The Effects of Robots on Labor Markets and Political Attitudes: The Case of China*

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Abstract

Robots have been increasingly adopted in production processes throughout the world. This paper evaluates the impact of industrial robots on labor markets and political attitudes in China. Based on robot data from Chinese customs, I construct a direct measurement of robot exposure for each prefecture. Exploiting the variation in robot exposure across years and prefectures, I find that robots have no effect on general employment and wages but increase employment and lower wages in the private sector. However, I find important effects on unrest: one more robot per thousand workers leads to 1.6 times more episodes of labor unrest. This indicates the displacement effects of robots on labor could generate substantial discontent among some sectors, even though may not generate aggregate negative employment effects. I also explore the effects on individual attitudes using the China Family Panel Studies. I construct an individual exposure to robots based on occupational vulnerability. I find that exposure to robots negatively affects people's evaluation of the government's performance and trust in the local government.

Keywords: Robots, China, Employment, Political Attitudes
JEL codes: J23, J24, O33, P16

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1 Introduction

Industrial robots are rising in the world, especially in China. According to the International Federation of Robotics (IFR), the global stock of multipurpose industrial robots in 2019 is 2.7 million, and the number is 0.14 million in China.[1] Robot intensity, measured by the number of multipurpose industrial robots in operation per 10,000 persons employed, is 15 for China in 2010, much lower than the world average of 48. In 2017, robot intensity in China exceeded the world average and increased to 187 in 2019. However, the impact of robots on labor markets and political attitudes is less explored. This is important to study because robots can replace workers and create new jobs, therefore the total effect may be ambiguous and differ across contexts.[2]

To study the effects of robots on the labor market, this paper uses imported industrial robots during 2000-2015 from the Chinese General Administration of Customs.[3] The advantage of these data is that I can aggregate the number of robots for each firm to measure robots at the prefecture level directly. The literature widely uses robot data from IFR, which are measured at the country-industry-year level. For each year and prefecture, the index of robot exposure is constructed by the total number of robots in the last five years averaged by employment in 2000. I exploit the variation of robot exposure across prefectures and years. Using employment and wage data from the China City Yearbook and China Regional Statistical Yearbook, I find that robot exposure does not affect general (un)employment and wages in China. However, there is some heterogeneity regarding firm types. Robots help the private sector grow. Specifically, one more robot per thousand workers would increase the employment share in the private sector by 0.634 percentage points and lower the wages by about 4.2%. There are no significant effects for state-owned firms. This heterogeneity may be in part explained by the fact that workers in Chinese state-owned firms are difficult to fire.

Robots directly displace workers from tasks that they were previously performing (displacement effect). To examine the displacement effect of robots, I use the number of strikes in China as another outcome. Based on data from China Strikes (2003-2012) and the China Labor Bulletin (2011-2015), I find that higher robot exposure is also

1. The International Organization for Standardization (ISO) 8372: 2012 defines multipurpose industrial robots as ”An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications.”

2. See Acemoglu and Restrepo (2019) for a framework of robots both displace labor and create new tasks.

3. Without further notation, robots in this paper refer to multipurpose industrial robots.

associated with more strikes, especially in the manufacturing industry. Specifically, one more robot per thousand workers causes more unrest. Though there are no effects on general employment and wages, the displacement effects of robots are reflected by more labor unrest.

Furthermore, I evaluate the effects of robot exposure on individual employment and political attitudes towards the local government. Political attitudes toward local government are important. For example, low trust in local government may underpin the stability of the authoritarian state. The individual-level data are from the China Family Panel Studies (CFPS), a biennial panel survey conducted since 2010. To my knowledge, CFPS is the only national survey that includes questions on political attitudes towards the Chinese government. The sample is restricted to people aged 16-65. I exploit the variation of robot exposure at the prefecture and occupation levels. Based on individual characteristics (i.e., age, gender, education, parents' occupations) in baseline survey 2010 and the occupation exposure score to robots from Webb (2019), the predicted occupation exposure to robots is constructed for each individual.

The results suggest that robot exposure has no significant effect on employment whose occupations are moderately affected by robots, but significantly negative effects for people highly exposed to robots. Specifically, if the individual exposure to robots increases by one standard deviation, one more robot per thousand workers causes people 3.8 percentage points less likely to be employed. Moreover, more exposed individuals report that the employment problem in China is more severe.

To study the effects of robots on political attitudes in China, two measurements are used: the rating of government achievement and trust in local government. I find that more exposure to robots causes people to trust the local government less. Moreover, people whose occupations are more negatively affected by robots further evaluate the local government's performance lower and show less trust in the local government. This suggests that the adoption of robots may have unintended detrimental effects on political trust in an authoritarian context.

This paper is related to two threads of literature. The first relevant body of literature is the effects of robots on the labor market. Acemoglu and Restrepo (2020) find that one more robot per thousand workers in the US reduces the employment-to-population ratio by 0.2 percentage points and wages by 0.42%. In contrast, Klenert, Fernandez-Macias, and Antón (2020) find that we find that the adoption of robots is linked to an increase in aggregate employment. Using firm-level data of Canada, Dixon, Hong, and Wu (2021) document that the adoption of robots is associated with an increase in total employment within the firm. Focusing on Denmark, Humlum (2019) finds that industrial robots have increased average real wages by 0.8% but have lowered real wages of production workers employed in manufacturing by 6%.

There is a growing body of papers studying the impact of robots in the Chinese context (see for instance Fan, Hu, and Tang 2021; Tang, Huang, and Liu 2021 and Wang, Zhang, and Liu 2022); [4] Most relevantly, Giuntella, Lu, and Wang (2019) analyze the effects of robot exposure on the Chinese labor market. Based on robot data from IFR and the employment composition, they construct the robot exposure at the prefecture level. They find negative effects of robot exposure on employment and wages, both at the prefecture level and individual level. In addition, they provide evidence that robot exposure causes more labor-related strikes. Compared to this study, I construct individual occupation exposure to robots and estimate the effects of robots on labor markets and political attitudes together exploiting a different dataset of robots. This could help shed light on policy decisions to improve political trust in the time of automation. Cheng et al. (2019) use both aggregate industry-level and firm-level data to document the adoption of robots by China's manufacturers and explain from both the supply (government policies) and demand (labor costs) sides why robots have risen so quickly in China. They also point out that the overall perception of robots in China has always been positive, which is different from the negative sentiment about robots in many countries due to the displacement effects of robots. In contrast with their conclusion, I find that robot exposure causes people to trust the local government less, and the effects are larger for those whose occupations are more vulnerable to robots.

This paper also adds the literature on robots and politics. See Gallego and Kurer (2022) for a review of literature on technological change and political behaviors. Frey, Berger, and Chen (2018) study the 2016 US presidential election and find that voters in regions more exposed to robots in manufacturing were more supportive of the Republican candidate, Donald Trump. Based on data on eleven countries from the European Social Survey, Im et al. (2019) find that a higher risk of automation motivates the

4. Fan, Hu, and Tang (2021) study the effects of minimum wages on firms' robot adoption, and they find that a 10% increase in the minimum wage over 2008-2012 would increase the probability of a firm adopting robots by 0.11 percentage points. Tang, Huang, and Liu (2021) study how the adoption of industrial robots affects the employment structure and show that firms adopting robots employ more highly skilled and highly educated workers. Wang, Zhang, and Liu (2022) find that robot adoption significantly encourages firms to hire more employees, particularly those with high education or skills.

vote for radical right parties. Finally, Anelli, Colantone, and Stanig (2021) investigate the effects of robot exposure on electoral outcomes in 14 Western European countries during 1993-2016 by using district-level and individual-level voting data. They found that higher robot exposure at the individual level causes poorer perceived economic conditions and well-being, low satisfaction with the government and democracy, and reduced perceived political self-efficacy. Compared to their studies, I contribute to estimating the effects of robots on political attitudes in an authoritarian context.

The remainder of this paper proceeds as follows. Section 2 describes the data. Section 3 presents the empirical strategies for analysis at the prefecture and individual levels. Section 4 shows the results on employment, wages, strikes and individual political attitudes. Section 5 concludes.

2 Data

2.1 Robots

Robots data are from the Chinese customs database in the period 2000-2015.[5] It covers the universe information of Chinese exports and imports at the HS 8-digit and firm-level. The data are detailed, including the name of Chinese firms, firms' contact information, import and export values, quantities, and customs regime. I aggregate the number of robots imported by each firm into prefecture-level data by the firms' location. I include only multipurpose industrial robots.[6] During 2000-2015, there are 4822 import records of multipurpose industrial robots.[7]

Another source of robots is the World Robotics Industrial Robots from IFR. The primary source is nearly all major industrial robot suppliers worldwide. Moreover, several national robot associations collect data on their national robot markets and provide their results as secondary data to the IFR. The data are available at the country-year-industry level and have information on multipurpose industrial robots' operational stock and installation. Figure 1 compares the number of multipurpose

5. The 2016 data are also available, but the quantity information is missing. Only the number of robots for each province is available for later periods.

6. The 8-digit HS code for multipurpose industrial robots is 84795010, and 84795090 is for other unspecified industrial robots. Different kinds of robots may work and replace labor differently. Therefore this paper only focuses on multipurpose industrial robots.

7. 2181 records are wholly foreign-owned; 887 are from joint ventures; 757 are state-owned enterprises, and 941 are private enterprises.

industrial robots from the customs database and IFR. The data from the customs follow IFR data except for 2015. One pattern is that, before 2015, almost all the multipurpose industrial robots are imported from other countries. During 2009-2013, the customs data are even higher than IFR data, and one potential reason is that robot suppliers underreport their sales with the increase of robots. In 2015, the significant drop in customs data may have been caused by the Chinese government's emphasis on the domestic industrial robot industry since December 2013.[8] The overlook of the domestic multipurpose industrial robots (2000-2015) would not be a problem according to the comparison.

For the main analysis, I use robot data from the Chinese customs data. The biggest advantage is that the number of robots can be directly aggregated to the prefecture level. The IFR source is widely used in the literature since it contains robot data for different countries. I use IFR data as well for robustness check (See Appendix A).

The data on occupational exposure to robots are from Webb (2019). He constructs a new and objective measure of the exposure of occupations to automation by quantifying the overlap between the text of technology patents and the text of job descriptions. Specifically, he extracts verb-noun pairs from patent texts and task descriptions, measures the overlap, and then aggregates the task-level scores to produce the exposure score for each occupation. According to this measurement, occupations like forklift drivers and operating engineers are most exposed to robots, and payroll and timekeeping clerks and art/entertainment performers are least exposed.

2.2 Prefecture-level Variables

2.2.1 Employment and Wages

Information at the prefecture level is from China City Yearbooks and China Regional Economic Statistical Yearbooks, including rich information at the prefecture-level. Population, employment in the private sector, and average wage are from China City Yearbook (2005-2015), and general employment, employment in state-owned firms, unemployment rate, and average wages for state-owned firms and private ones are from China Regional Economic Statistical Yearbooks (2005-2015). The variable of the pop-

8. In December 2013, the Chinese government published the document named "Guideline on Promoting the Development of the Industrial Robot Industry", which addressed the weaknesses in China's industrial robotics industry and promoted the adoption of industrial robots. Further, in 2015, robotics was defined as one of the ten core industries in the "Made in China 2025" plan.

ulation includes migrants as well and is obtained by GDP divided by GDP per capita.[9] The employment data by industry in 2000 are from China's 2000 census.[10]

2.2.2 Strikes

Strikes data are drawn from two sources, i.e., China Strikes and the China Labor Bulletin (CLB). China Strikes is created by Manfred Elfstrom mapping labor unrest across China. Its purpose is to build as complete a record as possible concerning how, where, why, and what results in Chinese workers defending their rights and interests. The dataset covers the 2003-2012 period. The information on labor unrest was principally collected by carefully reading state media, foreign media, blogs, internet forums, and dissident sources. For supplementation, users can also submit reports on any strike or protest that China Strikes have been missed and are verified carefully. Each item includes the title, location, date, description, and type. There were 1471 cases of strikes during 2003-2012.

CLB maintains a similar map of labor unrest, regularly updated and covers 2011 to the present. It is a non-governmental organization based in Hongkong and is the most comprehensive dataset about labor conflicts in China. During 2014-2016, CLB relied on the data collection of two mainland activists who published their results online each day.[11] This data are widely used in the literature (e.g., Campante, Chor, and Li 2019; Giuntella, Lu, and Wang 2019)

Figure 2 shows the number of strikes according to China Strikes and CLB. The dotted parts show data from China Strikes (2003-2012) and the real parts for data from CLB (2011-2015). The red line is the total cases of strikes, and the blue one is for strikes in the manufacturing industry. During 2003-2011, the number of strikes increases very slowly but has grown rapidly since 2012. The consistency of these two sources in 2011 and 2012 also verifies the reliability of the data.

9. Before 2004, GDP per capita was based on *Hukou* population but changed to the population including migrants since 2004.

10. The 2000 census data are from https://international.ipums.org/international/.

11. Starting from 2017, CLB started its own search, collecting the information twice a week, so the number of cases has not kept up with the past. With this consideration, this paper only uses CLB data up to 2016.

2.3 Individual Employment and Political Attitudes

Individual variables are from the China Family Panel Studies (CFPS) 2010, 2012, and 2014 waves. CFPS is a nationally representative panel survey of the Chinese community, families, and individuals. CFPS was launched in 2010 by Peking University and is conducted every two years. This survey includes rich information on individual characteristics. Most relevantly, it contains questions about political attitudes towards the local government. Specifically, two following questions are included: 1 trust in local government (0-10, higher means more trust); 2 What is your overall evaluation of the work of the local government in the last year? (1-5, and higher means more positive attitudes). CFPS also covers two questions about employment. One is whether the individual is employed, and the other is the rating of the general employment problems in China (1-10, and a smaller value means that the employment problems are more severe). The variable of *employed* is available for 2010, 2012, and 2014 waves, and the variable of *employment problem* can only be obtained in the 2012 and 2014 waves. Regarding the political attitudes, trust in local government is available in the 2012 and 2014 waves, while the variable of rating of local government's work can be obtained in all three waves. Finally, I restricted the sample to people aged 16-65, and 45,775 observations are kept. 75.81% are surveyed in all three waves.

3 Identification Strategy

3.1 Prefecture-level

The exposure to robots for each prefecture is constructed in the following way.

$$RobotExposure_{pt} = \frac{\sum_{i=t-1}^{t-5} Robot_{pi}}{L_p^{2000}} \tag{1}$$

Here $Robot_{pi}$ is the total number of robots imported by firms in prefecture p and year i. L_p^{2000} is the employment (1,000 workers) for prefecture p in 2000. Instead of using the employment in each year, the employment in 2000 is used because employment markets may change with the adoption of robots, and in 2000 robots are few. So, one robot exposure means the total number of robots imported in the last five years per thousand workers. Figure 3 shows robot exposure at the prefecture level in 2005 and

2015.[12] Robot exposure has variations across prefectures and years.

The specification for the analysis at the prefecture level is as follows.

$$Y_{pt} = \beta_1 RobotExposure_{pt} + \gamma' X_{pt} + \delta_p + \mu_t + \varepsilon_{pt} \tag{2}$$

Here Y_{pt} is the outcome variables of interest for prefecture p at year t, including employment-to-population ratio (%), employment ratio in the state-owned sector (%), employment ratio in the private sector (%), unemployment rate (%), average wages, average wages in the state-owned sector, average wages in the private sector, and the number of strikes. $RobotExposure_{pt}$ is the robot exposure for prefecture p at year t, which is defined as in Equations (1). X_{pt} is for the population. δ_p are prefecture fixed effects, and μ_t are year fixed effects. ε_{pt} is the error term clustered at the prefecture level. β_1 is the coefficient of interest which captures the causal effect of one more robot per thousand workers on outcomes. The underlying assumption is that, in the absence of robot adoption, the evolution of employment and labor unrest would have been similar in prefectures.

3.2 Individual-level

Robots affect occupations differently. For example, industrial truck and tractor operators are more negatively affected by robots than teachers. Therefore, I exploit the variation of occupational exposure to robots. To address the concern that people exposed to robots may have already changed their occupations, I use the predicted value of occupational exposure to robots. Specifically, I construct the individual occupational exposure to robots in Equation (3). This strategy is inspired by Anelli, Colantone, and Stanig (2021), where they predict the individual vulnerability to robots based on potential occupations and occupational exposure to robots.

$$OccExp_i = \sum_j \widehat{\Pr}(o_i = j \mid \text{age, gender, edu, residence, parents' occupations}) * \theta_j \tag{3}$$

Here $OccExp_i$ is the predicted occupational exposure to robots for individual i. $\widehat{\Pr}(o_i = j \mid \text{age, gender, edu, residence, parents' occupations})$ is the predicted probability of individual i working in occupation j. The model is estimated using the CFPS 2010 wave,

12. Data for Taiwan, Hong Kong, and Macao are not included and are labelled as 0 for simplicity.

based on information including age, gender, years of education and whether parents work in similar occupations.[13] The estimation is weighted using individual weight. θ_j is the exposure to robots for occupation j, which is from Webb (2019) and matched with occupation classifications in CFPS by International Standard Classification of Occupations in 1988 (ISCO-88). $\widehat{\Pr}(o_i = j) * \theta_j$ is the robot exposure for individual i with potential occupation j. Sum over all the potential occupations and $OccExp_{it}$ is the predicted occupational exposure to robots for each individual i. For easy interpretation, the index is standardized.

The specification to estimate the effects of robots on individual employment and political attitudes is as follows in Equation (4).

$$Y_{ipt} = \beta_2 RobotExp_{pt} + \beta_3 RobotExp_{pt} * OccExp_i + \rho\prime X^1_{ipt} + \gamma\prime X^2_{pt} + \mu_t + \eta_i + \varepsilon_{ipt} \qquad (4)$$

Here Y_{ipt} is the outcome of interest, including job status, rating of the employment problems, trust in the local government, and rating of local government's achievement in the last year, for individual i in prefecture p and year t. $RobotExp_{pt}$ is robot exposure for prefecture p in year t defined in Equation (1). $OccExp_i$ is the standardized predicted occupational exposure to robots for individual i at year t. X^1_{ipt} are individual-level time-varying controls, including age, education, income, urban or rural. X^2_{pt} are control variables at the prefecture-level, including the logarithm of GDP per capita. η_i are individual fixed effects that absorb the time-invariant individual characteristics. The average differences across years are controlled for in year fixed effects μ_t. ε_{ipt} is the error term clustered at the prefecture level. β_2 and β_3 are the coefficients of interest. β_2 captures the impact of robots (one more robot per thousand workers) on people with moderate occupational exposure to robots. β_3 captures the impact of robots on people with one standard deviation higher occupational exposure to robots compared to people with moderate occupational exposure to robots. The underlying assumption is that, in the absence of robot adoption, the evolution of political attitudes would have been similar in prefectures.

13. For people aged 16-22, education information is not used in estimation since they are young and perhaps have not finished schooling. 22 is the expected age to finish college in China. For people aged 23-65, years of education are included as a predictor.

4 Results

4.1 Summary Statistics

Table 1 presents the summary statistics of key variables. On average, robot exposure, defined as in Equation (1), is 0.044. The average numbers of employment in state-owned and private firms are 0.194 million and 0.186 million. The average unemployment rate is 3.378%.[14]. The average number of strikes was 0.432 during 2003-2012 but rapidly increased to 3.885 during 2011-2015. The average age for the individual sample is 43.396, and they, on average, have 7.683 years of education. 65.9% of them have a job, and the rating of employment problems in China is 3.739. The trust in local government scores 4.860 out of 10, and the rating of local government's work last year is 3.497 out of 5.

4.2 Main Results

Table 2 shows the effects of robot exposure on employment and wages at the prefecture-level during 2005-2015. All the results control for year fixed effects, prefecture fixed effects, and population. Standard errors are clustered at the prefecture-level. Column 1 is for employment-to-population ratio, and columns 2 and 3 focus on employment in the state-owned sector and the private sector, respectively. The coefficient on robot exposure in column 1 is positive but statistically insignificant. This suggests that robot exposure has no significant effect on general employment. But when the analysis is conducted for employment in the state-owned and private sectors separately, the coefficients on robot exposure are 0.126 and 0.634, respectively, and marginally significant for the private sector. This suggests that the effect of robots are heterogeneous in terms of sectors. Specifically, when robots per 1000 workers increase by one, the employment ratio in the private sector would increase by 0.634 percentage points. Regarding the unemployment rate (column 4), the coefficient on robot exposure is negative but insignificant. As mentioned before, the data on unemployment are moderately missing, but still, this could provide some evidence. In terms of wages, column 5 shows that robot exposure does not affect general wages. Columns 6 and 7 present the impact of robots on wages in state-owned firms and private firms, respectively. Robot exposure does not significantly affect the wages in state-owned firms but significantly lowers the

14. The variable of the unemployment rate is partly missing.

wages in private sectors. Specifically, one more robot per thousand workers lowers the wages in the private sector by 4.2%. The heterogeneity could be partially explained by the fact that workers in state-owned firms can not be fired easily, and the wages are stable. These results for the private sector suggest that robots help the private sector grow.

To study the displacement effects of robots, I use the number of strikes in each prefecture as another outcome of interest. Table 3 shows the effects of robot exposure on the number of strikes in China. Strike data during 2005-2012 and 2011-2015 are from China Strikes and CLB, respectively. I control for year fixed effects, prefecture fixed effects, and population. Standard errors are clustered at the prefecture-level. Columns 1 and 3 use the number of all strikes as the dependent variable, while columns 2 and 4 focus on strikes in the manufacturing industry, where robots are concentrated. In column 1, the coefficient on robot exposure is 5.643 and highly significant. When using strikes in the manufacturing industry only, the coefficient becomes 3.854, which is reasonably minor but still significant at the 5% level. Using strike data from CLB (columns 3 and 4), the coefficients are similar but more nosily estimated. These results suggest that robot exposure causes labor unrest in China. Specifically, one more robot per thousand workers is related to about five more cases of strikes and about 4 cases concentrated in the manufacturing industry.

Will the negative displacement of robots on labor change people's attitudes towards the government, even in an authoritarian context? I approach this question using individual level panel data from CFPS. Table 4 presents relevant results. Year fixed effects and individual fixed effects, the logarithm of GDP per capita and individual characteristics including age, years of education, urban or rural, and the logarithm of personal income are controlled for. Standard errors are clustered at the prefecture-year level. Before studying the effects on political attitudes, I evaluate the effects of robots on individual employment status (column 1) and the rating of employment problems in China (column 2). For people who have average predicted occupational exposure to robots, robot exposure has no significant effects on employeemnt. The coefficient on the interacted term is -0.038 and significant at the 1% significance level. When the predicted occupation exposure to robots increases by one standard deviation, the effect of robot exposure on being employed would decrease by 3.8 percentage points. Column 2 suggests that people who have larger occupational exposure to robots think the employment market is more severe.

The results on political attitudes on presented in Table 4 columns 3 and 4. The dependent variable in column 3 is the rating of the government's performance during the last year, which ranges from 1 to 5. The coefficient on robot exposure is -0.038 though insignificant. When the occupation exposure to robots increases by one standard deviation, the effect would be 0.022 lower. The outcome variable in column 4 measures trusts in local government, which is a number between 1 and 10. The coefficient on robot exposure is -0.115. This suggests that with one more robot per thousand workers, people with average occupation exposure to robots would have 0.115 lower trusts in the local government. When the occupation exposure to robots increases by one standard deviation, the effect would be 0.115 lower. This means that one more robot per thousand workers would lower the trust in local government by 2.37% (i.e., 0.115/4.844) lower, and comparing with people who have average occupation exposure to robots when occupation exposure increases by one standard deviation, the effect of robot exposure on trust towards local government would further decrease 2.37%.

5 Conclusion

This paper investigates the impact of robots on the labor market and political attitudes towards the local government in China. I find that at the prefecture level, robots have no significant effects on overall employment, but heterogeneity exists in the state-owned and private sectors. Robots cause more employment in the private sector but do not affect employment in the state-owned sector. Regarding average wages, higher robot exposure lowers wages in the private sector. Robots also cause more labor unrest in China. Specifically, one more robot per thousand workers causes strikes to increase by about 5 cases and about 4 in the manufacturing industry.

People within the same prefecture can also be affected by robots differently, and the effects depend on how the occupations are vulnerable to robots. This paper finds that higher robot exposure causes individuals to be more likely to be jobless, and the negative effect is more significant for individuals whose potential occupations are more vulnerable to robots. Consistent with the negative attitudes towards robots documented in the literature, this study shows that higher robot exposure would lower people's ratings of the local government's performance. The negative effect is significantly larger for people whose occupations are more vulnerable to robots. Robots also cause people to show less trust in the local government. One more robot per thousand workers would cause people whose occupations are moderately exposed to robots to trust the local government 2.37% less. The effect is heterogeneous regarding occupation exposure to robots. Compared to people whose occupations are exposed to robots on the average level, the impact of robot exposure on people whose occupations are exposed to robots one more standard deviation would further trust the local government 2.76% less.

Adopting robots may affect people's attitudes toward the government, even in an authoritarian context. To improve political trust, the government may need to consider better those more negatively affected by automation.

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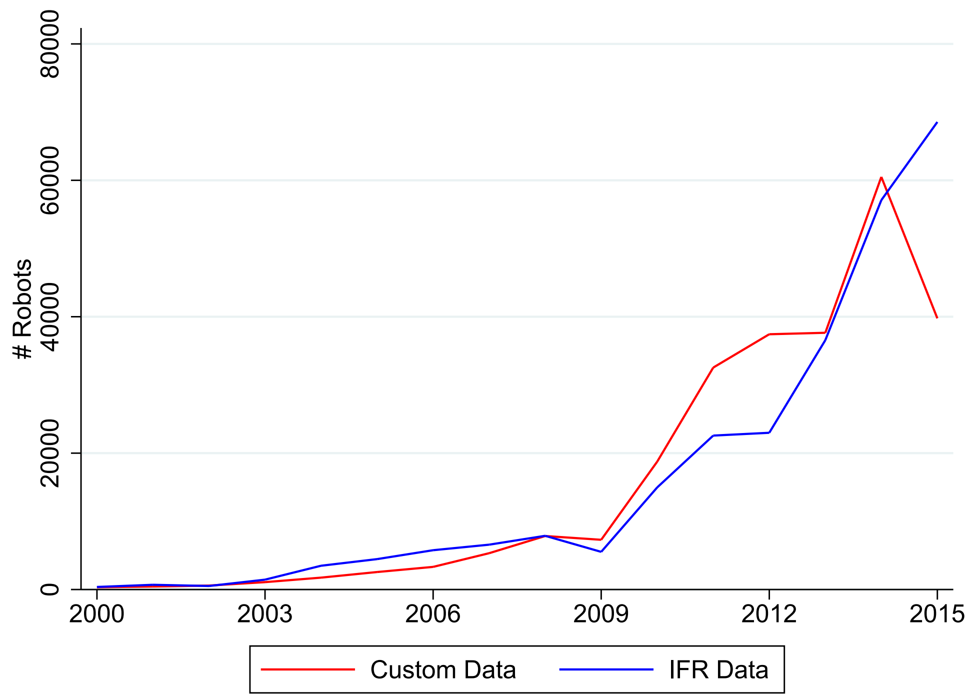
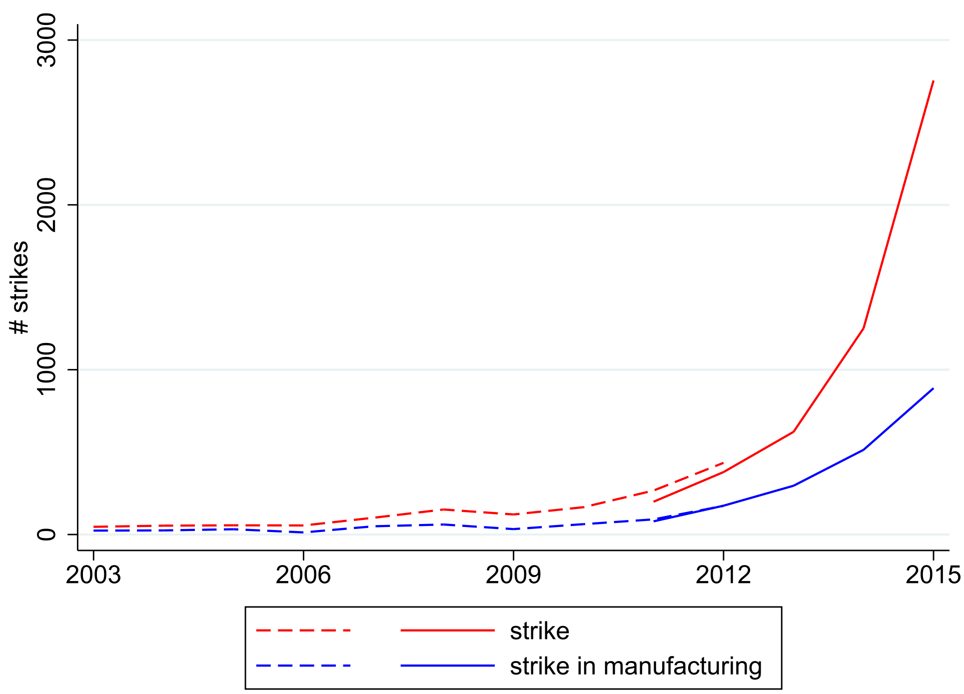
Figures and Tables

Figure 1: The Comparison of Robots from Customs Database and IFR



Notes: This figure compares the number of multipurpose industrial robots from two different sources from 2000 to 2015. The red line indicates robot data from Chinese customs and the blue line presents robot data from the International Federation of Robotics (IFR).

Figure 2: The Number of Strikes in China

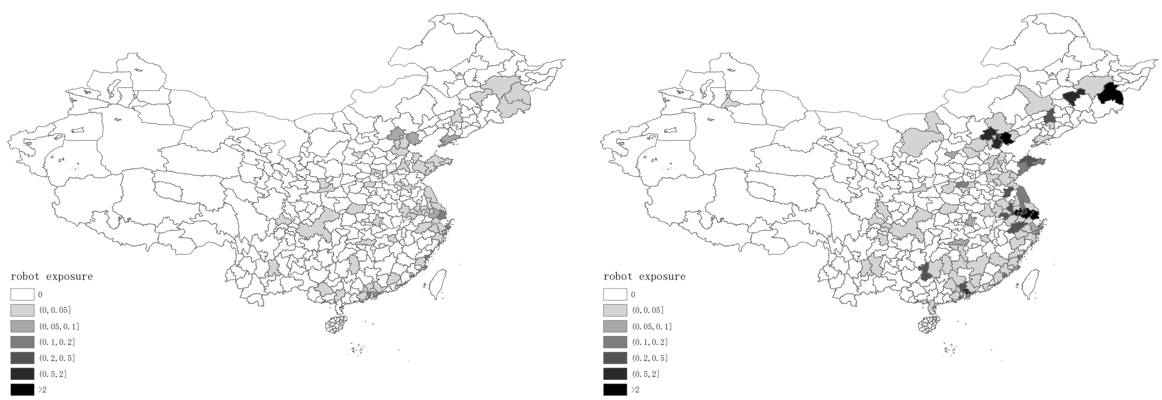


Notes: This figure presents the number of strikes in China since 2003. The red lines show the total number of strikes, and the blue lines show the number of strikes in the manufacturing industry. The data during 2003-2012 (dashed lines) are from China Strikes which are created by Manfred Elfstrom. The data during 2011-2015 are from the China Labour Bulletin.

Figure 3: Robot Exposure

(a) 2005

(b) 2015



Notes: This figure presents exposure to robots at the prefecture level. The robot exposure is calculated by the sum of robots imported in the last five years divided by employment in 2000. Panel (a) presents robot exposure in 2005, and Panel (b) presents robot exposure in 2015.

Table 1: Descriptive Statistics of Key Variables

	Obs.	Mean	Std. Dev.	Min.	Max.
Prefecture-Level Variables					
Robot Exposure	3245	0.044	0.381	0.000	10.116
Employment (million)	2874	2.468	1.754	0.045	16.688
State-Owned	2845	0.194	0.182	0.012	1.950
Private	2479	0.186	0.311	0.000	4.200
Unemployment Rate(%)	1573	3.378	0.850	0.480	8.300
Average Wage	3134	32971.460	14682.800	4958.000	1.15e+05
State-Owned	2481	35157.826	16138.973	7488.000	1.28e+05
Private	1866	26384.679	12733.135	5339.000	86715.000
# Strikes					
2003-2012	3370	0.432	1.769	0	48
2011-2015	2022	3.885	8.460	0	112
Individual-Level Variables					
Occ. Exp.	48546	0.020	1.072	-1.493	15.571
Age	48658	43.396	12.127	16	65
Male	48658	0.473	0.499	0	1
Years of Education	48658	7.683	4.482	0	22
Income	42774	11591.034	20735.299	0.000	1.80e+06
Employed	33312	0.612	0.487	0	1
Employment Problem	29868	3.739	2.543	0	10
Trust in Local Govt.	30543	4.860	2.557	0	10
Rating of Local Govt.	45375	3.497	0.891	1	5

Notes: This table shows the summary statistics for key variables.

Table 2: The Effects of Robot Exposure on Employment and Wages

	employment/pop(%)			unemp. rate(%)	average wages (log)		
	all	state-owned	private		average	state-owned	other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot Exposure	0.470	0.126	0.634*	-0.035	-0.001	0.022	-0.042**
	(1.617)	(0.125)	(0.352)	(0.023)	(0.007)	(0.049)	(0.017)
Observations	2,821	2,751	2,434	1,552	3,119	2,375	1,793
R-squared	0.771	0.918	0.838	0.787	0.967	0.970	0.960
Year FE	Y	Y	Y	Y	Y	Y	Y
Prefecture FE	Y	Y	Y	Y	Y	Y	Y
Mean Dep Var	57.435	4.984	4.118	3.379	10.301	10.359	10.064
Mean Indep Var	0.030	0.036	0.023	0.051	0.046	0.030	0.028

Notes: Population, employment in the private sector, and average wage are from China City Yearbook (2005-2015), and general employment, employment in state-owned firms, unemployment rate, and average wages for state-owned firms and private ones are from Regional Statistical Yearbook (2005-2015). All regressions control for the population. Standard errors in parentheses are clustered at the prefecture-level. ***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: The Effects of Robot Exposure on Strikes

	2005-2012 (China Strikes)		2011-2015 (CLB)	
	All	Manufacturing	All	Manufacturing
	(1)	(2)	(3)	(4)
Robot Exposure	5.643***	3.854**	4.361	3.046
	(2.164)	(1.675)	(3.035)	(2.058)
Observations	1,438	1,438	2,276	2,276
R-squared	0.765	0.797	0.682	0.650
Year FE	Y	Y	Y	Y
Prefecture FE	Y	Y	Y	Y
Mean Dep Var	3.529	1.345	0.583	0.227
Mean Indep Var	0.086	0.086	0.021	0.021

Notes: Strike data during 2005-2012 and 2011-2015 are from China Strikes and CLB, respectively. All the regression control for the population. Standard errors, shown in parentheses, are clustered at the prefecture-level. ***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: The Effects of Robot Exposure on Individual Employment and Political Attitudes

	Employed	Rating of empl. problem (1-10)	Rating of govt achievement	Trust on local govt
	(1)	(2)	(3)	(4)
Robot Exp	-0.056	0.035	-0.038	-0.115**
	(0.039)	(0.066)	(0.023)	(0.055)
Robot Exp. * Occ. Exp.	-0.038***	-0.076**	-0.022*	-0.115***
	(0.014)	(0.036)	(0.013)	(0.040)
Observations	31,370	17,762	38,422	18,424
R-squared	0.686	0.635	0.560	0.703
Year FE	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y
Mean Dep. Var.	0.621	3.764	3.486	4.844
Mean Indep. Var.	0.161	0.358	0.245	0.350

Notes: The individual-level data are from CFPS 2010, 2012, and 2014 waves. The job information is from 2010 and 2012 waves. A rating of employment problem (1-10, and a smaller value for higher severity of the employment environment) is available for the 2012 and 2014 waves. Occupation Exposure is Standardized. Age, years of education, urban or rural, income logarithm, and GDP per capita are controlled for in all specifications. Standard errors, shown in parentheses, are clustered at the prefecture level. ***p < 0.01, ** p < 0.05, * p < 0.1

Appendix A: IV Result

Considering the potential endogeneity of firms importing robots, I instrument the robot exposure using robots in South Korea. The construction of the instrument variable is as in the Equation (A1). $\sum_{i=t-1}^{t-5} Robot_{ij}$ is the sum of South Korea's robot installation for industry j during the last five years. The sum is divided by the employment of industry j at the baseline year 2000 in South Korea. ℓ_{pj}^{2000} is the employment share of industry j of prefecture p in China. Sum over all the industry j, which would be the instrument variable for robot exposure for prefecture p in year t. For South Korea, the year-industry installation of robots is from IFR (2020), and the employment data for each industry in 2000 are from Asia KLEMS.[15] The data on prefecture-industry employment share in China are from the China 2000 census.

$$\text{RobotExposure (IV)}_{pt} = \sum_j \ell_{pj}^{2000} \left(\frac{\sum_{i=t-1}^{t-5} Robot_{ij}}{L_{j,2000}} \right)_{\text{South Korea}} \tag{A1}$$

The instrument variable only exploits the industry expansion of adopting robots in South Korea. According to IFR (2020), the five major markets for robots are China, Japan, the United States, South Korea, and Germany, and both China and South Korea have increased rapidly since 2000. Another reason why South Korea is chosen is that South Korea is close to China and has many similarities with China. Therefore, robot exposure in South Korea should be correlated with that in China. However, robot exposure in South Korea should not have direct effects on employment and political attitudes towards the local government in China other than through the impact on robot exposure in China.

Considering the potential endogeneity problem of importing robots by firms, I use the IV constructed in Equation A1. Table A1 presents the IV results on employment and wages at the prefecture-level. Panel A shows the baseline OLS results. Panel B present the results of 2SLS. The F statistics are smaller than 10. Therefore the results of 2SLS are less precise. Nevertheless, the sign of each coefficient could provide some suggestive evidence.

15. Asia KLEMS was initiated in December 2010 to build a database and conduct international productivity comparisons among Asian countries. The counterpart in European countries is EU KLEMS.

Table A2 presents the effects of robots on strikes using IV. Based on the period 2005-2012, the F statistic in the first stage is 5.375. The 2SLS results in Panel B show that one more robot per thousand workers would increase the number of strikes by 26.430 and increase strikes in the manufacturing industry by 17.954 cases, which are all statistically significant. In columns 3 and 4, the data on strikes during 2011-2015 are from CLB. One more robot per thousand workers would increase the number of strikes by 16.804 and increase strikes in the manufacturing industry by 10.453 cases. The first stage results bring the concern of weak IV problems, which make the standard errors in 2SLS larger. Still, the signs are consistent with the baseline results.

The IV results at the individual level are presented in Table A3. Panel B shows the 2SLS results. The signs are consistent with the baseline but insignificant.

Table A1: The Effects of Robot Exposure on Employment and Wages (IV Results)

	employment/pop			unemp. rate(%)	wages		
	all	state-owned	priavte		average	state-owned	other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: OLS results						
Robot Exposure	0.470	0.126	0.634*	-0.035	-0.001	0.022	-0.042**
	(1.617)	(0.125)	(0.352)	(0.023)	(0.007)	(0.049)	(0.017)
	Panel B: 2SLS						
Robot Exposure	6.518*	0.667*	7.126**	-0.160	-0.090	-0.088	-0.095
	(3.853)	(0.386)	(3.366)	(0.248)	(0.067)	(0.059)	(0.070)
Observations	2,821	2,751	2,434	1,552	3,119	2,375	1,793
Year FE	Y	Y	Y	Y	Y	Y	Y
Prefecture FE	Y	Y	Y	Y	Y	Y	Y
First Stage F Statistic	5.045	5.062	7.431	7.217	7.259	4.407	4.333

Notes: Standard errors in parentheses are clustered at the prefecture level. ***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A2: The Effects of Robot Exposure on Strikes (IV Results)

	2005-2012 (China Strikes)		2011-2015 (CLB)	
	All	Manufacturing	All	Manufacturing
	(1)	(2)	(3)	(4)
	Panel A: OLS results			
Robot Exposure	5.643***	3.854**	4.361	3.046
	(2.164)	(1.675)	(3.035)	(2.058)
	Panel B: 2SLS			
Robot Exposure	26.430**	17.954**	16.804***	10.453***
	(11.624)	(8.669)	(5.687)	(3.462)
Observations	1,438	1,438	2,276	2,276
Year FE	Y	Y	Y	Y
Prefecture FE	Y	Y	Y	Y
First Stage F Statistic	5.375	5.375	7.368	7.368

Notes: Standard errors in parentheses are clustered at the prefecture level. ***p $<$ 0.01, ** p $<$ 0.05, * p $<$ 0.1

Table A3: The Effects of Robot Exposure on Individual Employment and Political Attitudes (IV Results)

	Employed	Rating of empl. problem (1-10)	Rating of govt achievement	Trust on local govt
	(1)	(2)	(3)	(4)
		Panel A: OLS		
Robot Exp.	-0.056	0.035	-0.038	-0.115**
	(0.039)	(0.066)	(0.023)	(0.055)
Robot Exp. * Occ. Exp.	-0.038***	-0.076**	-0.022*	-0.115***
	(0.014)	(0.036)	(0.013)	(0.040)
		Panel B: 2SLS		
Robot Exp.	-0.167	0.051	-0.110	-0.279
	(0.154)	(0.128)	(0.102)	(0.225)
Robot Exp. * Occ. Exp.	-0.067	-0.046	-0.038	-0.185
	(0.048)	(0.068)	(0.031)	(0.120)
Observations	31,370	17,762	38,422	18,424
Year FE	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y
First Stage F Statistic	36.236	71.716	53.334	66.815

Notes: Standard errors in parentheses are clustered at the prefecture-year level. ***p < 0.01, ** p < 0.05, * p < 0.1