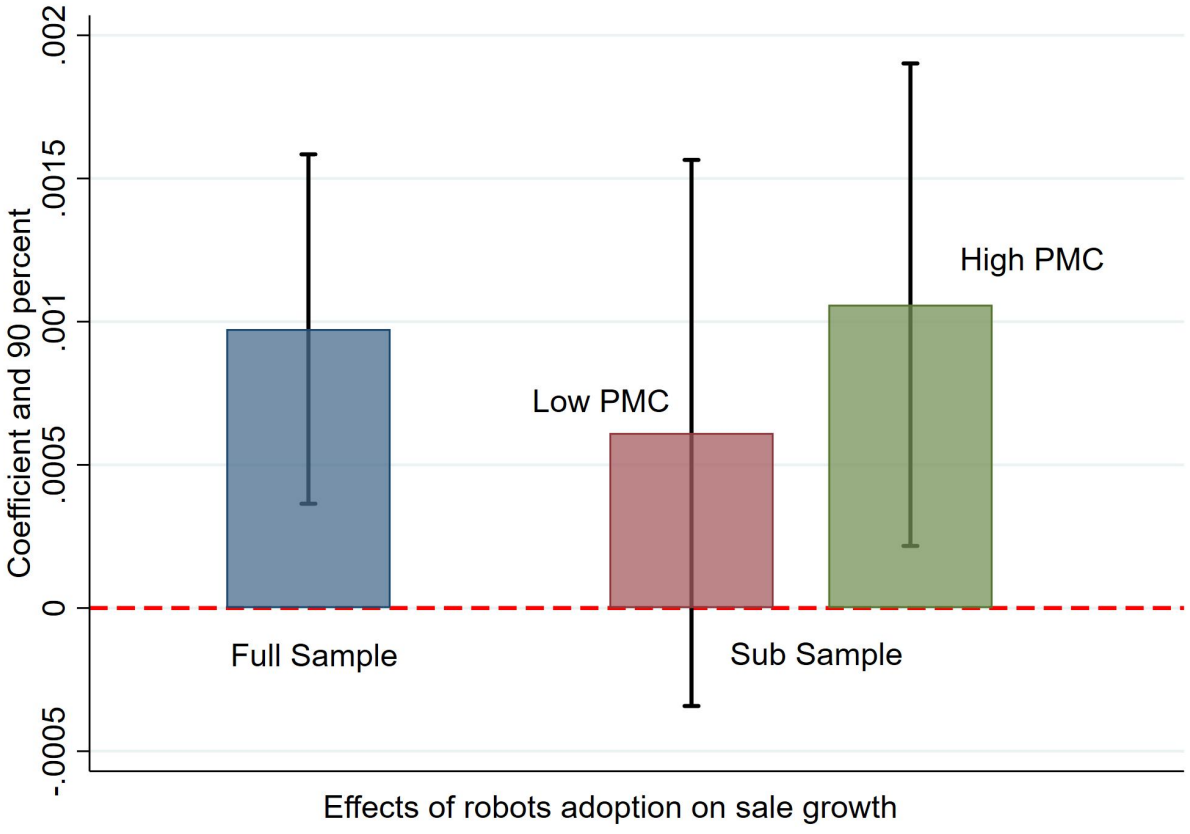


Figure 5 Effects of robots adoption on sale growth of the firm varying different PMC

Notes: Based on the calculated PMC index, we categorize firms into two groups using the median of each year as the cutoff: those facing higher PMC and those facing lower PMC.

4.4 Heterogeneity

4.4.1 Financial Constraints

The effect of product market competition on firms' adoption of industrial robots may depend on firms' financial capacity. Although stronger competition can increase firms' incentives to undertake intelligent transformation, the actual implementation of such transformation typically requires substantial upfront investment in equipment, system integration, and organizational adjustment. Therefore, whether competitive pressure can be translated into robot adoption may crucially depend on the severity of firms' financing constraints.

Firms with relaxed financial constraints possess a distinct advantage in absorbing these strategic investment risks, making them substantially more likely to adopt industrial robots on a larger scale. Industrial robots are highly specific assets, whose value is closely tied to particular production processes and they are difficult to redeploy once installed, implying greater investment irreversibility and higher risk for firms (Kulatilaka, 1984; Sachs et al., 2015). Therefore, in theory, firms with higher financing constraints have neither the incentive nor the ability to adopt industrial robots even when facing intense PMC, while the opposite holds true for firms with lower financing constraints.

To examine this heterogeneity, we use the WW index proposed by Whited and Wu (2006) to measure firms' degree of financing constraints, and divide the sample into low- and high-financing-constraint groups. The regression results are reported in Columns (1)-(2) of Table 6. The results reveal a clear pattern. For firms with high financing constraints, the coefficient on PMC is statistically insignificant, suggesting that although these firms may also face strong competitive pressure, they lack sufficient financial resources to undertake robot-intensive upgrading. In contrast, for firms with low financing constraints, the coefficient on PMC is 1.3220 and statistically significant at the 1% level, and the difference has passed the Fisher's permutation test. This indicates that product market competition significantly promotes robot adoption only when firms possess adequate financial capacity.

The results are consistent with the existing research, suggesting that financing constraints shape firms' ability to adjust their production structure and workforce composition. In particular, when financing constraints are severe, firms face greater difficulty in adapting to

capital-skill complementary production and in undertaking technology-intensive upgrading (Allub et al., 2024). Building on this insight, we argue that financing constraints are likely to serve as an important boundary condition in the relationship between product market competition and robot adoption. Specifically, firms facing stronger financing constraints are subject to tighter capital flow pressure and higher adjustment costs, which reduce their ability to respond to external competitive pressure through investment in industrial robots.

4.4.2 Supply Chain Stability

The effect of product market competition on firms' adoption of industrial robots may also depend on the stability of their supply chains. A stable supply chain is an important foundation for firms to organize production efficiently and a key condition for fully realizing the gains from new-quality productive forces (Ivanov & Dolgui, 2020). In addition, recent research suggests that the application of artificial intelligence is highly associated with both lower supplier volatility and customer volatility (Modgil et al., 2022 Modgil et al., 2022). These arguments imply that firms with more stable upstream and downstream relationships are better positioned to implement intelligent upgrading when facing external competitive pressure. Industrial robot adoption is not an isolated investment decision; its effectiveness depends heavily on the smooth coordination of procurement, production, and sales. When a firm operates within a more stable supply chain, it faces lower uncertainty in input supply and product demand, making it easier to absorb the fixed costs of automation and to realize the productivity gains from robot adoption. By contrast, when supplier and customer relationships are less stable, greater uncertainty and coordination frictions may weaken firms' incentives or ability to respond to competitive pressure through robot-based upgrading. Therefore, supply chain stability is likely to serve as an important boundary condition in the relationship between product market competition and robot adoption.

To examine this heterogeneity, we follow Wu and Yao (2023) and construct a measure of firm-level supply chain concentration using the average of the procurement ratio from the top five suppliers and the sales ratio to the top five customers. This indicator captures the degree to which firms maintain concentrated relationships with major upstream and downstream partners, which we use as a proxy for supply chain stability. We then divide the sample into low- and high-supply-chain-stability groups. The regression results are reported in Columns (3)-(4) of Table 6. The results reveal significant heterogeneity across the two groups, and the difference in coefficients passes the Fisher's permutation test, confirming the statistical

reliability of the heterogeneity pattern. Specifically, in the group with high supply chain stability, the coefficient on PMC is positive and significant at the 1% level, indicating that the promoting effect of product market competition on robot adoption is stronger and more robust for these firms. In the group with low supply chain stability, the coefficient on PMC remains positive but is significant only at the 10% level, suggesting that the positive effect still exists but is economically weaker.

This difference can be understood from the economic nature of supply chain relationships. A higher degree of supply chain concentration usually reflects closer and more stable collaboration with core suppliers and customers, as well as greater investments in relationship-specific assets. Under these conditions, the efficiency gains generated by robot adoption are more likely to be transmitted along the production chain through coordination and synergy effects, thereby strengthening firms' incentives to improve automation and supply chain matching efficiency. By contrast, firms with lower supply chain concentration tend to have looser upstream and downstream ties, greater transactional uncertainty, and higher coordination costs. These factors weaken the extent to which external competitive pressure can be translated into actual robot adoption, resulting in a more moderate effect.

Table 6 Heterogeneity Analysis

	Low financing constraints	High financing constraints	Low supply chain stability	High supply chain stability
	(1)	(2)	(3)	(4)
	Robot	Robot	Robot	Robot
PMC	**1.3220*** **	**0.0335**	**0.4108***	**1.0692*** **
	(0.2571)	**(0.2051)**	**(0.2189)**	**(0.2553)**
Controls	Yes	Yes	Yes	Yes
_cons	144.8543	56.4080	328.5036***	-21.4691
	(109.0100)	(76.3743)	(90.0096)	(65.7153)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Robot _diff	***		**	
p-value	0.000		0.026	
N	5367	5388	5174	5204
Adjusted R^2	0.716	0.717	0.708	0.735

This table reports subsample regressions. Firms are split by financing constraints measured using the WW index and by supply chain stability measured by supplier–customer concentration. The dependent variable is Exposure. PMC is product market competition. All regressions include firm and year fixed effects. Control variables follow Table 3. P-values from Fisher permutation tests for coefficient differences are reported. Standard errors are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

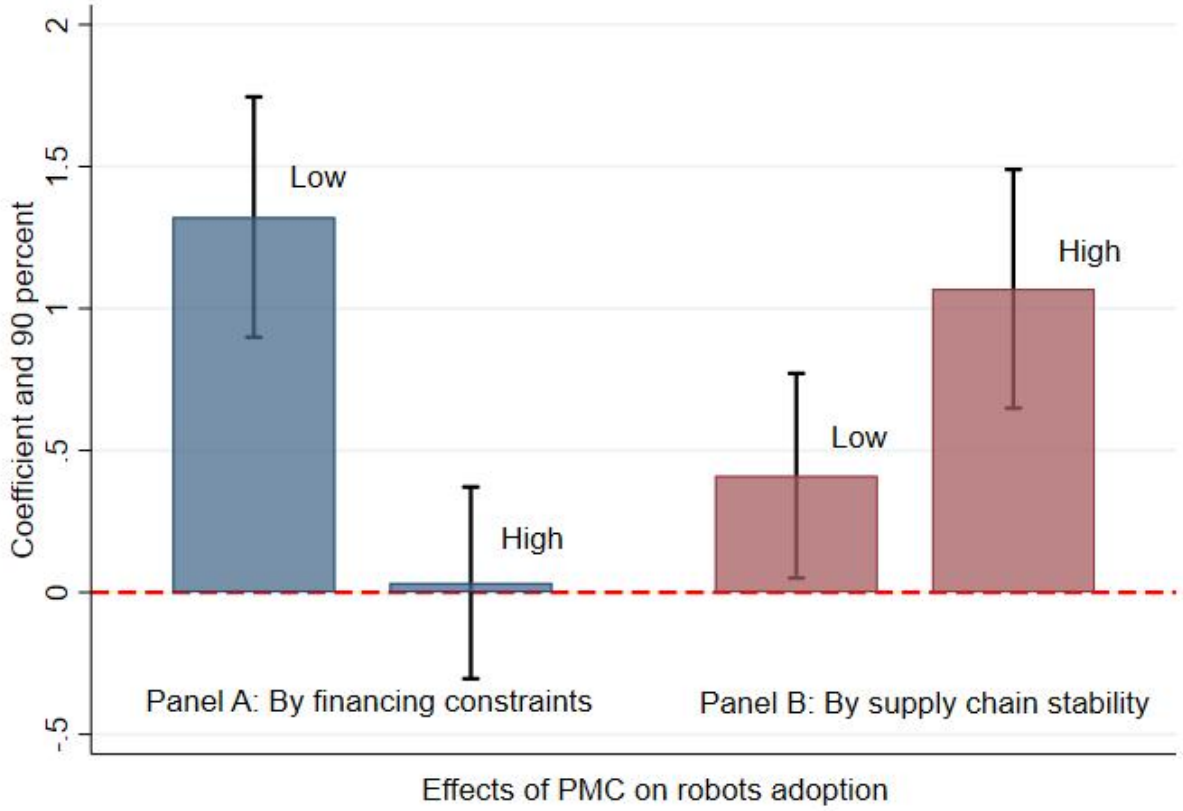


Figure 6 Heterogeneity Analysis

5. Conclusion

This paper examines whether and how product market competition drives firms' industrial intelligent transformation. Using data on Chinese A-share listed manufacturing firms from 2011 to 2019, we find that stronger product market competition significantly promotes firms' adoption of industrial robots, and this result remains robust across a range of specifications and identification strategies. By shifting the analytical focus from internal labor-cost considerations to external product-market pressure, this study provides a new perspective on the market-driven forces behind the transition from "Made in China" to "Intelligent Manufacturing in China."

Further analysis shows that this effect operates through two main channels: product innovation and market share expansion. Firms can use industrial robots not only to improve production efficiency, but also to enhance product differentiation and strengthen market competitiveness under intense rivalry. In addition, the effect of product market competition on robot adoption is more pronounced among firms with lower financing constraints and greater

supply chain stability, suggesting that while competition creates incentives for intelligent upgrading, firms' financial capacity and operational resilience shape their ability to implement such transformation.

This study has several important implications. For firms, the results suggest that industrial robot should not be viewed solely as a cost-reduction tool, but also as a strategic instrument for enhancing product competitiveness, expanding market presence, and strengthening long-term survival under intense rivalry. Firms therefore need to make automation and intelligent upgrading decisions not only according to internal production conditions, but also in response to changing competitive signals in the product market. For policymakers, our findings imply that improving fair and effective market competition may itself stimulate firms' technological upgrading. At the same time, policies aimed at easing financing constraints, strengthening supply chain coordination, and improving the broader allocation of production factors can help firms better translate competitive pressure into intelligent transformation. In this sense, a well-functioning market environment and supportive institutional conditions are complementary in promoting manufacturing upgrading.

This study also has limitations. Our measure of robot adoption captures firm-level exposure rather than direct deployment, the causal interpretation still requires caution despite extensive robustness checks, and the sample of listed manufacturing firms may limit the generalizability of the findings. Future research could further explore other channels, such as organizational restructuring, labor upgrading, or export adjustment, to deepen our understanding of firms' intelligent transformation.

REFERENCES

Acemoglu, D., & Autor, D. H. 2011. Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics*, 4(4): 1043–1171.

Acemoglu, D., & Restrepo, P. 2017. Robots and jobs: Evidence from U.S. labor markets. *NBER Working Paper* No. 23285.

Acemoglu, D., & Restrepo, P. 2020. Robots and jobs: Evidence from U.S. labor markets. *Journal of Political Economy*, 128(6): 2188–2244.

Aghion, P., Antonin, C., & Bunel, S. 2019. Artificial intelligence, growth and employment: The role of policy. *Économie et Statistique / Economics and Statistics*, 1: 1–26.

Allub, L., Erosa, A., & Mei, Y. 2024. Financial frictions, firm dynamics, and capital-skill complementarities. *Review of Economic Dynamics*, 49: 1–28.

Autor, D. H., & Dorn, D. 2013. The growth of low-skill service jobs and the polarization of the U.S. labor market. *American Economic Review*, 103(5): 1553–1597.

Babar, M., & Habib, A. 2021. Product market competition in accounting, finance, and corporate governance: A review of the literature. *International Review of Financial Analysis*, 73: 101607.

Bena, J., & Simintzi, E. 2025. Machines could not compete with Chinese labor: Evidence from U.S. firms' innovation. *Review of Finance*, 29(6): 1619–1661.

Bertrand, M., & Mullainathan, S. 2003. Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy*, 111(5): 1043–1075.

Brynjolfsson, E., & McAfee, A. 2014. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. New York: Norton.

Chen, Y., Liu, Z., & Wang, Y. 2017. Patent quality and firm innovation. *China Economic Review*, 46: 1–15.

Clarkson, P. M., Kao, J. L., & Richardson, G. D. 1994. The voluntary inclusion of forecasts in the MD&A section of annual reports. *Contemporary Accounting Research*, 11(1): 423–450.

Feng, G., & Wang, J. 2020. Corporate social networks and innovation: Evidence from China. *Journal of Mathematical Finance*, 10(4): 529–548.

Frey, C. B., & Osborne, M. A. 2017. The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114: 254–280.

Giroud, X., & Mueller, H. M. 2011. Corporate governance, product market competition, and equity prices. *Journal of Finance*, 66(2): 563–600.

Graetz, G., & Michaels, G. 2018. Robots at work. *Review of Economics and Statistics*, 100(5): 753–768.

Hoberg, G., & Phillips, G. M. 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5): 1423–1465.

Hotelling, H. 1929. Stability in competition. *Economic Journal*, 39(153): 41–57.

Hsieh, C.-T., & Klenow, P. J. 2009. Misallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics*, 124(4): 1403–1448.

Li, L., Wang, X., & Bao, Q. 2021. The employment effect of robots: Mechanism and evidence from China. *Management World*, 37(9): 104–119.

Liu, H., Hu, H., Zhang, S., & Sun, L. 2023. Supply chain digitalization and firm performance. *Business and Management Journal*, 45(5): 78–98.

Porter, M. E. 1998. *Competitive strategy: Techniques for analyzing industries and competitors*. New York: Free Press.

Ren, T., & Wang, Y. 2019. Product similarity and market competition. *China Industrial Economics*, 4: 95–112.

Wang, Y., & Dong, W. 2020. How the rise of robots has affected China's labor market. *Economic Research Journal*, 55(10): 159–175.

Wei, Z., & Zhu, C. 2019. Excess goodwill and product market competitiveness. *China Industrial Economics*, 11: 174–192.

Wu, Q., & Yao, Y. 2023. Firm digital transformation and supply chain configuration. *China Industrial Economics*, 8: 99–117.

Xu, H., & Ni, X. 2024. The spillover effect of brand rating on peer firms' product strategy. Working paper.
Yan, X., Yu, S., & Zheng, X. 2025. Is government subsidy efficient? Evidence from SMEs' automation in China. China Economic Review, 102566.
Yang, Y., & Tang, M. 2025. Digital economy, executive risk preference, and intelligent transformation. *International Review of Economics & Finance*, 102: 104389.
Yu, M., He, M., & Zhang, M. 2024. Talent introduction policies and manufacturing intelligence. *China Industrial Economics*, 5: 116–134.
Zhang, F., Liu, X., Wu, L., & Yin, X. 2019. Product innovation or service transition? *China Industrial Economics*, 7: 101–118.
Miura T. A Complete Guide to Strategies for Mitigating Price Competition: The Co-opetition Approach[J]. Available at SSRN 5371718, 2025.
Chen X, Chen F, Liu X, et al. The impact of industrial robot uses on the labor cost stickiness of Chinese firms[J]. Journal of Accounting Literature, 2026, 48(2): 472-507.
Kulatilaka N. Financial, economic and strategic issues concerning the decision to invest in advanced automation[J]. THE INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH, 1984, 22(6): 949-968.
Acemoglu D. When does labor scarcity encourage innovation?[J]. Journal of Political Economy, 2010, 118(6): 1037-1078.
Sachs J D, Benzell S G, LaGarda G. Robots: Curse or blessing? A basic framework[R]. National Bureau of Economic Research, 2015.
Xiang J, Kong D, Zhang F. Labor cost, robots, and product quality[J]. China Economic Review, 2025, 90: 102373.
Puttero S, Verna E, Genta G, et al. Collaborative robots for quality control: an overview of recent studies and emerging trends[J]. Journal of Intelligent Manufacturing, 2025: 1-37.
Rüßmann M, Lorenz M, Gerbert P, et al. Industry 4.0: The future of productivity and growth in manufacturing industries[J]. Boston consulting group, 2015, 9(1): 54-89.
Chopra S, Sodhi M S. Supply-chain breakdown[J]. MIT Sloan management review, 2004, 46(1): 53-61.
Wu F, Yeniyurt S, Kim D, et al. The impact of information technology on supply chain capabilities and firm performance: A resource-based view[J]. Industrial Marketing Management, 2006, 35(4): 493-504.
Acemoglu, D., & Autor, D. H. 2011. Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics*, 4(4): 1043–1171.
Acemoglu, D., & Restrepo, P. 2017. Robots and jobs: Evidence from U.S. labor markets. *NBER Working Paper* No. 23285.
Acemoglu, D., & Restrepo, P. 2020. Robots and jobs: Evidence from U.S. labor markets. *Journal of Political Economy*, 128(6): 2188–2244.
Acemoglu, D. 2010. When does labor scarcity encourage innovation? Journal of Political Economy*, 118(6): 1037-1078.*
Aghion, P., Antonin, C., & Bunel, S. 2019. Artificial intelligence, growth and employment: The role of policy. *Économie et Statistique / Economics and Statistics*, 1: 1–26.
Allub, L., Erosa, A., & Mei, Y. 2024. Financial frictions, firm dynamics, and capital-skill complementarities. *Review of Economic Dynamics*, 49: 1–28.

Autor, D. H., & Dorn, D. 2013. The growth of low-skill service jobs and the polarization of the U.S. labor market. *American Economic Review*, 103(5): 1553–1597.

Babar, M., & Habib, A. 2021. Product market competition in accounting, finance, and corporate governance: A review of the literature. *International Review of Financial Analysis*, 73: 101607.

Bena, J., & Simintzi, E. 2025. Machines could not compete with Chinese labor: Evidence from U.S. firms' innovation. *Review of Finance*, 29(6): 1619–1661.

Bertrand, M., & Mullainathan, S. 2003. Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy*, 111(5): 1043–1075.

Brynjolfsson, E., & McAfee, A. 2014. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. New York: Norton.

Bartik, T. J. 1991. Who benefits from state and local economic development policies?.

Chen, Y., Liu, Z., & Wang, Y. 2017. Patent quality and firm innovation. *China Economic Review*, 46: 1–15.

Cheng, H., Jia, R., Li, D., & Li, H. 2019. The rise of robots in China. Journal of Economic Perspectives, 33(2), 71-88.

Chen, X., Chen, F., Liu, X., et al. 2026. The impact of industrial robot uses on the labor cost stickiness of Chinese firms. Journal of Accounting Literature*,, 48(2): 472-507.*

Chopra, S,. Sodhi, M, S. 2004. Supply-chain breakdown. MIT Sloan management review*, 46(1): 53-61.*

Clarkson, P. M., Kao, J. L., & Richardson, G. D. 1994. The voluntary inclusion of forecasts in the MD&A section of annual reports. *Contemporary Accounting Research*, 11(1): 423–450.

Feng, G., & Wang, J. 2020. Corporate social networks and innovation: Evidence from China. *Journal of Mathematical Finance*, 10(4): 529–548.

Frey, C. B., & Osborne, M. A. 2017. The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114: 254–280.

Fang, L. H., Lerner, J., & Wu, C. 2017. Intellectual property rights protection, ownership, and innovation: Evidence from China. *The review of financial studies*, 30(7), 2446-2477.

Giroud, X., & Mueller, H. M. 2011. Corporate governance, product market competition, and equity prices. *Journal of Finance*, 66(2): 563–600.

Graetz, G., & Michaels, G. 2018. Robots at work. *Review of Economics and Statistics*, 100(5): 753–768.

Giuntella, O., Lu, Y., & Wang, T. 2025. How do workers adjust to robots? Evidence from China. *The Economic Journal*, 135(666), 637-652.

Hoberg, G., & Phillips, G. M. 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5): 1423–1465.

Hotelling, H. 1929. Stability in competition. *Economic Journal*, 39(153): 41–57.

Hsieh, C.-T., & Klenow, P. J. 2009. Misallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics*, 124(4): 1403–1448.

Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. *International journal of production research*, 58(10), 2904-2915.

Kastalli, I. V., & Van Looy, B. (2013). Servitization: Disentangling the impact of service business model innovation on manufacturing firm performance. *Journal of operations management*, 31(4), 169-180.

Kulatilaka, N. 1984. Financial, economic and strategic issues concerning the decision to invest in advanced automation. *THE INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH*, 22(6): 949-968.

Li, L., Wang, X., & Bao, Q. 2021. The employment effect of robots: Mechanism and evidence from China. *Management World*, 37(9): 104–119.

Liu, H., Hu, H., Zhang, S., & Sun, L. 2023. Supply chain digitalization and firm performance. *Business and Management Journal*, 45(5): 78–98.

Loncan, T. 2023. Product market competition and FDI decisions. *Journal of Financial and Quantitative Analysis*, 58(6), 2617-2656.

Lu, Y., Tao, Z., & Zhu, L. 2017. Identifying FDI spillovers. *Journal of International Economics*, 107, 75-90.

Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience: learning from Covid-19. *The international journal of logistics management*, 33(4), 1246-1268.

Miura T. A Complete Guide to Strategies for Mitigating Price Competition: The Co-opetition Approach[J]. Available at SSRN 5371718, 2025.

Porter, M. E. 1998. *Competitive strategy: Techniques for analyzing industries and competitors*. New York: Free Press.

Puttero, S., Verna, E., Genta, G., et al. 2025. Collaborative robots for quality control: an overview of recent studies and emerging trends. Journal of Intelligent Manufacturing, *1-37.*

Rüßmann, M., Lorenz, M., Gerbert, P., et al. 2015. Industry 4.0: The future of productivity and growth in manufacturing industries. Boston consulting group*, 9(1): 54-89.*

Sachs, J, D., Benzell, S, G., LaGarda, G. 2015. Robots: Curse or blessing? A basic framework. National Bureau of Economic Research*, 2015.*

Wu, F., Yeniyurt, S., Kim, D., et al. 2006. The impact of information technology on supply chain capabilities and firm performance: A resource-based view. Industrial Marketing Management*, 35(4): 493-504*

Xu, H., Ni, X. 2024. The spillover effect of brand rating on peer firms' product strategy. Working paper.

Xiang, J., Kong, D., Zhang, F. 2025. Labor cost, robots, and product quality. China Economic Review*, 2025, 90: 102373.*

Yang, Y., & Tang, M. 2025. Digital economy, executive risk preference, and intelligent transformation. *International Review of Economics & Finance*, 102: 104389.

Yu, M., He, M., & Zhang, M. 2024. Talent introduction policies and manufacturing intelligence. *China Industrial Economics*, 5: 116–134.

Zhang, F., Liu, X., Wu, L., & Yin, X. 2019. Product innovation or service transition? *China Industrial Economics*, 7: 101–118.

Appendix A. Variable Definitions

Variable	Definition
Robot	The firm-level exposure to robots, measured as the interaction term between industry-level exposure to robots and the firm's baseline production worker weight.
PMC	The average cosine similarity of product description texts between the firm and its peers in the same segmented market, constructed via clustering analysis
Size	The natural logarithm of firm's total assets
ROA	The ratio of the firm's annual net profit to total year-end assets
Lev	The ratio of firm's book value of liabilities to total assets
PPE	The ratio of firm's net book value of property, plant and equipment to total assets.
Invest	The ratio of the firm's annual net capital expenditure to total assets.
HHI	Herfindahl-Hirschman Index. The sum of the squares of each firm's operating revenue share in the corresponding manufacturing sub-industry
LnIntelligence	The natural logarithm of one plus industrial intelligence-related investments, which are identified from financial statements of construction-in-progress and R&D outlays.
Ipatnum	The natural logarithm of 1 plus the number of the firm's granted invention patents in the year
Growth	The year-on-year growth rate of the firm's annual operating revenue
WW index	The financing constraints index constructed following the classic formula of Whited & Wu (2006).
supply chain stability	The Herfindahl-Hirschman Index of the procurement share of the firm's top 5 suppliers.

Appendix B Identification and construction of robot adoption variable

Table 1 Keywords about industrial intelligence

Dimension	Keywords
production application	robots; robotic arms; manipulators; palletizers; human–machine collaboration; CNC machine tools; production lines; fully automated; automation; automatic control; automatic inspection; automatic monitoring; automated production; automated lines; automated assembly lines; automated production lines; automated flow lines; intelligent logistics; intelligent production lines; smart workshops; digital workshops; unmanned factories; smart factories; intelligent automation; intelligent informatization; intelligent manufacturing; cloud manufacturing; smart manufacturing; flexible manufacturing;
technical application	artificial intelligence; intelligent control; intelligent sensing; machine vision; machine learning; deep learning; neural networks; image understanding; human–machine interaction; autonomous programming; digital twins; simulation verification; face recognition; speech recognition; identity verification; autonomous driving; natural language processing; AI; CNC; Internet of Things; Internet; Ethernet.

Corresponding Chinese keywords

Dimension	Keywords
生产应用	机器人、机械臂、机械手、码垛机、人机协作、数控机床、生产线、自动、智能物流、智能产线、智能车间、数字化车间、无人工厂、智能工厂、智能自动化、智能信息化、智能制造、云制造、智慧制造、柔性制造
技术条件	人工智能、智能控制、智能感知、机器视觉、机器学习、深度学习、神经网络、图像理解、人机交互、自主编程、数字孪生、仿真验证、人脸识别、语音识别、身份验证、自动驾驶、自然语言处理、AI、数控、物联网、互联网、以太网

Taking Guangdong PaiSheng Intelligent Technology Co., Ltd. (300176.SZ) as an example, Table 2 presents the construction-in-progress projects disclosed in it's 2019 annual report. We use keyword matching to identify industrial intelligence–related projects, specifically those marked in bold, and take the amounts transferred to fixed assets for these projects as our firm-level measure of industrial intelligence adoption intensity.

Table 2 2019 Annual Report - Construction in Progress Projects from GuangDong PaiSheng Intelligent Technology Co.,Ltd.（300176.SZ）

Project Name (项目名称)	Beginning Balance (期初余额)	Additions During Period (本期增加金额)	**Amount Transferred to Fixed Assets During Period (本期转入固定资产金额)**
Vertical machining center (立式加工中心机)	34,139,464	1,771,309	30,484,322
Ube 1650T die-casting machine (宇部1650T压铸机)	15,764,537	3,416,595	19,181,132
UMC-HT20170708-1UB2500IV cold-chamber die-casting machine with	10,069,571		**10,069,571**

automatic molten-metal feeding device (1 unit (UMC-HT20170708-1UB2500IV 冷室压铸机及自动给汤装置 1 台)			
JMC machining and automation line (江铃机加自动线)	5,170,940		
Yizumi horizontal cold-chamber die-casting machine DM2000H (伊之密卧式冷室压铸机 DM2000H)	3,837,607		3,837,607
Machining workshop (机加厂房二期工程)	3,394,957	6,371,659	
1650T robot integration system (1650T 机器人集成系统含手爪)	2,372,200		**2,372,200**
1650T robot integration system (1650T 机器人集成系统不含手爪)	2,031,400		**2,031,400**
HYJC20180213-(01-04) CNC lathes (HYJC20180213-（01-04）数控车床 4 台)	1,804,301		**1,804,301**
Peripheral robotic intelligent equipment and systems for die-casting machines (压铸机周边机器人智能设备及系统)	1,444,444		
Mesh-belt shot-blasting cleaning machine (网带式抛丸清理机)	780,000		666,667
Guangzhou Yuchang bus-duct trough and railing installation project (广州裕昌母线槽桥架及护栏安装工程)	678,784		678,784
ZHT-ND20181010 gas-fired aluminum-alloy solution-aging T7 heat-treatment production line (ZHT-ND20181010 燃气铝合金固溶时效 T7 热处理生产线 1 套)		2,876,130	
Urban Beauty 1903 & 1904 (都市丽人 1903、1904)		5,034,386	
Donghan Intelligent GFCS11 automation line installation (东焊智能 GFCS11 自动线安装)		3,060,345	
Dafeng Ritter recast sand-core equipment (大丰瑞泰尔重铸砂芯设备)		1,860,00	
Yizumi 4400T robot integration system (伊之密 4400 吨机器人集成系统)		1,275,862	
GLOBALS12.22.10-Green model coordinate measuring machine (GLOBALS12.22.10-Green 型三坐标测量机)		1,044,248	
Peripheral equipment for die-casting machines (压铸机周边设备)		1,024,138	

Appendix C Product innovation mechanism

The empirical results support the product innovation mechanism. The result in Column (1) demonstrates that by increasing exposure to robots (i.e., enhancing their intelligence level), firms can significantly raise their product innovation level. Furthermore, we divide sample into two parts based on the yearly median product market competition that firms faced, the results are shown in Column (2)-(3), we find that when firms facing high level of PMC, their robots adoption will lead to more product innovation. Specifically, when firms face more intense external competition, they are more inclined to increase the adoption of robots to enhance their innovation capability, thereby improving their core competitiveness.

Table 1 product innovation

	Full Sample	Sub Sample-Low PMC	Sub Sample-High PMC
	(1)	(2)	(3)
	Ipatnum	Ipatnum	Ipatnum
Robot	**0.0018****	**0.0010**	**0.0034*****
	(0.0008)	**(0.0012)**	**(0.0013)**
Controls	Yes	Yes	Yes
_cons	-0.1393	-7.7310	-1.0196
	(3.6866)	(6.3970)	(3.9090)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Robot _diff	-	-0.0024*	
p-value	-	0.085	
N	8390	4077	4032
Adjusted R^2	0.479	0.473	0.503

This table examines the product innovation mechanism. The dependent variable is the natural logarithm of one plus number of invention patents (*Ipatnum*). *Robot* measures industrial robot adoption, which is a Bartik-style measure (Bartik, 1991) to capture firm-level exposure to robots using data from IFR. PMC is product market competition. Column (1) uses the full sample to test the relationship between the Product innovation and PMC. In column (2) and (3), observations are classified into High or Low groups according to the year median level of PMC. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix D Product market share

The empirical results support the product market share mechanism. The results in Column (1) show that firms can significantly expand their product market share by increasing exposure to robots. Furthermore, we divide sample into two parts based on the yearly median product market competition that firms faced, the results are shown in Column (2)-(3), we find that when firms facing high level of PMC, their robots adoption will lead to more product

market share. Specifically, when firms face more intense external competition, they are more inclined to increase the adoption of robots to expand their market share, thereby enhancing their core competitiveness to cope with such external competitive pressure.

Table 1 product market sale growth

	Full Sample	Sub Sample- Low PMC	Sub Sample- High PMC
	(1)	(2)	(3)
	Growth	Growth	Growth
Robot	0.0010***	0.0006	0.0011**
	(0.0004)	(0.0006)	(0.0005)
Controls	Yes	Yes	Yes
_cons	-4.1872***	-3.3014***	-4.5201***
	(0.4813)	(0.7554)	(0.7231)
Firm FE	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes
Robot _diff	-	-0.0005*	
p-value	-	[0.09]	
N	9755	4717	4729
Adjusted R^2	0.191	0.206	0.225

This table examines the product market share channel. The dependent variable is the growth rate of firm market share measured as firm sales divided by total industry sales. *Robot* measures industrial robot adoption, which is a Bartik-style measure (Bartik, 1991) to capture firm-level exposure to robots using data from IFR. PMC is product market competition. Column (1) uses the full sample to test the relationship between the product market share and PMC. In column (2) and (3), observations are classified into High or Low groups according to the year median level of PMC. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.