Robots in Chinese firms*

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Abstract

We use Chinese firm-level data from financial statements and customs records to identify which firms import industrial robots and then estimate the impact of firm-level robot adoption on firm-level outcomes for the period of 2000-2010. We find that manufacturing firms that adopt robots in China experience an increase in employment, wages, value-added and productivity, but a decline in their labor shares. These estimates are approximately 4 times larger than the estimates from advanced countries.

JEL Classification: E22, E23, E24, J23, J24, O33

Keywords: robots, automation, employment

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1 Introduction

As advancing technologies are increasingly automating work, it is important for policymakers and academic researchers to understand the firm-level adjustments of such technologies. One such type of technology is an industrial robot, which is specifically designed to automate production tasks that would otherwise be performed by human workers. On one hand, these machines can generate significant productivity effects, and on the other hand, they can also displace labor. Empirical evidence when using firm-level information on robot use, investment, or adoption generally suggest that more automation leads to more employment by the automating firms (Koch et al. (2021), Bessen et al. (2020), Dixon et al. (2021), Acemoglu et al. (2020), Humlum (2019), Aghion et al. (2022b), Acemoglu et al. (2023)). These studies have been implemented for France, Spain, Netherlands, Denmark, and Canada. However, these results may not be informative regarding what the labor market impact might be for countries that are not at such an advanced stage of development. This paper is the first to study the effects of industrial robot adoption on labor in a developing country context at the firm-level and attempts to fill this gap. Since labor costs are lower in developing countries and workers may be concentrated in labor-intensive manufacturing industries, it is unclear whether adoption of robots by manufacturing firms would generate higher productivity effects or higher displacement effects. Acemoglu and Restrepo (2019) estimate that one new robot displaces roughly 3 to 6 workers within the local labor market in the United States. Considering the fact that China has roughly 10 times more workers in the manufacturing sector alone compared to the United States, it is crucial to know what the effects of such automation may be for China.[1]

China has some notable features that make it suitable as well as an interesting case for studying these impacts. Firstly, China is the world's largest user of industrial robots since 2016 overtaking Japan (Cheng et al. (2019)). At the same time, wages have been rising in China (Li et al. (2012)). More than 40 percent of the working population is migrant in nature.[2] Also, China is the world's largest producer of automobiles and electronics - the two industries which use the most robots (Cheng et al. (2019)).

[1]According to the Bureau of Labor Statistics, as of February 2022, there were approximately 12.9 million workers employed in the manufacturing industry in the United States. In contrast, according to the National Bureau of Statistics of China, as of 2020, there were approximately 140 million workers employed in the manufacturing industry in China.

[2]According to the National Bureau of Statistics, there were an estimated 292 million rural migrant workers in China in 2021, comprising nearly 40 percent of the entire working population, and this does not include urban migrants.

There are two contrasting views regarding how automation and employment are related.[3] On one hand, automation may reduce both the aggregate number of jobs and wages. On the other hand, automating firms become more productive and employ more people. Prior literature has estimated this relationship using either the International Federation of Robotics (IFR) data on number of robots, text analysis of patents, or more recently, firm-level information on robot adoption.

In this paper, we use firm-level data from China's National Bureau of Statistics (NBS) Annual Survey of Industrial Firms (ASIF) for the period 2000-2010, linked with firm-level data on imports and exports from China's General Administration of Customs. This allows us to observe what each firm imports and exports at the 6-digit Harmonized System (HS) level, and therefore, we can observe which firms imported industrial robots. Using this information, we estimate the effect of being a robot-adopting firm on several firm level outcomes such as employment, wages, value-added, labor productivity, and the labor share. We find that firms that adopt robots in China experience an increase in employment, wages, value-added and productivity, but a decline in their labor shares. The firm-level analysis supports prior evidence from advanced countries, thereby suggesting that firms that do adopt robots seem to hire more workers than they seem to displace regardless of where they are located.

This paper contributes to the literature in the following ways. First, we confirm that findings from advanced countries regarding the effect of robot adoption extend to China's case. We find that robot adoption is associated with a 61 percent increase in employment from 2000 to 2007, 82 percent increase in value-added, 22 percent increase in labor productivity defined as value-added over employment, and 17 percentage point decrease in the labor share. While these estimates are the same direction as those observed in France, Netherlands, and Spain, the magnitude is quite different. Comparing with Acemoglu et al. (2020), robot adoption in France is associated with a 20 percent increase in value-added and a 4.3 percentage point decline in the labor share. Robot adoption seems to play a significant role in influencing firm outcomes in China. Our estimates are roughly 4 times larger.

Second, evidence for developing countries is sparse. Two papers are closely related to our study. Calì and Presidente (2022) use IFR data on robots and find that in Indonesia, there are significant productivity and employment gains from automation in manufacturing. In contrast, Giuntella and Wang (2019) use aggregate data from Chinese prefectural cities and individual longitudinal data from China, to find a large negative impact of robot exposure on employment and wages of Chinese workers. This paper advances this literature as the first to analyse this question using firm-level

[3] Aghion et al. (2022a) provides a comprehensive review of the impacts of automation on labor demand

information on robot adoption. Since the lack of firm-level data has often precluded more in-depth analysis in this area (Raj and Seamans (2018)), our study allows us to investigate this question more thoroughly.

The rest of the paper is organized as follows. Section 2 discusses in more detail the related literature and theoretical motivations of our study. Section 3 describes the data and discusses observed patterns, section 4 discusses the empirical strategy and results of the firm-level analysis and section 5 concludes.

2 Theoretical and Empirical Background

The automation technology studied in this paper is an *industrial robot*. The IFR defines an industrial robot as "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes"[4]. In other words, these machines do not need a human operator and can be programmed to perform several manual tasks. Industrial robots are different from other kinds of equipment and modern manufacturing investments, and therefore this paper and related studies that focus on industrial robots are meant to investigate the role of the kind of technology that is specifically meant to automate production tasks that would otherwise be done by human workers.

Studies focusing on industry-level implications of robots typically find negative effects on employment and wages. Using IFR data on the stock of robots, Acemoglu and Restrepo (2020) estimate negative impacts on workers in US local labor markets. These effects are more pronounced among low- and mid-skill workers who are more exposed to the spread of industrial robots. Using the same data, Dauth et al. (2018) find that robots led to job losses in manufacturing that were offset by job gains in the services sector in Germany. Graetz and Michaels (2018), Acemoglu and Restrepo (2020), and Acemoglu and Restrepo (2022) also find negative effects on the labor share at the industry level.

Firm-level evidence is also mixed. Several papers find positive impacts on employment. Using Dutch firm-level data on automation investment, Bessen et al. (2020) find that firms that have automation events experience higher employment and revenue growth and this effect arises for both manufacturing and non-manufacturing firms. Using Canadian firm-level data on robot imports, Dixon et al. (2021) find that investment in robots is associated with increases in total firm employment, but decreases in total number of managers. Acemoglu et al. (2020) find labor share declines, value-added and productivity increases, share of production workers decreases in France.

[4]Source: International Federation of Robots

Using various different measures of modern capital investment in France, Aghion et al. (2022b) find that at plant, firm, and industry level, the effect of capital investments on employment is positive. Barth et al. (2020) find overall positive effects on wages in Norway but also find that industrial robots increase wages for high-skilled workers relative to low-skilled workers, thereby increasing the skill-premium within firms. Bonfiglioli et al. (2020) also find negative impacts on low-skilled workers in France. In contrast, Aghion et al. (2022b) find that employment effects are positive even for unskilled production workers in France. Hirvonen et al. (2022) find that firms used new technologies to produce new types of output rather than replace workers with technologies within the same type of production in Finland. The results contrast with the ideas that technologies necessarily replace workers or are skill-biased.

In order to theoretically understand the implications of technology for labor demand and productivity, we turn to Acemoglu and Restrepo (2019), which uses a task-based framework. The net effect is comprised of three components. First, a positive productivity effect, such that labor demand increases for all workers. Second, a negative displacement effect, such that some tasks previously performed by labor are now capital-intensive. Third, a positive reinstatement effect, such that new tasks are created. The total effect is ambiguous and depends on the strength of the components. At the firm-level in China, it appears that there is a displacement effect, since the labor share decreases for robot-adopting firms. It also seems that the productivity effect dominates, since most of the firm-level outcomes increase for robot-adopting firms.

3 Data Description and Robot Adoption in China

The firm-level data comes from China's National Bureau of Statistics (NBS) Annual Survey of Industrial Firms (ASIF) for the period 2000-2015. This dataset includes information on all state-owned enterprises (SOEs) and non-state-owned enterprises with sales over 5 million RMB in 2000-2010 in the industries of mining, manufacturing, and public utilities. For the period 2011-2015, this dataset includes firms with sales over 20 million RMB. Since the sample changes significantly after 2010, we restrict our main analysis to the period of 2000-2010.

There is detailed accounting information from the balance sheets, profit and loss sheets and cash flow statements, such as the names of the firms, year of establishment, sales, output, employment, wages, location, industry and other variables that allow us to calculate firm-level total factor productivity (TFP). For the year 2004, we also have some additional information on firm employment by gender, education and skill level.

Table 1: Descriptive statistics of Robot Adopters: 2000-2007

Variable	Obs	Mean	Std. dev.
Employment	7,086	1,424.21	4271.60
Mean wages	7,086	26.46	22.81
Value-added	6,050	307698.5	1492174
Labor productivity	5,930	176.8071	326.14
Labor share	6,045	0.49	3.29

We follow the data cleaning steps outlined in Brandt et al. (2012), Feenstra et al. (2014) and Yu (2015). We exclude firms with less than eight employees and drop observations that report missing or negative values for the following variables: total sales, total revenue, total employment, and total wage payments. Then, we match firms over time and deflate nominal variables based on consumer price index at the regional level, ex-factory producer price index and intermediate input deflator at the industry-level. We also unify the industry information based on Chinese Industry Classification in 2002, and supplement the provincial information in terms of firms' information on address and county.

Data on imports and exports come from China's General Administration of Customs for 2000-2015. This dataset covers the universe of China's exporters and importers at the 8-digit Harmonized System (HS) product level and includes information on each product's quantity, value, type of trade (i.e., processing or non-processing), source of imports and destination of exports. These two data sets are then merged using the names of firms. Our matched sample consists of 837,827 unique firms, out of which 2,329 have imported robots in any year in the sample.

Tables 1 and 2 show the descriptive statistics of firm-level outcomes separated for robot adopters and non-adopters. Robot adopters are firms which have imported robots between 2000 and 2007, identified by the six-digit HS code 847950 for industrial robots. Our sample of firms is restricted to the manufacturing sector, which accounts for over 80 percent of China's industrial robot use (Cheng et al. (2019)). These statistics reveal that robot adopters are on average larger, employ 6 times more people, pay 2 times more wages, are more productive and have lower labor shares when compared to non-adopters.

In the time period we study, China was not producing industrial robots[5], and therefore, we are able to use robot imports as a measure of robot adoption. Furthermore, the data distinguishes

[5] Cheng et al. (2019) use firm registration data from the State Administration for Industry and Commerce (SAIC) to identify robotics firms and find that in 2005, China had only 221 registered robotic firms, and this number grew massively to 6,478 in 2015 following aggressive promotion of the production of industrial robots by the Chinese government from 2013.

Table 2: Descriptive statistics of Non-Robot Adopters: 2000-2007

Variable	Obs	Mean	Std. dev.
Employment	1,677,907	244.14	860.54
Mean wages	1,677,907	13.6	62.74
Value-added	1,428,393	21259.23	167874.2
Labor productivity	1,426,063	100.90	269.04
Labor share	1,418,471	0.65	71.01

Table 3: Operational Stock of Industrial Robots (in thousands) by country

Year	World	China	United States	France	Spain	Netherlands
1995	605.0	0.0	56.9	13.3	4.9	1.6
2000	750.7	0.9	89.9	20.7	13.2	2.6
2005	917.9	11.6	140.0	30.2	24.1	3.2
2010	1059.2	52.3	173.2	34.5	28.9	5.4

Source: International Federation of Robotics (2021)

between processing firms and non-processing firms. By excluding processing firms, we remove the possibility that Chinese firms in our sample import robots and then re-export them. For potential domestic resellers of robots, we can exclude them by focusing only on manufacturing firms, as large sellers of robots are likely to be wholesale firms.

Figure 1 shows the 2004 composition of employees in our sample. In figure 1, we see that on average, robot adopting firms employ more people for all five categories of education – graduate, undergraduate, professional education, senior high school, and junior high school or below. Robot adopting firms hire the most number of people with senior high school degrees as opposed to the lowest category of education, whereas non robot adopting firms hire the most number of people from the lowest category of education. In figure 2, we see the composition of different job titles. Both robot adopters and non adopters employ more people with job titles that are ranked much lower compared to people with job titles that are ranked very high. In figure 3, we see the composition of different skills – technicians and workers. Both types of firms employ many more workers compared to technicians. While they hire nearly similar number of junior and senior technicians, both types of firms hire nearly double the number of intermediate workers, compared to senior workers.

Table 3 compares China's overall robot adoption to the world as well as advanced countries for which our research question has been explored. In the time period we study, China's stock of robots is a small fraction of the world's operational stock of robots. Lastly, figure 4 shows aggregate imports of industrial robots by year. This data is from the UN Comtrade database.

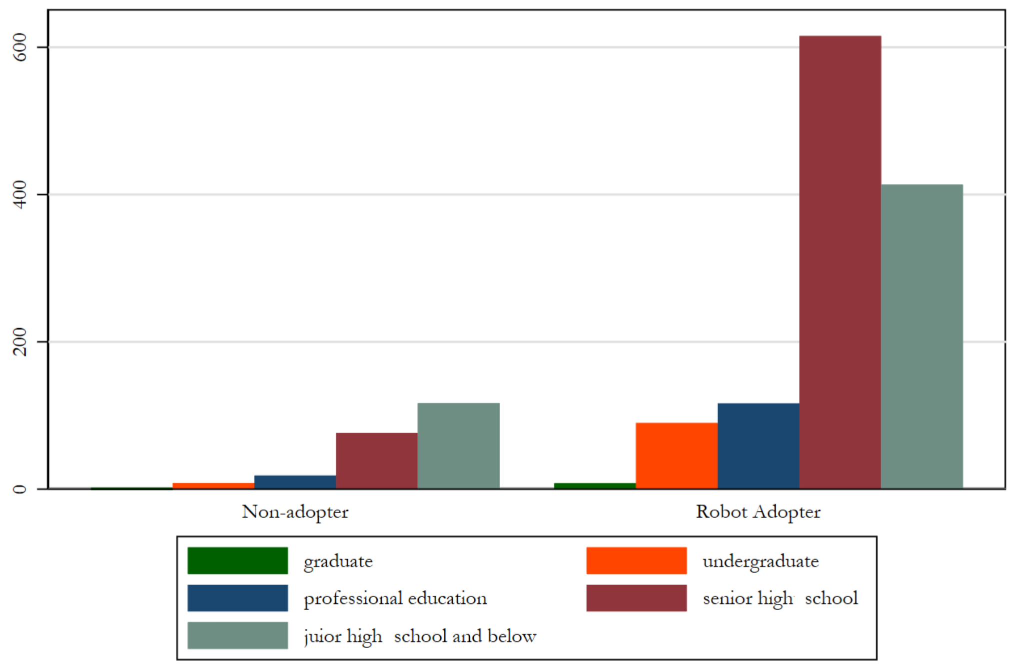

Figure 1: Average number of employees by level of education in 2004

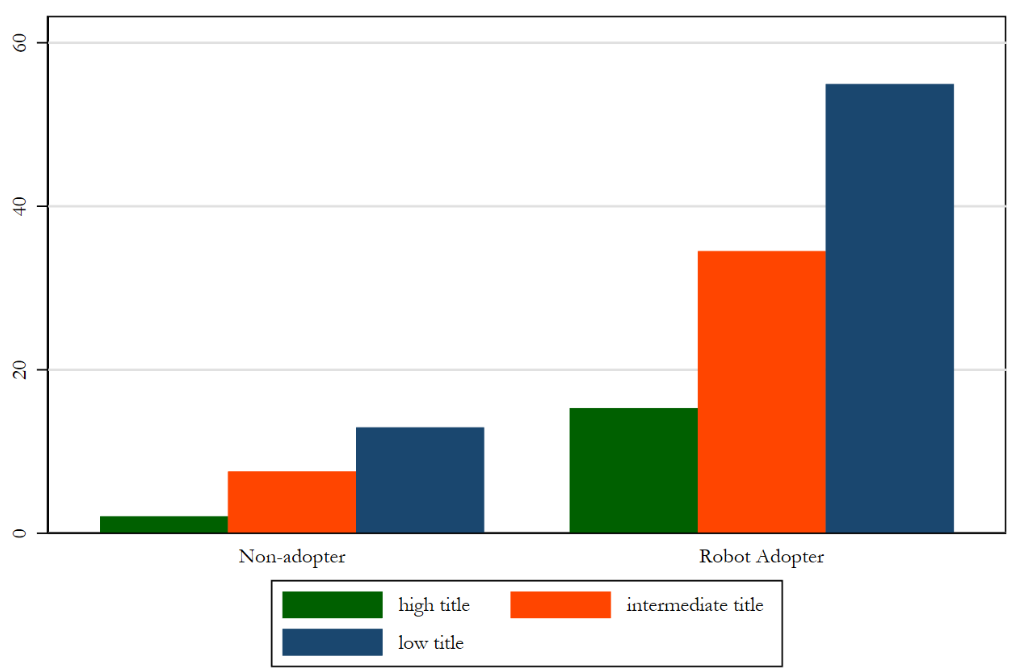

Figure 2: Average number of employees by job title in 2004

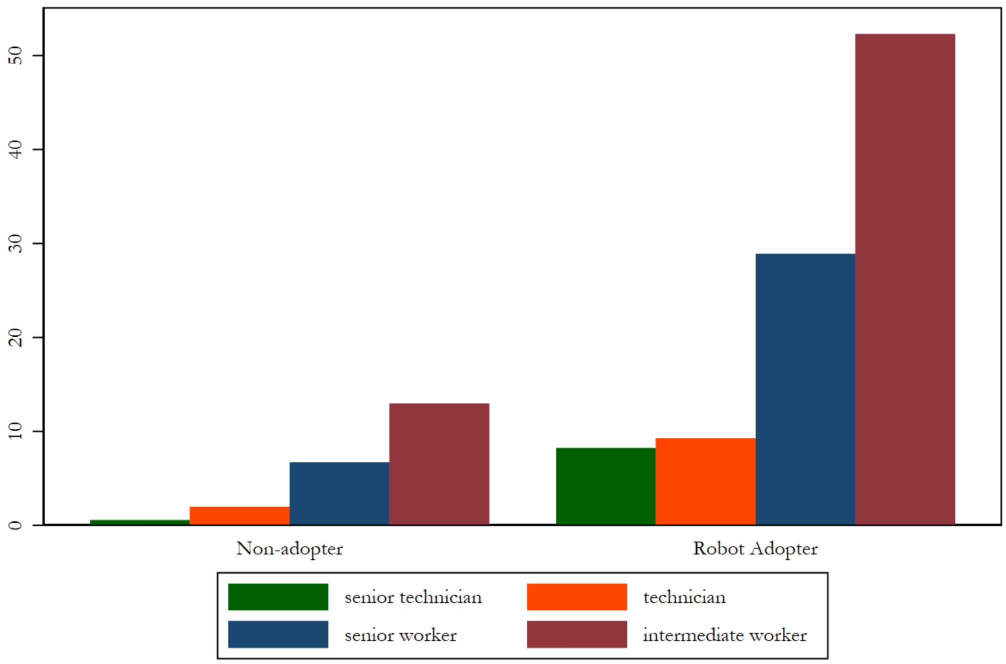

Figure 3: Average number of employees by level of skill in 2004

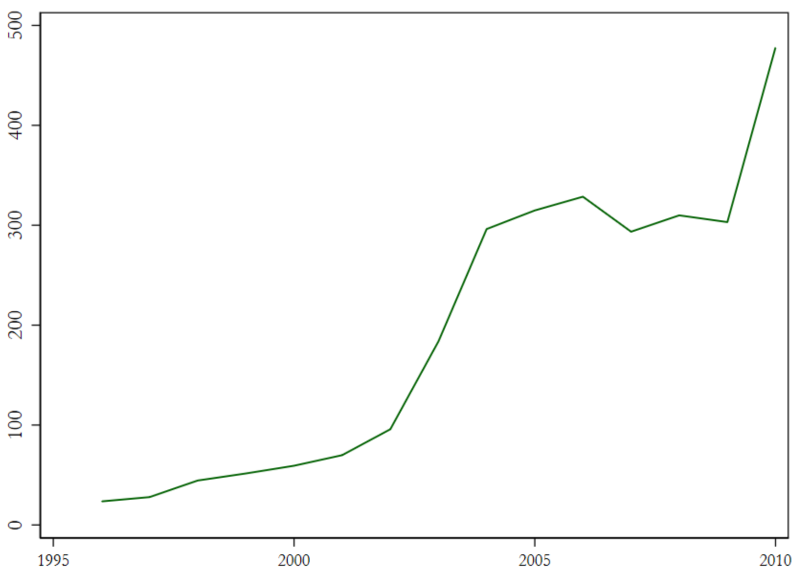

Figure 4: Chinese imports of industrial robots (in million USD)

4 The Impact of Robot Adoption

4.1 Empirical Strategy

To study firm-level changes in employment, wages, value-added, productivity, and labor share, we estimate the following model:

$$\Delta lny_f = \beta Robot_f + controls_f + \gamma_j + \gamma_r + \epsilon_f; \tag{1}$$

where f indicates firm. The outcome variable is a long difference over the entire period from 2000-2007. $Robot_f = 1$ if the firm imported robots at any point during this time period. y_f is employment, mean wages, value-added, productivity (output per worker), and labor share. Controls at firm-level include log employment in 2000, log value added per worker in 2000 and a dummy for whether the firm is a state-owned enterprise. γ_j is industry fixed effect for the main industry in which each firm operates, and γ_r is the region fixed effect for the province in which each firm operates. Standard errors are clustered at the firm level. Regressions are weighted by employment in 2000, where specified. This specification is identical to Acemoglu et al. (2020).

In the next part of the analysis, we consider only the sample of robot importing firms, and construct an alternative measure following Bonfiglioli et al. (2020). $RobotIntensity_f$ is defined as the log of the ratio between the cumulative imports of industrial robots for each firm in each year and the total capital stock for each firm in each year.

A positive demand shock may influence firm outcomes as well as influence a firm to adopt more robots. Therefore, this specification may be subject to potential omitted variables bias. To deal with this issue, we use as instruments the price of Japanese robots at the industry level from Adachi et al. (2020). Since Japan is a major exporter of robots to the global market, especially China, these robot prices capture the effect of improving technologies that lead to lower costs of robots, which then prompt firms to adopt them. These robot prices would be correlated with the decision to adopt robots by Chinese robots but should be unrelated to firm outcomes.

Using robot prices as our instrument, we estimate the following model:

$$lny_{ft} = \beta RobotIntensity_{ft} + \gamma_f + \gamma_r + \epsilon_{ft}; \tag{2}$$

where f indicates firm. The outcome variable is at the yearly level from 2000-2007. $RobotIntensity_{ft} = log(\frac{RobotStock_{ft}}{CapitalStock_{ft}})$. y_f is employment, mean wages, value-added, productivity (output per worker), and labor share. γ_f is firm fixed effect, and γ_r is the region fixed effect for the province in which each firm operates. Standard errors are clustered at the firm level.

Table 4: The impact of robot adoption on firm level outcomes: 2000-2007

	Employment	Mean wages	Value-added	Labor productivity	Labor share
	(1)	(2)	(3)	(4)	(5)
Robot adoption	0.611***	0.054	0.824***	0.217***	-0.166***
	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)
Employment in 2000	-0.227***	0.049***	-0.249***	-0.0234***	0.073***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Value-added per worker in 2000	0.227***	-0.167***	-0.380***	-0.605***	0.438***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
If firm is a state-owned enterprise	-0.184***	-0.04	-0.218***	-0.033	-0.017
	(0.05)	(0.04)	(0.08)	(0.07)	(0.07)
Observations	47,134	46,894	46,993	46,993	46,774

Notes: Robust standard errors in parentheses, clustered at the firm level. The estimations comes from specification (1). The coefficients are statistically significant at the *10%, **5%, or ***1% level.

4.2 Firm-level evidence

Tables 4 and 5 show the results for the unweighted and weighted estimation in (1). We find that firms that adopt robots in China experience an increase in employment, wages, value-added and labor productivity, but a decline in their labor shares. Mean wages are defined as total wages over employment, labor productivity is value-added over employment, and labor share is total wages over value-added. Unweighted estimates suggest that robot adoption is associated with a 61 percent increase in employment from 2000 to 2007, 82 percent increase in value-added, 22 percent increase in labor productivity defined as value-added over employment, and 17 percentage point decrease in the labor share. The effect on mean wages is statistically insignificant. Employment-weighted estimates suggest that robot adoption is associated with a 27 percent increase in employment, 17 percent increase in mean wages, 53 percent increase in value-added, 27 percent increase in labor productivity. The effect on labor share is negative but insignificant.

Table 6 show the results of our sub-sample analysis of robot adopting firms. Instead of a robot dummy, we consider the importance of robots in the firms' capital stock. We find that firms that on average have greater proportion of robots in their capital stock lower their employment and value-added. As discussed in Section 4.1, this specification is subject to bias. By incorporating Japanese robot prices at the industry level in the analysis, we find that indeed, firms that on average have greater proportion of robots in their capital stock do not lower their employment or value-added. There is no effect detected.

Table 5: The impact of robot adoption on firm level outcomes: 2000-2007 - weighted estimates

	Employment	Mean wages	Value-added	Labor productivity	Labor share
	(1)	(2)	(3)	(4)	(5)
Robot adoption	0.272***	0.172***	0.532***	0.265***	-0.096
	(0.08)	(0.06)	(0.10)	(0.08)	(0.09)
Employment in 2000	-0.177***	0.07***	-0.123***	0.054***	0.019
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Value-added per worker in 2000	0.284***	-0.218***	-0.315***	-0.598***	0.382***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
If firm is a state-owned enterprise	-0.425*	0.0352	-0.457	-0.0377	0.0412
	(0.24)	(0.08)	(0.43)	(0.23)	(0.17)
Observations	47,134	46,894	46,993	46,993	46,774

Notes: Robust standard errors in parentheses, clustered at the firm level. The estimations comes from specification (1). Employment in 2000 is used as weights. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

Table 6: The impact of greater robot adoption among adopting firms: 2000-2007

	Employment	Mean wages	Value-added	Labor productivity	Labor share
	(1)	(2)	(3)	(4)	(5)
OLS - Robot Intensity	-0.131***	-0.0186	-0.188***	-0.0535	0.0298
	(0.03)	(0.03)	(0.06)	(0.04)	(0.04)
2SLS - Robot Intensity instrumented	0.673	1.029	3.11	3.229	0.715
by Robot Prices	(1.37)	(1.67)	(12.93)	(13.01)	(5.27)
Observations	2,070	2,070	1,767	1,744	1,767

Notes: Robust standard errors in parentheses, clustered at the firm level. The estimations comes from specification (2). The coefficients are statistically significant at the *10%, **5%, or ***1% level.

5 Concluding remarks

This paper investigates the effect of industrial robots on employment and other firm-level outcomes and finds a positive employment effect. This impact is nearly 4 times larger than those in advanced economies. Since labor costs are lower in China, there a much higher proportion of unskilled and less educated workers, and because more than 40 percent of the Chinese working population is migrant in nature, one might have expected severe displacement effects at the firm-level. It appears however that firms adopting robots in fact hire more workers, even though their labor share decreases.

Contrasting with the negative sentiment about robots in many countries due to their potential to replace jobs, the overall perception of robots in China is positive according to a survey of workers and firms conducted by Cheng et al. (2019). Although their paper primarily focuses on the rapid rise of robots in China that occurs after the period of study in this paper, it helps shed some light on our results. The positive perception of robots could be due to the Chinese belief that advance in science and technology is essential for China's rise as a world power.

In a future version of this paper, we aim to provide a complete picture regarding robot adoption in China, by including an industry level analysis as well as a local level analysis. Since we know the location of firms in our dataset, we will be able to measure local level robot adoption more precisely than previous studies. We are also looking to do an in-depth study of industrial policy in China to identify a plausibly exogenous variation that will be allow us to analyze this question even more accurately.

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