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Robots and analyst forecast precision: Evidence from Chinese manufacturing

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ABSTRACT

This paper investigates whether industrial robot adoption in manufacturing industries improves subsequent analyst forecast performance. The evidence suggests that the adoption of industrial robots has a positive correlation with analyst forecast precision, reflected as lower analyst forecast bias and forecast dispersion. It is also found that enhancing total operating efficiency and promoting information dissemination are two possible channels through which industrial robot adoption improves analyst forecast precision. Furthermore, cross-sectional analyses show that the positive link is more pronounced in more ex-ante uncertain firms and private firms. Overall, our paper provides comprehensive evidence for the industrial robot spillover effect on corporate activities.

1. Introduction

Technology is always considered as a source of faster productivity growth. The first industrial robot, the Unimate, was developed by George Devol and Joseph Engelberger. Over the next few decades, advances in robotics led to a new industrial revolution. The International Federation of Robotics (IFR) estimates that in 2017, there were around 2.1 million stand-alone industrial robots installed worldwide, with a shipment of 381,000 units globally. The early adoption of industrial robots suggests that advances in robotics may lead to a new industrial revolution over the next few decades, fostering the growing perception that robotics will radically transform the workplace in upcoming decades (Brynjolfsson & McAfee, 2014; Ford, 2015). All the forecasts echo the notion that the development of industrial robots will reshape everything in our daily lives.

The rise of robot technology has sparked an intense debate about the economic effects of robot adoption. The published literature documents that greater penetration of robots into the economy obviously affects wages and employment, productivity, economic growth obviously (Dauth, Findeisen, Südekum, & Woessner, 2017; Acemoglu & Restrepo, 2018, 2019, 2020; Bessen, 2019; Fu, Bao, Xie, & Fu, 2021; Koch, Manuylov, & Smolka, 2021 etc.), but nevertheless there is limited evidence focusing on the robotic technology and micro-level consequences. Archival evidence mainly studies firm-level total factor productivity (Graetz & Michaels, 2018; Kromann, Skaksen, & Sørensen, 2011), firm investment (Benmelech & Zator, 2022) and innovation (Blöcher & Alt, 2021; Kumaresan & Miyazaki, 1999). However, the spillover effect beyond these intuitive consequences of industrial robot adoption is less explored. Porter and Millar (1985), and Xiao, Dyson, and Powell (1996) emphasize that information technology affects the corporate financial reporting process and information users' decisions significantly. Industrial robot adoption is a symbol of digital transformation and artificial intelligence application in the manufacturing industry (Graetz & Michaels, 2018; Haenlein & Kaplan, 2021; Kumaresan & Miyazaki, 1999). Thus, we expect such new technology reform will also have some impact on corporate information dissemination, and influence information users' behaviors. Analysts are one of the most important information channels for investors and other market participants to learn about a company's financial performance and prospects. Therefore, our study aims to enrich the empirical evidence of micro-level outcomes of industrial robot adoption and investigate its effect on analyst forecast precision.

Compared with the U.S. or other developed capital markets, Chinese stock market synchronicity is relatively high and external investors find it difficult to obtain enough effective firm-specific public information because of the weak regulation environment and investor protection.

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Exploring more private information is urgent for analysts to make precise forecast decisions. Thus, we expect that industrial robots in China will noticeably generate incremental value in the field of private information collection. We also probe the mechanism through which industrial robots exert a positive impact on analyst forecast behavior. On one hand, operating efficiency will witness the direct effect brought about by industrial robot adoption. Industrial robots are expected to help firms reduce labor costs and optimize the labor structure significantly as they handle the performing of repetitive tasks, carry out precise movements, and can work for extended periods without tiring. Besides, industrial robots play an important role in enhancing product quality, productivity, and growth, enabling a higher total factor productivity (TFP). Upon the introduction of industrial robots, firms can better sustain a stable output and reduce the prospective volatility. The information delivered to analysts will be less uncertain, resulting in a less biased forecast.

On the other hand, the indirect effect of industrial robot application is the facilitation of information dissemination. The adoption of robotic technology is often indexed to measure a company's willingness to invest in innovation and stay ahead of industry trends. As a result, analysts covering the manufacturing industry may view companies that adopt industrial robots as attractive investment opportunities and increase their coverage of such firms. From the perspective of manufacturing companies, the embracement of industrial robots helps themselves with funding through building analysts' confidence which indirectly increases the richness of the information content and reduces information uncertainty thereby allowing firms' performance to flourish. Furthermore, site visit incentives may also contribute to the increase in forecast precision. During site visits, analysts can observe the productivity level of a company and ask questions relating to operation details. They will then build up a better picture of the firm's future prospects, arriving at better forecast outcomes and less divergency from the real outcome (Cheng, Du, Wang, & Wang, 2016).[1]

Applying Acemoglu and Restrepo's (2020) equilibrium model to the Chinese manufacturing industry, we construct firm-level industrial robot penetration during the period of 2011–2019. Our findings suggest that the introduction of industrial robots and analyst forecast dispersion/error exhibit a significantly negative relationship. Furthermore, we find that increasing operating efficiency and information dissemination are two possible channels through which industrial robots may narrow analyst forecast dispersion/error. Cross-sectional tests document that the optimistic role of industrial robots in analyst forecast precision is more pronounced in private firms, firms with environmental uncertainty, and higher-growth or labor-intensive firms. Finally, we conduct a series of robustness checks and provide further support for our main findings including propensity score matching (PSM), change analysis, adding additional control variables, using alternative proxies, and controlling for industry and year trends.

This study makes several contributions to the literature. First, this work generates fresh insights into the impact of industrial robot adoption on corporate analyst forecast behavior. Most existing studies have investigated the effect of industrial robot adoption on macro-level consequences such as economic growth, productivity, and employment (Acemoglu & Restrepo, 2018, 2020; Aghion, Antonin, & Bunel, 2019; Ballestar, Díaz-Chao, Sainz, & Torrent-Sellens, 2020; Berg, Buffie, & Zanna, 2018; Kromann, Malchow-Møller, Skaksen, & Sørensen, 2020; Wang, Wang, & Song, 2022; Zeira, 1998). To date, there are few studies that explore the spillover effect of industrial robot adoption on capital markets. Acemoglu and Restrepo (2020) construct a regional-level proxy for industrial penetration in the US. Building on their methodology, we include a firm-level proxy to measure industrial penetration.

Second, analysts are crucial information intermediaries in the capital market who accumulate personal reputations through making professional forecasts and providing useful suggestions to external investors. Existing literature documents a negative relationship between analysts' collection of information and forecast bias. To be specific, many research scholars are dedicated to tracking the influence of firm-specific disclosure characteristics or private ties (Bhushan, 1989; Fei, 2022; Green, Jame, Markov, & Subasi, 2014; Libby, Tan, & Hunton, 2006; Soltes, 2014; Zhang, 2006). Even though industrial robots have continued to undergo improvements in recent decades, few empirical studies have explored the effect of industrial robot adoption in finance and accounting areas. It is found that analysts in China's emerging market rely more on private information gathering due to the limited public information disclosure. Therefore, emerging markets such as China can better experience industrial robots' advantage in regard to private information compared with developed capital markets. We aim to fill this void by studying how analysts incorporate industrial robot information when making forecast decisions using the Chinese setting.

The remainder of the paper proceeds as follows. Section 2 presents the related literature and hypothesis development. Section 3 shows the sample and the empirical research design. Sections 4 and 5 report the main empirical results and additional analyses, respectively. The last section concludes the paper.

2. Literature review and hypothesis development

2.1. Institutional background in China

Analysts place importance on the influence of information intermediation and information provision on the capital market (Bhushan, 1989). For example, investors actively react positively or negatively to analysts' predicted changes in company outlook. In addition, analyst forecasts are often used by companies themselves to communicate their financial performance and prospects to investors and other stakeholders. To achieve precise forecast outcomes, analysts need the expertise to seek both public and private information. They collect as much public information as possible from corporate financial reporting, corporate announcements, and media reports, and make efforts to explore private information through different channels such as conference calls, site visits to firms, and nondisclosed content like confidential treatment orders (Cheng et al., 2016; Fei, 2022; Keskek, Tse, & Tucker, 2014).

Numerous researchers have shown that information quality and analysts themselves who under pressure may affect analysts' forecast behavior (Rodríguez-Pérez & Van Hemmen, 2010; Yu, 2008). These articles all focus on the developed American capital market, where the position of analyst or institutional investor is crucial, and firms have strong incentives to cater to their forecast outcomes. Degeorge, Patel, and Zeckhauser (1999) show that a great number of firms have inducements to meet or beat analyst forecasts, which is further confirmed by Doyle, Jennings, and Soliman (2013) through the analysis of non-GAAP earnings opportunistically defined by firm managers.

Furthermore, in the US, institutional investors, such as hedge funds, mutual funds, pension funds, and other large investment groups, have private accesses, named conference calls, to discuss and communicate information about their investments. A typical conference call starts with opening remarks by management followed by a question-and-answer session with invited analysts, during which details not contained in the press release are often disclosed (Kimbrough, 2005). Analysts can acquire superior private information by gaining insight into the performance of a particular company. Mayew, Sharp, and Venkatachalam (2013) find that analysts who attend conference calls produce relatively accurate forecasts of upcoming annual earnings than those who do not.

China is the second-largest economy of the world, but it is still a

[1] Companies in the U.S. and Europe do not maintain archival records of site visits and/or prohibit the distribution of such information (Cheng et al., 2016). Since 2009, the Shenzhen Stock Exchange mandates that all the listed firms on the exchange must disclose detailed information about site visits. This provides us the opportunity to analyze whether industrial robots' application can attract more analyst site visits, thereby promoting analysts' private gathering of information and improving their forecast precision.

developing country suffering from opaque information, low-quality financial information and weak investor protection (Piotroski, Wong, & Zhang, 2015). Chinese listed firms usually have a high ownership concentration which results in little room for individual investors to impact corporate activities. Hu, Lin, and Li (2008) show that Chinese analysts are still in fledging profession. The position of Chinese analyst or institutional investor is much weaker compared to that in developed capital markets. Chinese listed firms do not provide channels like conference calls in the US to institutional investors. Therefore, site visits are Chinese analysts' last resort to gather private information. In most circumstances, analysts initiate the site visits themselves and bear all the incurred expenses. In general, firms do not refuse their requests for on-site visits and the details are determined together by analysts and firms' managers. Cheng, Du, Wang, and Wang (2019) show that a regular visit lasts three to four hours including introduction, Q&A session, and a two-hour site tour that provides analysts the chance to hold in-depth conversations with managers and observe facilities. In 2009, the Shenzhen Stock Exchange (SZSE) required listed companies to disclose their site visit information to public. Therefore, we also analyze whether industrial robot adoption can attract analysts at their own expense to conduct site visits.

2.2. Related literature on industrial robots

The International Federation of Robotics (2014) defines an industrial robot as an automatically controlled, reprogrammable, and multipurpose machine. Technological changes in recent decades show that robots are not restricted to manufacturing but can operate in diverse applications including space and underwater exploration, construction, medical, entertainment, defense, and welfare (Kumaresan & Miyazaki, 1999). Industrial robots are large, heavy, and rigid bodies that are installed to perform jobs that would otherwise be very difficult and dangerous for human, such as carrying huge loads across factories (Sherwani, Asad, & Ibrahim, 2020). The comparison demonstrates an industrial robot's capacity to increase efficiency, productivity, and safety in the workplace. With the development of technology, robotics will become even widely used around the world.

Industrial robots have become an increasingly important topic of research in economics due to their potential impact on productivity, employment, and trade. Archival studies discuss the impact of industrial robot adoption on the labor market and economic development. Generally, industrial robots can help firms increase their productivity and efficiency. Prettner (2016) believes that the use of robots can indeed promote the economy and help society achieve permanent growth. Similarly, Graetz and Michaels (2017) conduct a more formal econometric study and find that adoption is associated with boosts to labor productivity. Berg et al. (2018) show that robotics is good for growth and bad for equality. Kromann et al. (2020) investigate the effects of automation on total factor productivity (TFP) and find that more intensive use of industrial robots has a significantly positive effect on TFP. Ballestar et al. (2020) show that robotic devices are associated with better performance and higher productivity. In recent days, scholars have paid attention to energy use closely related to industrial production especially in China due to the severe resource and environmental problems (Fan, Zhang, & Zhang, 2020; Zhang, Da, Zhang, & Fan, 2021). Huang, He, and Lin (2022) find that the adoption of robots in production can significantly increase firms' energy efficiency. Yu, Wang, Wei, and Zeng (2023) reveal that cities' carbon emissions have been significantly reduced by the application of industrial robots.

However, industrial robot adoption may be harmful to the labor market. Acemoglu and Restrepo (2018) show that robots may compete against human labor in production and reduce employment and wages significantly. Jung and Lim (2020) indicate that the expansion of industrial robot adoption is leading to a reduction of unit labor costs, but an increase in the hourly compensation level. In addition, technical innovation generates knowledge spillovers as documented by existing literature (Keller, 2004). Industrial robot adoption obviously enhances firms' innovation to a great extent. Kumaresan and Miyazaki (1999) state that robotics stimulates the Japanese national system of innovation.

2.3. Related literature on analyst forecast behavior and hypothesis development

Analysts serve as key information intermediaries between public firms and investors (Han, Jin, Kang, & Lobo, 2014). Investors and traders zero in on forecast dispersion when making decisions because it provides insights into the level of uncertainty or risk associated with a particular security or asset. Analysts' coverage decisions are affected by cost-benefit balance. The effort required to follow firms is the primary concern for analysts (Barth, Kasznik, & McNichols, 2001; Bhushan, 1989). Higher information asymmetry will generate higher costs of covering such target. Zhang (2006) observes that greater information uncertainty predicts more forecast errors. Analysts must overcome the uncertainty inherent in the values of such firms.

Their superior forecast performance can be affected by firm characteristics (Lang & Lundholm, 1996; O'Brien & Bhushan, 1990), firm-specific experience (Mikhail, Walther, & Willis, 1997), brokerage firm size (Clement, 1999; Jacob, Lys, & Neale, 1999) and so on. More recent studies have begun to focus on how analysts' private ties affect on their prediction behavior such as geographic proximity (Malloy, 2005), CEO/CFO ties (Green et al., 2014; Soltes, 2014), and so on. To determine what kind of firms to follow, analysts balance the cost including time, effort and attention and the benefits derived from following such firms.

There are some studies that exploit China's unique national circumstances and find that analysts can enhance the information environment significantly. Analysts engage in information production to help investors make investments based on their analysis, forecasting, and recommendations (Cao, Ma, & Wan, 2019; Chan & Hameed, 2006). Kong, Lin, Wang, and Xiang (2021) investigate the impacts of natural disasters on security analysts' earnings forecast and find that analyst forecasts react significantly to external economic events.

Our study focuses on corporate innovation activities and analyst forecasting behavior. Existing studies support the claim that analysts indeed consider firms' innovation activities when developing their forecasts (Barth et al., 2001; García-Meca & Martínez, 2007; Jia, 2017). Meanwhile, industrial robots are distinguished from innovation in that innovation activities involve risk-taking and are less comparable around the market. There is no common metric across companies that analysts can use to facilitate more precise valuations (Fleischer & Baum, 2010; Zuckerman, 2004). The positive outcomes generated by industrial robots' application are of no doubt.

We argue that industrial robot adoption can benefit analyst forecast precision through both direct operating efficiency improvement and indirect information uncertainty reduction. At the direct effect level, the introduction of robots helps firms optimize their operating efficiency including increasing labor efficiency, enhancing production efficiency, and mitigating profit uncertainty. First, automation will boost labor productivity because industrial robots can directly substitute some unskilled workers. An earlier preliminary study by Fleck (1984) estimates that one robot can replace two to six workers on average. Industrial robots are argued to have already deeply impacted the labor market and are expected to transform it in the decades to come (e.g., Brynjolfsson & McAfee, 2014; Ford, 2015). Greater penetration of robots into the economy affects wages and employment negatively because of a displacement effect (Acemoglu & Restrepo, 2020).

Second, industrial robot adoption can enhance production efficiency and mitigate profit volatility. Some scholars have studied the microeconomic implications of robot adoption for firm-level outputs. Koch et al. (2021) use Spanish manufacturing firms as the main subject and reveal strong evidence that firms which adopt industrial robots perform better compared with non-adopters. Specifically, the IFR estimates that the total market of industrial robotic systems was already USD 48 billion in 2017. Of this revenue, the robot itself creates about 30% of the revenue, accessories make up about 25%, and services including auxiliary hardware, software and programming, and installation generates the remaining 45%. Moreover, industrial robot adoption can help standardize the manufacturing process and guarantee high-quality products. By automating repetitive tasks and providing real-time data on production processes, industrial robot adoption can help firms lower their profit uncertainty and volatility to some extent. In sum, accompanied by higher revenue and lower costs generated by industrial robots' application, total operating efficiency can be enhanced significantly. Analysts and other stakeholders are able to have a precise understanding of what is happening on the factory floor. Therefore, industrial robot adoption can help enhance operation stability, thus, increasing analyst forecast precision intuitively.

At the indirect effect level, the adoption of industrial robots can deliver a positive signal to the capital market and strengthen the information dissemination procedure to external stakeholders. Balancing the cost and benefit of covering specific firms is the main concern of analysts. Firms may disclose industrial robot adoption in industry reports, company financial statements, surveys of manufacturers, and other sources. Analysts can use data on the adoption and use of industrial robots to develop their forecasts and insights. It allows them to make informed forecasts and recommendations based on objective and quantitative data. So, the application of industrial robots can help firms attract more analyst coverage. Archival studies find that a drop in analyst coverage causes an increase in the cost of capital and earnings management, brings about a decrease in investment efficiency, weakens investment and financing activities, reduces stock liquidity, and increases firms' ex ante expected crash risks (Kelly & Ljungqvist, 2012; Derrien & Kecskés, 2013; Balakrishnan, Billings, Kelly, & Ljungqvist, 2014; Chen, Harford, & Lin, 2015; Irani & Oesch, 2016; Kim, Lu, & Yu, 2019). Since an increase in analyst coverage improves information quality and reduces uncertainty, their forecast will be in greater agreement with real cases.

Furthermore, industrial robots may help firms attract more analyst site visits. Analysts are expected to care about a firm's usage of industrial robots as it can have a significant impact on the firm's financial performance, efficiency, and competitive positioning. It is important for them to factor this new technology into their forecasting and evaluation. In recent years, with the development of transportation, analysts have faced increasing chances to visit the firms which they cover (Cheng et al., 2016; Solomon & Soltes, 2015). Typically, they can conduct research, tour facilities, and review financial statements and other issues to gain a better understanding of the company's business and prospects. They can also the top management team questions directly about corporate strategy and competitive positioning. Site visitation forms an important source of information collection by analysts. Cheng et al. (2016) find that analysts through site visits can effectively improve their forecast precisions if certain segments of the firm being followed are growing faster than others or have different risk profiles. According to the above direct- and indirect-effect arguments, we refer to our hypothesis:

Hypothesis. *Industrial robot adoption will significantly increase analyst forecast precision, concretely exhibited as lower analyst forecast dispersion and forecast error.*

3. Research design

3.1. Empirical model

To analyze the impact of industrial robot adoption in manufacturing industries on analyst forecast performance, we use the following model to perform our tests:

$$Fbias_{i,t+1}/Fdisp_{i,t+1} = \alpha + \beta_1 Robot_{i,t} + \beta_2 Controls_{i,t} + \text{Firm fixed effects} + \text{Year fixed effects} + \varepsilon_{i,t} \tag{1}$$

The dependent variables, $Fbias_{i,t+1}$ and $Fdisp_{i,t+1}$, measure analyst forecast performance, capturing analyst forecast bias and analyst forecast dispersion using the measures of Behn, Choi, and Kang (2008). We use the leading value of dependent variables to mitigate the reverse causality issue. The independent variable, $Robot_{i,t}$, measures the exposure of firms to industrial robots by referring to the method of Acemoglu and Restrepo (2020). In detail, we use the following models:

The first step is to calculate the industrial robot penetration index at the industry level in Eq. (2), denoted as $PR_{j,t}$.

$$PR_{j,t} = \frac{MR_{j,t}}{L_{j,t=2010}} \tag{2}$$

where $MR_{j,t}$ is the stock of industrial robots in Chinese industry *j* and year *t*. $L_{j,t=2010}$ is the employment in Chinese industry *j* in the year 2010. $PR_{j,t}$ denotes the industrial robot penetration in Chinese industry *j* and the year *t*.

The second step is to construct the industrial robot penetration index at the firm level as in Eq. (3).

$$CHFexposure\ to\ robots_{i,j,t} = \frac{PWP_{i,j,t=2011}}{ManuPWP_{t=2011}} * \frac{MR_{j,t}}{L_{j,t=2010}} \tag{3}$$

where $CHFexposure\ to\ robots_{i,j,t}$ denotes the industrial robot penetration for firm *i* in Chinese industry *j* and year *t*. $\frac{PWP_{i,j,t=2011}}{ManuPWP_{t=2011}}$ is the proportion of employees in the production department for firm *i* in industry *j* to the median proportion of employees in the production department for all firms. We follow Wang and Dong (2020) and Wang, Lee, and Li (2022) and use $CHFexposure\ to\ robots_{i,j,t}$ to decompose the penetration of industrial robots from the industry level to the firm level to examine the firm-level penetration of industrial robots. $Robot_{i,t}$ is the natural logarithm of $CHFexposure\ to\ robots_{i,j,t}$.

We also control for certain firm-level factors that may affect the analyst forecast performance identified in previous studies (e.g., Behn et al., 2008; Cheng et al., 2016; Kong et al., 2021). These controls include analyst coverage (*Analyst*), forecast horizon (*Horizon*), firm size (*Asset*), financial leverage (*Lev*), sales growth rate (*Growth*), return on assets (*ROA*), log value of board members (*Boardsize*), proportion of independent directors (*Indep*), ownership of the top five largest shareholders (*Sh5*), ownership concentration (*ShHHI*), information transparency (*Accm),* the Big4 auditors (*Big4*), market index (*Index*), and firm and year fixed effects. All continuous variables are winsorized at the top and bottom 1%. Detailed definitions of all variables existing in this study are listed in the Appendix. The coefficient β_1 is of our primary interest. If a significantly negative sign is observed, our research hypothesis is supported.

3.2. Sample selection

Our research sample in this paper covers all the Chinese manufacturing industry A-share listed firms from 2011 to 2019. The sample starts from 2011 because the use of industrial robots in China has shown a rapid upward trend after 2011. Our main data of the stock of robots by industry are extracted from the IFR, which is a yearly survey of data documented by robot suppliers. Other research data are from the China Stock Market and Accounting Research (CSMAR) database. We delete observations without sufficient information to compute control variables. The final sample includes 9419 firm-year observations.

4. Empirical results

4.1. Summary statistics

Fig. 1 shows the changes in installations and operational stock of industrial robots in China from 2011 to 2019. It shows a significantly increasing trend, particularly in the recent five years. The annual installations of industrial robots increased from 22,577 units in 2011 to 139,859 units in 2019. The annual operational stock of industrial robots amounted to about 780,000 units in 2019, which is ten times higher than the corresponding number (74,000 units) in 2011.

Panel A, Table 1 reports the summary statistics of variables used in our main regression. The mean (median) value of analyst forecast bias is 0.0364 (0.0201) with a standard deviation of 0.0488. *Fbias* ranges from 0.0001 to 0.3272 which exhibits a large variance between different analyst forecasting outcomes. Analyst forecast dispersion, *Fdisp*, has a mean value of 0.0245 with a standard deviation of 0.0237. The mean (median) of industrial *robot* is 1.8310 (2.0043). One firm has two analyst followings on average and the logarithm of the average gap between the forecast date and the corresponding date of the actual financial report is 5.1667.

In Panel B of Table 1, we compare the means and the medians of *Fbias* and *Fdisp* by dividing observations to high vs. low industrial robot adoption subgroups. Both the mean and the median values of *Fbias* and *Fdisp* are smaller in the higher industrial robot subgroup. The *t*-test for mean value comparisons and p-test for median value comparisons are significant at the 1% level, supporting our hypothesis that firms with a higher level of industrial robot adoption reduce their analyst forecast bias and dispersion. The untabulated results of the correlation matrix shows that the industrial robot adoption (*Robot*) is negatively correlated with analyst forecast bias (*Fbias*) and dispersion (*Fdisp*). This provides preliminary support to our hypothesis that industrial robot adoption helps analysts increase their analyst forecast precision.

4.2. Main results

Our hypothesis predicts a positive link between industrial robot adoption and analyst forecast precision. The multivariate results are presented in Table 2. Columns (1) and (2) show the baseline results by using analyst forecast bias and analyst forecast dispersion as the main dependent variables separately after excluding all control variables. We observe that the basic link between industrial robot adoption and analyst forecasting behavior is indeed significant. The coefficients of *Robot* are both negative and significant at the 1% level (coefficients: −0.0043 with t-value −3.09 and − 0.0022 with t-value −3.80). After including a set of control variables, we present the results in Columns (3) and (4). Consistent with our prediction, there is a significant and negative relationship between industrial robot adoption and analyst forecast bias and dispersion. The coefficients of *Robot* are −0.0040 and − 0.0021 which are also both significant at the 1% level, suggesting that the adoption of industrial robots is significantly positively associated with firms' analyst forecast precision reflected as lower analyst forecast bias and dispersion. The coefficients of other control variables are generally consistent with our expectation. Firms with more analyst coverage exhibit a negative forecast bias and dispersion as more analyst following can help mitigate the information uncertainty. Larger firms have complex operational procedures and the analyst forecast precision will decrease significantly.

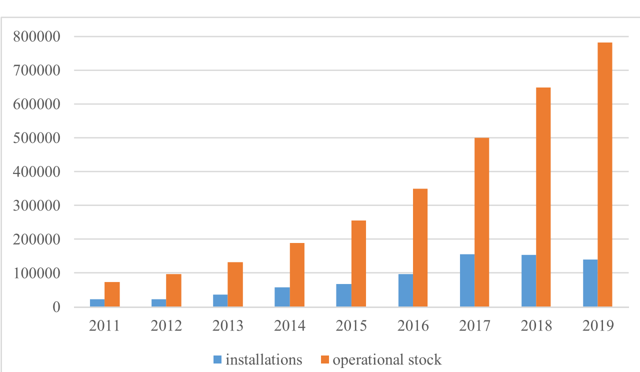

Fig. 1. China's installations and operational stock of industrial robots.

4.3. Possible mechanisms

In this section, we aim to identify the possible channels through which industrial robot adoption affects analyst forecasting behavior. Because of our previous argument, analysts adjust forecast decisions according to the direct operating efficiency enhancement and indirect information dissemination capacity. For the channel of operating efficiency, we first systematically test whether adopting industrial robots helps firms increase their labor efficiency by analyzing employee numbers, high-skilled labor proportions, and total labor cost. Then, we examine whether robots can also increase TFP and reduce profit volatility risk. Regarding the channel of information dissemination, we evaluate whether robots affect analyst forecast behavior by attracting analyst coverage and site visits. Empirically, we refer to the path analysis approach of Bauer, Fang, Pittman, Zhang, and Zhao (2020) for a mechanisms test. The path model, Eqs. (4)–(5), is as follows.

$$Mv_{i,t} = \alpha_0 + \alpha_1 Robot_{i,t} + \alpha_2 Controls_{i,t} + Firm\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{i,t} \tag{4}$$

$$Fbias_{i,t+1}/Fdisp_{i,t+1} = \gamma_0 + \gamma_1 Robot_{i,t} + \gamma_2 Mv_{i,t} + \gamma_3 Controls_{i,t} + Firm\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{i,t} \tag{5}$$

where $Mv_{i,t}$ is the mediator variable that proxies for operating efficiency and information dissemination, including labor efficiency (*Labor_Com/ Labor_Num/ Labor_Str*), productivity efficiency (*TFP/EarningVol*), and information dissemination (*Analyst/Visit*). The control variables are consistent with the above model. Firm fixed effects and year fixed effects are also included. The product of path coefficient $\alpha_1 * \gamma_2$ measures the magnitude of the indirect path from industrial robot adoption to analyst forecasting behaviors through operating efficiency or information dissemination.

Specifically, we use the total salary costs (*Labor_Com*), the number of employees (*Labor_Num*), and the proportion of high-skilled employees who are defined as holding a graduate degree or above (*Labor_Str*) as main mechanism variables. Our expectation is that firms with industrial robots can reduce the number of employees and total salary costs, and increase the proportion of high-skilled employees. In the first stage, we use *Labor_Com, Labor_Num*, and *Labor_Str* as dependent variables and analyze the relationship between industrial robot adoption and labor efficiency. The results are presented in Columns (1), (4) and (7), Panel A, Table 3. Coefficients of *Robot* in Columns (1), (4) and (7) are −0.0261 ($t = -5.22$), −0.0438 ($t = -7.18$), and 0.0768 ($t = 2.05$), suggesting that industrial robot adoption reduces the total labor cost and employee number, and increase high-skilled employees' proportion. In the second stage, we include both industrial robot and mechanism variables in the model and re-run the main regressions. The results are presented in Columns (2), (3), (5), (6), (8) and (9), Panel A, Table 3. The negative sign of *Robot* and positive sign of *Labor_Com* in Columns (2) and (3) show that industrial robot adoption increases analyst forecast bias through reducing the total labor cost. In summary, the results in the second stage provide partial support that reducing labor cost is one possible channel through which industrial robot adoption enhances analyst forecast precision. By analyzing Columns (5) and (6), and (8) and (9), we conclude that reducing employee numbers and increasing the high-skilled labor proportion are another two possible channels through

Table 1
Descriptive statistics and univariate analysis.

Panel A: Descriptive Statistics.

Variable	N	Mean	Sd	Min	P25	P50	P75	Max
Fbias	9419	0.0364	0.0488	0.0001	0.0085	0.0201	0.0434	0.3272
Fdisp	9419	0.0245	0.0237	0.0008	0.0088	0.0167	0.0316	0.1326
Robot	9419	1.8310	1.8294	−5.1775	0.0000	2.0043	3.3194	5.8382
Analyst	9419	2.0627	0.8713	0.6931	1.3863	2.0794	2.7081	3.9890
Horizon	9419	5.1667	0.3953	2.3979	5.0555	5.2297	5.3802	5.8397
Asset	9419	22.2903	1.1532	19.8721	21.4659	22.1321	22.9215	25.9995
Lev	9419	0.4043	0.1866	0.0398	0.2527	0.4006	0.5464	0.8521
Growth	9419	0.2025	0.4105	−0.5109	0.0097	0.1294	0.2820	4.5661
Roa	9419	0.0644	0.0581	−0.3050	0.0333	0.0574	0.0917	0.3239
Boardsize	9419	2.1359	0.1896	1.6094	1.9459	2.1972	2.1972	2.7081
Indep	9419	0.3737	0.0536	0.3333	0.3333	0.3333	0.4286	0.5714
Sh5	9419	0.5338	0.1428	0.1855	0.4289	0.5343	0.6351	0.8789
ShHHI	9419	0.1586	0.1078	0.0136	0.0784	0.1325	0.2107	0.5922
Accm	9419	0.0564	0.0396	0.0019	0.0290	0.0463	0.0728	0.2816
Big4	9419	0.0599	0.2373	0.0000	0.0000	0.0000	0.0000	1.0000
Index	9419	9.5863	4.6782	0.6900	5.2900	9.7700	13.5500	16.9400

Panel B: Univariate Analysis

	Obs	Mean (Median)	Obs	Mean (Median)	Differences
	low industrial robot firms		*high industrial robot firms*		
Fbias	4710	0.0376(0.0216)	4709	0.0352(0.0188)	0.0024***(24.1564***)
Fdisp	4710	0.0263(0.0178)	4709	0.0227(0.0156)	0.0037***(31.9993***)

Note: This table indicates statistical description and univariate analysis of the research variables of our primary interest. Panel A reports the descriptive statistics on dependent, independent, and control variables in our main regression. Panel B reports the results of univariate analysis of *Fbias* and *Fdisp* for low industrial robot adoption firms and high industrial robot adoption firms. We present the differences in mean and median. *** denote a significance level of 0.01. Robot sample together with other controls spans the 2011–2019 and analyst forecast sample ranges from 2012 to 2020. To alleviate impacts of outliers, we winsorize all continuous variables at 1st and 99th percentiles. See Appendix for variable definitions.

which industrial robot adoption increases labor efficiency.[2]

The effects of industrial robot adoption on production activities are summarized in Panel B, Table 3. To proxy for productivity efficiency, we follow Blundell and Bond (1998) and calculate the TFP denoted as *TFP*. In Column (1), the coefficient of *Robot* is positive and significant at the 1% level suggesting that industrial robot adoption significantly improves firms' TFP. In Columns (2) and (3), we present the second-stage results by using analyst forecast bias and dispersion as the main dependent variables. Overall, the negative signs of *Robot* and *TFP* illustrate that boosting TFP can be treated as another possible channel. From Column (4)–(6), we use three years earnings volatility to represent profit sustainability (denoted as *EarningVol*). The results are consistent with our expectation that reducing profit volatility brought about by industrial robot adoption leads to higher analyst forecast precision.

The next group of possible channels is that firms adopting industrial robots help firms attract analyst coverage and site visit indirectly. As industrial robot adoption can mitigate information uncertainty, analysts will face a lower cost to follow such firms. In addition, analysts care about corporate innovation and technical progress (Barth et al., 2001; García-Meca & Martínez, 2007; Jia, 2017). Firms adopting industrial robots may stimulate analysts' incentive to visit the target firms and furthermore Cheng et al. (2016) find that analysts' site visits help improve their forecasting performance. Thus, we expect that industrial robot adoption can improve analyst forecast precision by indirectly affecting analyst behavior such as attracting more coverage and site visit. The results are documented in Panel C, Table 3. In Column (1) of Panel C, Table 3, we analyze the impact of industrial robots on analyst coverage which is calculated as the natural logarithm of one plus the total number of analysts following the firm. The coefficient of *Robot* is 0.0216 with a t-value of 1.71 that is significant at the 10% level indicating that industrial robot adoption increases the analyst coverage level. Columns (2) and (3) present the regression results by including both industrial robot adoption and analyst coverage. *Analyst* exhibits negative and significant coefficients (−0.0057, $t = -6.80$; −0.0018, $t = -4.67$) suggesting that analyst coverage increasing can help reduce forecast bias and dispersion. Meanwhile, the coefficients of Robot still remains negative and significant. In sum, the results in the first three columns of Panel C support the notion that increasing analyst coverage is another possible channel through which industrial robot adoption increases their forecasting performance indirectly. The next three columns document the results by using site visit as the mediator variable. *Visit* represents the frequency of analyst site visits which is calculated as the natural logarithm of the number of analysts' firm site visits. Column (4) reports the first stage result by regressing *Robot* on *Visit*. The coefficient is positive and significant (0.0410, $t = 2.02$). Columns (5) and (6) report the second stage results by regressing both *Robot* and *Visit* on analyst forecast bias and dispersion. Both coefficients of *Robot* and *Visit* are negative and significant at the 1% and 10% levels separately. Accordingly, site visitation serves as another possibility through which industrial robot adoption affects analyst forecasting performance.

4.4. The effect of environmental uncertainty

To further investigate whether our main results vary due to environmental uncertainty, we conduct a branch of cross-sectional analyses. Industrial robot adopton's ability to mitigate information uncertainty directly or indirectly contributes to lower analyst forecast bias and dispersions. In this section, we examine the impact of other environmental uncertainty factors on this relationship. Table 4 presents the results of cross-sectional tests from three aspects including business complexity proxied by corporate subsidiary amounts, business growth proxied as sales growth rate, and labor intensity proxied by the ratio of

[2] For the channel of employee numbers, we further test the effect of industrial adoption robot on the number of low-skilled and high-skilled employees. The uncalculated results indicate that low-skilled employees are more likely to be replaced by industrial robot compared to high-skilled employees, consistent with Acemoglu and Restrepo (2020).

Table 2
Main regression: robot adoption and analyst earnings forecasts.

Variable	(1)	(2)	(3)	(4)
	$Fbias_{t+1}$	$Fdisp_{t+1}$	$Fbias_{t+1}$	$Fdisp_{t+1}$
Robot	**−0.0043*****	**−0.0022*****	**−0.0040*****	**−0.0021*****
	(−3.09)	**(−3.80)**	**(−3.27)**	**(−3.70)**
Analyst			−0.0057***	−0.0018***
			(−5.94)	(−3.91)
Horizon			0.0165***	0.0058***
			(12.97)	(10.67)
Asset			0.0296***	0.0094***
			(11.00)	(8.83)
Lev			−0.0087	−0.0151***
			(−1.09)	(−4.30)
Growth			−0.0178***	−0.0057***
			(−10.12)	(−8.07)
Roa			−0.0910***	−0.0553***
			(−5.56)	(−7.53)
Boardsize			0.0144**	0.0004
			(1.99)	(0.11)
Indep			−0.0002	0.0072
			(−0.01)	(0.75)
Sh5			−0.0270**	0.0020
			(−2.05)	(0.30)
ShHHI			−0.0032	−0.0032
			(−0.15)	(−0.32)
Accm			0.0481**	0.0540***
			(2.29)	(5.38)
Big4			−0.0078	−0.0036
			(−1.39)	(−1.46)
Index			−0.0000	0.0000
			(−0.05)	(0.07)
Constant	0.0580***	0.0309***	−0.6987***	−0.2070***
	(13.63)	(17.19)	(−10.88)	(−7.99)
Firm & Year	Yes	Yes	Yes	Yes
N	9419	9419	9419	9419
R^2	0.1013	0.1383	0.2005	0.2024

Note: This table shows the main result of the impact of robot adoption of firms on analyst earnings forecasts, with the first two columns without firm-level controls and the last columns with all the controls. The dependent variable is *Fbias* and *Fdisp*, and the independent variable is *Robot*. Firm fixed effects and year fixed effects are also included. All the variables are defined in the Appendix. Here, *, ** and *** denote 10%, 5% and 1% levels of significance.

employee salaries to sales. Higher business complexity, higher sales growth and higher labor intensity deliver a more uncertain signal to outsiders about the firm.

We then transform these three variables into dummy indicators. *Subf* is defined as 1 if the number of subsidiaries surpass the year-industry-median value and zero otherwise. Analyst forecast bias is used as the main dependent variable, and the subgroup tests are summarized in Columns (1) and (2) of Panel A. The coefficient of *Robot* is negative and significant at the 10% level when $Subf = 1$ indicating an enhancement of industrial robot adoption's impact in complicated firms with more subsidiaries. The next column shows the interaction test. $Robot \times Subf$ is negative and significant supporting the notion that the information promotion role of industrial robot adoption is more significant in more uncertain firms (Coefficient, −0,0024; t-value, −2.27). Columns (4)–(6) document the results using analyst forecast dispersion as the main dependent variable. The results are consistent with the first three columns.

The second indicator, *Dgro*, is defined as 1 if the firm's sales grow at a rate exceeding the year-industry-median value and zero otherwise. Subgroup analyses are reported in Panel B, Columns (1), (2), (4) and (5). Coefficients of *Robot* are negative and significant in the higher sales growth subgroup in Columns (1) and (4). Interaction studies in Columns (3) and (6) suggest that the interaction of $Robot \times Dgro$ is negative and significant in Column (3) at the 1% level, but insignificant in Column (6). These results provide partial support that the positive relation between industrial robot adoption and analyst forecast precision is more pronounced in higher sales growth firms.

The last indicator, *LabInt,* is defined as 1 if the ratio of employee salaries to sales surpasses the year-industry-median value and zero otherwise. Industries such as manufacturing and technology are often capital-intensive. Labor-intensive firms often involve a significant amount of human labor and there may be a higher risk to predict the production condition resulting in higher information uncertainty. By analyzing both subgroup and interaction tests in Panel C, we find that all the coefficients of *Robot* in subgroup analyses are negative and significant. By comparing the coefficient number, the effect of industrial robot adoption has a larger impact in the $LabInt = 1$ subgroup. If analyzing the interaction term, $Robot \times LabInt$, coefficients are −0.0016 and − 0.0005 with t-values of −2.50 and − 1.68 that are significant at the 5% and 10% levels. In sum, the results in Panel C show that the positive relation between industrial robot adoption and analyst forecast precision is more pronounced in labor-intensive firms.

To summarize, we demonstrate that the improvement by industrial robot adoption to analyst forecast precision is more pronounced in firms with larger environmental uncertainty reflected as having more business subsidiaries, higher sales growth, and more labor-intensive observation.

4.5. The effect of state ownership

As documented by previous studies, Chinese local governments exert pressure on brokerages, urging analysts to engage in overly optimistic earnings forecasting of state-owned enterprises (SOEs). Due to political pressure, Chinese studies find that analysts employed by SOEs issue more optimistic forecasts for investment boosting or political goals (Firth, Lin, Liu, & Xuan, 2013; Hou, Li, Teng, & Hu, 2022). Another reason why analyst forecast precision is reduced in SOEs is that these enterprises should take the responsibility of social equity and full employment, and they cannot be totally market oriented. In sum, the complex situation is an obstacle to analysts making precise forecasts on SOEs.

For these reasons, we predict that the role of industrial robots will be attenuated in SOEs. We define *SOE* as 1 if the firm is controlled by local/central government, and 0 otherwise. A subgroup test and interaction test are employed, and we document the results in Table 5. We set analyst forecast bias as the dependent variable in the first three columns and analyst forecast dispersion in the rest. By comparing Columns (1) and (2), we find that the coefficient of *Robot* is only negative and significant when $SOE = 0$, suggesting that the positive effect of industrial robot adoption is more effective in private firms as they have little concern about political and macroeconomic pressure. Columns (4) and (5) display similar results to Columns (1) and (2). Columns (3) and (6) present an interaction study and the coefficient of $Robot \times SOE$ is significantly positive in Column (6), partially consistent with subgroup analyses.

5. Robustness checks

5.1. Propensity score matching

As the decision to adopt industrial robots may be endogenous and our industrial robot number is derived from industry-level data, we apply a collection of propensity score matching approaches to ensure consistency. The treatment group and control group are filtered by using the following criteria individually (1) whether firms are included in China intelligent manufacturing demonstration project or not (*PRobot*); (2) whether firms' MD&A session in their annual report includes the word "robot" or not (*RRobot*); (3) whether firms' MD&A session includes "robot" or "automation" or not (*RARobot*); (4) whether firms' MD&A session includes "robot" or "automation" or "intelligentiation" or not (*RAIRobot*). The propensity score in the matching process is obtained from a logistics estimation based on firm's financial ratios including firm size, financial leverage, sales growth rate, return on assets, log value of board members, proportion of independent directors, ownership of top

Table 3
Possible mechanisms.

Panel A: Labor Efficiency (Operating Efficiency - Labor Efficiency).

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Labor_Com	$Fbias_{t+1}$	$Fdisp_{t+1}$	*Labor_Num*	$Fbias_{t+1}$	$Fdisp_{t+1}$	*Labor_Str*	$Fbias_{t+1}$	$Fdisp_{t+1}$
Robot	**−0.0261*** (−5.22)**	**−0.0039*** (−4.16)**	**−0.0019*** (−4.48)**	**−0.0438*** (−7.18)**	**−0.0033*** (−3.50)**	**−0.0020*** (−4.62)**	**0.0768** (2.05)**	**−0.0034*** (−3.62)**	**−0.0020*** (−4.65)**
Labor		**0.0057*** (2.65)**	**0.0039*** (3.92)**		**0.0033* (1.89)**	**0.0002 (0.20)**		**−0.0006** (−2.16)**	**−0.0000 (−0.13)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.9907*** (23.32)	−0.7277*** (−17.74)	−0.2273*** (−11.88)	−5.4780*** (−21.12)	−0.6843*** (−16.84)	−0.2070*** (−10.83)	−10.3480*** (−6.48)	−0.7091*** (−17.91)	−0.2081*** (−11.18)
Firm & Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9407	9407	9407	9326	9326	9326	9326	9326	9326
R^2	0.7925	0.1999	0.2034	0.5007	0.2005	0.2031	0.1078	0.2006	0.2031

Panel B: Productivity Efficiency (Operating Efficiency - Productivity Efficiency)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	TFP	$Fbias_{t+1}$	$Fdisp_{t+1}$	*EarningVol*	$Fbias_{t+1}$	$Fdisp_{t+1}$
Robot	**0.0577* (1.89)**	**−0.0032 (−1.43)**	**−0.0018* (−1.66)**	**−0.0026** (−2.22)**	**−0.0037* (−1.67)**	**−0.0017 (−1.55)**
TFP/EarningVol		**−0.0028* (−1.81)**	**−0.0002 (−0.30)**		**0.0908*** (4.55)**	**0.0186* (1.85)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.3716*** (4.46)	−0.6959*** (−17.56)	−0.2048*** (−11.09)	−0.4478*** (−13.16)	−0.6438*** (−15.32)	−0.2203*** (−10.92)
Firm & Year	Yes	Yes	Yes	Yes	Yes	Yes
N	9415	9415	9415	8262	8262	8262
R^2	0.5502	0.2006	0.2030	0.1234	0.2252	0.2205

Panel C: Information Dissemination

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Analyst	$Fbias_{t+1}$	$Fdisp_{t+1}$	*Visit*	$Fbias_{t+1}$	$Fdisp_{t+1}$
Robot	**0.0216* (1.71)**	**−0.0040*** (−4.27)**	**−0.0021*** (−4.74)**	**0.0410** (2.02)**	**−0.0057*** (−4.31)**	**−0.0029*** (−4.93)**
Analyst/Visit		**−0.0057*** (−6.80)**	**−0.0018*** (−4.67)**		**−0.0033*** (−3.57)**	**−0.0007* (−1.66)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−9.3318*** (−17.60)	−0.6987*** (−17.66)	−0.2070*** (−11.22)	1.3760* (1.72)	−0.6906*** (−13.31)	−0.2042*** (−8.78)
Firm & Year	Yes	Yes	Yes	Yes	Yes	Yes
N	9419	9419	9419	6056	6056	6056
R^2	0.1831	0.2005	0.2024	0.2377	0.2274	0.2187

Note: This table presents the possible channels through which the firms' robot adoption affects analyst earnings forecasts from the operating efficiency and information dissemination. Following Bauer et al. (2020) path analysis, we use labor efficiency (*Labor_Com, Labor_Num, Labor_Str*), productivity efficiency (*TFP*), profit sustainability (*EarningVol*), and information dissemination (*Analyst, Visit*) as the intermediary variables separately. In the first stage, we run robot application on intermediary variable. In the second stage, we add both robot application and intermediary variable together in the analysis, separately. Firm fixed effects and year fixed effects are also included. All the variables are defined in the Appendix. Here, *, ** and *** denote 10%, 5% and 1% levels of significance.

five largest shareholders, ownership concentration, information transparency, the Big4 auditors, analyst coverage and forecast horizon. For each treatment firm (*PRobot* = *1*), we select one control firm (*PRobot* = *0*) with the closest propensity score, and these firms constitute the propensity-score matched control sample. The results by using *PRobot* as division breakpoint are reported in Columns (1) and (2), Table 6. *Robot* has a negative link with $Fbias_{t+1}$ and $Fdisp_{t+1}$ confirming the baseline finding. In the following columns, we use *RRobot, RARobot, RAIRobot* as main division benchmarks. The coefficients of *Robot* are all negative and significant regardless of analyst forecast bias (*Fbias*) or analyst forecast dispersion (*Fdisp*) as the main dependent variables. Overall, the results in Table 6 support the assertion that industrial robot adoption can increase analyst forecast precision through reducing analyst forecast bias and dispersion.

5.2. Change analysis

To ensure the reliability and robustness of our results, we perform change analysis to test whether industrial robot adoption decreases analyst forecast bias and dispersion. In Table 8, the dependent variable is the change of analyst forecast bias, denoted as $\Delta Fbias_{t+1}$. It is calculated by the variation in analyst forecast bias from the previous year to the current year. *ΔRobot* represents the variation in industrial robot adoption from last year to this year. Besides, all the control variables are also measured by their changes.

The results are reported in Table 7. The coefficient of *ΔRobot* is −0.0031 (t = −1.42) that is negative but insignificant if using the change of analyst forecast bias as the main dependent variable. Column (2) presents the result by using the change analyst forecast dispersion as the main dependent variable. The coefficient of *ΔRobot* is −0.0018 (t = −1.66) indicating that when industrial robot adoption increases in firms, analyst forecast dispersion will decrease significantly. The above

Table 4
Cross-sectional analysis—environmental uncertainty.

Panel A: Business Complexity

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Subf = 1	*Subf* = 0	Full sample	*Subf* = 1	*Subf* = 0	Full sample
	$Fbias_{t+1}$	$Fbias_{t+1}$	$Fbias_{t+1}$	$Fdisp_{t+1}$	$Fdisp_{t+1}$	$Fdisp_{t+1}$
Robot	**−0.0036***	**−0.0029**	**−0.0026****	**−0.0037*****	**−0.0001**	**−0.0014****
	(−1.90)	**(−1.46)**	**(−2.00)**	**(−3.97)**	**(−0.08)**	**(−2.49)**
Robot× Subf			**−0.0024****			**−0.0012****
			(−2.27)			**(−2.44)**
Subf			0.0032			0.0019
			(0.92)			(1.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.7044***	−0.7366***	−0.6894***	−0.2131***	−0.1804***	−0.2059***
	(−7.27)	(−7.94)	(−10.74)	(−5.61)	(−4.97)	(−8.00)
Firm & Year	Yes	Yes	Yes	Yes	Yes	Yes
N	4744	4585	9329	4744	4585	9329
R^2	0.2064	0.2001	0.2014	0.1965	0.2267	0.2023

Panel B: Business Growth

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Dgro = 1	*Dgro* = 0	Full sample	*Dgro* = 1	*Dgro* = 0	Full sample
	$Fbias_{t+1}$	$Fbias_{t+1}$	$Fbias_{t+1}$	$Fdisp_{t+1}$	$Fdisp_{t+1}$	$Fdisp_{t+1}$
Robot	**−0.0053*****	**−0.0023**	**−0.0030****	**−0.0025*****	**−0.0015***	**−0.0020*****
	(−3.13)	**(−1.41)**	**(−2.46)**	**(−3.11)**	**(−1.83)**	**(−3.49)**
Robot× Dgro			**−0.0020*****			**−0.0002**
			(−3.65)			**(−0.85)**
Dgro			0.0007			−0.0012*
			(0.48)			(−1.78)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.6577***	−0.7641***	−0.7002***	−0.1852***	−0.2322***	−0.2060***
	(−8.66)	(−6.48)	(−10.89)	(−5.92)	(−4.92)	(−7.94)
Firm & Year	Yes	Yes	Yes	Yes	Yes	Yes
N	4827	4592	9419	4827	4592	9419
R^2	0.1671	0.2004	0.2031	0.1760	0.2128	0.2037

Panel C: Labor Intensity

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	LabInt = 1	*LabInt* = 0	Full sample	*LabInt* = 1	*LabInt* = 0	Full sample
	$Fbias_{t+1}$	$Fbias_{t+1}$	$Fbias_{t+1}$	$Fdisp_{t+1}$	$Fdisp_{t+1}$	$Fdisp_{t+1}$
Robot	**−0.0048*****	**−0.0028****	**−0.0033*****	**−0.0034*****	**−0.0012***	**−0.0018*****
	(−3.03)	**(−2.17)**	**(−3.41)**	**(−4.93)**	**(−1.82)**	**(−4.07)**
Robot× LabInt			**−0.0016****			**−0.0005***
			(−2.50)			**(−1.68)**
LabInt			0.0038**			0.0017**
			(2.07)			(1.97)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.6817***	−0.7783***	−0.6993***	−0.2021***	−0.2354***	−0.2077***
	(−10.91)	(−12.47)	(−17.67)	(−7.36)	(−7.65)	(−11.25)
Firm & Year	Yes	Yes	Yes	Yes	Yes	Yes
N	4791	4628	9419	4791	4628	9419
R^2	0.1832	0.2115	0.2012	0.1806	0.2187	0.2028

Note: This table presents the results by distinguishing environmental uncertainty. We use business complexity, business growth and labor intensity of firms to capture the environmental uncertainty, which are reported in Panel A, Panel B, and Panel C respectively. Firm fixed effects and year fixed effects are also included. All the variables are defined in the Appendix. Here, *, ** and *** denote 10%, 5% and 1% levels of significance.

results partially support the notion that industrial robot adoption leads to better analyst forecast precision.

5.3. Adding additional control variables

In previous regression studies, we included a battery of control variables to mitigate the concern that the main findings may suffer from the issue of omitted variables. In this section, we further integrate additional control variables to strengthen the persuasiveness incrementally. First, we include an employee-level characteristic named *Labor_Str*. Analysts may also rely on other technological information to make forecast decisions besides industrial robots. *Labor_Str* represents the labor structure, which is the proportion of employees with highly educated degrees above postgraduate. Second, as industrial robots are concentrated in manufacturing firms, such firms always heavily rely on tangible assets. We add firm-level property, plant and equipment in the regression. *PPE* is defined as the ratio calculated as fixed assets adjusted by total assets. Finally, to control for the macro-level factor effect, we append provincial GDP. *GGDP* is the provincial GDP where the firm is located. The results are presented in Table 8. The coefficients of *Robot*

Table 5
Property Right.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	$SOE = 1$	$SOE = 0$	Full sample	$SOE = 1$	$SOE = 0$	Full sample
	$Fbias_{t+1}$	$Fbias_{t+1}$	$Fbias_{t+1}$	$Fdisp_{t+1}$	$Fdisp_{t+1}$	$Fdisp_{t+1}$
Robot	**−0.0009**	**−0.0059*****	**−0.0037*****	**−0.0012**	**−0.0025*****	**−0.0025*****
	(−0.46)	**(−3.54)**	**(−2.82)**	**(−1.32)**	**(−3.52)**	**(−4.16)**
Robot× SOE			**−0.0009**			**0.0013****
			(−0.70)			**(2.18)**
SOE			0.0106			−0.0039
			(1.57)			(−1.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.6197***	−0.7043***	−0.6973***	−0.1907***	−0.2348***	−0.2087***
	(−6.90)	(−7.86)	(−10.92)	(−4.48)	(−7.13)	(−8.01)
Firm & Year	Yes	Yes	Yes	Yes	Yes	Yes
N	3290	6129	9419	3290	6129	9419
R^2	0.1544	0.2272	0.2011	0.1803	0.2291	0.2033

Note: This table presents the results by distinguishing property rights. We classify our sample into state-owned enterprises group and non-state-owned enterprises group. The variable *SOE* is a dummy variable with a value of one for the state-owned enterprises group and a value of zero otherwise. Firm fixed effects and year fixed effects are also included. All the variables are defined in the Appendix. Here, *, ** and *** denote 10%, 5% and 1% levels of significance.

Table 6
Propensity score matching.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Fbias_{t+1}$	$Fdisp_{t+1}$	$Fbias_{t+1}$	$Fdisp_{t+1}$	$Fbias_{t+1}$	$Fdisp_{t+1}$	$Fbias_{t+1}$	$Fdisp_{t+1}$
Robot	**−0.0075*****	**−0.0054*****	**−0.0035**	**−0.0053*****	**−0.0027****	**−0.0018*****	**−0.0040*****	**−0.0016****
	(−3.21)	**(−4.75)**	**(−0.97)**	**(−3.77)**	**(−2.26)**	**(−3.23)**	**(−3.05)**	**(−2.52)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.6774***	−0.3001***	−0.6938***	−0.2832***	−0.6968***	−0.2393***	−0.7415***	−0.2149***
	(−6.06)	(−5.54)	(−5.32)	(−5.64)	(−13.56)	(−10.12)	(−12.96)	(−7.87)
Firm & Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1754	1754	2218	2218	6530	6530	5376	5376
R^2	0.2215	0.2359	0.2293	0.2511	0.2084	0.2346	0.1973	0.1946

Note: This table reports the results using propensity score matching (PSM) procedure. Firm fixed effects and year fixed effects are also included. All the variables are defined in the Appendix. Here, *, ** and *** denote 10%, 5% and 1% levels of significance.

Table 7
Change analysis.

Variable	(1)	(2)
	$\varDelta Fbias_{t+1}$	$\varDelta Fdisp_{t+1}$
ΔRobot	**−0.0031**	**−0.0018***
	(−1.42)	**(−1.66)**
Controls	Yes	Yes
Constant	−0.0014	−0.0073***
	(−0.78)	(−8.27)
Firm & Year	Yes	Yes
N	7123	7123
R^2	0.1024	0.1283

Note: This table reports the results of a change model. We calculate the difference of all variables between year t and year t-1 of the regression model. Firm fixed effects and year fixed effects are also included. All the variables are defined in the Appendix. Here, *, ** and *** denote 10%, 5% and 1% levels of significance.

are both negative and significant at the 1% level regardless of using analyst forecast bias or dispersion as dependent variables. (See Table 8.)

5.4. Extending the sample period

The sample ends in 2019 because the data regarding industrial robot adoption is now only available for 1993 to 2019 as provided by the IFR. In order to enhance the robustness, discussing the relationship between industrial robot adoption and analyst forecast performance during 2019–2022 would be necessary. Therefore, we try to construct a new robot variable by capturing the words about robots from firms' MD&A session in their annual report, and re-test the relationship between robots and analyst forecasting performance during 2011–2022. The dependent variables and control variables cover 2011–2021 and the independent variables are during 2012–2022. As seen in Columns (1) and (2), Table 9, *Robot_R* is negatively related to *Fbias* and *Fdisp*, which supports the claim that industrial robot adoption can increase analyst forecast precision sustainably even after extending the sample period.

Considering that the results may suffer interference from COVID-19, we further test how COVID-19 affects the relationship between robots and analyst forecasting performance. *Covid19* equals 1 if the year is after 2019 and 0 otherwise. Columns (3) and (4) show that the interaction of *Robot_R* × *Covid19* is negative and significant in Column (4) at the 5% level, but insignificant in Column (3). These results provide partial support that the positive relation between industrial robot adoption and analyst forecast precision is more pronounced in the pandemic period of COVID-19.

5.5. Other robustness checks

We perform several other robustness tests and present them in Table 10, including (1) using two alternative proxies of analyst earnings forecasts in the first four columns; (2) controlling for the interactive effect of province and industry effects; and (3) filtering the observations without a robot. Columns (1) and (2) calculate analyst forecast bias and dispersion by exchanging the adjusted denominator, i.e., stock price, with total assets. Columns (3) and (4) transform the continuous dependent variable to dummy ones. We define *DFbias* as 1 if *Fbias* is larger than last year's value, otherwise 0. Similarly, *DFdisp* equals 1 if *Fdisp* is larger than last year, otherwise 0. In Columns (5) and (6), we include *Industry*×*Province* in the bottom to control for the interactive effect of province and industry. In the last two columns, we only include

Table 8
Adding additional control variables.

Variable	(1) $Fbias_{t+1}$	(2) $Fdisp_{t+1}$
Robot	**−0.0033***** **(−2.74)**	**−0.0020***** **(−3.51)**
Analyst	−0.0057*** (−5.80)	−0.0018*** (−3.86)
Horizon	0.0163*** (12.90)	0.0058*** (10.62)
Asset	0.0304*** (11.13)	0.0098*** (8.99)
Lev	−0.0122 (−1.53)	−0.0158*** (−4.38)
Growth	−0.0175*** (−9.89)	−0.0057*** (−7.92)
Roa	−0.0898*** (−5.47)	−0.0549*** (−7.45)
Boardsize	0.0147** (2.03)	0.0001 (0.03)
Indep	0.0030 (0.15)	0.0066 (0.67)
Sh5	−0.0269** (−2.05)	0.0026 (0.39)
ShHHI	−0.0027 (−0.13)	−0.0039 (−0.38)
Accm	0.0467** (2.23)	0.0550*** (5.45)
Big4	−0.0077 (−1.34)	−0.0033 (−1.31)
Index	−0.0000 (−0.02)	0.0000 (0.07)
Labor_Str	−0.0006 (−1.57)	−0.0000 (−0.08)
PPE	0.0075 (0.83)	0.0069 (1.41)
GGDP	−0.0076 (−0.54)	−0.0010 (−0.16)
Constant	−0.7178*** (−11.00)	−0.2162*** (−8.12)
Firm & Year	Yes	Yes
N	9326	9326
R^2	0.2007	0.2035

Note: This table reports the results of adding control variables. Firm fixed effects and year fixed effects are also included. All the variables are defined in the Appendix. Here, *, ** and *** denote 10%, 5% and 1% levels of significance.

Table 9
Extending the sample period.

Variable	(1) $Fbias_{t+1}$	(2) $Fdisp_{t+1}$	(3) $Fbias_{t+1}$	(4) $Fdisp_{t+1}$
Robot_R	**−0.0027**** **(−2.34)**	**−0.0011*** **(−1.67)**	**−0.0022*** **(−1.92)**	**−0.0003** **(−0.45)**
Robot_R× Covid19			**−0.0005** **(−0.19)**	**−0.0017**** **(−2.02)**
Covid19			−0.0179*** (−5.51)	−0.0239*** (−13.69)
Analyst	−0.0092*** (−11.50)	−0.0042*** (−9.39)	−0.0096*** (−11.99)	−0.0048*** (−10.74)
Horizon	0.0079*** (7.81)	−0.0017*** (−2.69)	0.0079*** (7.82)	−0.0017*** (−2.77)
Asset	0.0067*** (4.52)	0.0025*** (3.08)	0.0111*** (6.35)	0.0084*** (8.75)
Lev	−0.0052 (−0.87)	−0.0152*** (−4.45)	−0.0083 (−1.39)	−0.0193*** (−5.72)
Growth	−0.0061*** (−4.35)	−0.0024*** (−3.60)	−0.0068*** (−4.89)	−0.0033*** (−4.99)
Roa	−0.3577*** (−19.39)	−0.0686*** (−9.25)	−0.3566*** (−19.37)	−0.0672*** (−9.26)
Boardsize	0.0055 (0.97)	−0.0022 (−0.63)	0.0027 (0.46)	−0.0060* (−1.79)
Indep	0.0180 (1.11)	0.0056 (0.55)	0.0176 (1.07)	0.0051 (0.50)
Sh5	−0.0104 (−0.96)	0.0016 (0.25)	−0.0146 (−1.35)	−0.0040 (−0.62)
ShHHI	0.0185 (1.19)	0.0113 (1.16)	0.0118 (0.76)	0.0021 (0.22)
Accm	0.0721*** (4.86)	0.0504*** (5.17)	0.0629*** (4.35)	0.0379*** (4.07)
Big4	−0.0053 (−1.27)	−0.0028 (−0.81)	−0.0045 (−1.11)	−0.0017 (−0.52)
Index	−0.0005 (−1.36)	−0.0008*** (−3.83)	0.0012*** (2.82)	0.0015*** (5.72)
Constant	−0.1182*** (−3.50)	0.0047 (0.25)	−0.2120*** (−5.41)	−0.1219*** (−5.56)
Firm & Year	Yes	Yes	Yes	Yes
N	11,065	11,065	11,065	11,065
R^2	0.2749	0.1110	0.2792	0.1392

Note: This table shows the main result of the impact of robot adoption of firms on analyst earnings forecasts from 2011 to 2022. The dependent variable is *Fbias* and *Fdisp*, and the independent variable is *Robot_R*. Firm fixed effects and year fixed effects are also included. All the variables are defined in the Appendix. Here, *, ** and *** denote 10%, 5% and 1% levels of significance.

observations with industrial robot adoption. All the eight columns report a negative and significant sign supporting the main argument that industrial robot adoption is negatively related to analyst forecast bias and dispersion.

6. Conclusion

The goal of this study is to investigate the impact of industrial robot adoption in the manufacturing industry on analyst forecast precision. Using Chinese listed firms from 2011 to 2019, we find an optimistic and significant relationship between industrial robot adoption and analyst forecast precision. We further explore the possible channels through which industrial robot adoption influences analyst behavior. Specifically, industrial robot adoption helps firms improve their operating efficiency and promote information dissemination. Thus, analysts can grasp more certain information in these firms and make more precise forecast decisions. Additionally, the usage of industrial robots enables the firm to attract more analyst coverage and site visits, thus improving analyst forecasting performance.

Chinese listed firms encompass SOEs to a large extent whose primary function is divergent from maximizing firm-level benefits like private firms. These firms always take responsibility for protecting social stability. By analyzing the property right influence, we find that the optimistic role of industrial robots in analyst forecasting performance is more significant in private firms.

We further identify how the relationship between industrial robot adoption and analyst forecast behavior varies due to other environmental uncertainty factors. Using both subgroup analyses and interaction analyses, we find that the role of industrial robots is more pronounced when firms face more environmental uncertainty proxied by higher business complexity, higher business growth, and higher labor intensity.

In conclusion, our study provides fresh empirical evidence on the role of industrial robots in the capital market. Analysts are one of the most important information intermediaries in the capital market and help firms attract potential investors. They make forecast decisions based on collected private and public information. Meanwhile, industrial robot adoption plays a vital role in modern manufacturing industries. It helps firms increase the productivity and efficiency of their manufacturing operations significantly. But the spillover role of industrial robot adoption in other firm activities is still underexplored. We provide supporting evidence for the value-creation role of industrial robots from the perspective of analyst forecasting performance.

In summary, the paper sheds light on the idea that industrial robot adoption not only promotes productivity and labor efficiency, but also plays an important role in affecting analysts' information extraction behavior. Firms can invest real effort in industrial robot adoption to attract more analysts' attention so as to enhance market valuation. This

Table 10
Other robustness check.

Variable	(1) $AFbias_{t+1}$	(2) $AFdisp_{t+1}$	(3) $DFbias_{t+1}$	(4) $DFdisp_{t+1}$	(5) $Fbias_{t+1}$	(6) $Fdisp_{t+1}$	(7) $Fbias_{t+1}$	(8) $Fdisp_{t+1}$
Robot	**−0.0058***** **(−3.34)**	**−0.0018**** **(−2.06)**	**−0.1316**** **(−2.24)**	**−0.1227**** **(−2.14)**	**−0.0087***** **(−8.60)**	**−0.0056***** **(−10.72)**	**−0.0026*** **(−1.71)**	**−0.0020***** **(−2.91)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.6616*** (−7.21)	−0.0686* (−1.73)	–	–	−0.5723*** (−10.52)	−0.1547*** (−6.97)	−0.7185*** (−10.08)	−0.2132*** (−7.34)
Firm & Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Province	No	No	No	No	Yes	Yes	No	No
N	9419	9419	8729	8729	9419	9419	7355	7355
R^2	0.0769	0.1105	0.2290	0.1990	0.1512	0.1291	0.1986	0.2016

Note: This table shows various robustness checks including (1) using alternative proxy of analyst earnings forecasts in the first four columns; (2) controlling for interactive effect of province and industry effects; (3) filtering the observations that without robot. Firm fixed effects and year fixed effects are also included. All the variables are defined in the Appendix. Here, *, ** and *** denote 10%, 5% and 1% levels of significance.

study suffers from some limitations. A first point is the lack of alternative proxies for firm-level industrial robot adoption. Referring to existing literature, we construct the firm-level industrial robot data indirectly. Future research can consider how to improve the calculation method in the research. Second, the paper mainly focuses on analysts' reaction to industrial robot adoption. A future line of research can also be to expand the study to other participants in the capital market.

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Data availability

The data that has been used is confidential.

Appendix A. Variable definitions

Variable	Definition and Calculation
Fbias	Analyst forecast bias using the measure of Behn et al. (2008). $Fbias_{i,t+1} = \lvert Mean(FEPS_{i,t+1})\text{-}MEPS_{i,t+1}\rvert / PRICE_{i,t}$, where $Mean(FEPS_{i,t+1})$ is the mean of analyst' s latesd forecasted earnings per share for firm *i* for year $t+1$, $MEPS_{i,t+1}$ is actual earnings per share for firm *i* for year $t+1$, $PRICE_{i,t}$ is the stock price for firm *i* for year *t*.
Fdisp	Analyst forecast dispersion using the measure of Behn et al. (2008). $Fdisp_{i,t+1} = SD(FEPS_{i,t+1})/PRICE_{i,t}$, where $SD(FEPS_{i,t+1})$ is the standard deviation of analyst' s latesd forecasted earnings per share for firm *i* for year $t+1$.
Robot	The exposure of firms to robots referring to the method of Acemoglu and Restrepo (2020).
Analyst	Natural logarithm of one plus total analyst number following the firm.
Horizon	Natural logarithm of the average days between the forecast date and the corresponding date of the actual financial report.
Asset	Natural logarithm of total assets.
Lev	Debt ratio equal total debt/total asset.
Growth	Firm's sales growth rate.
Roa	Return on assets, equals firm's earnings before interest and tax divided by total assets.
Boardsize	Natural logarithm of board directors in the firm.
Indep	The proportion of independent directors in the board.
Sh5	Sum of the ownership of the top five shareholders divided by total share amounts.
ShHHI	Sum of the squares of the ownership of the top ten shareholders.
Accm	Mean of past three years of absolute value of residuals estimated using the modified Dechow–Dichev (2002) model.
Big4	A dummy variable with a value of 1 when the external auditor is Big4 and 0 otherwise.
Index	Index of development of factor market and legal environment.
Labor_Com	Natural logarithm of the total salary
Labor_Num	Natural logarithm of the number of employees
Labor_Str	The proportion of employees with highly educated degree above postgraduate.
TFP	Blundell and Bond (1998) and calculate the total factor productivity
EarningVol	Three year earnings volatility.
Visit	Natural logarithm of the numbers of analysts' firm site visits.
SOE	A dummy variable with a value of one for the state-owned enterprises and a value of zero otherwise.
Subf	A dummy variable that equals one if the number of subsidiaries surpass the year-industry-median value and zero otherwise.
Dgro	A dummy variable that equals one if firm's sales growth rate surpasses the year-industry-median value and zero otherwise.
LabIntnt	A dummy variable that equals one if the ratio of employee's salary to sales surpasses the year-industry-median value and zero otherwise.
PRobot	A dummy variable that equals one if the firm entries China intelligent manufacturing demonstration project and zero otherwise.
RRobot	A dummy variable that equals one if the word of "robot" is disclosed in MD&A and zero otherwise.
RARobot	A dummy variable that equals one if the word of "robot, automation" is disclosed in MD&A and zero otherwise.
RAIRobot	A dummy variable that equals one if the word of "robot, automation, intelligentization" is disclosed in MD&A and zero otherwise.
PPE	Ratio equals fixed asset/total asset.
GGDP	Province's GDP growth rate.
Robot_R	Natural logarithm of the number of the words about robot from firms' MD&A session in annual report.
Covid19	A dummy variable that equals one if the year is after 2020 and zero otherwise.
AFbias	Analyst forecast bias adjusted by total asset instead stock price.
AFdisp	Analyst forecast dispersion adjusted total asset instead of stock price.

(*continued on next page*)

(*continued*)

Variable	Definition and Calculation
DFbias	A dummy variable that equals one if $Fbias_{i,t}$ is larger than $Fbias_{i,t-1}$ and zero otherwise.
DFdisp	A dummy variable that equals one if $Fdisp_{i,t}$ is larger than $Fdisp_{i,t-1}$ and zero otherwise.

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