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The Effects of Artificial Intelligence on the Labour Market: The Case of China

Yapay Zekanın İşgücü Piyasası Üzerindeki Etkileri: Çin Örneği

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Abstract

The aim of this study is to reveal the effects of artificial intelligence on China's labour market in the period 1991-2021. The ARDL approach is used to practically analyse the effects of artificial intelligence on China's labour market in the 1991-2021 period. In the model, Chinese data on variables such as unemployment, human capital, number of patents, R&D expenditures and labour force are used. The findings of the study show that the only significant determinant of unemployment in China is labour force. The result of this analysis, in which the effect of artificial intelligence on unemployment cannot be determined, once again confirms the fact that the Chinese government has implemented policies that keep unemployment more stable and policies towards the labour market in the 1991-2021 period.

Keywords: *Artificial Intelligence, Chinese Labor Market, ARDL Method.*

JEL Classification: *C01, J01, O10.*

Öz

Bu çalışmanın amacı, yapay zekânın 1991-2021 döneminde Çin'in emek piyasası üzerindeki etkilerini ortaya koymaktır. 1991-2021 döneminde yapay zekânın Çin'in emek piyasası üzerindeki etkilerini pratik olarak analiz etmek için ARDL yaklaşımı kullanılmıştır. Modelde işsizlik, beşeri sermaye, patent sayısı, Ar-Ge harcamaları ve işgücü gibi değişkenlere ait Çin verileri kullanılmıştır. Çalışmanın bulguları, Çin'de işsizliğin tek anlamlı belirleyicisinin işgücü olduğunu göstermektedir. Yapay zekânın işsizlik üzerindeki etkisinin belirlenemediği bu analiz sonucu, Çin hükümetinin 1991-2021 döneminde işsizliği daha istikrarlı tutmaya yönelik politikalar ve emek piyasasına yönelik politikalar uyguladığı gerçeğini bir kez daha teyit etmektedir.

Anahtar Kelimeler: *Yapay Zeka, Çin Emek Piyasası, ARDL Yöntemi.*

JEL Sınıflandırması: *C01, J01, O10.*

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1. Introduction

The relationship between artificial intelligence and labour force has been one of the most discussed economic issues for a long time. The results of research on the subject emphasise that this relationship is likely to have many different positive and negative consequences. On the one hand, while many professions and jobs are expected to disappear in a short time, on the other hand, new technologies such as automation and artificial intelligence change the structure of some professions and jobs and create a new occupational structure. Due to the gradual development of artificial intelligence, job losses are taking place and industrial work is about to disappear (Rifkin, 1995).

The rapid development in computer technologies has made it possible for many jobs and tasks performed by labour force to be performed by artificial intelligence (Brynjolfsson & McAfee, 2012; Alec Ross, 2016; Alexandre, 2017; Yang, 2018). Robots and artificial intelligence take over the tasks performed by employees such as secretarial, journalism, office staff and computer programming (Ford, 2015). It does not seem possible to prevent or slow down this technological development. These new developments that reduce wage costs can cause some problems in society. The most important of these are developments such as unemployment and wage inequality, which reduce the peace and welfare of society (Kaplan, 2015). This situation necessitates the invalidation of many human-specific skills and the emergence of new approaches for the existence of labour in economic life.

Thought currents that emphasise the positive effects of artificial intelligence rather than its negative effects on labour continue to develop (Autor, 2015; Baldwin, 2019). Developments that increase collaborative productivity and reduce workloads that reveal the harmony between human labour and artificial intelligence help to solve problems easily in many sectors. The measures and adaptation policies to be taken against the introduction of artificial intelligence into human life point to a transformation in many economic, social and cultural areas (Schwab, 2016). Despite all this change and transformation, artificial intelligence remains limited in its current form in the face of the superiority, richness and complexity of human intelligence (Ganascia, 2017). According to a report prepared by the World Economic Forum, the business world is heading towards a revolution, for better or worse, and it is predicted that by 2027, a quarter of today's jobs will have changed.

The aim of this study is to analyse how AI transforms China's labour market in the period 1991-2021. Accordingly, the study seeks an answer to the question 'How does artificial intelligence transform the labour market in China in 1991-2021?'. The main hypothesis of the study is 'Artificial intelligence affects the labour market in China in the period 1991-2021', while the alternative hypothesis is 'Artificial intelligence has no effect on the labour market in China in the period 1991-2021'. This study uses the ARDL approach to analyze the effects of artificial intelligence on China's labour market in the 1991-2021 period. In this context, Chinese data on variables such as unemployment, human capital, AI adaptation, labour force and national income are used. It is a new study on China in terms of the methodology and data period used. The inclusion of the aforementioned variables in the model with the ARDL approach makes an original contribution to the literature.

2. Literature Review

While some researchers insist that jobs will soon and inevitably disappear, others emphasise the radical change that new technologies such as automation and artificial intelligence will bring about in the nature of work. According to Rifkin (1995), an important figure of the first school of thought, job losses will occur due to the gradual development of artificial intelligence. Moreover, the computer age is such a revolution that industrial work as we know it today is on the verge of extinction.

One view, which bases the relationship between labour and AI on the struggle that may exist between the 'creative' human and the 'creature' machine, describes it as an unequal struggle due to the rapid evolution of machines performing tasks that are beyond the reach of ordinary mortals. Brynjolfsson and McAfee (2012) predicted that current human skills may become obsolete within a few decades. Thus, people will have to reinvent themselves in their approach to everyday life and the economy.

Brynjolfsson and McAfee (2014) emphasise that automation better meets wage requirements. They present Moore's Law, which implies that computers become more efficient, smaller, more practical, faster and cheaper over time as transistors in integrated circuits become more efficient. They will therefore be able to perform tasks originally reserved for humans. As technology accelerates and machines begin to take care of themselves, humans will be needed less and less. AI is already making ‘good jobs’ obsolete: many legal assistants, journalists, office workers and even computer programmers are about to be replaced by robots and AI (Ford, 2015).

Advances in robotics, machine learning and sensing have led to the development of artificial intelligence systems that rival and in some areas surpass human capabilities. Therefore, it does not seem possible to stop the development of new technologies. Automation driven by AI could significantly disrupt the labour market and displace workers in many sectors. While this will lead to higher unemployment and wage inequality, the effects of AI on employment will not be evenly distributed. Blue and white collar jobs involving repetitive tasks are more likely to be automated than those requiring creativity, empathy and adaptability. Moreover, socio-economic unrest will arise as layoffs become widespread (Kaplan, 2015). Similarly, Yang (2018) shows that technological advances and automation deprive people of their jobs, which inevitably leads to social inequality, political polarisation and a sense of worthlessness. Assuming that automation mainly benefits the rich, the huge income gap between rich and poor continues to widen. Economic and financial inequalities lead to political conflicts and even civil war. Emphasising that the gradual disappearance of routine and intermediate tasks will lead to the erosion of the middle class and increased social and economic inequalities, Frey and Osborne (2017) analysed the automation risk of 702 jobs in the United States and found that 47% of jobs in the United States are threatened by automation, especially in low-skilled sectors.

Ross (2016) shows how new technologies such as artificial intelligence and robotics will radically change some jobs and eliminate others. He also emphasises that, given advances in cloud computing and algorithms, new innovations in robotics are moving in the direction of full automation and that acceptance of new technologies will vary by culture, country and even level of economic development. For example, while people in countries such as the USA fear the consequences of artificial intelligence, people in countries such as Japan are more accepting of the use of robots. Ross (2016) also predicts that access to new innovations will be easier for rich countries than poor countries and that these countries will need to prepare to close the gap. This is because competition is no longer expected to be between man and man, but between man and machine (Alexandre, 2017).

The second school of thought opposes many of the theses of those who predict a radical change in the nature of work due to the gradual development of artificial intelligence. Schloss characterised this as a colossal mistake in 1892. He shows that the development of new technologies has a positive impact on job creation and encourages workers, especially in the creative and problem-solving sectors, to co-operate with AI tools. In short, co-operation between man and machine can significantly increase productivity and lighten the workload (Autor, 2015). Schwab states that the ongoing fourth industrial revolution is leading to changes in economic, social, cultural and industrial fields (Schwab, 2016). In contrast, artificial intelligence is limited in its current form and cannot reproduce the complexity and richness of human intelligence (Ganascia, 2017). Similarly, Baldwin (2019) argues that globalisation and robotics are not inevitably bad for workers. Rather, these forces should be seen as opportunities to create new jobs and improve living standards.

According to a report by the World Economic Forum, we are heading towards a revolution in the world of work, for better or worse. By 2027, a quarter of today's jobs will have changed.

3. Method, Model and Data

This section presents the variables used in the econometric model, the data relating to the variables and the model, and their graphical evolution. The impact of artificial intelligence on the Chinese labour market is estimated using the ARDL model.

3.1. Data Sources

This study is based on variables collected at the level of the International World Bank, UNESCO and OECD, covers a period of 31 years from 1991 to 2021. This period was chosen because of limited access to the data.

Table 1. Variables and Data Sources

Variables	Codes	Data proxy	Data sources
		Dependent variables	
Unemployment	Unempl	Unemployment, total (% of total labor force) (modeled ILO estimate)	The World Bank
		Independent variables	
AI adaptation	Ai_adopt	Technologies related to AI (patents, units)	OEDC
Gross Domestic Expenditure on R&D	Gerd	Gross Domestic Expenditure on R&D (US dollars, PPP converted, Millions, Constant prices, 2015)	OEDC
Human capital	Humcap	educational attainment (%)	UNESCO
Labor force	Labfor	Labor force, total	The World Bank

3.2. Model and Estimation Method

If two non-stationary time series, yt and xt, are integrated and stationary of the same order and the error term is stationary, then yt and xt are cointegrated (Enders, 1995: 219). If yt and xt series are cointegrated, OLS estimation of this equation can provide a consistent estimate for the parameters in the equation (Thomas, 1997: 428). When the residuals of the equation formed by yt and xt are calculated, the stationarity of the residuals implies a long-run relationship between these cointegrated series. In an economic model, the long-run relationship between variables can be revealed in more than one way. These are Engle Granger (1987) approach, Johansen approach and ARDL approach. Engle and Granger (1987) approach can be preferred due to some shortcomings as well as its ease of application. In addition, the Engle and Granger (1987) approach is primarily based on the fact that when economic theory does not specify the explained and explanatory variables with complete certainty, failure to choose the explained variable correctly affects the reliability of the estimation results (Hafer and Jansen, 1991; Kennedy, 1992). Secondly, the estimation method is considered in two steps. In the first step, it is accepted that the variables are cointegrated and residuals are obtained based on this acceptance. In the second step, the stationarity of the residuals is tested. However, accepting that the series are cointegrated without a prior test leads to an incomplete approach. In addition to all these, in the Engle and Granger (1987) approach, the number of long-run relationships between variables is unknown (Hafer and Jansen, 1991: 158). For this reason, an important problem arises when there are more than two variables in the model. Because, while the cointegration vector is considered unique in equations with two variables, it is not necessarily unique when there is more than one variable in the model (Miller, 1991:141).

The ARDL model is a much simplified version of the Engel Granger test and the Johansen test for analysing the possible presence of a cointegrating relationship between several variables that describe the behaviour or analysis of some economic or financial phenomenon. The ARDL model, as its name suggests, has two components. The first is the autoregressive component. And the second is the distributed lag component.

The ARDL (p,q) model can be written as :

$$Y_t = \beta_0 + \{ \beta_1 Y_{t-1} + \beta_2 Y_{t-2} \ldots\ldots + \beta_P Y_{t-p} \} + \{ \alpha_0 X_t + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} \ldots\ldots + \alpha_q X_{t-q} \} + \varepsilon_t \quad (1)$$

Autoregressive: Y_t is explained by its lagged values (p).

Distributed lag: Y_t is explained by the lags of the explanatory variable X_t (q).

The contribution of the ARDL model to the empirical literature is that it can be used to test for the presence of a cointegrating relationship between variables using a test known as the "Bounds Test", which was introduced by Pesaran et al (2001). The originality of this test compared with the Engel Granger test and the Johansen test is that it can be used in the case of a mixture of variables that are both I (0), i.e. stationary, and I (1), i.e. non-stationary, containing a unit root in their structure. This is a huge advantage in the empirical literature, because we are used to using unit root tests as an initial step before testing Co-integration. And in general, we have difficulty proving the presence of a unit root because either the structure of the time series is complex, or there is a lack of power and robustness in the tests we usually use (Dickey-Fuller augmented test, Phillips Perron test, etc.). So, by the way, to get around this constraint, we'll say that whatever the degree of integration of your variables, whether it's I (0) or I (1), there's no problem. We will nevertheless, using the ARDL model, try to test for the possible presence of a Co-integration relationship between these variables. The second advantage is that the ARDL model will consist of a single equation, so it will be easy to use and interpret. And finally, the variables in the ARDL model can have different lags.

In our study, we opted for the ARDL model to analyse the impact of artificial intelligence on the Chinese labour market. The use of the logarithmic approach is essential for this study, as it allows us to stabilise our variables while simplifying the mathematical expression. The estimated model is as follows:

$$\Delta \text{Inunempl}_t = a' + \sum_{k=1}^{n} b'_k\, \Delta ln\text{unempl}_{t-k} + \sum_{k=0}^{n} c'_k\, \Delta ln\text{Ai\_adopt}_{t-k} + \sum_{k=0}^{n} d'_k\, \Delta ln\text{Gerd}_{t-k} + \sum_{k=0}^{n} e'_k\, \Delta ln\text{Humcap}_{t-k} + \sum_{k=0}^{n} f'_k\, \Delta lnlabfor + \propto_1 lnunempl_{t-1} + \propto_2 lnAi\_adopt_{t-1} + \propto_3 lnGerd_{t-1} + \propto_4 lnHumcap_{t-1} + \propto_5 lnLabfor_{t-1} + \omega_t \quad (2)$$

Equation (2) represents the ARDL model for long-run coefficient estimates. Short-run dynamics are also added to the model and the short-run effect is estimated. As emphasised by Pesaran et al. (2001), while the coefficients of the first difference variables in equation (2) provide information about the short-run, long-run coefficient estimates are obtained by normalising ∝2, ∝3, ∝4, ∝5 and ∝6 to ∝1 (Bahmani-Oskooee and Fariditavana, 2015). 'Δ' denotes the first order differences of the variables. Since the bounds test is highly sensitive to the lag length of the F test, the lag lengths expressed by k in equation (2) should be determined (Bahmani-Oskooee and Goswami, 2003). Information criteria such as Akaike (AIC) and Schwarz (SIC), which are widely used in the literature, are utilised (Yılancı and Özcan: 2010). After determining the lag length, the F statistic is used to test the cointegration relationship. The F statistic has a non-standard distribution and its critical value varies depending on whether the variables are stationary at level and first difference, the number of variables, the presence or absence of a constant term and trend, and the sample size. These critical values are tabulated by Pesaran et al. (2001). In the application of small samples, the critical values of Narayan (2005) provide guidance. Hypotheses for cointegration test:

$$H_0 = \propto_1 = \propto_2 = \propto_3 = \propto_4 = 0 \quad (3)$$

$H_1 \neq 0$ and there is at least one α co-integrated vector.

If the calculated F statistic is outside these two limits, which are tabulated critical values, information can be given about whether the variables are cointegrated or not. If the calculated F statistic is greater than the upper bound of the critical values, the null hypothesis stating that there is no cointegration relationship between the variables is rejected. If this value is smaller than the lower bound of the critical values, the null hypothesis indicating that there is no cointegration relationship cannot be rejected. If the calculated F statistic is between the two critical boundary values, it is not possible to provide an explanation for the presence or absence of cointegration between the variables (Yılancı and Özcan: 2010). The short-term information of the variables can be obtained with the Error Correction Model as follows.

The short-term information of the variables can be obtained with the Error Correction Model as follows.

$$\Delta ln\text{Unempl}_t = a' + \sum_{k=1}^{n} b'_k\ \Delta ln\text{Unempl}_{t\text{-}k} + \sum_{k=0}^{n} c'_k\ \Delta ln\text{Ai\_adopt}_{t\text{-}k} + \sum_{k=0}^{n} d'_k\ \Delta ln\text{Gerd}_{t\text{-}k} + \sum_{k=0}^{n} e'_k\ \Delta ln\text{Humcap}_{t\text{-}k} + \sum_{k=0}^{n} f'_k\ \Delta ln\text{Labfor}_{t\text{-}k} + \beta\ ECM_{t-1} + \varepsilon_t \quad (4)$$

ECM is the error correction term. An error correction coefficient between 0 and -1 indicates that there is a convergence to the equilibrium value in the transition from the short run to the long run. A coefficient between -1 and -2 indicates that the error correction process shows fluctuations around the long-run equilibrium values that are gradually decreasing. An error correction coefficient value that is positive or less than -2 indicates a departure from equilibrium (Alam and Quazi, 2003).

3.3. Stationarity Test of Variables

The stationarity of the variables is a statistical and econometric tool which makes it possible to check the level of integration of the series and the possibility of co integration of the variables used in a model. For this reason, we will opt for unitary root tests which includes a multitude of tests including the Dickey-Fuller Augmented test (ADF), the Phillips Perron (PP), and KPSS tests.

Table 2. ADF Unit Root Test

Variables	ADF			
	At Level		First Difference	
	Intercept	**Intercept+Trend**	**Intercept**	**Intercept+Trend**
Lnunempl	-2.7800 **0.0731** *	-1.3676 **0.8499**	-3.6532 **0.0106** **	-4.5364 **0.0061** ***
Lnaiadopt	1.6176 **0.9992**	-2.5078 **0.3223**	-5.5017 **0.0001** ***	-5.0701 **0.0019** ***
Lngerd	-0.8182 **0.7994**	-1.8339 **0.6600**	-2.6191 **0.1021**	-3.1422 **0.1158**
Lnhumcap	-0.8705 **0.7836**	-4.5268 **0.0075** ***	-5.4372 **0.0001** ***	-5.4646 **0.0006** ***
Lnlabfor	-2.7541 **0.0779** *	-0.7541 **0.9587**	-0.6477 **0.8440**	-2.4290 **0.3579**

Note: *** indicates significance at the 1 percent level

Table 3. PP Unit Root Test

Variables	PP			
	At Level		First Difference	
	Intercept	**Intercept+Trend**	**Intercept**	**Intercept+Trend**
Lnunempl	-3.5481 **0.0134** **	-1.1001 **0.9123**	-3.5962 **0.0122** **	-4.8529 **0.0028** ***
Lnaiadopt	2.4295 **0.9999**	-2.3371 **0.4027**	-6.0348 **0.0000**	-11.0367 **0.0000**

			***	***
Lngerd	-0.6475 **0.8450**	-1.2472 **0.8817**	-3.2762 **0.0255** **	-3.2034 **0.1035**
Lnhumcap	-0.8705 **0.7836**	-1.8755 **0.6420**	-5.4372 **0.0001** ***	-5.4646 **0.0006** ***
Lnlabfor	-4.5179 **0.0012** ***	-1.2395 **0.8835**	-2.5896 **0.1065**	-5.8031 **0.0003** ***

Note: *** indicates significance at the 1 percent level

Table 4. KPSS Unit Root Test

Variables	**KPSS**			
	At Level		**First Difference**	
	Intercept	**Intercept+Trend**	**Intercept**	**Intercept+Trend**
Lnunempl	0.6190 **	0.1879 **	0.5455 **	0.2029 **
Lnaiadopt	0.6978 **	0.1890 **	0.3345	0.2585 ***
Lngerd	0.7191 **	0.1279 *	0.1733	0.1433 *
Lnhumcap	0.7233 **	0.0698	0.1257	0.0816
Lnlabfor	0.6180 **	0.1947 **	0.5614 **	0.1133

Note: *** indicates significance at the 1 percent level

According to the augmented Dickey-fuller test (ADF) and the Phillips perron (PP) test, we note a difference in the results. This difference does not affect the level of significance of critical values.

3.3.1. Co-Integration Relationship

The results of the unit root test indicate that the dependent variable is stationary at order (1). The other independent variables are stationary at orders (0) and (1). In this case, it is possible to test for a possible co-integration relationship between these variables using the ARDL model.

Table 5. F-Bounds and t-Bounds Test Results

F-Bounds Test		**Null Hypothesis: No levels relationship**		
Test Statistic	**Value**	**Signif.**	**I(0)**	**I(1)**
			Asymptotic: n=1000	
F-statistic	10.04231	10%	2.45	3.52
K	4	5%	2.86	4.01
		2.5%	3.25	4.49
		1%	3.74	5.06
Actual Sample Size	29		**Finite Sample: n=35**	
		10%	2.696	3.898
		5%	3.276	4.63
		1%	4.59	6.368
			Finite Sample: n=30	
		10%	2.752	3.994
		5%	3.354	4.774
		1%	4.768	6.67

As shown in the table above, the value of the F-Bounds test is 10.04231. This value is compared with I (0) and I (1) critical limits. For a sample of 1000 observations, the value of 10.04231 exceeds the upper critical limit of 4.01 at the 5% significance level. Therefore, according to the results of the F-Bounds test, the model exhibits symmetric/linear cointegration at 1%, 5% and 10% significance levels.

Considering that the data are annual, the maximum lag length is set as 2. The selected model was found to be ARDL (2,1,0,2,1). After setting the maximum lag length, the effective sample size is 29 observations. In this context, it is preferable to evaluate the results according to the value of 35 as it is closer to 29. For 35 observations, the upper critical value is 4.63 at 5% significance level. As seen in the table, the value of 10.04231 for 35 observations is above this critical threshold. Therefore, according to the results of the F-Bounds test, the model exhibits symmetric cointegration at the 5% significance level. A similar analysis is also valid for a sample of 30 observations and consistent results are obtained.

According to the table, for 30 observations, the F-Bounds value of 10.04231 exceeds the upper critical limit of 4.774 at the 5% significance level. This confirms that the model is symmetrically/linearly cointegrated at the 5% level even with a limited sample size.

3.3.2. ARDL Estimation Results

The positive coefficients of LnGERD, LnHUMCAP and LnLABFOR variables indicate that these variables directly affect the dependent variable LnUNEMPL. In other words, an increase in LnGERD, LnHUMCAP or LnLABFOR variables causes an increase in LUNEMPL, while a decrease in the same variables causes a corresponding decrease in LnUNEMPL.

Table 6. Estimation of Long Run Coefficients

Levels Equation				
Case 3: Unrestricted Constant and No Trend				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LnAIADOPT	-0.017914	0.024206	-0.740048	0.4688
LnGERD	0.031934	0.077497	0.412071	0.6852
LnHUMCAP	0.004891	0.204093	0.023964	0.9811
LnLABFOR	2.995338	0.670522	4.467171	0.0003***
EC = LnUNEMPL - (-0.0179*LnAIADOPT + 0.0319*LnGERD + 0.0049*LnHUMCAP + 2.9953*LnLABFOR)				

Note: *** indicates significance at the 1 percent level

However, the results of the long-term coefficients show that the coefficient of the LnAI_ADOPT variable is negative. This means that changes in LnAI_ADOPT affect LnUNEMPL in the opposite direction: An increase in LnAI_ADOPT decreases LnUNEMPL, while a decrease in LnAI_ADOPT increases LnUNEMPL.

Although an in-depth analysis of the variables LnAI_ADOPT, LnGERD and LnHUMCAP could be predicted, the respective coefficients are not statistically significant. In fact, the probabilities associated with these variables exceed the 0.05 significance level: The probability for LnAI_ADOPT is 0.4688, for LnGERD 0.6852 and for LnHUMCAP 0.9811. These values indicate that their impact on LnUNEMPL is not significant at the selected significance level.

The long-term coefficient of the LnLABFOR variable was estimated as 2.995338. This means that a 1% increase in the LnLABFOR variable will lead to an increase of approximately 0.03% (2.995338) in LnUNEMPL. Since this relationship is linear, the reverse effect is also valid: A 1% decrease in LnLABFOR will decrease LnUNEMPL by about 0.03%. This result is statistically significant at the 5% level as the associated probability (p-value) of LnLABFOR is 0.0003, i.e. less than 0.05.

This econometric analysis of unemployment in China shows that the labour force, although theoretically important, has a marginal effect on the unemployment rate with an effect of only 0.03%. In fact, the results of the study reveal that labour force is the only determining factor in this model. Moreover, human capital, AI adoption and gross domestic R&D expenditure do not show a significant relationship with the unemployment rate, although they are theoretically linked. This observation may indicate that human capital, AI adoption and gross domestic R&D expenditures do not play a decisive role in this particular case or that other unmeasured factors have a more pronounced effect.

Table 7. Estimation of Short Run Coefficients

ECM Regression Case 3: Unrestricted Constant and No Trend				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-46.33343	5.919476	-7.827285	0.0000***
D(LnUNEMPL(-1))	0.415738	0.135069	3.077960	0.0065***
D(LnAIADOPT)	-0.033242	0.010450	-3.180953	0.0052***
D(LnHUMCAP)	-0.332568	0.151935	-2.188882	0.0420**
D(LnHUMCAP(-1))	-0.375934	0.154884	-2.427189	0.0259**
D(LnLABFOR)	-1.723059	0.775930	-2.220636	0.0394**
CointEq(-1)*	-0.771374	0.098466	-7.833880	0.0000***

Note: *** indicates significance at the 1 percent level

When analysing the results of the short-term forecasts, the coefficient of the error correction term, denoted in the table as 'CointEq (-1)', must be negative with a probability of less than 5%. As shown in the table above, this coefficient is equal to -0.771374 with a probability of 0.0000. This observation indicates that the model is cointegrated, that is, its variables are linked in such a way that changes in one systematically follow changes in the other. According to the established criteria, a probability of less than 5% indicates that the coefficient is statistically significant. The negative sign of this coefficient reflects that any imbalance in the model tends to be corrected. It is important to note that although this coefficient is negative, it is less than or equal to 1 in absolute value. It is estimated that about 0.03 per cent of the impact on the unemployment rate will be absorbed in the next period. For the effect on the unemployment rate in China to disappear, the model needs to be corrected for a period of one year and thirty days. These results guarantee the existence of an error correction mechanism and therefore the existence of a long-term relationship or co-integration between the variables.

Table 8: Application of ARDL Diagnostic Tests

Diagnostic Tests		
	F-statistic	**Prob**
Jarque-Bera test for normality Prob>5%	1.097054	0.577800
	Obs*R-squared	**Prob.Chi**
Br-Godfrey LM test for serial correlation Prob>5%	2.433400	0.2962
Breusch-Pagan-Godfrey Prob>5%	9.773929	0.4605
ARCH's test for heteroskedasticity Prob>5%	0.462862	0.4963

Note: *** indicates significance at the 1 percent level

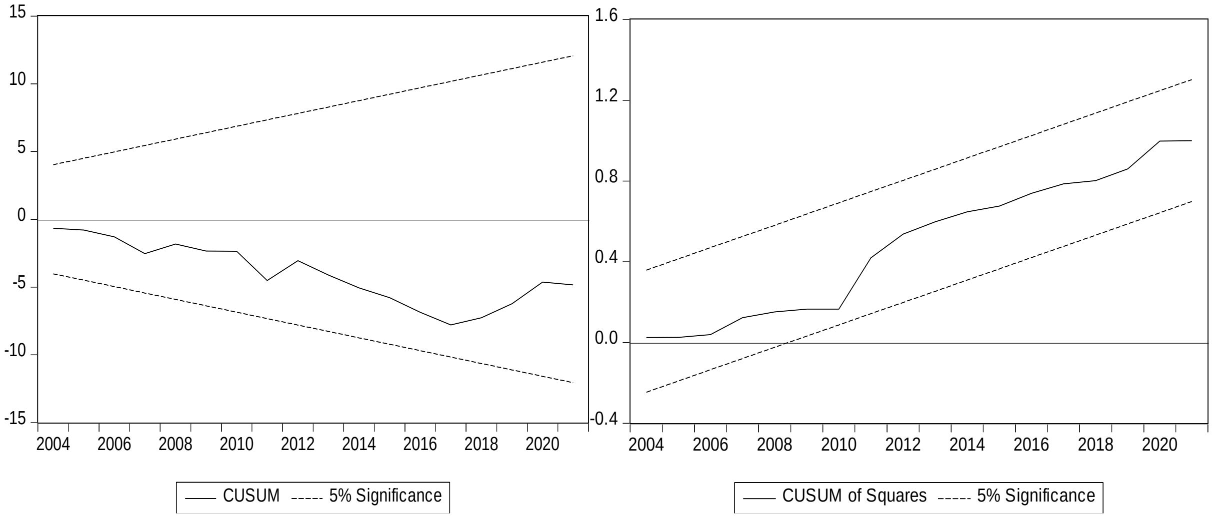
- Jarque-Bera test: The coefficient is 1.097054 with probability 0.577800. Since the probability is greater than 0.05, the model is normally distributed.

- Breusch-Godfrey test for autocorrelation (LM test): The coefficient obtained is 2.433400 with a probability of 0.2962. Since this probability is greater than 0.05, there is no autocorrelation in the model.

- Breusch-Pagan-Godfrey test: The coefficient is 9.773929 and the corresponding probability is 0.4605. Since this probability is greater than 0.05, there is no variance problem in the model.

- ARCH test: The coefficient is 0.462862 and the probability is 0.4963. Since the probability is greater than 0.05, there is no conditional variance problem in the model.

Figure 1: CUSUM and CUSUMQ Graphs



It is recommended to use the CUSUM and CUSUMQ techniques to check the stability of the long and short run parameters of the equation (Brown et al. 1975). These techniques, CUSUM based on the cumulative sum of the iterative residuals and CUSUMQ based on the cumulative sum of the square of the iterative residuals, have been partially applied. In fact, the above results show that the values of the CUSUM and CUSUMQ techniques remain within the critical values at the 5% significance level. This means that the model coefficients are stable.

Conclusion

China's unemployment rate has been stable over the period. This stability in the unemployment rate contrasts with the country's economic transformations, particularly the transition to a market economy, restructuring of state-owned enterprises and urbanisation. From 1991 to 2021, China's unemployment rate will fluctuate between 2.37% and 4.55%. However, the health crisis in 2020 led to an unusual increase in China's unemployment rate, hovering around 5%.

The findings of the study show that labour force is the only factor that has an impact on the unemployment rate in the long run for China. None of the variables such as the adoption of artificial intelligence, human capital or gross domestic product, R&D expenditures have any effect on the unemployment rate in China. Increases or decreases in these variables do not lead to a change in the unemployment rate.

The adoption of AI in China has had no impact on the unemployment rate in the long run. To claim that AI will replace humans is to ignore economic factors as well as the adaptive capacity of AI. Therefore, instead of seeing AI as a threat, it should be seen as a challenge, not an end. The recent policies of the Chinese government prevent the negativities that artificial intelligence may encounter in the labour market. Already a reality, automation and AI will undoubtedly revolutionise the business world and open up new opportunities for the development, management and maintenance of technologies. Adaptation, creativity and continuous learning to keep up with the labour market are the keys to success. Human-machine collaboration will become the norm, revolutionising the nature of jobs and sectors. It is therefore crucial to prepare for this transition in an ethical and inclusive way to ensure successful integration into this new era.

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