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Research on the Impact of Intelligent Manufacturing on Employment in Heilongjiang Province Based on DEA-Malmquist Index

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ABSTRACT
Intelligent manufacturing is promoting the transformation and upgrading of the manufacturing industry in Heilongjiang Province, and has an important impact on the employment of manufacturing labor.This paper use DEA-Malmquist index to calculate the total factor productivity of manufacturing industry, and use it to represent intelligent level of manufacturing industry.Taking the total factor productivity, output and wages of Heilongjiang manufacturing industry as explanatory variables, and the number of employees in Heilongjiang manufacturing industry as explained variables, on this basis, a fixed effect model is constructed for empirical analysis.The results show that in the short term, intelligent manufacturing has a significant inhibitory effect on the employment of manufacturing labor in Heilongjiang Province.
Keywords: *Intelligent, manufacturing, employment*

1. INTRODUCTION

In the 21st century, with the advancement of artificial intelligence, big data, and other technologies, the world has ushered in a new round of technological and industrial revolutions. With the support of new technologies, manufacturing industry has entered the stage of intelligent manufacturing. Heilongjiang Province is an old industrial base in China, and the development of intelligent manufacturing can promote its economic revitalization. In recent years, with the rise of labor costs, the advancement of intelligent manufacturing in Heilongjiang Province has accelerated. More and more manufacturing companies use intelligent robots to realize digital workshops and automated factories, and production efficiency has been greatly improved. However, labor intensity has dropped significantly, and some workers have lost their jobs. Employment is the biggest livelihood of the people, is related to social stability. How to solve the problem of machine substitution is very important. Therefore, this paper aims to analyze the impact of intelligent manufacturing on the employment of manufacturing labor in Heilongjiang Province, and puts forward several feasible suggestions based on the conclusion.

2. LITERATURE REVIEW

J. Zhou. et al. [1] proposed that intelligent manufacturing is the product of the deep integration of manufacturing industry and information technology. Its birth and evolution are accompanied by the development of information technology. After going through the digital manufacturing and digital networked manufacturing stages, intelligent manufacturing has now entered the digital networked intelligent manufacturing stage. From the concept and development of intelligent manufacturing, it can be seen that intelligent manufacturing essentially reflects technological progress. The impact of intelligent manufacturing on the employment of manufacturing labor can be understood as the impact of technological progress on the employment of manufacturing labor. The relationship between technological progress and employment is complex. The impact of technological progress on employment includes substitution effects and compensation effects. Which of the two effects is greater? Many scholars draw conclusions through empirical analysis.

Some scholars believe that technological progress will inhibit employment. M.C. Han et al. [2] studied the relationship between industrial robot density and employment over the years based on the data of 286 cities in China from 2013 to 2017. It is concluded that the application of industrial robots has a significant negative impact on the total employment in China's manufacturing industry. Some scholars remain optimistic. J. Luo et al. [3] used the panel data of China's manufacturing industry from 2003 to 2011 to empirically analyze that technological progress has a significant role in promoting the employment of high skilled labor. However, unlike the previous two viewpoints, some scholars believe that the impact of technological progress on employment cannot be viewed simply. X. Cai. et al. [4] used the manufacturing data of 28 provinces in China from 2003 to 2016 to construct a panel threshold regression model. It is concluded that when the productivity growth rate of artificial intelligence technology is less than 0.0282, a 1% increase in the use of artificial intelligence technology will reduce the proportion of manufacturing employment by 0.124%.

Conversely, when the productivity growth rate of artificial intelligence technology exceeds the threshold, a 1% increase in the use of artificial intelligence technology will increase the proportion of manufacturing employment by 0.179%. David [5] pointed out that on the one hand, labor positions are reduced due to the application of robots, and on the other hand, new jobs appear due to the application of robots.The net effect of technological progress on employment is not clear. Erikson [6] pointed out that the impact of technological progress on employment is different in the short-term and long-term. The reality in many countries shows that in the short term, the unemployment rate will increase with technological progress, but in the long term technological progress will not have a destructive effect on employment.

3. VARIABLES AND DATASOURCES

The time span of the data used in the empirical analysis of this paper is 2006-2016. During this period, China's "National Economic Industry Classification" was revised for the third time in 2011, and the manufacturing industry classification has undergone partial changes.Therefore, this paper first excludes 7 industries that cannot obtain complete and continuous data. They are rubber and plastic products industry, metal products industry, automobile manufacturing industry, railway, ship, aerospace and other transportation equipment manufacturing industry, waste resource comprehensive utilization industry, metal products, machinery and equipment repair industry, and other manufacturing industries.Then exclude the chemical fiber manufacturing industry with outliers in the data.Finally, this paper conducts research on the basis of the remaining 23 manufacturing sub-sectors.

3.1. Explained Variable

The impact of intelligent manufacturing on the employment of manufacturing labor in Heilongjiang Province studied in this paper refers to the quantitative impact.Therefore, we select the number of year-end employees in Heilongjiang manufacturing industry as the explained variable.The specific data comes from the 2007-2017 "China Labor Statistics Yearbook".

3.2. Explanatory Variables

3.2.1. Manufacturing output $- Y_{it}$

Employment is closely related to economic development. Therefore, this paper selects manufacturing output as one of the explanatory variables that affect the employment of manufacturing labor. The calculation process of manufacturing output is as follows. Based on 2005, use the ex-factory price index of industrial products to deflate the manufacturing output value (2006-2016) in Heilongjiang Province. The relevant data are from the 2007-2017 "Statistical Yearbook of Heilongjiang Province".

3.2.2. Manufacturing wage $- W_{it}$.

Wage is an important factor affecting labor employment. Therefore, this paper selects the manufacturing wage as one of the explanatory variables that affect the employment of manufacturing labor.The manufacturing wage calculation process is as follows. Taking 2005 as the base period and using the general consumer price index to deflate the average annual labor remuneration (2006-2016) of manufacturing industries in Heilongjiang Province.The relevant data comes from the 2007-2017 "China Labor Statistics Yearbook".

3.2.3. Manufacturing total factor productivity$-TFP_{it}$.

Total factor productivity is often used in theoretical circles to describe technological progress.Intelligent manufacturing essentially reflects technological progress.Therefore, this paper selects total factor productivity to represent the intelligent level of manufacturing in Heilongjiang Province, and uses it as one of the explanatory variables that affect the employment of manufacturing labor.There are many methods to calculate total factor productivity. This paper uses the DEA-Malmquist index method in data envelopment analysis. The data required for this method includes manufacturing output, labor input, and capital input in 23 sub-sectors of manufacturing in Heilongjiang Province from 2005 to 2016. The capital input calculation adopts Goldsmith's perpetual inventory method:

$$\mathrm{K_t} = \mathrm{K_{t-1}}(1-\partial) + \mathrm{I_t}/\mathrm{P_t} \tag{1}$$

$\mathrm{K_t}$ $r$epresents the capital stock in year t,$\mathrm{K_{t-1}}$ represents the capital stock in year t-1, ∂ represents the fixed asset depreciation rate, $\mathrm{I_t}$ represents fixed asset investment, and $\mathrm{P_t}$ represents the fixed asset investment price index. The depreciation rate is based on the research of Jun Zhang (2004), using 9.6% as the depreciation rate.The investment in fixed assets adopts the investment in fixed assets by industry (excluding rural households) in the "Statistical Yearbook of Heilongjiang Province". The base period capital stock adopts the net value of fixed assets of 23 sub-sectors in Heilongjiang Province in 2005. After the output, labor input and capital input are determined, the specific calculation steps of the Malmquist index are as follows. Each sub-sectors of the manufacturing industry is used as a decision-making unit,x represents the input variable, y represents the output variable, D is the distance function, t=1, 2...T period.The Malmquist index based on the technical conditions in the t period and the Malmquist index based on the technical conditions in the t + 1 period are:

$$M^t = D^t(x^{t+1}, y^{t+1})/D^t\,(x^t, y^t) \tag{2}$$

$$M^{t+1} = D^{t+1}(x^{t+1}, y^{t+1})/D^{t+1}\,(x^t, y^t) \tag{3}$$

The Malmquist index, which reflects the change in productivity from period t to period t+1, is the geometric mean ofM^tandM^{t+1}:

$$M = \left[\frac{D^t(x^{t+1},y^{t+1})}{D^t(x^t,y^t)} \times \frac{D^{t+1}(x^{t+1},y^{t+1})}{D^{t+1}(x^t,y^t)}\right]^{1/2} \quad (4)$$

DEAP2.1 is used for calculation. Due to space limitations, the following Table 1 only lists the average Malmquist Index of the 23 sub-sectors of the manufacturing industry in Heilongjiang Province from 2006 to 2016. M>1 indicates that the total factor productivity of the decision-making unit is in the increasing stage from t to t+1, M=1 indicates that the total factor productivity of the decision-making unit is in the constant stage from t to t+1, and M<1 indicates thatthe total factor productivity of the decision-making unit is in the decline stagefrom t to t+1.So far, the data of the explained variable and explanatory variables have been obtained. The following Table 2 is the descriptive statistics of the panel data.

Table 1 The average malmquist index of 23 sub-sectors of manufacturing in Heilongjiang province (2006-2016)

sub-sectors of manufacturing	Malmquistindex
Agricultural and sideline food processing industry	1.051
Food manufacturing	1.031
Wine, beverage and refined tea manufacturing	1.057
Tobacco products industry	1.011
Textile industry	0.987
Textile and Apparel Industry	0.915
Leather, fur, feather and its products and footwear industry	1.145
Wood processing and wood, bamboo, rattan, palm, grass products industry	1.165
Furniture manufacturing	1.015
Paper and Paper Products Industry	1.042
Printing and recording media reproduction industry	0.988
Culture, Education, Arts and Crafts, Sports and Entertainment Products Manufacturing	1.041
Petroleum processing, coking and nuclear fuel processing industries	1.031
Chemical raw materials and chemical products manufacturing	1.102
Pharmaceutical manufacturing	1.035
Non-metallic mineral products industry	1.135
Ferrous metal smelting and rolling processing industry	0.995
Non-ferrous metal smelting and rolling processing industry	1.026
General equipment manufacturing	0.874
Special equipment manufacturing	0.946
Electrical machinery and equipment manufacturing	0.991
Computer, communications and other electronic equipment manufacturing	0.955
Instrumentation Manufacturing	0.910

Table 2 Descriptive statistics of panel data

variables	Number of observations	Mean	standard deviation	minimum value	Maximumvalue
LnL	253	9.732	1.089	5.938	11.856
TFP	253	1.057	0.326	0.389	3.414
LnY	253	13.741	1.390	9.926	16.632
LnW	253	9.942	0.504	8.540	11.226

4. EMPIRICAL ANALYSIS

4.1. Model Setting and Related Testing

First construct the following model and then gradually test it:

$$\ln L_{it} = \beta_0 + \beta_1 \ln TFP_{it} + \beta_2 lnY_{it} + \beta_3 lnW_{it} + \varepsilon_{it} \quad (5)$$

Before estimating the panel data, it is necessary to carry out a unit root test for each variable involved to ensure that the data is stable and does not appear to be spurious regression. The data used for empirical analysis in this paper is the short panel data where the individual N is greater than the time dimension T. Such data is suitable for tests based on fixed T and n→ ∞. So this paper chooses IPS test .The specific unit root test results are shown in Table 3.The IPS test results of each variable showed that the P value was less than 0.05, and there was no unit root at the 5% significance level. The four variables are stationary. Next, select PLS, FE, and RE models. First perform the F test and choose between PLS model and FE model. Before F test, need to determine whether there is cross-sectional correlation. Fri test result: Pr=1.0000. According to the Pr value, accepting the null hypothesis, there is no cross-section related problem. Next, assuming heteroscedasticity and autocorrelation use the industry standard error of clustering to deal with autocorrelation and heteroscedasticity problems. Next the F test is performed on the industry dummy variables, and the result shows that the P value is 0. The result rejects the null hypothesis, there is individual effect, the Fe model should be chosen. Finally, the Hausman test is performed and result is shown in Table 4. The P value of Hausman test is 0, which rejects the null hypothesis, and the fixed-effect model should be selected.

4.2. Results and Analysis

The Table 5 is the estimated results of fixed effects. In the short term, intelligent manufacturing will inhibit the employment of manufacturing labor in Heilongjiang Province. The results reflect the actual situation in Heilongjiang to a certain extent. During the period from 2006 to 2016, technological advancement enabled many manufacturing companies in Heilongjiang Province to introduce intelligent equipment and production lines, eliminated a large number of low-skilled workers, streamlined organizations and reduced a large number of redundant employees. In addition, the development of artificial intelligence in the manufacturing industry in Heilongjiang Province is still in its infancy, and its role in driving emerging industries is obviously lagging behind. Therefore, in the short term, the substitution effect of intelligent manufacturing on the employment of manufacturing labor in Heilongjiang is greater than the compensation effect of intelligent manufacturing on the employment of manufacturing labor in Heilongjiang. The final performance is negative.

There is an inverse relationship between real wages and employment. In recent years, labor prices in Heilongjiang Province have risen, reducing the absorption of labor in the process of industrial development. Due to the increase in labor costs, companies have introduced intelligent production equipment, reduced the number of employees, and technology has replaced labor. Due to the increase inlabor costs, some companies have moved to areas where labor prices are relatively low, which has reduced labor demand to a certain extent.

Table 3 Unit root test results

variables	IPS
LnL	-6.3461***（0.0000）
LnTFP	-7.4703***（0.0000）
LnY	-2.0494**（0.0202）
LnW	-5.4816***（0.0000）

Note: The result is calculated by stata14 software, the P value in brackets,**, *** represent the significance level of 5% and 1% respectively

Table 4 Hausman test

Hausman	
Chi2(4)	29.67
P	0.0000

Note: The result is calculated by stata14 software

Table 5 Estimated results of fixed effects model

Explanatory variables	Std. Err	coefficient	t value	Pvalue
LnTFP	0.0710	-0.4113***	-5.79	0.000
LnY	0.0668	0.3225***	4.82	0.000
LnW	0.0955	-0.9261***	-9.70	0.000
-cons	0.5354	14.5149***	27.11	0.000

Note: The result is calculated by stata14 software, *** represents the significance level of 1%

Manufacturing output has a significant role in promoting the employment of manufacturing labor in Heilongjiang Province. The economic growth of Heilongjiang's manufacturing industry is still the main driving force for the employment of manufacturing labor. From the perspective of technological progress, intelligent manufacturing has improved production efficiency, reduced corporate costs, increased output value, and created more profits, thereby increasing some jobs and reducing unemployment.The development of artificial intelligence has also driven some emerging industries and new demands, increasing output value and increasing employment.

5. CONCLUSION AND SUGGESTION

Through analysis, we can draw the following conclusions. In the short term, the destructive effect of intelligent manufacturing on the employment of manufacturing labor in Heilongjiang is greater than the compensation effect of intelligent manufacturing on the employment of manufacturing labor in Heilongjiang. In the long run, the impact of intelligent manufacturing on the employment of manufacturing labor in Heilongjiang is uncertain. This paper has the following shortcomings: First, the sample time span is short and has not been updated to the latest year, and a few manufacturing industries are not included in the analysis. Second, there are certain limitations in using total factor productivity to represent the level of manufacturing intelligence.

Based on analysis, the following suggestions are made: First, increase policy support to promote the development of intelligent manufacturing. Improve fiscal security policies and set up special funds for intelligent manufacturing development. Strengthen financial support policies and appropriately increase loan lines for intelligent manufacturing enterprises. Second, actively encourage the development of new business formats to create more employment opportunities. Actively develop industries that support intelligent manufacturing, and form multiple service formats such as intelligent manufacturing R&D, design, testing, and maintenance. Provide more jobs and effectively solve the employment problem. Third, improve the quality of workers, strengthen their vocational training, and enhance their employability. Do a good job in the training of higher education and vocational education talents, focusing on training talents in data analysis, data collection, and intelligent manufacturing. Provide targeted vocational training for assembly line workers, administrative clerks, and other low- and medium-skilled labor groups that are most easily replaced by AI. Fourth, improve the employment guarantee mechanism and build an efficient reemployment service system. Efforts will be made to expand the coverage of unemployment insurance, continuously improve the unemployment insurance and minimum living standards, and give full play to the "safety net" role of social security.

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REFERENCES

[1] J. Zhou, P.G. Li, Y.H. Zhou, B.C. Wang, J.Y. Zang, L. Meng. Toward New-Generation Intelligent Manufacturing. Engineering. 4.1(2018):28-47.

[2] M.C. Han, Q.J. Han, L. Xia. The impact of industrial robot application on manufacturing employment: an empirical study based on the data of prefecture level cities in China. Reform. 03(2020):22-39.

[3] J. Luo, J.G. Chen. Trade in intermediate goods, technical progress and manufacturing employment. Asia Pacific Economy. 06 (2014): 49-58. DOI: 10.16407/j.cnki.1000-6052.2014.06.004.

[4] X. Cai, X.M. Huang. Will the artificial intelligence restrain employment in manufacturing, theoretical deduction and empirical test. Business research. 06 (2019): 53-62. DOI: 10.13902/j.cnki.syyj.2019.06.007.

[5] David H. Autor. Why are there still so many jobs, the history and future of workplace automation. Journal of Economic Perspectives. 29(3) (2015) 28. DOI: 10.1257/jep.29.3.3.

[6] Clas Eriksson. Is There a trade-off between employment and growth. Oxford Economic Papers, 49.1(1997) 77-88.