Technological Innovation Effect on Employment of Tertiary Sector in China: an ARDL Bounds Testing Approach

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Abstract
The world is currently witnessing great technological progress, known as the fourth industrial revolution. Although the industrial processes decrease employment in the primary and secondary sectors, it is unclear how technological improvement affects employment in the tertiary sector. This study aims to investigate the impact of technological change on employment numbers in the tertiary industry in China using an ARDL model. Using yearly data from 1991 to 2020, our results show that technological change in the form of the Contractual Value Deal in Domestic Technical Markets and Foreign Direct Investment has a long- and short-run impact on employment in the tertiary industry in China. Also, technological changes show a negative and positive effect on the number of employments in the tertiary industry in the short- and long-run, respectively. This finding implies that technological progress has a substitutive effect on employment in the short-run while creation effect in the long-run. A complete discussion of different specific industries lies beyond the scope of this study.

Keywords: *ARDL model, creation effect, substitutive effect, technological innovation, tertiary industry*

1.INTRODUCTION

The past decade has seen the rapid development of technology in many aspects, mainly based on automation and Information and Communication Technology (ICT), which has led to a substantial social impact on employment structure in the industrialized world. In 2017, the Chinese government issued new national plans for AI development, proposing the strategic goal that China will become one of the world's major artificial intelligence innovation centres by 2030. In the past ten years, the number of global artificial intelligence patent applications was 521,264. The number of patent applications in China was 389,571, ranking first in the world, accounting for 74.7% of the global total, 8.2 times that of the second-ranked U.S. patent applications. In recent years, introducing agricultural robots, 3D printing machines and self-driving cars has raised the fear of an upcoming massive technological unemployment again. Moreover, not only agricultural and manufacturing employment appears at risk, but also employees in services, including those jobs requiring cognitive skills, are no longer protected.

The tertiary industry is the services sector of an economy, encompassing medical providers, educators, financial services, science and technology, haircuts, and personal trainers, among many others. The number of employed persons in the tertiary industry keeps an augmenting trend within the 20 years. The total number of employed persons in the tertiary sector was about 202 million in 2001. After ten years of augmenting, the number reaches the same amount of employed persons with primary industry at about 270 million in 2011. Then the number of employed persons in the tertiary industry continued to boost, achieving a peak of 358 million in 2020.

Developing the tertiary sector plays a vital role in generating more employment opportunities and promoting the overall growth of the entire economy. Designing a future growth strategy aimed at expanding the tertiary sector has become an urgent concern of the Chinese government, especially under the downward trend of employment in the primary and secondary

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sectors. Recently investigators have examined the effects of technological innovation on employment. Frey & Osborne (2017) analyzed the data for 702 detailed occupations and concluded that about 47% of the US employment is at the risk of automation [8]. Yet, David (2015) claim that automation complements labour, increasing the demand for labour [5].

Previous studies have explored the relationships among the financial opening, wages, and employment creation at the tertiary level. Financial deepening shows a positive relationship with employment creation of the tertiary industry (Jing, 2015) [12]. Chi (2012) demonstrated that the exchange rate fluctuations might not consequently result in slower employment growth in the tertiary industry [4]. There are abundant theoretical and empirical studies on minimum wage and labour market. Neumark & Wascher (2006) found that about 85% of empirical findings conclude that an increase in the minimum wage reduces employment [14]. According to Flinn (2006), although an increase in the minimum wage may not raise the unemployment rate, it improves the welfare of labour market participants on both the supply and demand sides [7].

However, few scholars have systematic research into the link between technological change and employment in China's tertiary industry. These researches show that the industrial revolution caused a decline in employment in the primary and secondary sectors, but they have ignored investigating the tertiary sector's behaviour [11, 13]. This paper aims to explore the relationship between technological innovation and employment in the tertiary industry in China both in the short- and long-run. This project analyzes the expansion of the tertiary sector using qualitative and quantitative methods. The second section examines the theoretical framework of the labour market. The third section investigates the recent evolution of the relationship between innovation and employment using the ARDL bounds test approach.

2.REVIEWS OF LITERATURE

Some scholars believe that technological innovation will reduce the demand for human labour in the production sector, which in turn will increase the unemployment rate [6]. Susskind (2017) built a task-based model, believing that the use of highly intelligent machines will reduce the relative wage and income share of labour, reduce the task set of work, and ultimately lead to technological unemployment [18]. Based on the U.S. Department of Labor's Occupational Classification Database, Frey and Osborne (2017) constructed a Gaussian process classification model to classify 702 detailed occupations in the United States according to their sensitivity to automation [8]. Based on a study of the anticipated impact of machine learning and mobile robotics on existing works in the U.S. labour market, the results show that approximately 47% of occupations in the U.S. are at risk of being automated in the next 10 to 20 years.

Many scholars also support the view that technological progress has a creative effect on employment [3, 10]. Bloom (2018) estimate that due to the development of artificial intelligence, 734 million new jobs will be created in the world from 2010 to 2030 [2]. Acemoglu and Restrepo (2018) believe that from the perspective of the history of science and technology, while replacing some jobs, technological progress will create new jobs in the long-term, and the compensation effect produced by the new positions can offset the substitution effect [1]. Gregory (2016) studied the data of 27 European countries from 1999 to 2010 [9]. He found that the conventional substitution technological change made capital replace labour in production, reducing about 9.6 million jobs. In comparison, the spillover effect of product demand brought by technological progress increased nearly 21 million jobs. On the whole, technological progress has a positive impact on the employment of the European labour force.

3.RESEARCH METHODOLOGY

3.1. Theoretical Frameworks

Using the labour demand equation to specify the effect of technology on aggregate employment in the tertiary sector. Under certain conditions, the labour demand equation can be derived from the Cobb-Douglas production function. Suppose that the production function of Chinese enterprises is the basic Cobb-Douglas production function:

$$Y = AK^{\alpha}L^{\beta} \tag{1}$$

Total output Y is a function of capital input (K), labour input (L) and total factor productivity (A), where the share of capital is α, the share of labour is β, and total factor productivity A represents the technical level. It is assumed that the profit function of the manufacturer is:

$$\pi = pY - rK - wL \tag{2}$$

πrepresents the profit of the firm. P, r and w represent the price of the product, the wage of labour and the cost of capital, respectively. Take the partial derivative of L on both functions, and according to the profit maximization conditions, we get:

$$\frac{\partial Y}{\partial L} = \beta AK^{\alpha}L^{1-\beta} = \frac{\omega}{p} \tag{3}$$

Take the log form of both sides:

$$lnL = \frac{1}{1-\beta}\left(ln\beta + lnA + lnK - ln\frac{w}{p}\right) \tag{4}$$

Therefore, labour demand can be expressed as a function of capital stock (K), real wage (W) and total factor productivity (A):

$$lnL = \beta_0 + \beta_1 lnK + \beta_2 lnA - \beta_3 lnW + \mu \tag{5}$$

$$A = Bef^{(FDI, CVD)} \tag{6}$$

The total factor productivity is influenced by research and development and technology processes (including foreign direct investment and technology purchase). Expenditure on research and development activities (R&D), Contractual Value Deal in Domestic Technical Markets (CVD), Foreign Direct Investment (FDI), imports of capital goods, technology purchase, patent citations, the index of industrial robots are some of the most commonly used indicators of technological change. Remarkably, all these indicators catch different dimensions of technology. In this study, we use the Contractual Value Deal in Domestic Technical Markets (CVD) and Foreign Direct Investment (FDI) as technological progress to express total factor productivity.

There are two hypotheses in this article. Firstly, in the short term, technological advances lead to a high degree of automation, replacing routine workers of tertiary industry. Secondly, technological progress will create more jobs and increase workers employed in the tertiary sector in the long run.

3.2. Econometric Model

This research employs the ARDL model (Pesaran et al.,2001), which is appropriate for a limited sample size. In addition, the ARDL method has the following advantages compared with the traditional cointegration test model: it accurately estimates models ignorance of the variables stationary levels; also, it guarantees the consistent validity of the estimated results, even if the explanatory variables have endogeneity problems [15]. The analysis method of the ARDL model is generally divided into the following three steps. In the first step, unit root test is needed for the uniformity of each time series variable. Although the ARDL model is applicable to the case of time series with different orders, the order of uniformity of each variable is required to be no more than one. The second step is to test whether there is a long-term stable cointegration relationship among the variables and determine the direction of the interaction between the variables. In order to test the cointegration relationship, the following particular type of ARDL boundary cointegration test model -unrestricted error-correction model (UECM) can be built [16].

$$\begin{aligned} \Delta lnL_t = \beta_0 + \sum_{i=1}^{p} \beta_i \Delta lnL_{t-i} + \\ \sum_{j=0}^{q} \gamma_i \Delta lnCVD_{t-j} + \sum_{k=0}^{r} \delta_k \Delta lnFDI_{t-k} + \\ \theta_0 lnl_{t-1} + \theta_1 lnCVD_{t-1} + \\ \theta_2 lnFDI_{t-1} + e_t \end{aligned} \tag{7}$$

3.3. Data Description

The study uses yearly time series data from 1991 to 2020, providing 30 data points. As mentioned above, the dependent variable is the number of employments in the tertiary industry in China, obtained from the National Bureau of Statistics. The independent variables are FDI and CVD, obtained from the National Bureau of Statistics database and Year Book China. The contracts dealt in domestic technical markets include technology development, technology transfer, technology consultation, and technology service. To standardize the data, we took log form for all the variables. The descriptive statistics of variables are shown in Table 1.

Table 1. Descriptive statistics of variables

Variables	Obs	Mean	Std.Dev.	Minimum	Maximum
lnL	30	4.363	0.131	4.093	4.554
lnCVD	30	3.242	0.709	1.977	4.451
lnFDI	30	2.790	0.341	1.640	3.159

Notes: The results were calculated using the EViews 12.

The correlation coefficients of the number of employments in the tertiary industry with FDI and CVD are 93% and 99%, respectively. While the correlation coefficient of FDI and CVD is 89%, implying a positive (direct) correlation between the three variables. Even though the correlation between FDI and CVD is high, no collinearity exists because the VIF is less than 10 in both of them.

$$\begin{aligned} \Delta ln(L)_t = \beta_0 + \beta_1 \Delta ln(L)_{t-1} + \\ \beta_2 \Delta ln(L)_{t-2} + \gamma_0 \Delta ln(CVD)_t + \\ \gamma_1 \Delta ln(CVD)_{t-1} + \gamma_2 \Delta ln(CVD) \\ \gamma_3 \Delta ln(CVD)_{t-3} + \delta_0 \Delta ln(FDI)_t \\ \theta_0 ln(L)_{t-1} + \theta_1 ln(CVD)_{t-1} + \\ \theta_2 ln(FDI)_{t-1} + e_t \end{aligned} \tag{8}$$

The ranges of summation in the various terms of the UECM are from 1 to p, 0 to q, 0 to r, respectively. Thus, we should select the appropriate values for the maximum lags – p, q, and r. Estimating the regression shows that the optimum lag structure for the model is ARDL (2,3,0), as shown in function (8).

3.4. Unit Root Test

ARDL cointegration technique is preferable when the variables have different integration degrees, stationarity at level, stationarity at the first difference, or a combination of them. For this reason, we perform various unit root tests, including (Augment Dicky - Fuller) (ADF) and (Philip - Perron) (PP), to check if 2nd difference series exists. After we conducted Unit Root tests for the study variables, we adopted ADF and PP to ensure their standard deviation stability. According to Tables 2, all the variables are either I(0) or I(1).

Table 2. Results of the unit root test

Intercept				
Variables	ADF test	ADF test	PP test	PP test
	I(0)	I(1)	I(0)	I(1)
lnL	-3.745***	-2.204	-2.845*	-1.631
lnCVD	-0.738	-4.810***	-0.736	-6.472***
lnFDI	-6.602***	-4.505***	-4.835***	-12.517***
Trend and Intercept				
Variables	ADF test	ADF test	PP test	PP test
	I(0)	I(1)	I(0)	I(1)
lnL	-5.092***	-2.663	-3.227*	-2.660
lnCVD	-3.341*	-4.607***	-4.380***	-7.585***
lnFDI	-9.774***	-3.992*	-8.447***	-9.501***

Source: Asymptotic critical values are obtained from Pesaran et al. (2001): Table CI(iii) Case III: Unrestricted intercept and no trend.***, ** and * respectively denote significance levels of 1%; 5% and 10%.

Table 3. Results of the cointegration test

F-Bounds test		Null hypothesis: No level relationship		
Test Statistic	Value	Signif	I(0)	I(1)
F-statistic	7.052	10%	2.63	3.35
k	2	5%	3.1	3.87
		2.5%	3.55	4.38
		1%	4.13	5

3.5. Cointegration Test

ARDL cointegration technique (Pesaran et al.,2001) needs a single long-run relationship among the basic variables in a small sample size. A significant F-statistics (F-bound test) shows the long-run relationship of the underlying variables. Regarding Table 3, the F-statistics is 7.05, higher than the critical upper limits l(1), implying a cointegration relationship among the model variables.

4.EMPIRICAL RESULTS

4.1. Long-Run and Short-Run Result

Based on Table 4, CVD has a significant and positive relationship in the long-run with employment. According to the estimated coefficients and statistics, a one percent increase in the total volume of technical contract transactions causes a 0.185% increase in employment, significant at 1% level. The estimations show an inverse relationship of FDI and employment in the long-run at 10% statistical significance level.

Table 4. ARDL long-run estimates

Variables	Coefficient	Std.Error
lnCVD	0.185***	0.009
lnFDI	-0.048*	0.027

***, ** and * respectively denote significance levels of 1%; 5% and 10%.

However, regarding Table 5, the relationship between CVD and employment is negative and statistically significant at 1% level in the short-run. The estimated coefficient implies that a one percent increase in CVD causes a 0.139% decrease in employment in the tertiary industry in China in the short-run. The speed of adjustment CointEq(-1)* is -0.715, which is expectedly a negative value and statistically significant at 1% level.

Table 5. Results of ARDL (2, 3, 0) ECM model selected on AIC

Variables	Coefficient	Std.Error
D(LNL(-1))	0.161	0.106
D(LN CVD)	-0.098***	0.022
D(LN CVD(-1))	-0.143	0.051
D(LN CVD(-2))	-0.139***	0.044
Co intEq(-1) *	-0.715***	0.125

Notes: R-squared (0.856); R-bar-squared (0.830); SE of regression (0.0038);residual sum of squares (0.310E-3); DW-statistic (2.127); AIC (-8.165); Schwarz Criterion (-7.925). ***, ** and * respectively denote significance levels of 1%; 5% and 10%.

4.2. Diagnostic Tests

Based on Table 6 the results of diagnostic tests in show the validity and efficiency of the estimations. The estimated statistics of the LM serial correlation test is insignificant, accepting the null hypothesis of no serial correlation. Thus, this model has no serial correlation, and its errors are serially independent. Based on the normality test results, the Jarque-Bera statistics is statistically insignificant, accepting the null hypothesis of normal distribution. Therefore, the residual series are normally distributed. The heteroskedasticity test F-statistics is 1.765 and statistically insignificant, accepting the null hypothesis of homoscedasticity. Thus, there is no heteroskedasticity in this model.

Table 6. Results of residual diagnostic tests

A. Serial correlation	$\chi^2(2)=2.713(0.258)$	F(2,17)=0.949(0.407)
B. Normality	JB=1.001(0.606)	-
C. Heteroskedasticity	$\chi^2(7)=10.638(0.155)$	F(7,19)=1.765(0.154)

Note: A: Lagrange multiplier test of residual serial correlation.

B: Based on Jarque-Bera test of skewness and kurtosis of the residuals.

C: Based on the regression of the squared residuals on the squared fitted values.

The value in brackets is the corresponding p-value, respectively.

From Figure 1 and 2, the cumulative sum (CUSUM) and the cumulative sum of square (CUSUMSQ) test results confirm the long-run model's stability. The CUSUM and CUSUMSQ range within the boundaries, implying a "dynamically stable" model.

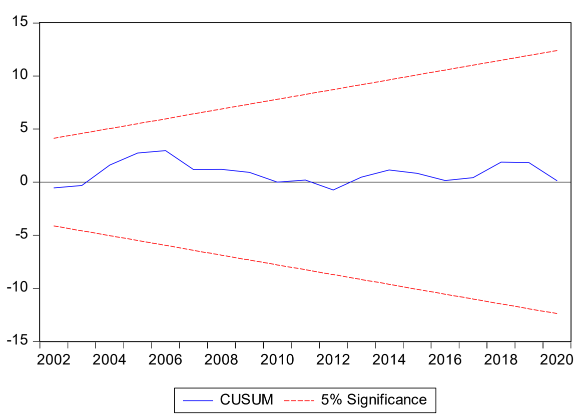

Figure 1: CUSUM test of recursive residuals

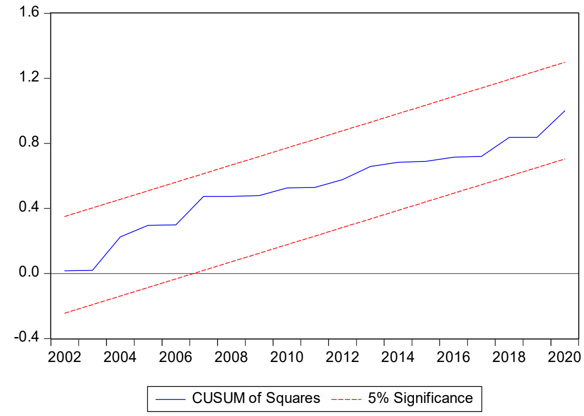

Figure 2: CUSUMSQ Test of recursive residuals

5.CONCLUSIONS

In the short term, an increase of one percent of the total volume of technical contract transactions will lead to a decrease by 0.1385% in the value of employment in the tertiary industry in China. Contractual Value Deal in Domestic Technical Markets is significant in the long term, and it is in a positive relationship with the amount of labour of Tertiary Industry in China. One percent increase in the total volume of technical contract transactions will lead to an increase of 0.185% of employment. As for the FDI variable, it is also related to an inverse relationship with the variable (employment) in the long term with a significant level (10%). The effect of FDI is not significant in the short term.

Emphasizing education and skill training, guiding the development of a highly-skilled labour force, encouraging the development of new industries, creating more employment opportunities, improving the social security system, and unemployment support policies are effective measures to balance technological innovation and employment in the labour force.

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