Proceedings of the 3rd International Conference on Business and Policy Studies
DOI: 10.54254/2754-1169/78/20241648

Robot Adoption and Employment in China

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Abstract: The research level of robotics in China is also at the forefront of the world, but there is no literature on the impact of robotics on the labor market in China. This paper examines the influence of robot adoption in the labor market based on regional and industry-level robot applications. This study concludes that robot adoption will considerably cut labor employment, particularly in industries where machines are more easily replaceable. The results are unaffected by substituting robot density for the dependent variable and controlling for the endogenous issue. This research contributes to the literature on robot installations and the labor market field by providing further empirical data for the structural transformation of China's labor market at a more granular level and in more industry sectors. This article suggests that policymakers in the robot sector should be concerned about the detrimental effects of robot policies on social employment and the unique characteristics of regional economies and industries.

Keywords: Economic development, Robot adoption, Robotics, Unemployment, China economy

1. Introduction

In recent years, the number of industrial robots has exploded. According to the International Federation of Robotics, the world's industrial robot stock reached 2.1 million units in 2017, primarily in the equipment manufacturing business and primarily for various complicated applications [1]. As a major manufacturing nation and the world's second-largest economy, China is a pioneer in the intelligent robotics business. Although China's industrial robotics industry is experiencing great demand and quick expansion, there is no clear and reliable consensus regarding robots' influence on the Chinese labor market. In an era of substantial demographic and labor force shifts, it is crucial to comprehend the influence of robotics on the labor market. Therefore, this article investigates the effect of robots on the Chinese labor market.

To determine whether "technological unemployment" exists, a portion of the existing literature has investigated the subject of whether robots will displace humans and how they affect employment levels and company productivity in the labor market [2-4]. However, these studies contain numerous debates and flaws. The literature generally focuses on a sample of industrialized countries and the period from 1990 to 2010. Due to the absence of early data on China, the small number of cross-country studies tend to exclude China from the sample, resulting in a relative lack of empirical information on the influence of robotic applications on the Chinese labor market. Simultaneously, the available empirical information based on industry and macro-levels is scant and starkly contradictory.

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For instance, Acemoglu and Restrepo find that robot adoption reduces employment levels and average salaries in the US labor market [5]. In contrast, Graetz and Michaels using a cross-country sample, find no substantial impact of robot adoption on the labor market [6].

The objectives of this study equip developing nations with perspective. In addition, this article gives perspectives on the economic impact of robotics applications when the new crown epidemic seriously affects the labor market. This research attempts a more extensive examination of the influence of robotics applications on the labor market. This research explicitly explores the effect of robot adoption on local labor market employment levels in various industries by combining data on robot adoption and labor force employment at the regional and industrial levels in China. On this premise, the research investigates how regional disparities in labor market structure influence the impact of robot applications on the labor market in terms of human capital, labor protection, and market development. The study reveals that using robots dramatically affects employment in the local labor force. In contrast, the region's urban unemployment rate mitigates the impact of this technical unemployment issue.

The following are the primary contributions of this paper: By introducing a cross-sectional approach and combining data on robot applications at the regional and industry levels, this paper provides more detailed evidence to overcome the limitations of existing studies that only examine the average effect at the industry or regional level, as well as new ideas and references to further explore and clarify the impact of robot applications on China's labor market. In addition, the research explores the spillover impacts of robot applications in the context of industrial chain orientation and labor substitutability.

2. Literature review and research hypothesis

In examining the influence of machine applications on the labor market, most of the literature tends to use a macro-level viewpoint, focusing on the impact of robot applications on the employment rate of the entire labor force. The vast majority of extant literature has a slanted view of technological advancement, stating that industrial machines are gaining advantages under challenging jobs.

According to Frey and Osborne, around 47% of vocations are significantly impacted by machine power [7]. This conclusion adds to concerns about future employment and labor market trends amid a major worldwide employment loss [8]. According to a portion of the available literature, industrial machines offer considerable substitution advantages and reduce labor force employment considerably. Using the United States as an example, Dinlersoz and Wolf and Acemoglu and Restrepo conclude that improvements in robotics and its adoption lead to large losses in both labor force employment and salaries [5,9]. Moreover, Acemoglu and Restrepo demonstrate that the effect of machine power on employment levels and labor pay is notably distinct from the effect of general capital additions such as IT [5]. Nonetheless, some studies imply that the use of machine power has a favorable impact on labor force employment, regulating the distribution of labor across industries and reducing employment in certain industries while increasing employment in other related businesses. Dauth and co. These studies concentrate on developed nations like North America and Europe but less on developing nations, and there is still no consensus at the macro-industry or micro-firm level.

The introduction of robots increases firms' production scale and profitability [6], which may boost firms' need for labor in situations where robots are not yet a complete substitute for labor [10-11]. In addition, the deployment of robots necessitates workforce adjustments for some businesses. Moreover, with the introduction of robots, some companies will need to improve their personnel or acquire a high human capital workforce to run and maintain the robots more effectively and fully unlock their productivity [2]. This could increase the demand for local labor in the same industry concurrently with the increase of capital elements or robots. On the basis of these two potential paths, this study proposes:

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The premise is that a scaled-up deployment of robots will lead to a decline in local employment in the same industry.

3. Methodology

3.1. Data

This article investigates the effect of robotics adoption on employment using industry-region level panel data from 2012 to 2017, mostly from the China Merchandise Trade Database, International Industrial Robotics Statistics, and the China Labor Statistics Yearbook. Two sets of robot adoption statistics are used to measure the amount of robot adoption at the industry-region level: the China Merchandise Trade Database and the International Industrial Robotics Statistics. The China Commodity Trade Database includes monthly statistics on the import and export of more than 15,000 commodities by trade mode from 31 Chinese provinces to more than 200 countries. This paper determines the number of robots imported from international industrial robot statistics obtained from the IFR, a database that provides authoritative data on industrial robot applications worldwide [5]. This study calculates the annual number of new robots added to each industry based on these facts. Due to the limited availability of robotics data, the sample period for this article spans from 2012 to 2017.

To examine the impact of robot applications on labor force employment, the number of urban labor force units employed and the average wage level in different regions and industries are extracted from the China Labor Statistics Yearbook, which is used to measure employment and labor cost changes in the labor market.

3.2. Variables

3.2.1. Robot adoption rate

To determine the amount of robot adoption in China, this paper examines the regional and industry levels of robot adoption. $\mathrm{RA}_{i,t}$ represents the natural logarithm of the number of new robots in province i in year t. $\mathrm{RI}_{i,t}$ represents the natural logarithm of the number of new robots in industry j in year t.

3.2.2. Labor force employment level

The following measures are established in this research based on industry and regional characteristics: 1) To assess the influence of robot applications on the employment rate of the industry's labor force, the $\Delta\mathrm{lnNum}_{i,j,t+1}$ is created. This variable is defined as the change in the natural logarithm of the number of employed persons in urban units in industry j in province i in year t+1. 2) To measure the transfer of labor from the industry to upstream and downstream industries, the $\Delta\mathrm{lnNum}_{i,jd,t+1}$ and $\Delta\mathrm{lnNum}_{i,ju,t+1}$ variables are constructed. These variables are the average change in the number of employed persons in urban units in important downstream and important upstream industries in industry j in province i in year t+l. The descriptive statistic is provided in Table 1.

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Table 1: Descriptive statistic

Variable	Obs	Mean	Std. Dev.	Min	Max
lnNum	7,065	.45125	.0406663	.3142963	.507314
RA	7,220	17.32686	3.044002	0	20.87651
RI	7,160	0.068739	0.092619	-0.25976	0.507583
RA _density	7,220	23.3848	31.34856	0	156.3451
RI_density	7,065	.2124452	.1437843	.0030246	.387143
group_province	7,220	15.92036	8.931324	1	31
group_Industry	7,220	25.88019	13.84637	1	49

Application distribution for robots. Figure 1 displays the size of new robots and the cumulative size from 2006 to 2017 based on IFR industry statistics. As depicted in Figure 1, the size of robot use in China has expanded year over year, notably after 2012. It is essential to examine the repercussions of this shift on employment in the labor market. Simultaneously, it is evident that the data distribution on the use of robots in China has good variability during the study period and that the results are trustworthy.

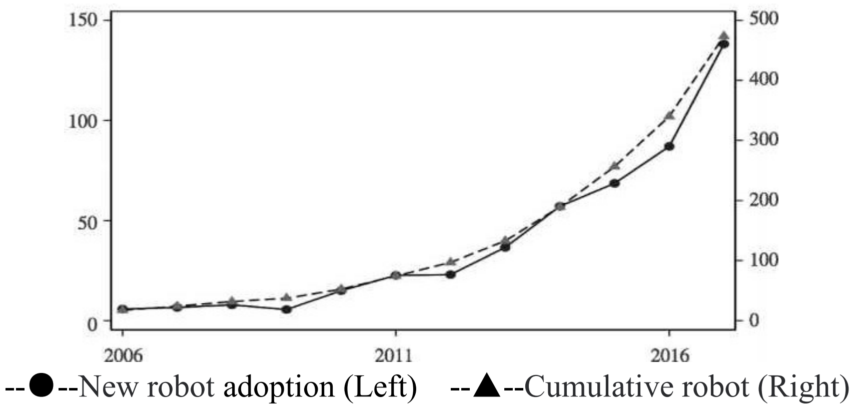

Figure 1: The scale of newly added robots and the change of cumulative robot scale in China from 2006 to 2017 [1].

4. Benchmark results and robustness tests

The benchmark regression is that

$$\Delta lnNum_{i,j,t+1} = a + \beta_1 RA_{i,t} * RI_{i,t} + Inudstry * Year + Province * Year + Industry * Province + \varepsilon \quad (1)$$

Where, i, represents a provincial administrative unit or municipality directly under the central government, j represents an industry sector in the National Economic Classification, and t represents the year. The explained variable $\Delta\mathrm{lnNum}_{i,j,t+1}$ represents the growth rate of labor employment in the following year, measured as the logarithmic increase in the number of i urban units employed in the j industry in t+1 year. $\mathrm{RA}_{i,t}$ represents the regional level of robotics application, and $\mathrm{RI}_{i,t}$ represents the industry level of robotics application. Other are fixed effects absorb the effects of the industry- and region-level control variables. All regressions in this paper are clustered at the industry level to eliminate possible heteroskedasticity and autocorrelation. In regression (1), the focus is on the coefficient of the cross-sectional term $\mathrm{RA}_{i,t} * \mathrm{RI}_{i,t}$. If this coefficient is significantly negative, it indicates that the growth rate of labor force employed in the same industry is lower when the number of robots used and the size of new robots is higher.

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4.1. Baseline result

Table 2 displays the results of the model's baseline estimation. The regression findings for all industries are displayed in column of all sample, where the regression coefficient of $RA_{i,t} * RI_{i,t}$ is 0.1773 and significant at the 1% level. Robots are primarily used in secondary industries, so the employment levels of their labor force are most likely to be affected by robots. The regression findings for the secondary industry subsample are displayed in Table 2. At the 1% significance level, the cross-sectional term has a coefficient of -0.2469 and is statistically significant. In addition, the IFR does not disclose the degree of robot use in all industries, both because very few robots are deployed in these areas and because the IFR focuses primarily on statistical industrial robotics.
Consequently, the results for the subsample of industries reported by the IFR are displayed in Table 2. The coefficient on the cross-sectional term is -0.1509 and is significant at the 1% level for the data. This result is comparable in magnitude and significance to the results of the entire sample. This indicates that the discrepancies in IFR industry coverage do not significantly impact the conclusions of this article.

From these findings, the paper concludes that the greater the scale of robot adoption, the more significant the decline in labor force employment growth in the same local industry. This conclusion is robust across the sample. This finding confirms the hypothesis presented in this research that robot adoption leads to technological unemployment in China in the short term. So, the hypothesis is tested to be true.

Table 2: Baseline regression

	$\Delta lnNum_{i,j,t+1}$		
	All sample	Secondary Industry	IFR industry
$RA_{i,t} * RI_{i,t}$	-0.1773***	-0.2469***	-0.1509***
	(-3.0053)	(-24.6001)	(-4.9642)
Cons	12.4710***	22.0421***	14.2871***
	(3.1098)	(23.1322)	(4.5492)
Fixed effect	Yes	Yes	Yes
Obs	7220	4740	4750
Adj R^2	0.3771	0.3539	0.3764

Note: *, ** and *** indicate that this coefficient is significant at the 10%, 5% and 1% significance levels respectively.

4.2. Test findings for robustness based on robotic use density

This paper has employed the scale of robot additions in baseline regressions and disregards the population base. To ensure the robustness of the results, this research calculates industry- and region-level densities of robot additions per capita, taking into account changes in labor resources across regions and industries. The $RA\_density_{i,t}$, is the ratio of robot additions in province i in year t to the number of urban units in the province's labor force, and the $RI\_density_{i,t}$ is the ratio of robot additions in industry j in year t to the number of labor force in the industry. The model was then performed using $RA\_density_{i,t}$ as a substitute for heart and $RI\_density_{i,t}$ as a substitute for model (1). Table 3 presents the results of the regressions.

The coefficient on the cross-sectional term $RA_{i,t} * RI_{i,t}$ is negatively significant at the 1% level for the complete sample, the secondary industry subsample, and the subsample of industries covered by the IFR only, as shown in Table 3. This implies that, even after accounting for the influence of the population base, the conclusion that the usage of robots has a large negative impact on employment at the industry and regional levels remains robust.

Table 3: Robust test: Using robot adoption density as the substitutes

	$\Delta lnNum_{i,j,t+1}$		
	All sample (1)	Secondary Industry (2)	All sample (1)
$RA\_Density_{i,t} * RI\_Density_{i,t}$	-0.0483***	-0.0702***	-0.0592***
	(-3.6272)	(-19.9521)	(-8.0948)
Cons	0.9016***	-0.3318**	-0.4042**
	(6.7734)	(-6.2057)	(-3.6392)
Fixed effect	Yes	Yes	Yes
Obs	7220	4740	4750
$AdjR^2$	0.3765	0.3536	0.3767

Note: *, **, and *** indicate that this coefficient is significant at the 10%, 5% and 1% significance levels, respectively.

4.3. Endogeneity treatment: based on the substitutable characteristics of industrial labor force

This paper finds that using robots affects labor force employment levels in the short term, but the result may be suffering from the endogenous problem caused by reverse causality. Industries with a high loss of labor resources have a greater incentive to invest in robots to alleviate the constraint of labor resources on business development. This research incorporates exogenous factors to quantify the chance of robots being utilised in a certain industry to bolster the reliability of the findings.

In truth, specific job duties are naturally more susceptible to being replaced in whole or part by machines. In the logistics industry, for instance, basic, repetitive, and labor-intensive product handling methods are highly susceptible to being replaced by handling robots. By counting the jobs involved in each industry and their corresponding job characteristics, it is possible to determine the likelihood of each industry itself being replaced by robots due to the operational characteristics of the job and that this likelihood is dependent on the natural properties of the various tasks thereby effectively eliminating potential endogenous problems. Based on 1980 US industrial job data, this article defines a position as "replaceable" if it is anticipated to be totally or substantially replaced by a robot in 2012 ($Replaceble_j$). Specifically, this article calculates the ratio of employment in the sector employing robotic arms to the total number of jobs in the business in 1980 and characterises this ratio as the percentage of roboticised tasks ($Handling_j$). Table 4 contains the findings of the regression analysis.

In Table 4, columns (1) and (2) present the results of the complete sample regression. The IFR industry subsample regression findings are displayed in columns (3) and (4) for robustness purposes. The cross-sectional coefficients are shown to be significantly negative for both the measure of industry substitutability based on the proportion of robotically tasks and the measure of industry substitutability based on the proportion of hours worked in substitutable jobs. The findings of this paper are further confirmed by the fact that the introduction of robots in industries with high labor substitutability leads to short-term technical unemployment in that industry's local labor market.

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Table 4: Endogeneity treatment: based on the substitutable characteristics of the industrial labor force

	$\Delta lnNum_{i,j,t+1}$			
	All sample		IFR Industry	
	(1)	(2)	(3)	(4)
$RA_{i,t} * Replaceble_j$	-10.7538***		-16.1186**	
	(-3.4057)		(-2.5532)	
$RA_{i,t} * Handling_j$		-2.5300*		-7.8857***
		(-1.9555)		(-4.0218)
Cons	84.4795***	9.7190*	125.3202**	34.3427***
	(3.4211)	(2.0352)	(2.5269)	(3.8748)
Fixed effect	Yes	Yes	Yes	Yes
Obs	7065	7065	4750	4750
$AdjR^2$	0.3777	0.3776	0.3770	0.3775

Note: *, ** and *** indicate that this coefficient is significant at the 10%, 5% and 1% significance levels respectively.

5. Conclusion

This paper used 2012-2017 data on robot adoption at the regional and industry levels in China, constructed cross-sectional terms to capture changes in robot adoption at the industry and regional levels, and combined this with labor force employment data to examine the impact of robot adoption on employment at a finer level. In light of the rich and non-negligible disparities across industries and regions in China, this article analyses further the differences in the labor market impact of robot adoption under different scenarios, taking into consideration the diverse cross-sectional characteristics of sectors and areas. This study aims to analyse the relevance of Keynesian 'technological unemployment' theory to the Chinese labor market and to understand the impact of robots on the structure of the Chinese labor market. The study concludes that using robots considerably reduces labor employment, and this conclusion holds true after accounting for any endogeneity difficulties. The use of robots will cause the problem of "technological unemployment". Therefore, government regulators should not only focus on robot development and large-scale application to promote the efficiency of production but also on the robot's influence on the labor market. They should notice the negative effect on labor employment and the stability of the employee's work.

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