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INDUSTRIAL ROBOT ADOPTION AND CORPORATE FINANCIAL RESTATEMENTS: EVIDENCE FROM CHINA

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Annotation. As a core technology driving the digital transformation of manufacturing, industrial robots have attracted growing scholarly interest in terms of their economic consequences within corporate governance research. However, existing literature offers limited systematic theoretical insight into how the adoption of industrial robots influences corporate financial restatements. To explore the relationship between industrial robot adoption and corporate financial restatements, drawing on information asymmetry and managerial myopia theories and using a sample of Chinese A-share manufacturing listed firms from 2010 to 2022, the impact mechanism of industrial robot adoption on corporate financial restatements is analyzed. Results reveal that: industrial robot adoption significantly reduces the likelihood of financial restatements, a result that remains robust under a series of sensitivity tests; (2) the reduction is primarily achieved through enhanced information quality and improved internal governance, whereas the risk-taking channel exhibits a masking effect; and (3) the restraining effect of robot adoption on financial restatements is more pronounced in non-state-owned enterprises, firms in more competitive industries, labor-intensive firms, and those facing more pessimistic analyst forecasts. The conclusions extend the theoretical boundaries of research on the economic consequences of industrial robots and offer valuable insights for policymakers seeking to advance smart manufacturing and improve the information environment of capital markets.

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Keywords: industrial robot adoption, financial restatements, information quality, internal governance, risk-taking.

JEL classification: M41, G34, O33.

Introduction

In recent years, with continuous breakthroughs in core robotic technologies and a sustained rise in labor costs, industrial robots have undergone rapid development and widespread adoption in the production sector (Arents and Greitans, 2022). Intelligent manufacturing is gradually becoming a significant engine driving global economic growth. According to data from the International Federation of Robotics (IFR), the total number of operational industrial robots worldwide had reached 4.282 million units by the end of 2023, marking a 10% year-on-year increase. Meanwhile, the number of newly installed robots in 2023 exceeded 500,000 units for the third consecutive year, highlighting a sustained demand for automation and intelligent production within global manufacturing. Industrial robots have become a key indicator for evaluating national levels of industrialization and informatization (Duan *et al*., 2023). As a core equipment of intelligent manufacturing and a vital vehicle of advanced technologies, industrial robots are fundamentally reshaping traditional production models. They are driving the industry's transition toward flexible and intelligent systems. Their widespread adoption is expected to enhance production efficiency, improve resource allocation, and accelerate the global manufacturing industry's shift toward high-quality development.

The increasing deployment of industrial robots has attracted considerable attention from researchers, particularly for its impact on the economic contribution of micro-enterprises, which has become a prominent research topic. Existing studies primarily examine their implications for labor market, export competitiveness, innovation capacity, and productivity. First, from the labor perspective, the automation driven by industrial robots is transforming the labor landscape, shifting employment from low-skilled positions toward more cognitive roles, (Acemoglu *et al*., 2022; Bessen, 2019; Bonfiglioli *et al*., 2024; Wang *et al*., 2024), significantly affecting firm-level employment structures (Acemoglu *et al*., 2020; Dixon *et al*., 2021). Second, regarding export competitiveness, several studies have indicated that industrial robots positively affect corporate exports by enhancing the quality and complexity of exported products, strengthening firms' competitive position in international markets (Alguacil *et al*., 2022; Hong *et al*., 2022; Zhang *et al*., 2023; Zhang *et al*., 2025). Third, with respect to firms' innovation, evidence shows that industrial robots can significantly foster firms' innovation activities by easing financial constraints, optimizing the human capital structure, and supporting greater R&D investment (Luo and Qiao, 2023; Wang *et al*., 2023; Zhong *et al*., 2023). Finally, for the productivity perspective, industrial robots drive growth by boosting production efficiency and optimizing resource allocation (Ballestar *et al*., 2020; Duan *et al*., 2023; Koch *et al*., 2021; Li *et al*., 2024). Nevertheless, some scholars point to a "productivity paradox," suggesting that in firms where tasks are less easily automated, further investment in industrial robots may bring diminishing returns or even reduce actual productivity (Zhang *et al*., 2024). In summary, existing research on micro-enterprises primarily focuses on how industrial robots affect labor structures, exports, innovation capabilities, and productivity. By contrast, the financial dimension remains underexplored, with relatively few studies investigating how robot adoption influences financial restatements and the mechanisms underlying this relationship. This study, therefore, investigates whether industrial robots can reduce the probability of financial restatements, providing a theoretical basis for assessing their economic effects on financial risk.

Financial restatements are corrections of prior accounting errors, indicating that earlier reports contained misstatements significant enough to affect users' judgments, reducing the reliability of accounting information.

Numerous factors influence the occurrence of financial restatements. From the external perspective, factors such as investor sentiment (Bouteska, 2019), corporate reputation (Cao *et al*., 2012), external auditing (Al-Hadi *et al*., 2023; Lobo and Zhao, 2013), and regulatory enforcement by securities authorities (Kedia and Rajgopal, 2011) have been demonstrated to play a role. From an internal perspective, executive backgrounds (Gao *et al*., 2024; Kuang *et al*., 2022), board characteristics (Das *et a*l., 2022), audit committee effectiveness (Oradi and Izadi, 2020), and employee turnover (Guo *et al*., 2016) have also been shown to shape the financial restatements. However, much of the existing literature concentrates on governance-related attributes, with relatively little attention to the applications of digital technologies, such as the adoption of industrial robots. As digital technology continues to evolve, industrial robots have become increasingly important in enhancing corporate information disclosure and mitigating financial risk. Nonetheless, their potential to reduce financial restatements remains underexplored. This study introduces information asymmetry and managerial myopia theories to analyze how the adoption of industrial robots may affect firms' misstatement and restatement risk, offering a theoretical foundation for the analysis. Within this framework, we address two specific research questions: (1) Does the industrial robot adoption significantly reduce the probability of financial restatements? (2) If so, through which mechanisms does this effect operate?

This study utilizes a sample of Chinese manufacturing enterprises to examine whether the adoption of industrial robots reduces financial restatements, primarily based on the following reasons. Firstly, according to data from the IFR, China has for several consecutive years retained its position as the leading global hub for industrial robotics, with both installation density and the scale of adoption steadily expanding. The "World Robot Report" indicates that there were 541,302 new installations of industrial robots globally in 2023. Among these, with 276,288 units installed, China contributed 51% of worldwide industrial robot installations, a figure more than triple that of the United States, Japan, South Korea, and Germany combined. By the end of the same year, China was estimated to have around 1.75 million industrial robots in operation, representing more than 40% of the world's total and securing the leading position globally. The accelerated expansion of robot utilization in Chinese manufacturing firms offers a valuable empirical setting for examining its impact on corporate financial behavior. Secondly, financial restatements have become increasingly frequent in China's stock market and appear to be misused (Niu and Jia, 2022). Some listed firms deliberately conceal or embellish their reports, leading to heightened financial risk. Multiple factors shape this phenomenon, including the regulation of information disclosure, the level of corporate governance, and managerial incentive structures (Hass *et al*., 2016; Huang *et al*., 2011). Against this backdrop, examining the effect of industrial robot adoption on financial restatements can shed light on its potential role in improving the quality of financial reporting.

This study offers three main contributions. First, it breaks new ground by examining the governance implications of industrial robot adoption through the lens of financial restatements, extending the literature on the economic consequences of robotics to the domain of financial reporting quality. While prior research has extensively documented the effects of robots on labor markets, firm innovation, and productivity, their connection to corporate financial risk remains underexplored. Our findings address this gap by demonstrating how robotic adoption reduces financial restatement, contributing novel insights to the intersection of corporate governance and digital transformation. Second, this study extends the literature on the determinants of financial restatements by introducing the perspective of industrial robot adoption. Prior research has predominantly emphasized internal and external governance factors, while largely neglecting the role of digital technologies, particularly the influence of industrial robots on financial reporting quality. Our work thus offers a novel viewpoint on the drivers of restatements and delivers practical implications for improving corporate financial reporting. Ultimately, this study establishes a theoretical framework to elucidate the connection between the adoption of industrial robots and financial restatements. The analysis is conducted through three potential channels: information quality, internal governance, and risk-taking. This deepens our understanding of how the two are connected and helps to open the "black box" behind their relationship. In addition, it examines heterogeneity across ownership type, industry competition, factor intensity, and analyst forecasts, further clarifying how the adoption of industrial robots affects financial reporting quality under various conditions. These insights provide policymakers and corporate managers with targeted evidence for improving financial information quality and mitigating financial risks.

The remainder of this paper is organized as follows. Section 1 introduces the theoretical background and hypothesis. Section 2 explains the research design. Section 3 reports the empirical results. Section 4 extends the analysis with heterogeneity tests, and Section 5 offers an in-depth discussion and interpretation of the results. The paper concludes by summarizing the main findings and highlighting the primary implications.

1. Theoretical Analysis and Hypothesis Development

According to information asymmetry theory, when external investors and corporate managers face unequal access to information, managers may exploit their informational advantage to engage in earnings management or accounting manipulation. Such practices, combined with estimation errors or misjudgments, can increase the probability of financial restatements (Dechow *et al*., 1996; Healy and Palepu, 2001). Managerial myopia theory further suggests that under pressure to deliver short-term performance or driven by personal incentives, managers often adopt practices that undermine long-term value, including earnings management and accounting manipulation. Meanwhile, weakening internal governance and control mechanisms heightens the risk of restatements (Bushee, 1998; Stein, 1989). Prior studies have demonstrated that enhanced information transparency and stronger governance structures can effectively mitigate information asymmetry and short-sighted managerial behavior, reducing the probability of errors in financial reporting (Doyle *et al*., 2007; Ndofor *et al*., 2015; Wang *et al*., 2025). Building on this, as digital transformation advances, digital technologies are regarded as a key driver for improving the quality of financial information and enhancing managerial efficiency (Liu and Liu, 2023). Related studies show that digital technologies have reshaped firms' information disclosure systems (Salijeni *et al*., 2021; Valentinetti and Flores Muñoz, 2021). This transformation promotes the standardization and automation of financial reporting and enhances the transparency and reliability of data (Perdana *et al*., 2023; Johri, 2025). In addition, by improving governance and the information environment, digital technologies enhance stakeholders' access to timely and accurate information (Seele, 2016), enhancing the overall informational efficiency of capital markets (Chen *et al*., 2022; Sun and Du, 2024). Against this backdrop, as a central component of intelligent manufacturing and a key carrier of digital technologies, the proliferation of industrial robots may exert a profound impact on corporate financial restatements.

On the one hand, the adoption of industrial robots can enhance the quality of corporate information, providing a solid informational foundation for reducing the probability of financial restatements. Owing to their high degree of automation and precise control (Arents and Greitans, 2022; Pramod, 2021), industrial robots enable real-time data collection, recording, and transmission in production, logistics, and inventory processes. This automation significantly improves the accuracy of data acquisition and lowers the risk of financial data distortion at its source (Wu and Liu, 2024). Moreover, through continuous monitoring and dynamic updating of financial information (Hu *et al*., 2024; Wang *et al*., 2023), industrial robots enable managers to detect potential irregularities at an early stage and mitigate distortions caused by delayed information. The data generated by robots is also highly traceable, which strengthens financial transparency and reduces the risk of misstatements arising from bias, omission, or manipulation. As a result, firms' financial reports are better able to reflect their actual operating conditions, lowering the probability of restatements. This mechanism is consistent with the information asymmetry theory, which posits that industrial robots enhance the information environment and help mitigate the risk of financial restatements.

On the other hand, industrial robots can help to curb managerial short-termism by improving firms' internal governance, offering an institutional barrier to financial restatements. Their adoption in business process automation enhances the standardization and transparency of production and operations, strengthening the internal control systems (Ashraf, 2025). Prior studies further suggest that the deployment of robots enhances overall governance efficiency within organizations by reducing process discrepancies and increasing the precision of performance assessment (Dixon *et al*., 2021). At the individual level, the adoption of industrial robots can also reduce managers' incentives for short-term earnings manipulation by optimizing compensation contracts and creating favorable conditions for effective governance. Supporting this, Teng *et al*. (2024) documented that robots mitigate managers' motivation for real earnings management by boosting product market performance and strengthening the incentive power of executive pay. In this way, by enhancing the internal governance environment, industrial robots help restrain managerial opportunism and short-termistic behavior. This outcome aligns with the managerial myopia theory, ultimately reducing the probability of financial restatements resulting from deficiencies in internal controls.

Additionally, industrial robots may reduce the probability of financial restatements by enhancing firms' risk-taking capacity. Risk management theory suggests that when a company's ability to bear risks is insufficient, it is more likely to resort to opportunistic accounting adjustments to cushion against external shocks, increasing restatement risk (Miller, 1992). Prior studies also show that firms with insufficient risk-taking capacity tend to respond more slowly to external shocks and exhibit weaker adaptive and risk management capabilities (Hunjra *et al*., 2024; Tsai and Luan, 2016). The adoption of industrial robots offers a viable approach to mitigating this issue. First, it elevates the level of intelligent management within firms (Hilb, 2020; Lopez-de-Ipina *et al*., 2023), strengthens their capacity to perceive and forecast changes in the operating environment (Zhou *et al*., 2024), and enables them to identify potential risks more accurately and take timely countermeasures. Second, robots enhance production flexibility, enabling enterprises to rapidly reallocate resources in response to market uncertainties, which in turn bolsters their adaptability and resilience (Liu *et al*., 2025; Pu *et al*., 2024). Consequently, as firms' capacity for risk-taking improves, the incentive for firms to make accounting adjustments for risk avoidance or coping with operational volatility weakens, leading to a corresponding reduction in the probability of financial restatements.

Based on the above analysis, this study proposes the following hypotheses:

H1: The adoption of industrial robots reduces the probability of corporate financial restatements.

H2: The adoption of industrial robots reduces the probability of financial restatements by improving information quality.

H3: The adoption of industrial robots reduces the probability of financial restatements by strengthening internal governance.

H4: The adoption of industrial robots reduces the probability of financial restatements by enhancing firms' risk-taking capacity.

2. Methodology

2.1 Sample Selection and Data Sources

Given the rapid rise in industrial robots adoption in China, particularly within the manufacturing sector since 2010, this study focuses on non-financial manufacturing firms listed on China's A-share market from 2010 to 2022. Based on this dataset, the following screening steps are applied. First, samples designated as Special Treatment (ST) or Particular Transfer (PT) is excluded. Second, samples with negative net assets are removed. Third, observations with missing values are eliminated. After implementing these procedures, 22,231 firm-year observations are retained for empirical analysis.

The data on financial restatements and other financial information for listed firms are obtained from the China Stock Market and Accounting Research (CSMAR) database. Industrial robot data are sourced from the IFR, which conducts annual surveys of global robot manufacturers and compiles a database of country-industry-year statistics covering worldwide industrial robot statistics. This database provides authoritative information on application areas, industry classifications, and robot types. In this study, the industrial robot data for listed manufacturing firms are derived by manually matching the two-digit industry codes of manufacturing enterprises with the IFR's industry classification system. The industry-level robot data are then allocated to the firm level through a distribution method, ensuring an accurate correspondence between firm-level information and robot usage. Additionally, all continuous variables in this study are winsorized at the 1st and 99th percentiles to mitigate the impact of extreme outliers.

2.2 Model Construction

To examine the effect of industrial robot adoption on corporate financial restatements, this study establishes the following baseline regression model:

$$Restate_{i,t} = \beta_0 + \beta_1 Robot_{i,t} + \sum Controls + \sum Industry + \sum Year + \varepsilon_{i,t} . \quad (1)$$

Based on the baseline model, we further developed a mediation model using Wen and Ye's (2014) method to assess the transmission effects of information quality, internal governance, and risk-taking. The specifications are as follows:

$$M_{i,t} = \alpha_0 + \alpha_1 Robot_{i,t} + \sum Controls + \sum Industry + \sum Year + \varepsilon_{i,t} . \quad (2)$$

$$Restate_{i,t} = \gamma_0 + \gamma_1 Robot_{i,t} + \gamma_2 M_{i,t} + \Sigma Controls + \Sigma Industry + \Sigma Year + \varepsilon_{i,t} . \quad (3)$$

2.2.1 Dependent Variables

The dependent variable, $Restate_{i,t}$, represents financial restatement. Following Ashraf (2025) and Naidu and Ranjeeni (2024), we defined it as a dummy variable. A value of 1 is assigned if a firm's annual report for the year contains misstatements that are corrected in a subsequent period, and 0 otherwise. This study focuses solely on restatements arising from substantive errors at the firm level, excluding those caused by revisions to Chinese Accounting Standards (CAS), uniform adjustments to accounting policies, or standardized disclosure formatting.

2.2.2 Independent Variables

The independent variable, $Robot_{i,t}$, measures the extent of industrial robot adoption. Based on the methodology of Acemoglu and Restrepo (2020), we constructed a firm-level industrial robot penetration ratio for Chinese listed manufacturing companies to measure the industrial robot adoption. The construction process is outlined as follows:

First, we matched the industry classifications of listed companies, defined by the China Securities Regulatory Commission (CSRC)'s *2012 Revised Guidelines for Industry Classification of Listed Companies*, with the corresponding categories from the IFR.

Second, we compute the industry-level robot penetration index as the ratio of the industrial robot stock in manufacturing industry *i* at time *t* to the industry's employment in the base year 2010.

Third, we derive the firm-level robot penetration index by adjusting the industry-level measure for each firm's employment composition. Specifically, the industry-level index is multiplied by the ratio of firm *j*'s (within industry *i*) share of production employees in 2011 to the median share across all listed manufacturing firms in that year. To address skewness, the natural logarithm of this value is taken, yielding the final measure of *Robot*.

$$Robot_{j,i,t} = \ln\left(\frac{AE_{j,i,t=2011}}{MAE_{t=2011}} \times \frac{IR_{it}^{China}}{L_{i,t=2010}^{China}}\right) \tag{4}$$

where IR_{it}^{China} is the stock of industrial robots in industry *i* for year *t* in China. $L_{i,t=2010}^{China}$ refers to the industry employment in the base year 2010 (in units of 10,000). The ratio $\frac{IR_{it}^{China}}{L_{i,t=2010}^{China}}$ yields the industry-level robot penetration rate for industry *i* in year *t*. $AE_{j,i,t=2011}$ is the proportion of production employees in firm *j* of industry *i* in 2011. $MAE_{t=2011}$ corresponds to the median share of production workers among all listed manufacturing firms in that year. The resulting index captures the extent of intelligent transformation in manufacturing firms driven by technological change. Note that a higher value indicates greater adoption of industrial robots and a more advanced level of intelligent manufacturing within the firm.

2.2.3 Mediating Variables

$M_{i,t}$ denotes the mediating variables, which are assessed from three perspectives: information quality, internal governance, and corporate risk-taking. First, for information quality, we employed the degree of accrual-based earnings management as an inverse proxy (Chaney *et a*l., 2011). Specifically, following the model of Dechow and Dichev (2002), we utilized the absolute value of the estimated residuals (*DA*) as the specific measure (Chen *et al*., 2022; Elaoud and Jarboui, 2017). A higher value indicates a higher level of earnings management and, correspondingly, lower information quality. Second, for internal governance, a firm's governance level is typically embodied in the effectiveness of its internal control mechanisms. Consistent with prior studies, we used the natural logarithm of the DIB Internal Control Index (*IC*), where higher values signify stronger internal control and governance. Finally, in line with Faccio *et al*. (2011), we capture firms' risk-taking capacity, reflecting their ability to withstand external uncertainty, by measuring the five-year standard deviation of return on assets (*Volatility*). Higher values of this indicator indicate greater operating volatility and, consequently, a higher risk-taking capacity.

2.2.4 Control Variables

Following Gafni *et al*. (2024), we incorporated the following control variables to mitigate the potential impact on financial restatements: firm size (*Size*), leverage ratio (*Lev*), profitability (*Roa*), gross profit margin (*Gropr*), cash flow ratio (*Cash*), firm growth capability (*Grow*), firm's listing age (*Age*), board size (*Board*), institutional investor shareholding ratio (*Inst*), auditor size (*Big4*), audit opinion (*Audop*), as well as industry and year fixed effects. The specific definitions of each variable are presented in *Table 1* below.

Table 1. Variable Definition

Variable	Symbol	Definition
Financial Restatement	*Restate*	Dummy variable, coded as 1 if the firm-year is subsequently identified as a misstatement year in a restatement announcement, and 0 otherwise. 、Restatements triggered by accounting standard updates, policy unification, or formatting requirements are excluded.
Industrial Robot Adoption	*Robot*	Measured as the firm-level industrial robot penetration index calculated according to Equation (4).
Information Quality	*DA*	Measured as the absolute magnitude of residuals obtained using the Dechow and Dichev (DD) accrual quality model.
Internal Governance	*IC*	Natural logarithm of the DIB Internal Control Index.
Risk-Taking	*Volatility*	Measured as the standard deviation of the firm's annual return on assets over the preceding five-year period.
Firm Size	*Size*	Natural logarithm of the total assets at fiscal year-end.
Leverage	*Lev*	Total liabilities divided by total assets at fiscal year-end.
Profitability	*Roa*	Net profit divided by the average total assets.
Gross Profit Margin	*Gropr*	Gross profit divided by operating revenue
Cash Flow Ratio	*Cash*	Net operating cash flow divided by total assets at fiscal year-end
Sales Growth	*Grow*	Growth rate of annual sales, calculated as ($Sales_t$ – $Sales_{t-1}$) / $Sales_{t-1}$.
Firm's Listing Age	*Age*	Natural logarithm of one plus the number of years since the firm's IPO
Board Size	*Board*	Natural logarithm of the number of board directors
Institutional Investor Shareholding Ratio	*Inst*	Ratio of institutional shareholdings to total outstanding shares.
Audit Firm Size	*Big4*	Dummy variable, coded as 1 if the firm is audited by a Big 4 auditor, and 0 otherwise.
Audit Opinion	*Audop*	Dummy variable, coded as 1 if the firm's financial statements receive an unqualified audit opinion, and 0 otherwise

Source: authors' own results.

3. Results Analysis

3.1 Descriptive Statistics

Table 2 reports the descriptive statistics. Financial restatements (*Restate*) have an average of 0.126, with a SD of 0.331, indicating a relatively low but dispersed incidence among sample firms. Industrial robot adoption (*Robot*) averages 0.188, and SD is 0.066, reflecting a modest current utilization of industrial robots and significant potential for broader adoption. Information quality (*DA*) averages 0.080, with a SD of 0.094, implying low overall earnings management yet considerable variation. Internal governance (*IC*) averages 6.322 (SD = 1.001), reflecting relatively sound internal controls in most firms. Risk-taking (*Volatility*) exhibits a mean of 0.356 and a SD of 0.319, suggesting substantial cross-firm heterogeneity in earnings volatility.

For the control variables, firm size (*Size*) averages 22.07 and its median (21.92) are closely aligned, suggesting a roughly symmetric distribution. The average leverage ratio (*Lev*) is 0.399, reflecting a moderate debt level. Firm profitability (*Roa*) averages 0.044 with a SD of 0.064, implying substantial variation in firm profitability. The gross profit margin (*Gropr*) averages 0.283 higher than its median (0.249) (SD = 0.170), indicating a right-skewed distribution driven by a subset of high-margin firms. Sales growth (*Grow*) averages 0.168, corresponding to an average operating revenue growth of approximately 16.8% for the sample firms. Regarding audit characteristics, only 4.8% of the sample firms engaged a Big Four auditor (*Big4*), while 97.4% received a unqualified audit opinion (*Audop*). Note that other controls exhibit patterns consistent with those observed in prior studies.

Table 2. Descriptive Statistics

Variable	*N*	*Mean*	*SD*	*Min*	*p50*	*Max*
Restate	22231	0.126	0.332	0	0	1
Robot	22231	0.188	0.066	0	0.204	0.283
DA	22231	0.080	0.094	0.001	0.050	0.555
IC	22231	6.322	1.001	0	6.500	6.886
Volatility	22231	0.356	0.319	0.024	0.251	1.580
Size	22231	22.07	1.160	19.98	21.92	25.64
Lev	22231	0.399	0.191	0.055	0.393	0.863
Roa	22231	0.044	0.064	-0.198	0.041	0.227
Gropr	22231	0.283	0.170	0.005	0.249	0.824
Cash	22231	0.050	0.066	-0.132	0.047	0.241
Grow	22231	0.168	0.349	-0.464	0.114	2.068
Age	22231	2.099	0.764	0.693	2.197	3.332
Board	22231	2.112	0.189	1.609	2.197	2.565
Inst	22231	0.373	0.229	0	0.376	0.859
Big4	22231	0.048	0.215	0	0	1
Audop	22231	0.974	0.159	0	1	1

Source: authors' own results.

3.2 Baseline Regression Results

Table 3 reports the results on the impact of industrial robot adoption on corporate financial restatements. Column (1), without control variables, shows that the coefficient of industrial robot adoption (*Robot*) on financial restatements (*Restate*) is significantly negative (−0.1352) at the 5% level, providing preliminary evidence that industrial robot adoption reduces the probability of financial restatements. After controlling for firms' fundamental and financial characteristics, the *Robot* effect retains a negative sign with statistical significance in column (2). Furthermore, when corporate governance and audit firm attributes are further included, as reported in column (3), the coefficient of *Robot* continues to be negative and statistically significant (-0.0805). In terms of economic implication analysis, a one-unit increase in industrial robot adoption corresponds to an approximate 8.05% decline in the probability of a restatement. These stepwise regression results confirm a robust negative relationship between industrial robot adoption and the probability of financial restatements. In other words, industrial automation can reduce financial reporting errors and adjustments, improving the quality of firms' financial information. This finding supports *Hypothesis H1*.

Regarding control variables, *Lev*, *Gropr*, *Grow*, and *Age* are positively and significantly associated with financial restatements, indicating that firms with higher leverage, higher gross profit margins, faster growth rates, and longer listing age are more prone to experience financial restatements. Conversely, *Size*, *Roa*, and *Cash* demonstrate negative correlations, suggesting that larger firms, those with stronger profitability and more abundant cash flow face a lower probability of issuing restated financial statements. Additionally, *Inst* has a significantly negative coefficient implies that institutional investors, through their monitoring role, contribute to curbing reporting errors and reducing the risk of financial restatements. Similarly, *Big4* is significantly negatively correlated with financial restatements, highlighting that high-quality audit services provided by Big4 accounting firms can effectively lower the risk of financial restatements. Lastly, *Audop* also exhibits a significantly negative coefficient, indicating that firms with higher-quality financial reporting, as reflected in receiving favorable audit opinions, are less likely to experience financial restatements.

Table 3. Baseline Analysis Results

Variable	(1)	(2)	(3)
	Restate	***Restate***	***Restate***
Robot	-0.1352*** (-3.9538)	-0.0800** (-2.3762)	-0.0805** (-2.3981)
Size		-0.0109*** (-3.4264)	-0.0027 (-0.7617)
Lev		0.0982*** (4.7200)	0.0777*** (3.7852)
Roa		-0.4908*** (-8.4252)	-0.3839*** (-6.6834)
Gropr		0.0516** (2.0036)	0.0382 (1.5103)
Cash		-0.1508*** (-3.3996)	-0.1483*** (-3.3599)
Grow		0.0270*** (3.4667)	0.0267*** (3.4447)
Age		0.0103** (2.3217)	0.0098** (2.2138)
Board			-0.0185 (-1.1604)
Inst			-0.0383*** (-3.0116)
Big4			-0.0345*** (-2.7749)
Audop			-0.1810*** (-7.9149)
Constant	0.1513*** (20.9705)	0.3310*** (5.1187)	0.3883*** (5.0244)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	22,231	22,231	22,231
Adj-R^2	0.025	0.042	0.051

Note: T-statistics are reported in parentheses and are based on firm-level clustered robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: authors' own results.

3.3 Robustness Tests

3.3.1 Instrumental Variable Approach

To mitigate possible endogeneity issues stemming from unobserved variables or reverse causality, we estimated the model using an Instrumental Variables (IV) approach. Specifically, the average industrial robot penetration of other firms in the same industry and year is used as the instrument. This choice is motivated by the following considerations. First, the relevance condition is satisfied because firms operating within the same industry-year face similar technological conditions, product-market competition, and supply-chain pressures, which generate peer effects. Consequently, peers' robot adoption exerts competitive pressure and knowledge spillovers that influence whether the focal firm adopts the technology. Second, in terms of exogeneity, peers' average robot penetration affects the target firm's technology choice primarily through competitive and imitation channels that lead the firm toward adoption. There is no theoretical rationale to suggest that peers' adoption would directly determine whether the focal firm restates its financial reports. Note that any effect on the focal firm's financial restatement outcome should therefore be indirect, and operating only through the focal firm's robot adoption (*Robot*). Taken together, this supports the instrument's theoretical validity in terms of both relevance and exogeneity. Operationally, we defined peer robot penetration (*Pe_Robot*) as the leave-one-out mean of *Robot* among all other firms in the same industry and year. As reported in column (2) of Table 4, the coefficient of *Robot* remains significantly negative, indicating that industrial robot adoption significantly reduces the probability of financial restatements. Moreover, the LM statistic and F statistic of the IV tests reject both the null hypotheses of under-identification and weak identification, respectively. These results confirm that, after accounting for endogeneity, our baseline findings remain robust and reliable.

Table 4. Endogenous Treatment: 2SLS Regression

Variable	（1） First stage regressions	（2） Second stage regressions
	Robot	***Restate***
Pe_Robot	0.737*** (20.7093)	
Robot		-1.9550*** (-6.8214)
Constant	0.0550*** (4.7207)	0.6922*** (7.8811)
Kleibergen-Paap rk LM statistic		337.381
Cragg-Donald Wald F		437.460
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	22,231	22,231
Adj-R^2	0.033	0.045

Note: T-statistics are reported in parentheses and are based on firm-level clustered robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: authors' own results.

3.3.2 PSM Matching

Given potential systematic differences in robot adoption among listed manufacturing firms, companies may self-select into adoption according to firm-specific characteristics, a process that may generate selection effects and issues of endogeneity. To mitigate this, we applied a Propensity Score Matching (PSM) approach. For treatment assignment, firms are assigned to the treatment group if their level of industrial robot adoption is above the industry-year median. Propensity scores were estimated through a logit specification, where Robot_dummy functioned as the dependent outcome and the control variables from Equation (1) entered as independent covariates. Based on these scores, one-to-one nearest-neighbor matching produces a matched sample of 12,420 firm-year observations. Following the matching procedure, diagnostic tests confirm that most covariates achieve balance, as statistical differences between the treatment and control groups are negligible (*Table* 5). Consequently, we re-estimated the baseline specification on the matched sample. As reported in *Table* 6, industrial robot adoption remains negatively associated with financial restatements at the 1% significance level ($\hat{a}$ = -0.1532), consistent with the main results.

Table 5. Endogenous treatment: covariate balance test PSM

Variable	**Unmatched**	**Mean**		**t-test**	
	Matched	**Treated Control**		**t**	**p>|t|**
Size	U	22.07	22.08	-0.710	0.478
	M	22.07	22.07	0.0600	0.951
Lev	U	0.399	0.399	-0.170	0.861
	M	0.399	0.401	-0.760	0.445
Roa	U	0.0436	0.0439	-0.340	0.730
	M	0.0436	0.0437	-0.100	0.922
Gropr	U	0.283	0.283	-0.170	0.866
	M	0.283	0.285	-1.150	0.250
Cash	U	0.0501	0.0499	0.230	0.820
	M	0.0501	0.0504	-0.350	0.724
Grow	U	0.168	0.168	0.0700	0.946
	M	0.168	0.168	0.0200	0.980
Age	U	2.111	2.112	-0.240	0.814
	M	2.111	2.111	0.350	0.728
Board	U	2.104	2.093	1.150	0.249
	M	2.104	2.103	0.160	0.875
Inst	U	0.372	0.373	-0.550	0.582
	M	0.372	0.373	-0.280	0.781
Big4	U	0.0466	0.0501	-1.210	0.227
	M	0.0466	0.0471	-0.160	0.873
Audop	U	0.975	0.974	0.420	0.673
	M	0.975	0.975	-0.040	0.966

Note: T-statistics are reported in parentheses and are based on firm-level clustered robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: authors' own results.

Table 6. Endogenous treatment: PSM regression

Variable	*Restate*
Robot	-0.1532*** (-3.3333)
Constant	0.4069*** (4.2990)
Controls	Yes
Industry FE	Yes
Year FE	Yes
N	12,420
Adj-R^2	0.048

Note: T-statistics are reported in parentheses and are based on firm-level clustered robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: authors' own results.

3.3.3 Alternative Independent Variable

Following Du and Lin (2022) and Graetz and Michaels (2018), we replaced the measure of industrial robot adoption with robot installation density. Specifically, the robot installation density index at the provincial level in China is first constructed using data on robot stock from the IFR database. Correspondingly, this provincial-level robot installation density is converted into a firm-level measure by incorporating a labor scale factor. Subsequently, Model (1) is re-estimated using this alternative variable. As shown in column (1) of *Table* 7, *Robot* retains a negative and significant coefficient at the 5% level, providing consistent evidence supporting our central hypothesis.

3.3.4 Alternative Models

Given that the dependent variable, financial restatement, is binary, the Logit and Probit models provide a more appropriate analytical approach. *Table* 7 displays the regression estimates, with column (2) reporting the Logit model and column (3) presenting the Probit model results. In both cases, the coefficient of *Robot* remains significantly negative, indicating that the results are still consistent with the main findings.

3.3.5 Alternative Sample

To control for and mitigate potential bias in model estimation arising from external shocks such as the COVID-19 pandemic, policy changes, or institutional shifts, we further adjusted the sample period. Specifically, we excluded observations from 2020 to 2022 and restricted the sample to the period from 2011 to 2019. This adjustment ensures that the pandemic or related factors do not influence the findings. As reported in column (4) of *Table* 7, the results provide additional support for our core findings.

3.3.6 Omitted Variables

In the baseline analysis, year and industry fixed effects are controlled for. Recognizing that the determinants of financial misstatements may vary across firms, we further included firm- and province-level fixed effects in our regression to address potential concerns about omitted variables. As shown in column (5) of *Table* 7, the coefficient of *Robot* is significantly negative at the 10% level, consistent with the main findings.

3.3.7 Persistence Test

The impact of industrial robot adoption on financial restatements may exhibit persistence over time. To examine whether industrial robots generate a lasting adverse effect, we re-estimated the model using the one-period lag of the key independent variable (*Robot)*.

Table 7. Other robustness tests

Variable	**Alternative Dependent Variable**	**Logit**	**Probit**	**Alternative Sample**	**Firm-Provincail effects**	**Persistence test**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Robot	-0.0107** (-2.3676)	-0.7850** (-2.4769)	-0.4135** (-2.4232)	-0.1139** (-2.4692)	-0.0641* (-1.8383)	-0.0638* (-1.7039)
Constant	0.3457*** (4.2287)	-0.0249 (-0.0460)	0.0463 (0.1580)	0.3426*** (3.5403)	-0.1683 (-0.9324)	0.4540*** (5.5444)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province & Firm FE	No	No	No	No	Yes	No
N	22,231	22,231	22,231	14,836	22,231	18,755
Adj-R^2/Pseudo R^2	0.051	0.067	0.061	0.040	0.234	0.046

Note: T-statistics are reported in parentheses and are based on firm-level clustered robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: authors' own results.

The result in column (6) of *Table* 7 shows that the lagged coefficient of *Robot* remains significantly negative, suggesting that the effect of industrial robot adoption on reducing financial restatements is sustained over time.

3.4 Mechanism Analysis

Table 8 presents the results of the stepwise regression tests with information quality, internal governance, and risk-taking as the mediating variables, respectively.

Table 8. Mechanism analysis results

Variable	(1) *DA*	(2) *Restate*	(3) *IC*	(4) *Restate*	(5) *Volatility*	(6) *Restate*
Robot	-0.0183** (-1.9969)	-0.0790** (-2.3559)	0.1948** (2.0427)	-0.0774** (-2.3125)	0.0527* (1.7949)	-0.0833** (-2.4029)
DA		0.0825*** (3.0005)				
IC				-0.0157*** (-4.7811)		
Volatility						0.0523*** (5.1703)
Size	-0.0053*** (-6.1496)	-0.0022 (-0.6357)	0.0577*** (5.2959)	-0.0017 (-0.5044)	-0.0279*** (-5.9912)	-0.0012 (-0.3428)
Lev	0.0127** (2.4955)	0.0766*** (3.7377)	-0.0748 (-1.1421)	0.0765*** (3.7552)	0.0598** (2.2013)	0.0745*** (3.6450)
Roa	0.0418*** (2.7210)	-0.3873*** (-6.7469)	2.7433*** (11.4181)	-0.3408*** (-5.9047)	-1.4055*** (-18.0000)	-0.3103*** (-5.4688)
Gropr	-0.0014 (-0.2384)	0.0383 (1.5173)	-0.0839 (-1.1151)	0.0368 (1.4657)	0.3642*** (10.4098)	0.0191 (0.7596)
Cash	-0.0486*** (-3.3716)	-0.1442*** (-3.2725)	-0.3266** (-2.2334)	-0.1534*** (-3.4751)	0.1393*** (2.8764)	-0.1555*** (-3.5283)
Grow	0.0536*** (16.1869)	0.0223*** (2.8267)	-0.0173 (-0.6730)	0.0264*** (3.4113)	0.0541*** (6.1192)	0.0238*** (3.0874)
Age	-0.0029** (-2.5692)	0.0101** (2.2688)	-0.0888*** (-7.2412)	0.0084* (1.9074)	0.0230*** (3.9979)	0.0086* (1.9570)
Board	-0.0177*** (-4.6913)	-0.0170 (-1.0677)	-0.0083 (-0.1999)	-0.0186 (-1.1764)	-0.0592*** (-2.9826)	-0.0154 (-0.9721)
Inst	0.0041 (1.2276)	-0.0387*** (-3.0386)	-0.0449 (-1.3437)	-0.0391*** (-3.0780)	-0.0867*** (-5.3018)	-0.0338*** (-2.6573)
Big4	0.0019 (0.6403)	-0.0347*** (-2.7862)	-0.0034 (-0.1025)	-0.0346*** (-2.7972)	0.0150 (0.9708)	-0.0353*** (-2.8656)
Audop	-0.0176*** (-4.1960)	-0.1796*** (-7.8386)	2.0724*** (15.1936)	-0.1485*** (-6.4153)	-0.3554*** (-13.7955)	-0.1624*** (-7.1651)
Constant	0.2453*** (13.1695)	0.3681*** (4.7298)	3.1675*** (12.5080)	0.4380*** (5.6793)	1.3351*** (13.2757)	0.3184*** (4.0869)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	22,231	22,231	22,231	22,231	22,231	22,231
Adj-R^2	0.159	0.052	0.182	0.053	0.163	0.053

Note: T-statistics are reported in parentheses and are based on firm-level clustered robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: authors' own results.

In column (1), *Robot* shows a significant negative relationship with *DA* at the 5% level, suggesting that adopting industrial robots helps constrain accrual-driven earnings manipulation and fosters higher-quality information disclosure. In column (2), *DA* is significantly positively related to *Restate* at the 1% level, while the coefficient of *Robot* remains significantly negative and its magnitude is smaller than in the baseline regression. This pattern supports the partial mediation hypothesis. Thus, Hypothesis *H2* is supported, demonstrating that the industrial robot adoption indirectly reduces the likelihood of financial restatements by improving information quality. In column (3), *Robot* is significantly positively associated with *IC*, suggesting that robot adoption enhances firms' internal control systems. Column (4) shows that *IC* is significantly negatively associated with *Restate*, and the coefficient of *Robot* remains significantly negative, indicating that robot adoption reduces the probability of restatements both directly and indirectly by strengthening internal control. The results provide support for *H3*, which pertains to the internal governance mechanism. Column (5) reports a positive relationship between *Robot* and *Volatility,* significant at the 10% level, suggesting that robot adoption increases firms' risk-taking capacity. However, column (6) shows that *Volatility* is significantly positively related to *Restate*. At the same time, *Robot* remains significantly negatively associated with it. This implies that greater risk-taking raises the probability of restatements, but the overall effect of robot adoption remains negative. Hence, the risk-taking channel exhibits a masking effect, and *H4* is not supported.

4. Heterogeneity Analysis

4.1 Ownership Structure Differences

Ownership structure serves as a key determinant of firm characteristics, leading to sharply contrasting governance practices, operational goals, and the degree of scrutiny they face (Connelly *et al*., 2010; Tang *et al*., 2018). State-Owned Enterprises (SOEs), subject to government oversight, often exhibit stable decision-making patterns but may face constraints in their incentive mechanisms and efforts to improve efficiency (Huang *et al*., 2024). By comparison, Non-State-Owned Enterprises (NSOEs) operate with a stronger market focus. Unencumbered by bureaucratic constraints, their management possesses greater autonomy in pursuing technological upgrades and efficiency gains. Consequently, during the adoption of industrial robots, NSOEs exhibit a stronger tendency to leverage this technology to enhance production efficiency, optimize financial management, and ultimately, reduce financial misreporting. We therefore posit that the effect of robot adoption in reducing financial restatements would be more pronounced in NSOEs. Based on ownership types, we divided the sample into SOEs and NSOEs subsamples, and the relationship was examined separately within each group. The results in columns (1) and (2) of *Table* 9 show that the coefficient on *Robot* is negative but insignificant for SOEs. In contrast, for NSOEs, the coefficient is significantly negative at the 5% level. This finding indicates that industrial robot adoption has a more substantial impact on mitigating financial restatements in NSOEs.

4.2 Industry Competition Level

In highly competitive industries, firms face intensified market pressures that place a premium on the accuracy and transparency of financial data (Majeed *et al*., 2018). Any occurrence of misreporting not only undermines investor confidence but can also substantially raise the cost of capital. Within this context, intense competition compels firms to adopt more reliable governance mechanisms. Industrial robots, serving as tools that enhance production efficiency and data processing accuracy, help reduce manual operational errors and improve the standardization and transparency of financial reporting. Therefore, we predicted that industrial robot application would have a more pronounced adverse effect on financial restatements for firms facing a higher degree of industry competition.

Following Saeed *et al*. (2023), we utilized the Herfindahl-Hirschman Index (HHI) to measure the level of industry competition where firms operate, where a higher index value indicates lower levels of competition. Based on the annual median HHI, industries were classified into low and high competition groups. As shown in columns (3) and (4) of *Table* 9, *Robot* shows a negative and significant effect at the 10% level in the low competition subsample, but the effect strengthens to the 5% level in more competitive industries, implying that robot adoption has greater mitigating power on financial restatements under intensified competition.

Table 9. Heterogeneity analysis (I): ownership structure and industry competition

Variable	(1) SOE	(2) NSOE	(3) Low industry competition	(4) High industry competition
Robot	-0.0370 (-0.5703)	-0.0855** (-2.1787)	-0.0605* (-1.6833)	-0.1843** (-1.9745)
Constant	0.1428 (1.2820)	0.4421*** (6.0926)	0.3010*** (4.7365)	0.9750*** (5.9397)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	6,176	16,055	19,341	2,890
Adj-R^2	0.067	0.052	0.048	0.083

Note: T-statistics are reported in parentheses and are based on firm-level clustered robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: authors' own results.

4.3 Enterprise Factor Intensity

There are significant differences in factor intensity across industries within the manufacturing sector. Labor-intensive firms, which rely heavily on low-skilled labor and human input in their production processes, experience a more pronounced substitution effect when they adopt industrial robots (Bachmann *et al*., 2024). For these firms, the deployment of industrial robots effectively reduces uncertainties inherent in manual operations and enhances the standardization and precision of production processes. These operational improvements are subsequently reflected in higher-quality financial reporting with fewer restatements. We therefore expect the negative relationship between industrial robot adoption and financial restatements to be particularly tangible in these settings.

Following Lannelongue *et al*. (2017), we measured firm-level factor intensity as the ratio of a firm's year-end net fixed assets to its total number of employees as a proxy for factor intensity. Specifically, firms with a ratio above the annual industry median are classified as capital-intensive, while those with a ratio at or below the median are categorized as labor-intensive. The subgroup regressions reported in columns (1) and (2) of *Table* 10 highlight a sharp contrast between labor- and capital-intensive firms. While the coefficient of *Robot* is negative but insignificant in capital-intensive enterprises, it is both negative and significant in labor-intensive firms. These findings suggest that the mitigating impact of industrial robot adoption on financial restatements is primarily concentrated in labor-intensive firms.

4.4 Analyst Forecasts

Analyst forecasts serve as an important mechanism for information dissemination in capital markets, and their degree of optimism about firms' earnings significantly affects managerial decision-making (Liu and Schneible, 2017; Liu and Kok Loang, 2023). When analysts exhibit pessimistic forecast bias, weakened market confidence often triggers heightened scrutiny from investors and regulators, increasing the pressure on management to improve information disclosure (Hirshleifer *et al*., 2021). In an effort to improve the accuracy and credibility of financial reporting, these firms exhibit greater motivation to adopt industrial robots to optimize production processes and financial management. This helps reduce manual errors and lowers the risk of financial restatements. Therefore, we estimated the restatement-reducing effect of industrial robots to be more substantial in firms with a pessimistic analyst forecast bias.

Following Chen *et al*. (2021) and Huang *et al*. (2022), we assessed analyst forecasts using signed forecast bias, calculated as (forecasted value - actual value) / |actual value|, to evaluate the degree of analysts' optimism about corporate earnings. To distinguish between optimistic and pessimistic expectations, the sample was classified using the industry-year median of analyst forecasts as the dividing threshold. As shown in *Table* 10 (columns 3 and 4), for firms with optimistic analyst forecasts, *Robot* exhibits a negative but insignificant coefficient, whereas for firms with pessimistic forecasts, it is both negative and significant. The findings imply that financial restatements are more strongly influenced by industrial robot adoption among firms facing more pessimistic expectations.

Table 10. Heterogeneity analysis (II): factor intensity and analyst forecasts

Variable	(1) Capital-intensive	(2) Labour-intensive	(3) Pessimistic forecast	(4) Optimistic forecast
Robot	-0.0349 (-0.9247)	-0.2546*** (-3.4618)	-0.1317*** (-3.0218)	-0.0039 (-0.0737)
Constant	0.2917*** (4.4268)	0.7300*** (5.4393)	0.3951*** (5.3327)	0.4251*** (4.1137)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	17,513	4,718	13,028	9,203
Adj-R^2	0.051	0.059	0.061	0.042

Note: T-statistics are reported in parentheses and are based on firm-level clustered robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: authors' own results.

5. Discussion

This study investigates the impact of industrial robot adoption on financial restatements in listed companies, and examines the underlying mechanisms through the lenses of information quality, internal governance, and risk-taking.

First, *Table* 3 shows that the adoption of industrial robots significantly reduces the probability of financial restatements. This effect remains robust after sequentially controlling for firm fundamentals, governance structures, and audit attributes. A series of robustness checks presented in Tables 4 through 7 further corroborates Hypothesis *H1*. This evidence indicates that industrial automation effectively mitigates the risk of misstatement in financial reports by reducing manual operational errors and enhancing the standardization of data processing, improving the reliability and transparency of corporate financial information. Our findings align with and extend the work of Ashraf (2025) and Goldfarb and Tucker (2019). They supported the view that automation and digital technologies enhance production efficiency and improve financial reporting quality by optimizing operational processes, serving as a critical tool for reducing misstatement risks and improving transparency. Consequently, as industrial robot adoption deepens, their impact is expected to evolve from mitigating financial restatement risks to strengthening financial governance and ultimately fostering greater transparency in capital markets.

Second, the results in *Table* 8 indicate that industrial robot adoption reduces restatement risk primarily through the information-quality and internal-governance mechanisms. Regarding the information-quality channel, robot adoption significantly lowers accrual-based earnings management, enhancing the reliability of financial reporting and indirectly reducing the incidence of financial restatements. These results support Hypothesis *H2*. In the internal governance channel, industrial robot adoption effectively strengthens internal controls and corporate governance, which subsequently curbs financial restatements, supporting Hypothesis *H3*. However, the risk-taking mechanism shows divergent results. Hypothesis *H4* predicted that robot adoption would reduce restatements by increasing risk-bearing capacity, but the empirical evidence fails to support this. The analysis reveals that while robot adoption does enhance corporate risk tolerance, this increased capacity paradoxically elevates restatement risk, as it fails to translate into better governance and instead encourages risk-taking that compromises reporting integrity. This finding is consistent with the arguments of DeFond and Jiambalvo (1994) and Efendi *et al*. (2007), who suggested that excessive risk-taking may incentivize opportunistic accounting behaviors, increasing the probability of restatements. This implies that while industrial robots improve information quality and internal governance, these positive effects may be partially offset by the concomitant rise in risk-taking. Overall, the results reveal a “double-edged sword” effect. Although robot adoption exerts a net reducing effect on financial restatements, this benefit can be partially suppressed through the risk-taking channel in specific contexts.

Third, the results in *Tables* 9 and 10 further reveal the boundary conditions of the impact of industrial robot adoption on financial restatements. Specifically, along the ownership dimension, we discovered that robot adoption significantly reduces restatements among NSOEs, but has no significant effect for SOEs. This result aligns with property-rights incentive theory, which holds that NSOEs, driven by more substantial market incentives, demonstrate greater initiative in enhancing efficiency and improving governance, making them more likely to adopt automation for financial discipline in financial reporting (Tang *et al*., 2018). At the industry level, the negative association between robot adoption and restatements is more pronounced in highly competitive environments, suggesting that market pressure amplifies the governance effect of technological adoption on financial transparency. Regarding the factor-intensity dimension, the effect is concentrated in labor-intensive firms, consistent with the technological displacement view, which suggests that these firms gain greater advantages when routine human tasks are replaced by automated processes (Bachmann *et al*., 2024). Finally, for the analyst forecast optimism dimension, robot adoption has a stronger lowering effect on financial restatements in firms with pessimistic analyst expectations. This suggests that when market confidence is weak and external scrutiny is stronger, firms have a greater incentive to utilize automation to enhance the accuracy and transparency of financial data, reducing external skepticism and the risk of restatement.

Conclusions and Implications

Conclusions. To clarify the impact of industrial robot adoption on corporate financial restatements, this study conducts an empirical analysis by using data from Chinese manufacturing listed firms between 2010 and 2022. The conclusions are as follows: (1) the adoption of industrial robots significantly reduces the probability of financial restatements. Controlling for possible endogeneity and conducting a series of rigorous sensitivity checks does not alter this fundamental finding. (2) The mechanism analysis reveals that robots reduce restatements primarily by enhancing the quality of accounting information and strengthening internal governance. In contrast, the risk-taking channel is not supported, indicating that while robot adoption improves efficiency, it also introduces a new risk trade-off by potentially increasing operational volatility. (3) The mitigating effect of robot adoption on restatements is more pronounced in NSOEs, firms operating in highly competitive industries, labor-intensive firms, and those facing more pessimistic analyst forecasts.

Managerial Implications. The findings offer several implications for practice. From an investor's perspective, the documented reduction in financial restatement risk associated with robot adoption suggests that a firm's level of intelligent automation can serve as a practical indicator for assessing the credibility of its financial disclosures and the robustness of its governance framework. Investors, particularly non-sophisticated retail investors who may lack the extensive resources for in-depth analysis, can utilize this observable signal to better evaluate investment risks and make more informed decisions. However, investors must avoid treating technology adoption as a standalone risk indicator. Instead, it should be integrated into a holistic evaluation of the firm's overall information environment and governance quality.

Second, from the firm's perspective, industrial robot adoption is not limited to production efficiency gains; it also functions as a governance instrument that promotes transparency in financial reporting and mitigates the risk of restatements. Firms should therefore develop tailored robot adoption strategies that are aligned with their specific industry characteristics and production models to mitigate financial reporting risks. On the one hand, they should identify pain points in financial management and production workflows, establish clear objectives for robot deployment, and utilize industrial robots to streamline processes and improve the accuracy and timeliness of information processing. On the other hand, firms should strengthen cross-functional coordination so that technology, finance, and operations work in lockstep. Alignment in process design and deployment will raise system-wide efficiency. The heterogeneity analysis provides further targeted insights: NSOEs should actively leverage policy incentives and governmental support to reduce the costs of intelligent transformation and enhance their competitive advantage. Firms in highly competitive industries can enhance synergies through supply chain integration and intelligent manufacturing optimization, improving operational efficiency and financial transparency. Labor-intensive enterprises are advised to accelerate the adoption of production automation to reduce their reliance on manual labor, mitigating the risk of information distortion and enhancing the accuracy and quality of their reporting. Lastly, firms facing pessimistic analyst forecasts can utilize robot adoption to enhance production stability and financial predictability, improving market perceptions, alleviating external monitoring pressure, and reducing tendencies toward earnings management.

Ultimately, for policymakers and supervisory authorities, this study highlights the need for enhanced policy guidance and institutional safeguards to facilitate the adoption of industrial robots. Policymakers should prioritize creating a stable institutional environment conducive to intelligent upgrading by refining the legal and regulatory framework and reinforcing enforcement mechanisms. In parallel, enhancing fiscal support through a mix of measures, including tax breaks, targeted subsidies, and preferential credit, would reduce the cost of adopting industrial robots and strengthen firms' incentives to pursue digital transformation. Furthermore, governments can facilitate the establishment of industrial collaboration platforms for smart manufacturing, promoting technological exchange and cooperation among enterprises, research institutes, and universities to accelerate the innovation and diffusion of robotic technologies. Through such policy support and platform building, regulators can effectively guide firms to advance technological upgrading and to elevate their financial governance standards and information transparency, contributing to the healthy development of capital markets.

Limitations and Future Directions. This study has several limitations. First, our firm-level measure of industrial-robot adoption is derived from an industry-level penetration index. While this approach effectively captures the sector-wide trend toward intelligent manufacturing, it may not fully capture firm-specific variations in adoption intensity or depth of implementation. Second, the mechanism analysis focuses on three channels: information quality, internal governance, and risk-taking. Although these mechanisms illuminate key ways in which robot adoption affects restatements, financial restatements are multifaceted governance outcomes that are influenced by managerial incentives, external audit oversight, and other factors as well. Finally, the generalizability of our findings may be constrained by the institutional context of China. Hence, future research is needed to examine whether these relationships hold in different countries and under varying institutional arrangements.

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PRAMONINIŲ ROBOTŲ DIEGIMAS IR ĮMONIŲ FINANSINIŲ ATASKAITŲ PERSKAIČIAVIMAI: KINIJOS ATVEJIS

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Santrauka. Pramoniniai robotai vertinami kaip pagrindinė technologija, skatinanti gamybos skaitmeninę transformaciją. Jie sulaukia vis didesnio mokslininkų dėmesio analizuojant jų ekonomines pasekmes įmonių valdysenos tyrimuose. Tačiau esamoje literatūroje trūksta sisteminių teorinių įžvalgų apie tai, kaip pramoninių robotų diegimas veikia įmonių finansinių ataskaitų perskaičiavimus. Siekiant ištirti ryšį tarp pramoninių robotų diegimo ir įmonių finansinių ataskaitų perskaičiavimų, remiantis informacijos asimetrijos ir vadovų trumparegiškumo teorijomis bei naudojant 2010–2022 m. Kinijos A tipo akcijų gamybos sektoriaus listinguojamų įmonių imtį, straipsnyje analizuojamas pramoninių robotų diegimo poveikio mechanizmas finansinių ataskaitų perskaičiavimams. Tyrimo rezultatai atskleidė, kad: (1) pramoninių robotų diegimas reikšmingai sumažina finansinių ataskaitų perskaičiavimo tikimybę, o šis rezultatas išlieka stabilus atlikus įvairius jautrumo testus; (2) šis sumažėjimas daugiausia pasiekiamas gerinant informacijos kokybę ir stiprinant vidaus valdyseną, o rizikos prisiėmimo kanalas pasižymi maskuojančiu poveikiu; ir (3) robotų diegimo ribojantis poveikis finansinių ataskaitų perskaičiavimams yra ryškesnis nevalstybinėse įmonėse, labiau konkurencingose pramonės šakose veikiančiose įmonėse, darbo jėgai imliose įmonėse bei įmonėse, susiduriančiose su pesimistiškesnėmis analitikų prognozėmis. Šios išvados praplečia teorinius pramoninių robotų ekonominių pasekmių tyrimus ir suteikia vertingų įžvalgų politikos formuotojams, siekiantiems skatinti išmaniąją gamybą ir gerinti kapitalo rinkų informacinę aplinką.

Reikšminiai žodžiai: pramoninių robotų pritaikymas; finansiniai perskaičiavimai; informacijos kokybė; vidinis valdymas; rizikos prisiėmimas.