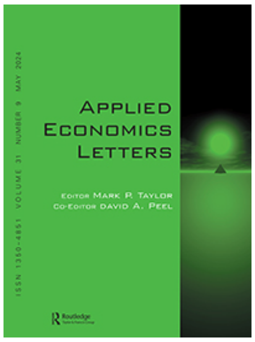

Routledge
Taylor & Francis Group

Applied Economics Letters

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/rael20

Do robots sharpen labour lawsuits in developing countries? Evidence from China

Jinyue Tang, Rui Xiao & Shougui Luo

APPLIED ECONOMICS LETTERS
https://doi.org/10.1080/13504851.2024.2347429

Do robots sharpen labour lawsuits in developing countries? Evidence from China

Jinyue Tang, Rui Xiao and Shougui Luo

Antai College of Economics and Management, Shanghai Jiao Tong University, Shanghai, China

ABSTRACT

This study mainly aims to understand whether the increasing adoption of industrial robots has spurred the strengthening of labour lawsuits. Based on city-level data in China during the period of 2007 to 2019, our analysis reveals a significant relationship between industrial robot shocks and the increase of labour lawsuits. The underlying mechanism is that labour are replaced by robots, especially in manufacturing industries. Firms will dismissal employees, reduce wages or insurances to save labour costs, thus resulting in more labour lawsuits.

KEYWORDS

robots; labour; lawsuits; employment; China

JEL CLASSIFICATION

J24; J53; O33

I. Introduction

The profound transformation brought about by robots has significantly reshaped labour market dynamics worldwide. The widespread integration of robots has garnered substantial attention from researchers, predominantly focusing on empirically evaluating its impacts on employment demand, structures, and productivity (Acemoglu and Restrepo 2020; Graetz and Michaels 2018; Yang 2022). Despite the growing body of literature in this domain, few studies have delved into whether robot shocks sharpen labour lawsuits, particularly under the context of developing countries. In this paper, based on city-level data from China, we investigate whether robot shocks affect labour lawsuits in local labour markets.

Our research aligns with two key strands of existing literature. The first strand centres on how the integration of robots influences local labour market dynamics. There is significant evidence that robots have displaced labour, especially jobs with routine and repeated tasks and low-skilled employees in traditional labour-intensive industries (Acemoglu and Restrepo 2020; Frey and Osborne 2017). Recent studies have also observed heterogeneity in these findings, associated with the sector considered and the type of workers (Mondolo 2022; Montobbio *et al.* 2023). In particular, the negative effects seem to be mostly related to workers whose tasks can be easily replaced by robots. Worker-level results from Acemoglu *et al.* (2023) show that directly-affected workers (e.g. blue-collar workers performing routine or replaceable tasks) face lower earnings and employment rates, while other workers indirectly gain from robot adoption. The second strand of literature delves into labour rights and legal protections, particularly in the context of developing countries characterized by less developed political systems, challenging labour conditions, and a predominant structure of labour-intensive industries (Messerschmidt and Janz 2023). Notably, efforts to enhance labour rights in developing countries have gained momentum over the past two decades. In China, the ratio of labour lawsuits to employees has risen from 0.2 cases per thousand people to 1.5 during the period 2000-2019, representing a 5.9-fold escalation.

This study contributes to the empirical investigation of the impact of robots on labour lawsuits with the case of China. Robots, known for substituting labour, particularly low-educated, low-skilled, and elder workers, trigger a negative labour demand shock. Responding to this shock, firms may resort to measures such as wage reduction, workforce downsizing, and breach of prior employment contracts, which leads to an uptick in lawsuits between workers and firms. Drawing on the panel data

CONTACT Rui Xiao ruixiao2021@163.com Antai College of Economics and Management Shanghai Jiao Tong University, 1954, Huashan Road, Shanghai, Xuhui 200030, China

covering 286 cities in China during the period 2007–2019, our empirical findings highlight a positive relationship between robot shocks and labour lawsuit increase. Besides, we also test the moderating effect of judicial quality, unionization, and Confucianism. The first two factors increase the costs of firms to break employment contracts, thus protect labour from wages reduction and dismissal (Yao and Zhong 2013). Confucius constructed Confucianism philosophies such as moral order, duty, and ethics during the Warring States period, which has influenced the culture and spirit of Chinese firms (Kung and Ma 2014). The third factor, Confucianism encourages managers of firms to act ethically and not deprive workers of their interests.

II. Data and methodology

Data

We use a panel data covering 286 cities in China during the period 2007–2019, consisting of 2,846 observations in total. Two datasets as follows are mainly used in this paper.

1) Robot data

The International Federation of Robotics (IFR) dataset supplies annual records of industrial robot adoption for each country, derived from yearly surveys conducted with robot suppliers. Following the methodology outlined in Acemoglu and Restrepo (2020), we compute city-year-level indicators of industrial robot shocks ($Robot_{it}$) as follows:

$$Robot_{it} = \sum_{j \in J} \frac{emp_{ij,t=2007}}{emp_{i,t=2007}} \frac{Robot_{jt}}{emp_{j,t=2007}} \quad (1)$$

where $Robot_{jt}$ refers to China's stock of industrial robots in industry j year t. $emp_{ij,t=2007}$, $emp_{i,t=2007}$ and $emp_{j,t=2007}$ denote the employment for city i in industry j, the employment for city i, and the employment for industry j in China, 2007, respectively.[1]

2) Labor lawsuit data

Officially established by the Supreme People's Court of China, the China Judgements Online website (https://wenshu.court.gov.cn) discloses judicial documents of all cases legally publishable. Boasting over 145.9 million documents and over 110.0 billion website visits (until Mar. 2024), this data source guarantees the reliability of our labour lawsuits data. We manually collect information on labour lawsuits for each city (LS_{it}) and confine our selection to civil first-instance trial procedures to eliminate duplication.

Empirical model

Based on the outlined data collection framework, we specify our empirical model as follows:

$$LS_{it} = \alpha + \beta\ Robot_{it} + \delta\ X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (2)$$

where i and t denote city and year, respectively; LS_{it} is the logarithm of the number of labour lawsuits in city i year t; $Robot_{it}$ is industrial robot shocks as defined in Equation (1); $\boldsymbol{X}_{it}$ is a vector of control variables, including population, GDP, infrastructure, average wage, education expenditure, industrial structure and foreign investment; u_i and ν_t denote city and time fixed-effects; ε_{it} is the error term. The statistics summary of variables is listed in Table A1, Appendix 1.

We also estimate the following model to test moderating effects:

$$LS_{it} = \alpha + \beta\ Robot_{it} + \gamma\ Robot_{it} \times M_{it} + \delta\ X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (3)$$

where M_{it} is the moderating variable used to explain underlying mechanisms, including the number of lawyers per person ($Lawyer_{it}$), the percentage of labour union members of total employment ($Union_{it}$), and the number of Confucius temples per person ($Confucius_{it}$).

To avoid bias caused by endogeneity, we follow the methodology advanced by Acemoglu and Restrepo (2020) and instrument *Robot* using an analogous indicator that

[1]There is a corresponding relationship between IFR industry classification and International Standard Industrial Classification (ISIC) revision 4 (UN 2008) (Jurkat *et al.* 2022).

measures robot shocks in the U.S. The IV ($Robot\_US_{it}$) for $Robot$ is depicted as follows:

$$Robot\_US_{it} = \sum\nolimits_{j \in J} \frac{emp_{ij,t=2007}}{emp_{i,t=2007}} \frac{Robot^{US}_{jt}}{emp^{US}_{j,t=1990}} \quad (4)$$

where ${Robot^{US}}_{jt}$ is industrial robot stock for industry j in year t in the U.S., and ${emp^{US}}_{j,t=1990}$ refers to the U.S. employment for industry j in 1990. The underlying assumption of IV construction is that both robot stocks of China and the U.S. reflect technological progress and robot demand, and the stock of the U.S. exerts no other direct influence on China's labour market.

Figure 1 illustrates a pronounced surge in both industrial robot installations and labour lawsuits. The compelling trend further reinforces the rationale behind our research question in this paper.

III. Empirical results

Baseline results

Table 1 presents the results of Fixed Effects (FE) estimations. Across all specifications, a robust, positive, and statistically significant relationship emerges between robots (*Robot*) and labour lawsuits (*LS*). In Column (1), the coefficient on *Robot* is positive and statistically significant, which indicates that a one-unit increase in industrial robots is associated with an average rise of 4.4% in total labour lawsuits. We further test the effect of robots on labour lawsuits for two main types of cause of action, including claims for labour reward (*LS1*) and social insurance disputes (*LS2*). Positive coefficient estimates on *Robot* are found, and both of them are significant. A one-unit increase in robots results in 4.3% increase in lawsuits for labour reward and 4.7% increase in lawsuits for insurance. Thus, increase in lawsuits caused by robots is

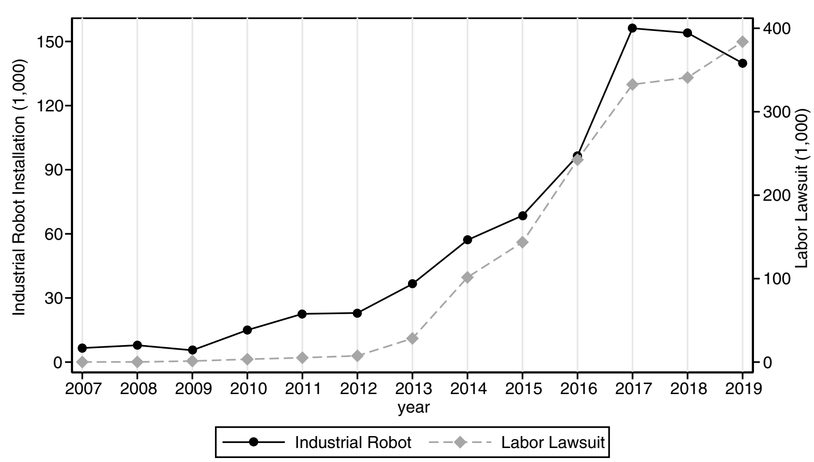

Figure 1. Industrial robot installations and labour lawsuits in China.

Table 1. The effect of robots on labour lawsuit in China.

Dep. var.:	(1) *LS*	(2) *LS1*	(3) *LS2*	(4) *LS_Per*	(5) *LS*	(6) *LS*
Robot	0.044***	0.043***	0.047***	0.031**	0.049***	0.147**
	(0.014)	(0.016)	(0.016)	(0.015)	(0.013)	(0.071)
Obs.	2,846	2,846	2,846	2,834	2,846	2,846
R2	0.881	0.851	0.799	0.615	0.887	-
First-stage regression						*Robot*
Robot_US						1.273***
						(0.298)
KP LM statistic						12.10
KP Wald F statistic						18.21

Note: Standard errors clustered on city-year level in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. All the coefficients are estimated with control variables, city FE and year FE. Same as follows.

related to worsen wage settings and social insurances.

Robustness checks

The results in benchmark regression are supported by a series of robustness checks. In Column (4), we first use a different dependent variable – the number of labour lawsuits per employee (*LS_Per*). In Column (5), we add province-specific linear time trend to avoid the bias caused by regional differences. Coefficient estimates are all positive and significant. In Column (6), following the IV method issued in Section II, results of IV estimation are consistent with FE estimation.

Mechanisms

We re-estimate Equation (2) to test the labour dynamics cross industries (Table 2). In Columns (1) - (5), the dependent variable is the number of employees in a specific industry, including mining (*Em1*), resources supply (*Em2*), real estate (*Em3*), public facility (*Em4*), and education (*Em5*). The labour force in industries such as mining and resources supply is dominated by low-skilled labour to perform repetitive non-cognitive tasks. Industrial robots will form a direct competition relationship with this part of labour force and cause employment in these industries to decline, which directly causes the increase of labour lawsuits. Specifically, a one-unit increase in industrial robots leads to an average employment decline of 0.5% in mining, and 1.2% in resources supply, as shown in Columns (1) and (2). In Columns (3) - (5), we find that employment in the service sector has risen, which is indirect evidence that labour in traditional manufacturing has been displaced by robots into the service sector. One indirect channel is that robots drive more workers into high-skilled industries, especially services, where workers are better paid and more empowered to protect their rights through labour litigation. In Column (6), the dependent variable is the ratio between the number of employees in high-skilled industries and those in low-skilled industries (*Em_Ratio*).[2] We find a positive and significant coefficient, which further confirms the transfer of labour from low-skilled industries to high-skilled ones.

Table 3. Moderating effect analysis.

Dep. var.: *LS*	(1)	(2)	(3)
Robot	0.222***	0.430***	0.069***
	(0.075)	(0.151)	(0.018)
Robot×Lawyer	−0.083**		
	(0.032)		
Robot×Union		−1.980**	
		(0.764)	
Robot×Confucius			−0.007**
			(0.003)
Obs.	2,458	2,846	2,308
R2	0.879	0.881	0.880

Table 3 lists the results of moderating effects.[3] Robots' effect on labour lawsuits is significantly lower in regions with more lawyers per person and labour union members per employee, as shown in Columns (1) and (2). This confirms our expectation that higher judicial quality and higher unionization protect labour from shocks of robots. Confucius temples per person(measured by *Confucius*) significantly reduces labour lawsuits arising from robot shocks.

IV. Conclusions

Studies on the effect of robot adoption or other applications of artificial intelligence technology on employment have overlooked their impact on labour

Table 2. The effect of robots on employment dynamics in China.

Dep. var.:	(1) *Em1*	(2) *Em2*	(3) *Em3*	(4) *Em4*	(5) *Em5*	(6) *Em_Ratio*
Robot	−0.005*	−0.012***	0.007***	0.005**	0.003*	0.068**
	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.031)
Obs.	2,849	2,849	2,849	2,849	2,849	2,457
R2	0.938	0.818	0.947	0.795	0.944	0.796

[2]Referring to Industrial Classification for National Economic Activities (GB/T 4754–2017), we classify 16 industries into high-skilled and low-skilled ones according to the percentage of employees with a college degree in each industry.
[3]Data of lawyers and union members are at province level, obtained from Statistical Yearbook of provinces and China Labour Statistical Yearbook; data of Confucius temples are at city level, obtained from Chinese Research Data Services Platform (CNRDS).

lawsuits. This study delves into the positive relationship between robots and labour lawsuits, and underscores the crucial need to prioritize firm-employee relations, particularly in developing countries where marketization, labour union power, and legal protections are still in nascent stages.

Our findings align with the literature, which emphasizes labour market disruptions caused by robot shocks (Acemoglu and Restrepo 2020; Graetz and Michaels 2018). Furthermore, we highlight the importance of proactively maintaining firm-employee relations and safeguarding labour rights against the background of advancing artificial intelligence.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the National Natural Science Foundation of China (Project no. 72174117).

References

Acemoglu, D., H. R. Koster, and C. Ozgen. 2023. *Robots and Workers: Evidence from the Netherlands*. NBER Working Paper No. w31009 March.

Acemoglu, D., and P. Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy* 128 (6): 2188–2244. https://doi.org/10.1086/705716.

Frey, C. B., and M. A. Osborne. 2017. "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Technological Forecasting and Social Change* 114:254–280. https://doi.org/10.1016/j.techfore.2016.08.019.

Graetz, G., and G. Michaels. 2018. "Robots at Work." *The Review of Economics and Statistics* 100 (5): 753–768. https://doi.org/10.1162/rest_a_00754.

Jurkat, A., R. Klump, and F. Schneider. 2022. "Tracking the Rise of Robots: The IFR Database." *Journal of Economics and Statistics* 242 (5–6): 669–689. https://doi.org/10.1515/jbnst-2021-0059.

Kung, J. K. S., and C. Ma. 2014. "Can Cultural Norms Reduce Conflicts? Confucianism and Peasant Rebellions in Qing China." *Journal of Development Economics* 111:132–149. https://doi.org/10.1016/j.jdeveco.2014.08.006.

Messerschmidt, L., and N. Janz. 2023. "Unravelling the 'Race to the bottom' Argument: Foreign Direct Investment and Different Types of Labour Rights." *World Development* 161:106097. https://doi.org/10.1016/j.worlddev.2022.106097.

Mondolo, J. 2022. "The Composite Link Between Technological Change and Employment: A Survey of the Literature." *Journal of Economic Surveys* 36 (4): 1027–1068. https://doi.org/10.1111/joes.12469.

Montobbio, F., J. Staccioli, M. Virgillito, and M. Vivarelli. 2023. "The Empirics of Technology, Employment and Occupations: Lessons Learned and Challenges Ahead." *Journal of Economic Surveys* 1–34. https://doi.org/10.1111/joes.12601.

Yang, C. H. 2022. "How Artificial Intelligence Technology Affects Productivity and Employment: Firm-Level Evidence from Taiwan." *Research Policy* 51 (6): 104536. https://doi.org/10.1016/j.respol.2022.104536.

Yao, Y., and N. Zhong. 2013. "Unions and workers' Welfare in Chinese Firms." *Journal of Labor Economics* 31 (3): 633–667. https://doi.org/10.1086/669819.

Appendix 1

Table A1. Description and statistics summary of variables.

Variable	Indicator	Mean	Std. Dev.	Min	Max
Dependent variable					
LS	Natural logarithm of the number of labour lawsuits	3.216	2.974	0.000	10.183
Independent variable					
Robot	Calculated from Equation (1)	0.629	1.959	0.000	43.409
Instrumental variable					
Robot_US	Calculated from Equation (4)	0.831	0.835	0.000	6.150
Control variables					
Pop	Population	0.484	0.360	0.038	3.188
GDP	Per capita GDP	4.452	2.886	0.407	21.549
Road	Length of roads	1.325	1.032	0.073	17.428
Wage	Average wage	4.747	2.006	1.216	17.321
EDU	Education expenditure	0.638	0.875	0.032	11.372
Industry	The ratio of GDP between the primary and secondary industries	0.277	0.211	0.001	1.893
FDI	Foreign investment	0.091	0.198	0.000	2.433
Obs	2,846				