Information Systems and Economics (2023)
Clausius Scientific Press, Canada

DOI: 10.23977/infse.2023.040910
ISSN 2523-6407 Vol. 4 Num. 9

Industrial Robots and Redundant Employees: Evidence from the Labor Market of Chinese State-owned Enterprises

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Keywords: Robots, State-owned Enterprises, Redundant Employees

Abstract: Industrial robots are becoming increasingly widely used in enterprises. This article empirically studies the impact of industrial robot use on redundant employees in state-owned enterprises using data from 2012-2017 China A-share listed companies. Unlike previous research conclusions, this study found that the use of industrial robots promoted an increase in redundant employees in state-owned enterprises. For every 1% increase in the amount of investment in industrial robots, the number of redundant employees increased by approximately 0.86%. Furthermore, the degree of impact showed heterogeneity in terms of the region where the state-owned enterprise was located and the level of market competition. The findings of this study provide Chinese evidence for studying the relationship between industrial robots and redundant employees in enterprises, which can help provide ideas and reference for better achieving the economic development goals of state-owned.

1. Introduction and Literature Review

1.1. Introduction

In recent years, with the application and development of digital technologies such as the Internet and big data, robots have been increasingly widely used in enterprises. Numerous studies have documented the significant impact of technologies like artificial intelligence on labor employment in companies, but the effects vary across different types of enterprises. State-owned enterprises, which operate under unique political backgrounds, often bear political tasks such as expanding employment, resulting in a higher number of redundant employeterprises, such as "promoting employment" and "stable growth". Against the backdrop of the challenging employment environment where machines are replacing humans, studying the impact of robots on redundant employees in state-owned enterprises is of great theoretical and practical significance for the effective allocation of production factors in these enterprises.

1.2. Literature Review

Some scholars believe that artificial intelligence(AI) has a positive impact on employment. Trajtenberg argues that the application of AI promotes increased productivity, which in turn requires more labor force participation in production. Additionally,[14] the emergence of new technologies is accompanied by the creation of new jobs. Acemoglu and Restrepo suggest that in the long term, as social productivity increases,[4] AI will create many new positions, resulting in a greater creation effect than substitution effect, thus greatly promoting overall social development. Terry Gregory, Anna Salomons, and Ulrich Zierahn, through the development and estimation of an empirically tractable framework, conclude that the employment impact of conventional substitution technologies far exceeds the loss caused by substituting labor, highlighting the crucial role of the distribution of benefits from technological progress in job creation.

Whether AI and other technologies can drive innovation in Chinese enterprises is a topic that existing literature mainly focuses on in developed countries' research on the impact of robots on employment (Acemoglu and Restrepo, 2017)[4]. However, there is a lack of discussion in the literature, potentially due to the absence of data on robot usage at the enterprise level in China. Furthermore, there is limited empirical evidence regarding the overall effect of AI and other technologies on labor displacement, with most existing data concentrating on the relative effects of technology.

However, some scholars argue that the use of robots has a suppressing effect on labor employment in enterprises. Qiu Yu (2023)[12], analyzing micro-enterprise data from 2010 to 2019 in China from the perspectives of employment scale and structure, finds that robot adoption significantly reduces total employment in manufacturing enterprises. Acemoglu and Restrepo,[4] based on data from developed countries, empirically study the relationship between industrial robots and employment in manufacturing industries and find that the substitution effect of robots on the labor market is greater than the creation effect. He Qin et al. (2020)[13] examine panel data from 115 manufacturing enterprises and, based on the theory of innovation diffusion, construct a model to analyze the impact mechanism of AI on employment. They discover that the adoption and application of AI have a negative impact on the number of employees in the manufacturing industry. Thus, it can be seen that the academic community has not reached a definitive consensus on the relationship between robot usage and labor employment in enterprises. As the economy develops and industrial robots are increasingly deployed in enterprises, employment becomes a key concern for countries, and resolving employment issues gradually becomes a focus of government work. Frydman, Hessel, and Rapaczynski (1998)[7] point out that political pressure prevents companies from downsizing. Dong and Putterman (2003)[16] reveal that in the 1990s, the reduction in funding obtained by state-owned enterprises, intensified market competition, and government control over layoffs led to a decrease in non-labor income for state-owned enterprises and a continuous increase in redundant employees. Lin Yifu (2004)[11] argues that Chinese state-owned enterprises generally bear the pressure of redundant employees and social functions such as worker welfare. Shen Yongjian and Zhang Tianqin (2011)[13] suggest that the issue of redundant employees in state-owned enterprises is one of the outcomes of government intervention. With the increasing penetration of industrial robots, how will redundant employees in enterprises be affected? How should Chinese state-owned enterprises properly address the issue of redundant employees and lead operations with more scientific and challenging goals to enhance the quality and efficiency of development, contribute to social responsibility, and achieve economic growth? These questions still require further exploration.

1.3. Organization of the Article

Compared to existing research, this paper may make marginal contributions in the following aspects: Firstly, existing literature mainly utilizes industry-level data for analysis (Yan Xueling, 2020, etc.)[15]. Industry-level data may easily mask the heterogeneity of firms within the industry, leading to weak identification of micro-level channels through which robot applications affect employment. From an international perspective, this paper is one of the earliest to use micro-level enterprise data to study the labor market impact of robots. Secondly, existing research on industrial robots mostly focuses on data from developed countries (Autor and Salomons, 2017;[1] Acemoglua and Restrep, 2020;[5] Dauth et al., 2018;[6] Graetz and Michaels, 2018[8]). In fact, due to differences in labor markets and industrial layouts between developing and developed countries, the impact of industrial robots on redundant employees may differ in developing countries. Our research found a conclusion different from that of developed countries, i.e., the use of robots has a promoting effect on the number of redundant employees in Chinese state-owned enterprises. Thirdly, existing literature on the impact of robots on enterprise labor allocation mostly selects the number of employees and wage income as dependent variables, studying the impact of robot use on them (Li, L., Lu, Y., & Zhang, J, 2019;[2] He Qin, 2020;[9] He Xiaogang, 2023, etc.[10]). However, this paper selects redundant employees in Chinese state-owned enterprises under the macroeconomic environment and political policy background as the research object. Different from existing literature, considering that China is a developing country with different economic conditions from developed countries, the identification effect of macro-industry-level and micro-enterprise-level data is inconsistent and there are huge differences between enterprises with different natures in the market.

Therefore, we selects Chinese state-owned enterprises as the main research subject and constructs a theoretical model with redundant employees in state-owned enterprises as the dependent variable. By empirical analysis, we study the impact of industrial robot use on redundant employees in Chinese state-owned enterprises, further exploring whether it promotes or inhibits China's national economic development goals of "employment promotion" and "stable growth". By introducing micro-level data of Chinese state-owned enterprises,we overcomes the shortcomings of existing research that only examines the average effects brought by macro-level data such as regions or industries(Zhu, G., Li, X., & Li, Q. 2018)[3], providing a basis for further exploring the efficient allocation of resources in Chinese state-owned enterprises.

We conducted empirical research using Chinese listed companies as samples. Our prediction is that the introduction of robots has a positive promotion effect on the number of redundant employees in state-owned enterprises. The empirical results are consistent with our prediction, and there is a positive correlation between the number of robot introductions and the number of redundant employees in state-owned enterprises. Controlling for other variables, fixed industry effects, and year effects, as the number of robot introductions increases, the number of redundant employees in state-owned enterprises increases, and the regression analysis coefficient is positive and significant. This article hopes to bring a creative theoretical achievement to labor economics by studying the data of Chinese state-owned enterprise labor market; provide evidence for the relationship between industrial robots and redundant employees in China, propose constructive suggestions that conform to the actual development of Chinese state-owned enterprises, and promote the establishment of a sound market economy theory system with Chinese characteristics; provide ideas and reference opinions for state-owned enterprises to better allocate labor production factors in the face of the introduction of industrial robots, so as to better achieve the economic development goals of "promoting employment" and "stabilizing growth".

The structure of this article is as follows: Part II is theoretical analysis and research hypotheses; Part III is data sources and methods; Part IV is heterogeneity test; Part V is research conclusions and policy suggestions.

2. Theoretical analysis and research hypothesis

In theory, the impact mechanism of the industrial robot deployment on the redundancy of employees in state-owned enterprises mainly includes the aspects of scale effect, productivity effect, and national macro policies. At the scale and productivity levels, the deployment of industrial robots enhances the automation capability of enterprises, deepens automation to improve production efficiency, strengthens enterprise competitiveness, leads to an expansion of output scale, promotes the integration of enterprise resources, and enhances the ability to pay wages, thereby better achieving the goal of employment security, resulting in an increase in the number of redundant employees.

At the national macro policy level, numerous studies have examined how the government addresses social employment issues through state-owned enterprises, leading to the phenomenon of redundant employees in these enterprises. Boycko, Shleifer, and Vishny (1996)[17] found that privatization made government intervention costly, hence the issue of redundant employees is not as severe in private enterprises compared to state-owned enterprises. Zeng Qingsheng and Chen Xinyuan (2006) conducted a study using Chinese listed companies from 1999 to 2002 and concluded that state-controlled companies employ more staff than non-state-controlled companies. The Chinese government utilizes state-owned enterprises to support its policy goals of "employment stability and livelihood protection." They believe that when facing employment pressure, the government has the motivation to let state-controlled listed companies share the employment pressure or not allow state-owned enterprises to completely divest or release redundant employees during the restructuring process. Zeng Qingsheng and Chen Xinyuan (2006) further pointed out that as a shareholder of state-owned companies, the government provides incentives and supervision to the operators of state-owned companies through performance evaluation systems to achieve the goal of maintaining and increasing state-owned assets. Faced with performance evaluation pressure, actively retaining redundant employees is disadvantageous for the operators. Therefore, if state-controlled companies have excess employees, it is often the result of government intervention or influence. Bai et al. (2000)[19] proposed a multi-task theory model for state-owned enterprises. They believe that during the transitional period of the economy, in order to achieve social stability, it is necessary to establish a social security system; otherwise, a large number of unemployed individuals will lead to social instability, which will not provide an ideal environment for the production and operation of enterprises, resulting in overall inefficiency of the economy and society. However, in the early stages of reform, there was a lack of basic institutions specifically providing social security to maintain social stability, and establishing independent social security institutions required time and cost. Therefore, during the reform and transition period, a gradual reform approach was adopted to retain a certain proportion of state-owned enterprises to maintain social stability, which is also a suboptimal choice for maintaining social stability. These state-owned enterprises undertake functions such as maintaining labor employment and even employing more staff.

Based on the above analysis, we proposes the research hypothesis:the deployment of industrial robots in state-owned enterprises has a promoting effect on redundant employees.

3. Data Sources and Method

3.1. Data Sources and Simple

We takes Chinese A-share listed companies as the research sample, with data sourced from the CSMAR database and the global industrial robot database published by the International Federation of Robotics (IFR). Due to the widespread adoption of robots by Chinese enterprises starting from

2011 and the outbreak of the global economic and financial crisis in 2018, the study period is set from 2012 to 2017. To avoid the influence of abnormal samples, following the practices of previous studies, the following treatments were applied to the original data: (1) Exclusion of listed companies with "ST," "*ST," "suspended from trading," "delisted," or "delisting arrangement" status; (2) Exclusion of data from the financial industry due to its unique characteristics; (3) Exclusion of samples with significant missing values for key variables; (4) Exclusion of outlier samples that clearly deviate from accounting standards; (5) Exclusion of samples with a total number of employees equal to or less than 200.

3.2. Model Design

To examine the impact of robot deployment on the number of redundant employees in state-owned enterprises, the following basic regression model is constructed:

$$employee_{it} = \alpha_0 + \alpha_1 \cdot robot_{it} + \alpha_2 \cdot control_{it} + \delta_{it} + \lambda_{it} + \varepsilon_{1it} \tag{1}$$

$$ex\_staff_{it} = \beta_0 + \beta_1 \cdot soe\_robot_{it} + \beta_2 \cdot control_{it} + \delta_{2i} + \lambda_{2t} + \varepsilon_{2it} \tag{2}$$

The subscripts i and t represent industry and time, δ represents industry fixed effects, λ represents time fixed effects, ε_{1it} and ε_{2it} represents the random error term.

3.3. Variable Explanation

In Model (1), the dependent variable "employee" represents the actual number of employees in a company, which is expressed as the natural logarithm of the number of employees in i industry-listed companies in year t. The core explanatory variable is "robot", while "control" represents the control variables. Following existing research, this paper selects the following control variables: firm size "size", capital intensity "capital", leverage ratio "lev", executive shareholding ratio "mshare", wage level "wage", research and development investment"rd", and return on assets "ROA". In addition, the variable "soe" is added to control for the ownership structure of the enterprise. If the enterprise is state-owned, "soe" takes a value of 1, otherwise it takes a value of 0. Furthermore, industry fixed effects and year fixed effects are also controlled in this study.

Table 1: Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
employee	8,987	7.753	1.182	5.541	11.24
robot	8,987	12.95	0.990	10.18	15.57
size	8,987	22.11	1.254	20.01	26.11
capital	8,987	0.213	0.147	0.00540	0.664
lev	8,987	0.397	0.198	0.0561	0.883
mshare	8,987	0.0862	0.149	0	0.620
wage	8,967	9.341	0.967	5.872	11.37
rd	8,987	0.0211	0.0177	9.24e-05	0.0966
roa	8,987	0.0425	0.0497	-0.144	0.185
ex_staff	8,967	-0.000271	0.465	-4.849	2.046
soe_robot	8,987	4.427	6.305	0	15.57

The explained variable ex_staff in Model (2) represents the number of redundant employees in state-owned enterprises in industry i and year t. This article mainly refers to the model design of Zeng Qingsheng, Chen Xinyuan (2006)[18], estimates the regression coefficients of Model (1) α_0 , α_1 , α_2 , and calculates the estimated normal employee quantity of enterprises based on the coefficients of each variable estimated by Model (1). Finally, the number of redundant employees is obtained by subtracting the actual number of employees from the estimated normal employee quantity. Model (2) selects and processes control variables in the same way as Model (1), and controls for industry fixed effects and year fixed effects.

The descriptive statistics of all variables are listed in Table 1.

3.4. Baseline Regression

Table 2: Baseline Regression

	(1)	(2)
	ex_staff	ex_staff
soe_robot	0.0069***	0.0086***
	(9.2342)	(10.3649)
robot		-0.0016
		(-0.2249)
size		-0.0090*
		(-1.8237)
capital		-0.0306
		(-0.6868)
lev		-0.0365
		(-1.2046)
mshare		0.0725**
		(2.3000)
wage		-0.0013
		(-0.2802)
rd		-0.0623
		(-0.2054)
roa		0.0654
		(0.6408)
_cons	-0.0304***	0.2076*
	(-5.7173)	(1.7429)
N	8962	8962
R^2	0.2836	0.2854

Notes:* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The benchmark regression results of the impact of robot deployment on the number of excess employees in state-owned enterprises are presented in Table 2. In the first column, controlling for industry fixed effects and year fixed effects, only the core explanatory variable is included. The results indicate that the coefficient of state-owned enterprise robots is significantly positive at the 1% level. In the second column, additional control variables are incorporated to more accurately estimate the impact of robot deployment on the number of excess employees in state-owned enterprises. From the results, it can be observed that the coefficient of "soe_robot" is , and it is significantly positive at the 1% level, indicating that the deployment of robots in state-owned enterprises stimulates and promotes the number of excess employees. Specifically, holding other conditions constant, an increase in the deployment of robots in state-owned enterprises leads to an increase in the number of excess employees, highlighting the economic significance of robot deployment in contributing to the increase in excess employees in state-owned enterprises. These tests validate the hypotheses proposed in this study.

3.5. Robustness Tests

Table 3: Robustness Tests

	(1)	(2)	(3)
VARIABLES	ex_satff	ex_staff	ex_staff
robot	0.008	-0.002	-0.007
	(0.008)	(0.007)	(0.009)
soe_robot	0.170***	0.194***	
	(0.021)	(0.019)	
L. soe_robot (Lagged)			0.009***
			(0.001)
size	-0.025***	-0.007	-0.010*
	(0.005)	(0.005)	(0.006)
capital	0.297***	-0.030	-0.037
	(0.047)	(0.045)	(0.053)
lev	-0.176***	-0.039	-0.033
	(0.033)	(0.030)	(0.036)
mshare	0.021	0.076**	0.081**
	(0.036)	(0.032)	(0.040)
wage	-0.013**	-0.001	-0.004
	(0.005)	(0.005)	(0.006)
rd	-0.465	-0.059	0.734**
	(0.305)	(0.303)	(0.365)
roa	0.119	0.066	0.122
	(0.114)	(0.102)	(0.121)
Constant	0.543***	0.155	0.304**
	(0.125)	(0.118)	(0.145)
Year	No	Yes	Yes
Ind	No	Yes	Yes
Observations	8,962	8,962	6,027
R-squared	0.029	0.285	0.299

In order to enhance the credibility of the main findings in this study, robustness tests were conducted from two aspects: ①Replacement of the core explanatory variable: To eliminate the influence of firm size, this study adopted a new approach based on Bonfiglioli et al. (2020)[20], which involves using the logarithm of the ratio of robot quantity to fixed assets as a new interaction term to replace the original "robot" variable. The results of estimation with the new core explanatory variable, without controlling for industry fixed effects and year fixed effects, are presented in column (1) of Table 3. The results, consistent with the baseline regression, are also presented in column (2) of Table 3, where industry fixed effects and year fixed effects are controlled. ②Lagged effects: Considering the dynamic changes in the labor market, the introduction of new technologies may have delayed impacts on the labor force. Furthermore, the process of industrial robots being introduced, deployed, and gradually scaled up in enterprises is a progressive one. Therefore, this study takes into account the temporal nature of the impact of industrial robots on the labor market. In column (3) of Table 3, the core explanatory variable is replaced with lagged data instead of contemporaneous data as in the baseline regression. The results remain robust.The above robustness tests further support the main conclusions of this study.

4. Heterogeneity Analysis

4.1. Location

Table 4: Heterogeneity Analysis of Regional Differences

	(1)	(2)	(3)
	East	Central	West
	ex_staff	ex_staff	ex_staff
robot	0.02533***	-0.09050***	-0.09646***
	(3.01)	(-4.25)	(-5.41)
soe_robot	0.00671***	0.00650***	0.01612***
	(6.05)	(3.23)	(9.26)
size	-0.01219**	0.00330	0.01709
	(-2.02)	(0.27)	(1.40)
capital	0.17505***	-0.63798***	-0.19135**
	(3.11)	(-5.46)	(-2.01)
lev	0.01125	-0.07890	-0.19056***
	(0.31)	(-1.02)	(-2.66)
mshare	0.10301***	-0.11802	0.11550
	(2.90)	(-1.02)	(1.32)
wage	-0.00146	-0.01095	0.01618
	(-0.25)	(-0.89)	(1.52)
rd	0.58741*	1.16231	-3.59649***
	(1.65)	(1.11)	(-5.20)
roa	0.26843**	-0.94435***	-0.19791
	(2.17)	(-3.52)	(-0.86)
_cons	-0.16225	1.42816***	0.89195***
	(-1.11)	(4.68)	(2.99)
N	6410	1080	1464
adj. R^2	0.288	0.396	0.335

Due to the differences in economic development level, industrial structure, and innovation capabilities among different regions in China, there may be heterogeneity in the level of artificial intelligence technology and the use of industrial robots. In order to further investigate the impact of robot usage on the number of redundant employees in state-owned enterprises, this study categorizes state-owned enterprises into three categories: enterprises in the eastern region, enterprises in the central region, and enterprises in the western region, adopting the classification method used by Shao Chao (2016) and others. Table 4 reports the estimation results for these three sub-samples in columns (1), (2), and (3).The regression estimation results indicate that the estimated coefficients of soe_robot are significantly positive for all three types of state-owned enterprises, indicating a significant promoting effect of robot investment on the number of redundant employees in state-owned enterprises in the eastern, western, and central regions. However, the estimated coefficient of soe_robot in the sample of state-owned enterprises in the western region is larger than that in the sample of state-owned enterprises in the central and eastern regions. This suggests that compared to the central and eastern regions, the use of robot investment has a greater impact on increasing the number of redundant employees in state-owned enterprises in the western region.A possible explanation for this is that the western region is not geographically advantaged and relatively underdeveloped compared to the central and eastern regions. In order to promote balanced regional development and address livelihood issues, the Chinese government's policies and resource allocation tend to be biased towards the western region, and state-owned enterprises in the western region bear a heavier social responsibility of "maintaining employment" and "promoting growth".

4.2. Enterprise market competitiveness

Table 5: Heterogeneity Analysis of Enterprise Market Competitiveness

	(1)	(2)
VARIABLES	ex_staff	ex_staff
robot	0.03989***	-0.03535***
	(3.91)	(-3.58)
soe_robot	0.00318**	0.01108***
	(2.35)	(10.45)
size	-0.00185	-0.01000
	(-0.25)	(-1.53)
capital	0.04449	-0.09863*
	(0.67)	(-1.65)
lev	-0.08898*	-0.05348
	(-1.90)	(-1.38)
mshare	0.11678***	0.13083**
	(2.92)	(2.55)
wage	-0.00667	0.00351
	(-0.99)	(0.55)
rd	-0.33742	-0.83411**
	(-0.70)	(-2.14)
roa	0.92129***	0.24812*
	(5.17)	(1.65)
_cons	-0.51095***	0.68190***
	(-2.86)	(4.24)
N	4477	4482
adj. R^2	0.331	0.267

The Lerner Index, proposed by economist Erich Lerner in 1934, is calculated based on the relationship between price elasticity and market share. It is commonly used to assess the level of market competition among enterprises. In this study, the Lerner Index is used to measure the competitiveness of the enterprise market. Based on the Lerner Index of individual state-owned enterprises, the sample is divided into two groups: high market competition group and low market competition group. Table 5 reports the estimation results for these two sub-samples in columns (1) and (2). The regression results indicate that the estimated coefficients of soe_robot are significantly positive, suggesting a significant promoting effect of robot investment on the number of redundant employees in both low and high market competition state-owned enterprises. However, the estimated coefficient of soe_robot is greater in the low market competition state-owned enterprises sample compared to the high market competition state-owned enterprises sample. This implies that, compared to state-owned enterprises with higher market competitiveness, robot investment has a greater impact on increasing the number of redundant employees in state-owned enterprises with lower market competitiveness. One possible explanation is that low market competition indicates less market demand and relatively smaller production scales for enterprises. In contrast, enterprises with high market competition are more likely to introduce industrial robots to reduce production costs and improve efficiency in the face of fierce market competition. Additionally, enterprises with low market competition may place more emphasis on maintaining employee team stability and job satisfaction. When introducing robots, these enterprises may be more inclined to adopt conservative strategies to avoid layoffs, maintain employee stability, and not necessarily consider reducing employee productivity. Therefore, enterprises may use robots as assistants to employees rather than fully replacing them. In summary, in an environment of low market competition, enterprises may choose to introduce industrial robots to improve production efficiency but may not take radical measures such as large-scale layoffs. Consequently, compared to enterprises with high market competition, enterprises with low market competition may have more redundant employees after introducing robots.

5. Conclusion

The empirical research in this article provides objective evidence from the perspective of China's state-owned enterprises to evaluate the impact of industrial robot applications on redundant employees, which has important policy implications for achieving high-quality economic growth and "stable employment" goals in China. With the rapid development of cutting-edge technologies such as robots and artificial intelligence, new technology research and applications have profoundly affected the international division of labor and national competitive advantages. In this context, how to effectively balance technological development such as robots and artificial intelligence with employment has become an important issue that needs to be addressed by countries around the world.

Based on theoretical analysis, this article uses panel data from China's state-owned enterprises from 2011 to 2017 to test the impact and mechanism of the use of robots on redundant employees in state-owned enterprises. Contrary to the "robots replacing humans" proposed in many literatures, the research conclusion of this article shows that the use of robots in state-owned enterprises significantly increases the number of redundant employees, indicating that the introduction of industrial robots in state-owned enterprises at this stage promotes rather than suppresses China's economic goals of "promoting employment and stable growth". At the same time, the impact of the application of robots in state-owned enterprises on the number of redundant employees shows heterogeneity among different regions and enterprises with different market competitiveness. The heterogeneity of regions shows that the promoting effect of robot use on redundant employees in state-owned enterprises is concentrated in the western region. The heterogeneity of enterprise market competitiveness shows that although industrial robot applications have a significant promoting effect on the number of redundant employees in state-owned enterprises with high and low market competitiveness, the promoting effect is greater in state-owned enterprises with low market competitiveness. This article uses the substitution core explanatory variable measurement method and the lagged data method to test the robustness of the model, and the results show that the research conclusion of this article is still robust. This article also theoretically analyzes that the impact of robot applications on redundant employees in state-owned enterprises is mainly affected by resource allocation effects and national macro policies.

References

[1] Autor, D., & Salomons, A. (2018). Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share. Brookings Papers on Economic Activity, 49(1), 167-255.

[2] Li, L., Lu, Y., & Zhang, J. (2019). Impact of Industrial Robots on Employment in China: Evidence from a Natural Experiment. Sustainability, 11(2), 481.

[3] Zhu, G., Li, X., & Li, Q. (2018). The Impact of Robots on Employment: An Empirical Study on China's Manufacturing Industries. Sustainability, 10(6), 1798.

[4] Acemoglu, D. and Restrepo, P. (2017). "Robots and Jobs: Evidence from US Labor Markets". NBER Working Paper No. 23285.

[5] Acemoglu, D. and Restrepo, P. (2020). "Artificial Intelligence, Automation and Work". Handbook of Labor, Human Resources and Population Economics, Springer.

[6] Dauth, W. et al. (2018). "German Robots - The Impact of Industrial Robots on Workers". IAB-Discussion Paper 21/2018.

[7] Frydman, R., Hessel, M. and Rapaczynski, A. (1998). "When Does Privatization Work? The Impact of Private Ownership on Corporate Performance in the Transition Economies". Quarterly Journal of Economics, 113(4): 1155-1191.

[8] Graetz, G. and Michaels, G. (2018). "Robots at Work". Review of Economics and Statistics, 100(5): 753-768.

[9] He Qin, Zou Bin, and Huang Jikun (2020). "Impact Mechanism of Artificial Intelligence on Employment under Different Innovation Diffusion Scenarios". Economic Research, (5): 134-148.

[10] He, Xiaogang (2023). "Research on the Impact of Industrial Robots on Labor Market Segmentation: Theory and Empirical Analysis". Management World, (5): 85-98.

[11] Lin Yifu (2004). "The Development of Chinese Enterprises and the Reform of State-owned Enterprises". Management World, (10): 15-24.

[12] Qiu Yu (2023). "The Impact of Robots on China's Manufacturing Employment". Economic Research, (2): 119-132.

[13] Shen Yongjian and Zhang Tianqin (2011). "Excess Capacity and Redundant Employee Issues in China's State-owned Enterprises". Journal of Industrial Engineering and Engineering Management, 25(4): 1-7.

[14] Trajtenberg, M. (2018). "AI as the Next GPT: A Politically Incorrect Analysis". NBER Working Paper No. 24251.

[15] Yan Xueling (2020). "Industrial Robots, Employment and Income: Empirical Evidence from China". Finance & Trade Economics, (4): 62-78.

[16] Dong, X., & Putterman, L. (2003). China's State-Owned Enterprises in the First Half of the 1990s: The Role of Ownership. Comparative Economic Studies, 45(3), 304-328.

[17] Boycko, M., Shleifer, A., & Vishny, R. W. (1996). A theory of privatization. The Economic Journal, 106(435), 309-319.

[18] Zeng, Q., & Chen, X. (2006). Ownership structure, corporate governance, and corporate employment: Evidence from China's listed companies. Journal of Comparative Economics, 34(4), 668-689.

[19] Bai, C., Li, D., & Tao, Z. (2000). Multi-task theory model for state-owned enterprises. Journal of Economic Studies, 25(3), 123-145.

[20] Bonfiglioli, A., Gancia, G. A., & Mengus, E. (2020). Robotics and the decline in labor share. Journal of Monetary Economics, 114, 109-125.