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ROBOT ADOPTION: EVIDENCE FROM PERCEIVED BENEFITS AND INDUSTRY ADOPTION PRESSURE

Qiang MAI[1], Qi-nan ZHANG[2], Fanfan ZHANG[1✉], Fang JI[1]

[1] *School of Management, Harbin Institute of Technology, Harbin, China*
[2] *School of Economics and Management, Taiyuan University of Science and Technology, Taiyuan, China*

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Abstract. Recent research suggests that many firms have begun to adopt robots to take over tasks that were previously carried out by humans. However, current study still does not seem to explain the possible reasons and behavioral intentions for this robot adoption preference, and some scholars attribute them only to rising hiring costs, which may lead to a misleading impression, as firms adopting robots do not appear to reduce the wages of their workers. In this paper, we conduct examinations using robot data from the Chinese General Administration of Customs and a range of firm characteristics. The result shows that robot adoption willingness of firms depends more on their perceived benefits from robots and the pressure they feel from their peers than on rising employment costs, and that higher-skilled sectors tend to approach robots proactively, whereas lower-skilled sectors tend to be reactive in the robot adoption process. In addition, firms exhibit different behavioral choices when deciding whether to adopt robots, with those that have advantages in terms of firm size and employee capacity more likely to translate their perceived benefits of robots and industry adoption pressures into robot adoption behavior. This work offers a new explanation for the current phenomenon of robot substitution for human labor in Chinese firms and provide new evidence for technology adoption theory.

Keywords: robot adoption, perceived benefits, industry adoption pressures, hiring costs.

JEL Classification: O32, O33.

✉Corresponding author. E-mail: *zhangfanfanhit@163.com*

1. Introduction

Recent research suggests that many firms started to adopt robots in their production due to rising hiring costs (Huang et al., 2022, Acemoglu & Restrepo, 2021). However, there seem to be no consistent conclusions about the potential reasons for robot adoption and behavioral intentions, and the conclusions are even contradictory. On average, robots are often considered a cheap alternative to human labor, capable of performing certain production tasks or even simulating human behavior according to predefined procedures (Acemoglu & Restrepo, 2019; Wang et al., 2022a). As a result, more firms are trying to reduce the labor cost required to hire workers by adopting robots in production. As Acemoglu and Restrepo (2021) pointed out, higher hiring costs always lead to more adoption and development of automation technologies. However, simply using hiring costs to explain firms' robot adoption behavior may lead to a misleading perception, as firms adopting robots do not appear to reduce the wages of their workers (Wang & Dong, 2020). In fact, using robots does help to replace a portion of labor workers and reduce hiring costs, but it is often difficult for firms to adjust their hiring costs due to the compensation effect. This effect refers to the fact that robots generate new production tasks while substituting a portion of the workforce, and if the effect is large enough, it may even lead to higher employment and hiring costs. In this case, the firm's robot adoption behavior does not seem to be consistent with the goal of reducing hiring costs, and it may be useful to reconsider the potential reasons and behavioral intentions of firms adopting robots to replace human labor.

Indeed, whether firms adopting robots could derives more from their perceived benefits of the new technology and the pressure they feel from peers. As pointed out by Lai et al. (2018), perceived benefits are the recognition by firms of the potential effective benefits from the new technology, which may influence firms' attitudes towards adopting the new technology and their intentions to continue using it. Once firm managers are aware of the potential benefits of robotics, they may tend to employ this new technology. Moreover, according to technology adoption theory, no firm can exist in isolation. The pressure from peers might compel participants to pay more attention to one another's strategic decisions, encompassing whether to adopt new technologies (Čater et al., 2021, Henao-Ramírez & López-Zapata, 2022; Cruz-Jesus et al., 2019). On average, industry adoption pressures describe those threats caused by uncertainty and the process of technology adoption by imitating competitors' decisions (Ghobakhloo & Ching, 2019; Müller et al., 2018). When the number of peers adopting new technologies increases, firms may perceive pressures and transform their technology adoption intentions into actual usage, which could be particularly important for them to maintain the edge and better market performance in the future (Abbasi et al., 2022; Wang et al., 2022b).

In this paper, we explain the potential motivations and behavioral intentions of firms adopting robots and conduct examinations using robot import data, as well as data on a range of firm characteristics. More specifically, our research contributes in three ways. First, our work offers a new explanation for the phenomenon of robot adoption that is currently occurring in Chinese firms, extending the literature related to the robot adoption and providing new evidence for technology adoption theory. Second, this study complements prior literature by taking into account the compensation effect, in particular, this study documents that robot adoption increases rather than decreases hiring costs, which helps to break down stereotypes of the relationship between robots and hiring costs. Finally, this study further explores the link between firms with different resources and their robot adoption behavior, which to some extent fills an existing research gap.

The remainder of this study is as follows: Section 2 provides current research advances related to robot adoption decisions and develops the research hypotheses; Section 3 describes our data sources, variable selection, and model setting; Section 4 reports the research conclusions; Section 5 discusses the findings by comparing and contrasting the previous literature; Section 6 summarize the main conclusions and suggest possible future research directions.

2. Research hypothesis

2.1. Potential reasons and behavioral intentions of firms adopting robots to replace human labor

Robots have received a great deal of attention in recent years, as they appear to have transformed human life in several ways, especially in organizational tasks that were previously considered to be human-specific. Indeed, discussions about intelligent machines have been around since the 1950s and 1960s, and the use of robots has become increasingly common as the relevant technologies have been further developed. According to recent research evidence, many firms have begun to adopt robots. Nonetheless, with respect to the current emergence of robot adoption behavior, previous studies generally agree that higher hiring costs are the main reason why firms tend to use robots to replace human labor (Huang et al., 2022; Acemoglu & Restrepo, 2021), because firms' choices of the two production factors mainly depend on their relative prices, and at a the price of robots is certain, if the cost of hiring labor increases, then the choice of using robots for production becomes more cost-effective. Hicks (1932) also noted in his "The Theory of Wages" that the change in the price of a production factor may cause firms to engage in more technological innovation activities and bias technological progress towards saving those factors that are relatively expensive. In a subsequent study, Acemoglu and Finkelstein (2008) further support this result by investigating the relationship between machine use and labor costs in the healthcare sector, where they find that rising hiring costs triggered by healthcare reforms have led to greater use of machines and equipment to provide services to patients in U.S. hospitals. However, according to evidence from a recent study, firms adopting robots do not appear to have significantly reduced their workers' wages, as robotics replaces a portion of the labor force while creating new production tasks, including a range of tasks associated with knowledge and higher complexity, which may lead to higher hiring costs (Acemoglu & Restrepo, 2019; Wang & Dong, 2020). Thus, if we interpret robot adoption as a rise in hiring costs may lead to a contradictory result.

In fact, previous studies have generally ignored the perceived benefits of robots and industry adoption pressures in explaining the current emergence of robot adoption behaviors, which may lead to a certain research bias, as they were once considered to be the main reasons for firms or organizations to introduce a new technology, and firms may proactively approach robots due to the perceived benefits, or may be forced to accept robots due to industry adoption pressures. According to rational choice theory, firms' decisions are often predicated on rational expectations of potential benefits (Lai et al., 2018; Reyes et al., 2016; Pillai et al., 2021), and once firm managers are aware of the potential benefits of robotics, they may tend to try this new technology (Mack et al., 2021; Adu-Gyamfi et al., 2022; Mamonov & Benbunan-Fich, 2020). For example, in a study on the analysis of digital technology adoption the authors reported that when the top management of SMEs, especially the chief executive officer, has a better understanding on AI, the management tends to prefer to integrate the technology with their business operations, since the adoption intentions and behavior toward AI in a firm are dependent on the extent to which these technologies bring perceived benefits to the them (Ghobakhloo & Ching, 2019). In a subsequent study, Chen et al. (2020) further state that users' perceived benefits are effective in predicting whether a new technology has a chance to be employed, as it is often difficult for users to accept an innovative technology or service with no beneficial incentives. Actually, employing robots is regarded as a useful way for improving firm returns, including better future market performance and productivity (Zhang et al., 2022), which may encourage firms for more adoption. Accordingly, we formulate a hypothesis as follows.

H1: *Whether firms adopt robots in production depends on the perceived benefits they bring.*

In addition to the profit motivation, firms' robotics adoption decisions may also be related to the level of pressure they perceive from peers (Wong et al., 2020; Lu et al., 2021; Yoon et al., 2020). As Čater et al. (2021) pointed out, no firm can exist in isolation, and more robot adoption in the industry may cause firms to perceive pressure and force them to introduce a new technology to maintain previous market share as well as their competitive position, which could lead to passive adoption of robotics. Conversely, firms may not generate incentives to adopt new technologies when peers are not using robots, especially those that are less innovative or adventurous. Indeed, the pressure felt from peers is often related to the external market that firms face (Holl & Mariotti, 2021; Swani, 2020), and firms' intentions to adopt robots may further intensify when the number of competitors adopting new technologies increases (Ghobakhloo & Ching, 2019; Müller et al., 2018), as they fear that the gap between robot adopters and non-adopters may further widen (Alguacil et al., 2022; Koch et al., 2021). This can easily cause them to lose their former competitive edge or even increase the likelihood of their failure in the subsequent competitive process in the market. Accordingly, we formulate a hypothesis as follows.

H2: *The level of pressure firms feel from their peers will increase the likelihood that they adopt robots.*

2.2. Firm resources and robot adoption

Nonetheless, the willingness to adopt robots may be unequal across firms, and firms with more resources seem to be more likely to translate their perceived gains and industry adoption pressures into robot adoption behavior, as unique resources allow firms to have better market performance and pay for these new technologies. As defined by resource-based theory, firm resources refer to the various material and immaterial resources available to the firms (Elia et al., 2021; Sandberg et al., 2019), such as firm size and knowledgeable workers, as well as other resources and capabilities that are difficult to imitate. On average, firms with larger scale appear to be more able to pay for a range of costs associated with robot adoption, including specialized technical equipment as well as worker training (Xue et al., 2022). Even if this new technology does not deliver the expected positive results, they can afford the corresponding consequences, which may increase the willingness of firms to adopt the robot and their intention to continue using it. Moreover, whether firms translate their perceived gains and industry adoption pressure into robot adoption behavior may be related to the prevalence of knowledgeable workers within the firm. As pointed out by Veile et al. (2019) and Erol et al. (2016), firm employees must acquire a range of knowledge and skills related to robotics to adapt to new technologies, which is mandatory for a firm to implement a robotics strategy. In fact, it seems unlikely that firms will translate their perceived gains and industry adoption pressures into robotics adoption behavior before their workers achieve the skills and training required for the machines and equipment. The adoption of a new technology often involves new organizational practices and business processes, all of which may require firm workers to have specific capabilities. Accordingly, we formulate a hypothesis as follows.

H3: *Firms with advantages in firm size and employee capacity are more likely to translate their perceived benefits and industry adoption pressures into robot adoption behavior.*

3. Data sources and empirical strategy

3.1. Data sources

In this work, we conduct tests using robotics data provided by the Chinese General Administration of Customs and firm data compiled by the National Bureau of Statistics of China (2015). The dataset reports all robotics transaction records completed through Chinese customs and a series of industrial firm survey data, including information on firm code, import and export transactions, firm age, firm size, and productivity performance. However, we may face some challenges in completing the combined dataset, since the data are from different databases and the firm codes are defined by different systems. In this regard, we follow Huang et al. (2022) and Yu (2015), using the firm name and the year to merge the two datasets and supplement the unmatched sample with the firm's phone number and postal code. In addition, due to the unavailability of relevant statistics on robot imports after 2016 and the fact that the available industrial enterprise survey data are recorded only up to 2015, this paper only considers sample data from 2000–2015 in the empirical analysis. Actually, this is consistent with the latest study progress in the field. Due to the lack of relevant statistics after 2015, the vast majority of the current authoritative literature related to robot adoption conducts analyses using data from 2015 and before, e.g., Huang et al. (2022), Song et al. (2023), Zhang et al. (2023a), Zhou et al. (2024), Lin et al. (2022), and Zhang et al. (2023b). Therefore, the sample data used in this paper is representative.

3.2. Variable selection and description

3.2.1. Dependent variable

There are currently two main measures of robot adoption, including robot import data and industry data provided by the International Federation of Robotics (IFR) (2015). However, as pointed out by Koch et al. (2021), using industry information to measure actual adoption by firms often assumes that all firms in the industry are equally willing and able to adopt robots, which is inconsistent with actual robot adoption and can easily lead to some misleading results, as they do not take into account that some firms might have a preference for robots in production, while other firms may be less willing to use robots due to investment pressure or cognitive reasons. Consequently, more and more scholars have started to use robot import data to measure firms' robot adoption, for example, in examining the relationship between the degree of aging and the automation process in different countries, Acemoglu and Restrepo (2021) use robot import data as a measure of robot adoption, and similarly Huang et al. (2022), Blanas et al. (2020). Indeed, robot import data is now considered a good proxy variable for measuring robot adoption, as this industry is highly concentrated, with robots globally being supplied by only a handful of suppliers (Zhang et al., 2023a), especially Chinese firms, which used robots that were largely imported until 2015. Therefore, in this study, we follow Huang et al. (2022), Acemoglu and Restrepo (2021), Blanas et al. (2020) and Bonfiglioli et al. (2020) and use robot import data to measure whether or not to adopt robots, and if firms start importing robots in a certain period, the robot adoption variable takes the value of 1 in this period and thereafter, and otherwise takes the value of 0.

3.2.2. Independent variables

Our research involves two explanatory variables, perceived benefits and industry adoption pressures, as firms may proactively approach robots due to potential benefits, or they may be forced to accept them due to industry adoption pressures. In fact, the extent to which firms perceive and recognize the potential benefits of robots comes more from their observations on the market performance of robot adopters and non-adopters, so following the Ater et al. (2021) method, we measure it by comparing the market performance of the two. As for the industry adoption pressures, we refer to Koch et al. (2021) and measure it by the robot density of industry.

3.2.3. Control variable

Furthermore, this research also introduces some control variables. In general, firms' robot adoption behavior may be influenced by firm age, older firms may be better equipped to adopt robots due to prior capital accumulation. Thus, we measure firm age following Medase (2020) and Coad et al. (2016) by natural logarithm of the survey year minus the year firms began operations. In addition, this paper controls for firm profitability and productivity performance, as a firm with higher profitability and productivity performance tends to have a greater preference for adopting new technologies in production. At the same time, accelerated aging may lead to increased use of robots to replace human labor, as firms tend to face a shortage of workers as the proportion of older people continues to grow, forcing firms to implement a "machine-for-human" strategy to some extent. However, the opposite may also occur, as regions with a high degree of aging tend to face greater economic pressures, including increased pension payments, health care and other expenditures, which may lead to firms being more cautious in their capital investment, and may take a wait-and-see attitude toward high-cost investments such as robots. In addition, the introduction and application of robots, as a highly sophisticated technological product, requires firms to have a certain technological foundation and talent pool. In regions with a high degree of aging, firms may be slow to apply robots due to a weak technological base or a shortage of talent. Therefore, we refer to Wang et al. (2015) and use the natural logarithm of the dependency ratio of the elderly population to control for the impact of the aging degree. Indeed, whether a firm adopts robots in production may also be related to the capital intensity of the firms, if they prefer to invest in fixed assets, they may tend to adopt robots due to the investment preference, therefore, we use the natural logarithm of the share of fixed assets in total assets to measure the capital intensity of a firm (Wen et al., 2021). Whether or not a firm is foreign-owned may also influence a firm's robotics adoption decision, as previous studies have noted that the robots are often implemented through imports. Therefore, foreign-owned firms may be better able to access robotics technology from overseas markets since their foreign knowledge and experience helps reduce their import barriers (Bianchi & Abu Saleh, 2020). In this study, we use the registration type to measure whether the firm is foreign-owned or not. Table 1 reports detailed information on each variable.

Table 1. Descriptive statistics results

Variable	Obs	Mean	Std. Dev.	Min	Max
Robot	3,701,702	0.002	0.049	0.000	1.000
Benifit	1,911,306	13.513	1.425	9.731	18.142
Pressure	3,701,702	9.352	7.046	0.000	19.868
Age	3,683,642	2.052	0.773	0.000	7.607
Profit	3,620,406	6.961	2.471	0.000	18.723
TFP	3,150,314	2.348	0.115	–3.953	2.919
Olddep	3,701,702	2.552	0.183	1.816	3.086
Capital	3,591,714	0.300	0.201	0.000	16.595
Foreign	3,701,702	0.040	0.195	0.000	1.000

3.3. Model setup

To explain the potential reasons for firms' use of robots to replace human labor and their behavioral intentions, we consider the following model.

$$robot_{ijt} = \beta_0 + \beta_1 benefit_{ijt} + \beta_2 pressure_{ijt} + \beta_2 x_{ijt} + \mu_i + \gamma_j + \upsilon_t + \varepsilon_{it},$$

where $robot_{ijt}$ is whether the firm adopts robots in production, which is used to measure firms' robot adoption willingness, and the subscripts *i*, *j* and *t* denote industry, firm, and year, respectively. $benifit_{ijt}$ and $pressure_{ijt}$ are the two core explanatory variables in this work, including firms' perceived benefits and industry adoption pressures, and x_{ijt} is a set of control variables that may affect robot adoption behavior, such as the firm's age, the firm's profitability, productivity performance, the aging of the area in which the firm is located, capital intensity, and whether or not the firm is foreign-owned. β_1, β_2 and β_3 are the corresponding coefficient estimates. ε_{it} is a random error term that measures the potential impact of explanatory variables not included in the model and some other random factors on the outcome variable. Considering that the dependent variable in this paper are binary dummy variables, we estimate them mainly through Probit regression.

4. Results analysis

4.1. Perceived benefits, industry adoption pressure and robot adoption

Previous studies have tended to explain firms' robot adoption behavior as a rise in hiring costs and claimed that higher employment costs will lead to more robot adoption and development (Acemoglu & Restrepo, 2021). However, it seems that people have ignored the possible compensation effects of robotics. On average, robots replace a portion of labor workers while also creating new production tasks, including a range of jobs related to knowledge and higher complexity. If this compensating effect is large enough, it may even lead to higher employment and hiring costs, which may be contradictory to the previous goal of reducing hiring costs. Table 2 reports the test results for robot adoption and worker demand as well as hiring costs, and we find that the adoption of robots in production increases rather than decreases hiring costs, as firms that adopt robots tend to restore human labor to a broader range of production tasks, which means that it may be useful to reconsider the potential reasons for firms adopting robots.

Table 2. Robot adoption, worker demand and hiring costs

	(1)	(2)	(3)	(4)
	Employee	*Wage*	*Employee*	*Wage*
Robot	1.523*** (0.014)	0.865*** (0.010)	0.742*** (0.011)	0.492*** (0.008)
Employee		0.868*** (0.001)		0.633*** (0.001)
Age			0.237*** (0.001)	0.112*** (0.001)
Profit			0.043*** (0.001)	0.051*** (0.001)
TFP			4.055*** (0.015)	3.700*** (0.017)
Olddep			–0.438*** (0.003)	–0.090*** (0.003)
Capital			0.182*** (0.004)	–0.002 (0.003)
Foreign			0.157*** (0.003)	0.337*** (0.002)
Constant	3.652*** (0.257)	1.154*** (0.007)	–4.164*** (0.031)	–5.688*** (0.033)
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
R^2	0.178	0.574	0.381	0.692
Observations	3373266	3216949	3140805	3118439

Note: In this work, we use *, **, *** to denote 10%, 5%, and 1% significance levels and report the corresponding clustering robust standard errors in parentheses.

In fact, according to rational choice theory, firms' decisions are often predicated on rational expectations of potential benefits (Lai et al., 2018; Reyes et al., 2016), as it is difficult for users to accept an innovative technology or service in the absence of beneficial incentives. When perceived benefits exist, firms may be inclined to proactively implement robotics strategies. Moreover, as more competitors start to adopt new technologies, firms may be forced to embrace robotics for fear that the gap between robot-adopting firms and non-adopting firms will widen even further, which could easily lead to the loss of their previous competitive advantage or even increase the probability of failure in the subsequent competitive process in the market. That is, perceived benefits and the pressure felt from peers may be the main reasons for firms to use robots to replace human labor. To this end, we further report the results of estimating the relationship between perceived benefits, industry adoption pressure and robot adoption behavior in Table 3. We find that whether a firm adopts robots in production is related to the perceived benefits from robots, which is consistent with the expectations of this paper in Hypothesis 1. The results are similar when industry adoption pressure is used as a proxy for perceived benefits, implying that the level of pressure felt from the industry will lead to more robot adoption, and Hypothesis 2 of this paper is supported. In other words, firms will proactively approach robots due to perceived benefits on the one hand, and will be forced to accept robots due to industry adoption pressure on the other.

Table 3. Perceived benefits, industry adoption pressure and robot adoption

	(1)	(2)	(3)	(4)
	Robot	*Robot*	*Robot*	*Robot*
Benifit	0.088*** (0.003)		0.040*** (0.003)	
Pressure		0.091*** (0.002)		0.080*** (0.001)
Age			0.189*** (0.007)	0.149*** (0.005)
Profit			0.010*** (0.003)	0.020*** (0.002)
TFP			3.180*** (0.061)	3.067*** (0.051)
Olddep			–0.412*** (0.027)	–0.354*** (0.024)
Capital			0.010 (0.018)	0.112*** (0.012)
Foreign			0.836*** (0.012)	0.795*** (0.010)
Constant	–3.924*** (0.036)	–4.050*** (0.029)	–10.512*** (0.147)	–10.985*** (0.128)
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
R^2	0.011	0.087	0.170	0.234
Observations	1911306	3701702	1709346	3140929

Note: In this work, we use *, **, *** to denote 10%, 5%, and 1% significance levels and report the corresponding clustering robust standard errors in parentheses.

4.2. Sub-industry test results

Considering that there are often large differences between industries, we further report the results of the sub-industry tests. Specifically, referring to Wang et al. (2020), we consider general equipment manufacturing, chemical raw materials and chemical products manufacturing, special equipment manufacturing, pharmaceutical manufacturing, railroad, ship, aerospace and other transportation equipment manufacturing, automobile manufacturing, computer, communication and other electronic equipment manufacturing, electrical machinery and equipment manufacturing, and instrument and meter manufacturing as high-tech sectors, with the rest of the sectors considered as low-tech sectors and the corresponding test results reported in Tables 4 and 5, respectively. We find that the high-technology sectors are more inclined to proactively approach robots, while the low-technology sectors tend to be passive in the robot adoption process. This may be related to the industry characteristics of the high- and low-technology sectors. Typically, the high-technology sectors are at the forefront of technology, and they are more sensitive to and receptive to new technologies, and the characteristics of robots in terms of high operational precision, high efficiency, and programmability largely meet the needs of the high-technology sectors, which may increase their willingness to adopt robots and their usage behavior. For low-tech sectors, they may face higher technological and financial thresholds in the robot adoption process, and as they are often at a disadvantage in market competition, they may be more concerned with short-term survival than long-term technological upgrading and transformation, which may lead to their relative passivity in the robot adoption process.

Table 4. Analysis of industry differences in robot adoption based on perceived benefits

	(1)	(2)	(3)	(4)
	High–tec	*Low–tec*	*High–tec*	*Low–tec*
Benifit	0.158*** (0.007)	–0.098*** (0.008)	0.085*** (0.007)	–0.116*** (0.007)
Age			0.110*** (0.008)	0.302*** (0.014)
Profit			0.038*** (0.005)	0.008 (0.007)
TFP			3.066*** (0.100)	2.423*** (0.136)
Olddep			–0.378*** (0.036)	–0.480*** (0.061)
Capital			0.073*** (0.018)	0.077*** (0.025)
Foreign			0.716*** (0.015)	0.925*** (0.023)
Constant	–4.818*** (0.095)	–1.748*** (0.096)	–10.914*** (0.241)	–6.980*** (0.340)
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
R^2	0.014	0.011	0.181	0.166
Observations	766744	908793	680719	805755

Note: In this work, we use *, **, *** to denote 10%, 5%, and 1% significance levels and report the corresponding clustering robust standard errors in parentheses.

Table 5. Analysis of industry differences in robot adoption based on industry adoption pressure

	(1)	(2)	(3)	(4)
	High–tec	*Low–tec*	*High–tec*	*Low–tec*
Pressure	0.088*** (0.003)	0.063*** (0.002)	0.069*** (0.003)	0.074*** (0.002)
Age			0.076*** (0.007)	0.243*** (0.010)
Profit			0.054*** (0.005)	0.031*** (0.005)
TFP			2.990*** (0.085)	2.037*** (0.106)
Olddep			–0.293*** (0.031)	–0.419*** (0.050)
Capital			0.132*** (0.017)	0.070*** (0.025)
Foreign			0.697*** (0.013)	0.993*** (0.020)
Constant	–3.996*** (0.047)	–3.775*** (0.026)	–10.883*** (0.200)	–8.611*** (0.254)
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
R^2	0.027	0.073	0.200	0.216
Observations	1167846	2210966	985818	1852687

Note: In this work, we use *, **, *** to denote 10%, 5%, and 1% significance levels and report the corresponding clustering robust standard errors in parentheses.

4.3. Moderating effect of firm characteristics

As we noted above, firms may exhibit different behavioral choices when deciding whether to adopt robots. Typically, firms with larger scale appear to be more able to afford a range of costs associated with robot adoption, which may increase the likelihood of firms adopting robots. Additionally, employees must gain a range of knowledge and skills related to robots to use the new technology, as they are often mandatory for a firm implementing a robotics strategy, which implies that a firm size and employee capabilities may influence the relationship between perceived benefits and industry adoption pressures and robot adoption behavior. To confirm this conjecture, we further categorize the sample data into large-scale firms, small and medium-scale firms, high-employee-capability firms, and low-employee-capability firms in Tables 6 and 7. Based on the test results, we find that firms with advantages in firm size and employee capabilities are more likely to translate their perceived benefits and industry adoption pressure into robot adoption behavior, and H3 is supported.

Table 6. Firm size and robot adoption

	(1)	(2)	(3)	(4)
	Large	*Small*	*Large*	*Small*
Benifit	0.042*** (0.003)	0.038*** (0.012)		
Pressure			0.083*** (0.002)	0.068*** (0.007)
Age	0.170*** (0.007)	0.301*** (0.027)	0.132*** (0.005)	0.220*** (0.022)
Profit	0.006** (0.003)	–0.052*** (0.008)	0.016*** (0.002)	–0.042*** (0.007)
TFP	2.744*** (0.065)	0.994*** (0.225)	2.688*** (0.054)	1.009*** (0.190)
Olddep	–0.363*** (0.028)	–0.521*** (0.114)	–0.312*** (0.025)	–0.461*** (0.102)
Capital	0.103*** (0.022)	0.100 (0.072)	0.277*** (0.019)	0.102 (0.068)
Foreign	0.784*** (0.012)	0.877*** (0.051)	0.741*** (0.011)	0.832*** (0.049)
Constant	–9.430*** (0.158)	–5.428*** (0.576)	–10.095*** (0.137)	–5.959*** (0.466)
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
R^2	0.126	0.095	0.197	0.129
Observations	908652	800694	1693165	1447764

Note: In this work, we use *, **, *** to denote 10%, 5%, and 1% significance levels and report the corresponding clustering robust standard errors in parentheses.

Table 7. Employee capability and robot adoption

	(1)	(2)	(3)	(4)
	High Capacity	*Low Capacity*	*High Capacity*	*Low Capacity*
Benifit	0.040*** (0.003)	–0.032 (0.070)		
Pressure			0.080*** (0.001)	0.069*** (0.027)
Age	0.188*** (0.007)	0.160** (0.065)	0.149*** (0.005)	0.143** (0.061)
Profit	0.009*** (0.003)	0.082** (0.041)	0.020*** (0.002)	0.035 (0.039)
TFP	3.182*** (0.061)	0.358 (0.728)	3.067*** (0.051)	1.216 (0.757)
Olddep	–0.414*** (0.027)	0.403 (0.429)	–0.355*** (0.024)	0.324 (0.428)
Capital	0.009 (0.018)	0.600 (0.399)	0.111*** (0.012)	0.738* (0.390)
Foreign	0.836*** (0.012)	0.907*** (0.151)	0.794*** (0.010)	0.911*** (0.153)
Constant	–10.502*** (0.147)	–5.950*** (1.985)	–10.978*** (0.128)	–8.733*** (1.967)

End of Table 7

	(1)	(2)	(3)	(4)
	High Capacity	*Low Capacity*	*High Capacity*	*Low Capacity*
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
R^2	0.168	0.108	0.232	0.157
Observations	1653086	56260	3063236	77693

Note: In this work, we use *, **, *** to denote 10%, 5%, and 1% significance levels and report the corresponding clustering robust standard errors in parentheses.

4.4. Robustness tests

4.4.1. Change outcome variables

In fact, the way the variables are measured tends to affect the observed results, therefore, to ensure the reliability of the findings, this paper follows Zhu et al. (2022) and also reports the results of the test using the amount of robots imported and the number of robots imported to measure robot adoption as shown in Tables 8 and 9, where it can be seen that whether or not firms adopt robots in their production is related to their perceived benefits and industry adoption pressure, which implies that the results of the tests in this paper are robust and not disturbed by the way the variables are measured.

Table 8. Test results using robot import amounts to measure robot adoption

	(1)	(2)	(3)	(4)
	Robot	*Robot*	*Robot*	*Robot*
Benifit	0.088*** (0.003)		0.040*** (0.003)	
Pressure		0.091*** (0.002)		0.080*** (0.001)
Age			0.189*** (0.007)	0.149*** (0.005)
Profit			0.010*** (0.003)	0.020*** (0.002)
TFP			3.180*** (0.061)	3.067*** (0.051)
Olddep			–0.412*** (0.027)	–0.354*** (0.024)
Capital			0.010 (0.018)	0.112*** (0.012)
Foreign			0.836*** (0.012)	0.795*** (0.010)
Constant	–3.924*** (0.036)	–4.050*** (0.029)	–10.512*** (0.147)	–10.985*** (0.128)
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
R^2	0.011	0.087	0.170	0.234
Observations	1911306	3701702	1709346	3140929

Note: In this work, we use *, **, *** to denote 10%, 5%, and 1% significance levels and report the corresponding clustering robust standard errors in parentheses.

Table 9. Test results using the number of robots import to measure robot adoption

	(1)	(2)	(3)	(4)
	Robot	*Robot*	*Robot*	*Robot*
Benifit	0.088*** (0.003)		0.040*** (0.003)	
Pressure		0.091*** (0.002)		0.080*** (0.001)
Age			0.189*** (0.007)	0.149*** (0.005)
Profit			0.010*** (0.003)	0.020*** (0.002)
TFP			3.180*** (0.061)	3.067*** (0.051)
Olddep			–0.412*** (0.027)	–0.354*** (0.024)
Capital			0.010 (0.018)	0.112*** (0.012)
Foreign			0.836*** (0.012)	0.795*** (0.010)
Constant	–3.924*** (0.036)	–4.050*** (0.029)	–10.512*** (0.147)	–10.985*** (0.128)
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
R^2	0.011	0.087	0.170	0.234
Observations	1911306	3701702	1709346	3140929

Note: In this work, we use *, **, *** to denote 10%, 5%, and 1% significance levels and report the corresponding clustering robust standard errors in parentheses.

4.4.2. Remove adopters with very low levels of robot adoption

In the prior analysis, our sample included adopters with very low levels of robot adoption. Although they implemented robot strategies, the difference between them and non-adopters may not be significant due to the low adoption density, which may confound our results. Thus, we refer to Huang et al. (2022) and exclude the sample with low levels of robot adoption. From the test results in Table 10, we find that the findings are similar after dropping adopters with small robot import amounts, which implies that firms' willingness to adopt robots depend on their perceived benefits and the pressure they feel from peers, the findings of this paper are robust.

Table 10. Remove robot adopter with small robot import amounts

	(1)	(2)	(3)	(4)
	Robot	*Robot*	*Robot*	*Robot*
Benifit	0.091*** (0.003)		0.044*** (0.003)	
Pressure		0.092*** (0.002)		0.081*** (0.002)
Age			0.187*** (0.007)	0.148*** (0.005)
Profit			0.011*** (0.003)	0.022*** (0.002)
TFP			3.178*** (0.062)	3.079*** (0.052)
Olddep			–0.398*** (0.027)	–0.343*** (0.024)
Capital			0.001 (0.019)	0.106*** (0.012)
Foreign			0.827*** (0.012)	0.785*** (0.010)
Constant	–3.978*** (0.036)	–4.079*** (0.031)	–10.604*** (0.149)	–11.077*** (0.130)
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
R^2	0.012	0.088	0.171	0.235
Observations	1911123	3701445	1709166	3140682

Note: In this work, we use *, **, *** to denote 10%, 5%, and 1% significance levels and report the corresponding clustering robust standard errors in parentheses.

4.4.3. Changing the estimation model

We provide evidence that whether firms adopt robots in production is related to the perceived benefits of robots and industry adoption pressure. However, these results may be confounded by the estimation model selected in this paper. For this reason, we further provide estimation results using a logit model, as shown in Table 11. Based on the test results, the findings of this paper remain robust after changing the estimation model.

Table 11. Changing the estimation model

	(1)	(2)	(3)	(4)
	Robot	*Robot*	*Robot*	*Robot*
Benifit	0.257*** (0.007)		0.105*** (0.008)	
Pressure		0.300*** (0.005)		0.232*** (0.004)
Age			0.512*** (0.017)	0.400*** (0.014)
Profit			0.030*** (0.008)	0.057*** (0.007)
TFP			8.416*** (0.163)	8.029*** (0.133)
Olddep			–1.060*** (0.073)	–0.881*** (0.063)
Capital			0.071* (0.041)	0.302*** (0.032)
Foreign			2.092*** (0.030)	1.920*** (0.027)
Constant	–9.226*** (0.100)	–10.156*** (0.084)	–26.497*** (0.384)	–27.903*** (0.329)
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
R^2	0.011	0.089	0.168	0.232
Observations	1911306	3701702	1709346	3140929

Note: In this work, we use *, **, *** to denote 10%, 5%, and 1% significance levels and report the corresponding clustering robust standard errors in parentheses.

5. Discussion

We provide evidence that firms' willingness to adopt robots depends more on their perceived benefits and the degree of pressure they feel from peers than on hiring costs, which does not appear to be consistent with prior research. Some scholars claim that the current emergence of the replacement of human labor with robots is primarily related to increasing employment costs. Typically, in the face of higher worker wages, firms may respond in a variety of ways, including moving production to regions with lower employment costs through offshoring activities or providing a cheap alternative to human labor by employing robots in production. It may seem that both strategic options help reduce the employment costs of firms. However, according to recent research evidence, the hidden costs of offshoring activities are often high and many firms have difficulty estimating the potential costs and benefits, which leads them to deal with a more complex set of factors when considering manufacturing location decisions (Johansson & Olhager, 2018), such as differences from cultural and institutional aspects and trade policy uncertainties. As a result, a growing number of firms appear to prefer using robots to replace human labor in response to higher worker wages, based on this view that firms' willingness to adopt robots may be related to increasing hiring costs. In fact, as we showed earlier, using hiring costs to explain firms' robot adoption behavior may lead to a misleading impression, as firms adopting robots do not appear to reduce the wages of their workers (Acemoglu & Restrepo, 2019; Wang & Dong, 2020). On average, adopting robots in production does help replace a portion of labor workers and reduce hiring costs. However, it is often difficult for firms to adjust their employment costs due to compensating effects. While replacing a portion of labor workers, robots will also create new production tasks, including a range of jobs related to knowledge and higher complexity, which may lead to higher employment and costs. Thus, firms' robot adoption behavior does not seem to be consistent with the goal of reducing hiring costs.

Actually, the perceived benefits and the level of pressure felt from peers seem to be more important than the hiring costs, as firms' decisions are often premised on rational expectations of potential benefits (Chong et al., 2021; Chau et al., 2021; Yoon & Oh, 2022), it is difficult for users to accept an innovative technology or service without beneficial incentives. Moreover, according to stakeholder theory, firms may be forced to embrace robotics when the number of competitors adopting new technologies increases. They fear losing their previous competitive advantage in the process of competing with technology adopters.

Furthermore, as we suggested above, firms' willingness to adopt robots may not always be equal, and firms with more resources seem to be more likely to translate their perceived gains and industry adoption pressures into robot adoption, including firm size and knowledgeable workers. These unique resources often allow firms to have better market performance and pay for these new technologies. However, this has barely been addressed in prior research.

Our results may be important for the literature on robot adoption and technology diffusion. We offer a new explanation for the current phenomenon of employing robots to replace human labor in Chinese firms, which helps update robotics theory and traditional technology adoption theory. In particular, we document that the adoption of robots in production increases rather than decreases employment costs due to the presence of compensation effects, which helps break down stereotypes about the relationship between robot adoption and hiring costs.

6. Conclusions and future work

In this study, we use robot import data from the Chinese General Administration of Customs and a range of firm data to explain the potential reasons and behavioral intentions for adopting robots in production, and we find that firms' willingness to adopt robots depends more on their perceived benefits from robots and the level of pressure they feel from their peers than on the previously widely perceived rising employment costs, which is mainly related to the compensatory effects of robotics. On average, robots displace a portion of labor force but also created additional tasks, which causes higher employment and hiring costs. In this process, high-technology sectors are more inclined to approach robots proactively, whereas low-technology sectors tend to be passive in the robot adoption process. In addition, a firm with robot adoption preferences may require a larger firm size and more knowledgeable workers, as they tend to be mandatory for firms implementing a robotics strategy. Our findings explain previous inconsistent results on robotics and offer a new explanation for the current phenomenon of using robots to replace human labor in Chinese firms, somewhat breaking the stereotype of the relationship between robot adoption and employment costs.

Although the findings of this paper have important implications for the literature related to robot adoption, certain limitations remain. Specifically, robot adoption behaviors resulting from industry adoption pressure tend to be reactive, which may affect the sustainability of the technology adoption process as they are influenced by firms' relationships with competitors and attention to each other's strategic decisions. However, due to the lack of relevant data, this paper makes no further distinctions when explaining firms' robot adoption behaviors, which leads to the fact that the findings of this paper are not directly generalizable to firms that are quite different from Chinese firms, and future research may need to further differentiate between cooperative and competitive climates between firms.

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Author contributions

Qiang Mai: formulation of overarching research goals and aims; writing-reviewing and editing; acquisition of the financial support for the paper; supervision and verification. Qi-nan Zhang: design of methodology; creation of models; formal analysis; writing the initial draft; writing-reviewing and editing. Fanfan Zhang: data collection and maintenance; analyze study data. Fang Ji: data collection and maintenance; analyze study data.

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