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 firms that adopt robots in China experience an increase in employment, wages, value-added and productivity, but a decline in their labor shares.

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1 Introduction

As advancing technologies are increasingly automating work, it is important for policmakers and academic researchers to understand the firm-level adjustments of such technologies. 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), Aghion et al. (2022b)). These studies have been implemented for France, Spain, Netherlands, and Canada. However, the labor market impact of such automation may not be similar for all kinds of countries. This paper is the first to study the effects of automation on labor in a developing country context at the firm-level. Labor costs are lower in developing countries compared to these advanced countries. Moreover, workers may be concentrated in labor-intensive manufacturing industries.

China has some notable features that make it suitable 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)). Also, China is the world's largest producer of automobiles and electronics - the two industries which use the most robots (Cheng et al. (2019)).

There are two contrasting views regarding how automation and employment are related[1]. 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 for the period 2000-2010, linked with data on imports and exports come 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, total factor 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.

This positive employment effect may be because firms that have greater potential to grow and are already more productive are the ones to adopt robots. Such a specification is therefore subject

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

to bias as a positive demand shock may influence firm outcomes positively and at the same time influence a firm to adopt robots. To deal with this issue, we use as instruments the price of Japanese robots from Adachi et al. (2020). Since Japan is a major exporter of robots to the global market, including 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.

2 Data

The firm-level data comes from China's National Bureau of Statistics (NBS) annual survey of industrial firms 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 and education level. We follow the data cleaning steps outlined in Brandt et al. (2012), which includes construction of industry concordances and programs to match firms over time. According to Brandt et al. (2012), this sample consists of only 20 percent of all industrial firms that are present in the full Census. However, the remaining 80 percent firms with sales below 5 million RMB account for 28.8 percent of employment, 9.9 percent of output, and 2.5 percent of exports. Thus, our sample of larger firms captures the bulk of economic activity.

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,

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

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

identified by the six-digit HS code 847950 for industrial robots. Industrial robots are defined as "automatically controlled, re-programmable, multipurpose manipulators programmable in three or more axes". They are designed to replace human tasks. Our sample of firms is restricted to the manufacturing sector.

These statistics reveal that robot adopters are on average larger, employ more people, pay more wages, are more productive and have lower labor shares when compared to non-adopters.

3 Empirical Strategy

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

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

where f indicates firm. The outcome variable is a long difference over the entire period from 2000-2010. $Robot_f = 1$ if the firm imported robots at any point during this time period. y_f is employment, mean wages, value-added, productivity (output per worker or total factor productivity), and labor share. Controls include log employment in starting year, log value added per worker in starting year 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. Standard errors are clustered at the firm level.

Tables 3 and 4 show the results for the unweighted and weighted estimation in (1). We

Table 3: The impact of robot adoption on firm level outcomes: 2000-2007

	Employment (1)	Mean wages (2)	Value-added (3)	Labor productivity (4)	Labor share (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.

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/employment, labor productivity is value-added/employment, and labor share is total wages/value-added.

Since our estimates potentially suffer from bias, we implement an instrumental variables estimation using Japanese robot prices as an instruments. This portion of the paper is a work-in-progress and results will be updated soon.

4 Concluding remarks

This paper investigates the effect of industrial robots on employment and other firm-level outcomes and finds a positive employment and wage effect. The next version of the paper will include results using our instrumental variable strategy as well results using a plausibly exogenous variation from Chinese industrial policy. It addition to a firm-level analysis, it will also include industry-level analysis as well as local labor markets analysis, thus providing a complete picture of the effects of industrial robots in Chinese firms.

Table 4: 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.

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