Research on the Impact of Artificial Intelligence and Other Technologies on Urban Labor Market

Yanfang Zhang

Department of Basic Education, BUA, Beijing, China

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Abstract: With the development of artificial intelligence and other technologies, people have begun to pay attention to and study the impact of technological progress on the labor market. This paper analyzes the two opposite effects of technological progress on the employment market, and summarizes the relevant research results of foreign and domestic literature. Based on the annual data of different provinces of 2009-2017, this paper uses the methods of cluster analysis and regression analysis to explore China's computer information technology, economic development and labor market, and study the impact of artificial intelligence development level and regional development level on urban labor force employment and wages. Data calculation and statistical analysis are completed with Excel and SPSS18.0. The results show that the division of China's artificial intelligence development level and its impact on the labor market are geographically related.

1. Introduction

Human fears of "technical unemployment" [1-2] have begun since the Second Industrial Revolution. In recent years, the impact of artificial intelligence has become a topic in employment research, and it is also an important consideration for many Chinese candidates for College Entrance Examination to choose their majors. But the history of industrialization shows that the main impact of technological progress is the structural restructuring of the labor market. In the long run, technological progress will have two opposite effects on the employment market: The first is the destruction effect. Technology replaces labor and causes unemployment; the second is the capitalism effect. Technology promotes the increase of productivity, thereby promoting the expansion of the industry and higher demand for labor (Frey and Osborne, 2017). Technological changes did lead to short-term unemployment in a small range, but did not cause large-scale long-term unemployment [1] [3]. With the development of information technology and artificial intelligence in modern society, new technological progresses will not only replace manual labor and mechanical work in the labor market, but also a lot of cognitive work [4], and there will even be robots beyond human learning abilities.

2. Literature Review

Autor et al. (2003) proposed the ALM (Artificial Intelligence and Labor) model. They believed that automation would put low-skilled workers out of work but benefit high-skilled workers [4-7]. Goos and Manning (2007) have studied the nature of labor market polarization brought about by technological progress. They believed that technological progress increased high-income cognitive jobs and low-income manual labor occupations, but hollowed out middle-income jobs [8]. Economists analyzed and demonstrated the impact of technological progress on the labor market and the employment population with the data of various countries. Brynjolfsson and McAfee (2011) believed that the development of more advanced software technologies made the labor market redundant. Michaels, Natraj and Van (2014) studied 17 developed countries, and believed that from 1993 to 2007, the working hours of high-skilled workers were increased, but intermediate-skilled workers were sacrificed [8-9]. Cortest et al. found that over the past 35 years, technological progress

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in the United States has mainly replaced middle-income jobs, especially routine operations, and those at greater risk of being replaced are mainly those with low incomes and low education levels [10, 11].

According to the data of Wuzhen Institute, global artificial intelligence enterprises are concentrated in a few countries such as the United States, Britain, and China. The number of enterprises of the top three: the San Francisco Bay Area, New York, and Beijing, China account for 16.9%, 4.8%, and 4.0% of the world respectively. This highlights the rapid growth of China's artificial intelligence industry [10]. For the research on the impact of artificial intelligence development on the labor market in China, most are literature review papers, few are quantitative analysis papers [5, 8, 10, 12]. Wenkai SUN [10] used the formula decomposition method to divide the age, education level and gender of the population, and studied the change of employment structure of routine work and non-routine work in China. Yuanyuan MENG [5], Rongjie LV [8] and Mengge XU [12] all used the linear regression method and combined with the regional economic development to study the impact of the development of artificial intelligence and other information technology on the labor market. The selection of variables in this paper refers to Rongjie LV method. Hierarchical cluster analysis and linear regression analysis are used for data analysis.

3. Empirical Analysis

The data are from the provincial annual data in the China Statistical Yearbook (2009-2017). The average data of 31 provinces and cities across the country were taken as samples. Based on statistical data on the number of urban residents employed, urban per capita disposable income, regional GDP and total fixed-asset investment in information service transfer computer services and software, the cluster analysis method was used to classify the provinces and explore China's computer information technology and economic development and labor market; The data from 31 provinces and cities across the country and the average values of the three major economic zones (east, central and western) over the years were taken as samples, and a linear regression model was established to study the impact of artificial intelligence development level and regional development level on labor force employment and wages. Data calculation and statistical analysis are completed with Excel and Spss18.0.

Cluster analysis was performed based on the average of the number of urban residents employed, urban per capita disposable income, regional GDP and total fixed-asset investment in information service transfer computer services and software of 2013~2017. Hierarchical Cluster analysis method was used. The distance calculation formula uses the Squared Euclidean distance.

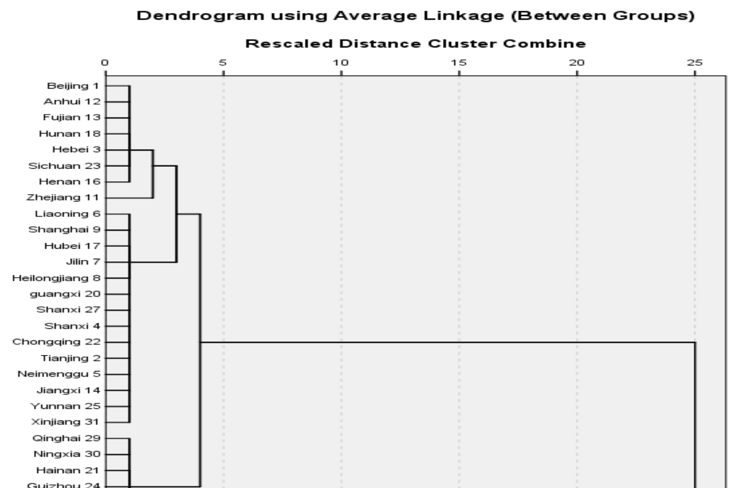

Figure 1 Cluster analysis tree diagram

It can be seen from the tree diagram (Figure 1) that when the distance is greater than 10, it is divided into two categories, among which Jiangsu, Guangdong and Shandong are one category, and the remaining provinces and cities are one category. When the distance is greater than 5 and less than 10, it is divided into three categories. Shandong is one category, Jiangsu and Guangdong are one category, and the rest are one category. When the distance is greater than 3 and less than 5, it is divided into four categories. Qinghai, Ningxia, Hainan, Guizhou, Gansu and Tibet are a new category. Except for Hainan, a special province, the rest are all western regions, the economic development of which is similar. The classification results fully show that China's labor market (employment, per capita disposable income) has a strong regional character, which is inseparable from the regional development level and the development of information technology such as artificial intelligence of the local area.

In order to further study the impact of China's artificial intelligence development level and regional development level on the labor market, the following linear regression models are established by taking the average value of statistical data over the years as the research object:

Model 1: $employment = a + a_1 AI + a_2 GDP + \varepsilon_1$

Model 2: $salary = b + b_1 AI + b_2 GDP + \varepsilon_2$

Among them, employment represents the number of people in employment (the number of urban residents in employment), salary represents the salary level (urban per capita disposable income), AI represents the artificial intelligence development level (total fixed-asset investment in information service transfer computer services and software), GDP represents regional development level (GDP). The model of labor force employment is based on the data of 2009-2017; Because the survey scope, methods and indicator calibers of data of 2013 and after by the National Bureau of Statistics are different, the model of the impact on wages is based on the data of 2013-2017.

3.1 National Sample Analysis

Table 1 lists a linear regression model of the artificial intelligence development level and employment and wages with the data of 31 provinces and cities across the country as samples.

Table 1 Linear regression model of the data of provinces and cities across the country

Sample of 31 provinces and cities across the country		Model 1: Labor force employment (ten thousand people) ($employment$)	Model 2: Urban per capita disposable income (RMB) ($salary$)
Variable	Constant term	70.454**	25748.715***
	Artificial intelligence development level	0.228* (Beta: 0.054)	7.300 (Beta: 0.108)
	Regional development level	0.021*** (Beta: 0.919)	.021 (Beta: 0.310)
Multiple correlation coefficient R		0.966	0.408
Square of adjusted multiple correlation coefficient R2		0.929	0.107
F value in the analysis of variance table		198.243***	2.793*

Note: *** means significant at P <0.01 level, ** means significant at P <0.05 level, * means significant at P <0.1 level.

It can be seen from the results of F test (Model 1 in Table 1) that the linear relationship between the artificial intelligence development level, regional development level and employment is very significant (P<0.01), the multiple correlation coefficient is 0.966 and the square of the multiple correlation coefficient is 0.929. It indicates that the regression equation explained 92.9% of the degree of variation of the entire dependent variable. It can be seen from the Beta value that regional development level has the greatest impact on employment, followed by artificial intelligence development level. It indicates that the regional development level plays a major role in local labor force employment so far, and its role is greater than the artificial intelligence development level in a single industry. It can be seen from Model 1 that the labor force employment is positively correlated with the artificial intelligence development level and regional development level, indicating that the development of artificial intelligence technology is conducive to the employment of urban labor force in China as a whole. At the same time, the higher the regional development level, the better the region's labor force employment.

In Model 2, the development of artificial intelligence is positively correlated with wage income, indicating that the development of artificial intelligence technology has promoted the improvement of people's living standards. However, the results of F test (Model 2 in Table 1) show that the linear relationship between the artificial intelligence development level, regional development level and wages is only significant at the level of $P<0.1$. It can be seen from the square of multiple correlation coefficient 0.107 that the regression equation can explain the degree of variation of the dependent variable urban per capita disposable income is only 10.7%. In addition to the constant terms, the t test of the model coefficients is also not significant. The regression effect of model 2 (wage level model) is not as good as that of model 1 (regional development level model).

3.2 The Eastern, Central and Western Economic Belts are taken as Samples for Analysis

According to the division method of China's three major economic belts used on the website of the National Bureau of Statistics, the classification of provinces and cities in China are shown in Table 2.

Table 2 Division of China's three major economic belts

Eastern region	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan
Central region	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan
Western region	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shanxi, Gansu, Qinghai, Ningxia and Xinjiang

Due to the small sample size, the regression effect of Model 2 is not ideal, the linear relationship between the independent variable (the artificial intelligence development level and the regional development level) and the dependent variable (wage level) is not significant, and the test fails. FTherefore, for the analysis of the data of the three major economic belts, only Model 1 is listed (Table 3).

Table 3 Linear regression model of data of China's three major economic belts

		Eastern region samples - Model 1: Employment (ten thousand people) ($employment$)	Central region samples - Model 1: Employment (ten thousand people) ($employment$)	Western region samples - Model 1: Labor force employment (ten thousand people) ($employment$)
Variable	Constant term	60.057	147.804	35.233
	Artificial intelligence development level	0.736 (Beta: 0.181)	-1.131 (Beta: -0.197)	-0.066 (Beta: 0.017)
	Regional development level	0.018*** (Beta: 0.804)	0.028*** (Beta: 0.978)	0.026*** (Beta: 0.968)
R		0.963	0.948	0.953
Adjusted R2		0.910	0.859	0.887
F value in the analysis of variance table		51.333 ***	22.280***	44.215***

Note: *** means significant at P<0.01 level, ** means significant at P<0.05 level, * means significant at P<0.1 level.

It can be seen from the results of F test (Table 3) that the linear relationship between the artificial intelligence development level, regional development level and employment in the eastern, central and western major economic belts is very significant ($P<0.01$), which is suitable for establishing a linear regression model. The multiple correlation coefficients in the eastern, central and western regression models are 0.963, 0.948 and 0.953, and the squares of the adjusted multiple correlation coefficients are 0.910, 0.859 and 0.887. It indicates that the regression equation explained over 85% of the degree of variation of the entire dependent variable. It can be seen from the Beta value that regional development level has the greatest impact on employment in the three regions, followed by artificial intelligence development level. It indicates that the regional development level plays a major role in local labor force employment so far, and its role is greater than artificial intelligence and other individual industries. It can be seen from the model coefficients that the labor force employment in the three regions is positively correlated with the regional development level. The higher the regional development level, the better the labor force employment in the region. But only the labor force employment in the eastern region is positively correlated with the artificial intelligence development level, and they are negatively correlated in the central and western regions. It indicates that the development of artificial intelligence technology is beneficial to the employment of China's urban labor force in the eastern region, but replaces the labor force in the central and western regions. The development level of artificial intelligence technology has aggravated the work polarization in China's labor market to a certain extent.

4. Conclusion and Suggestion

The research results show that the level of labor market employment is closely related to regional development. On a national scale, the development of artificial intelligence has promoted the benign development of the labor market and increased the employment rate and per capita disposable income of urban residents. However, it has been shown that in the relatively underdeveloped central and western regions, artificial intelligence can replace low-tech labor force. When productivity increases, the capital effect of the development of artificial intelligence appears, promoting the expansion of the industry and increasing employment. It has been reflected in the eastern part of China.

It is suggested to optimize social resources by enhancing regional cooperation and exchanges. Establish a sound market competition and exit mechanism in the promotion of artificial intelligence and other technologies in the central and western regions. Make enterprise transformation and individual post transfer smooth. The government shall provide support and preferential policies for enterprises in terms of loans and taxes. Give full play to the advantages of colleges and universities, and vigorously develop training and employment through modern science and technology such as the Internet. At the same time, develop the original characteristic industries in the central and western regions, establish talent introduction policies, promote the regional economic development, and form a virtuous circle.

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