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ANALYSIS OF THE IMPACT OF TECHNOLOGICAL FACTORS ON STRUCTURAL UNEMPLOYMENT IN DEVELOPED COUNTRIES

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Introduction. Technology is a significant factor in economic development and social life. Technology has always had an impact on humanity. One of the main levers of technology influence is the labor market. In the modern world, characterized by rapid technological progress, understanding the complex relationship between the level of technology development and the labor market is essential. Technological transformations contribute to changes in the structure of employment, which leads to discussions among scientists about the impact of technology on unemployment. An important question arises: will the number of jobs created as a result of technological development continue to be greater than the number of jobs eliminated as a result of technological progress? Therefore, the investigation of the impact of technological factors on unemployment, namely on structural unemployment, is relevant, as it helps to understand whether countries characterized by a higher level of technological development also have a higher level of structural unemployment. Also, a survey of this problem will be useful in creating state social policy and regulating unemployment.

It is also worth emphasizing the relevance of examining the impact of technology on the labor market in developed countries. The trends that currently dominate the labor markets of developed countries will eventually reach technologically lagging countries. At the same time, new trends in the labor market are formed first in developed countries. Therefore, to obtain more relevant and accurate results on the current impact of technology on the labor market, it is advisable to analyze the labor market of developed countries.

Analysis of recent research and publications. The impact of technology on unemployment and the labor market in general has been studied at various times by economists such as P. Romer [1], D. Autor [4], D. Lederman [15], Y. Tang [8], A. Pardosi [7], and others. International organizations, such as the World Bank, OECD and ILO, also pay considerable attention to the problem under investigation. However, considering the rapid development of technologies in recent decades, it is appropriate to regularly analyze the processes associated with technological transformations to obtain the most relevant results.

Objectives of the article. The purpose of the research is to analyze the impact of a level of technological development of a country on structural unemployment. This research should find out how to distinguish structural unemployment, analyze the impact of technological factors on structural unemployment in developed countries, and, if possible, analyze the relationship between the level of technological development of a country and the duration of unemployment.

The main material of the study. Technologies have a decisive impact on the economy, contributing to economic growth, improving living standards and increasing labor productivity in the economy, which in turn leads to an increase in the resources required to invest in technological development. To ensure technological prosperity, it is necessary to invest in research and development and import technology from abroad [1]. Technological development is also determined by educational, social, and political factors [2].

The impact of technology on the labor market is to increase productivity and reduce the share of physical and low-skilled labor [3]. Throughout history, technological transformations have led to a shift in labor from physical to intellectual labor, from agriculture to industry, and later to services [4].

Technological progress affects the labor market in three main ways: by changing the structure of employment, increasing labor productivity, and creating and simultaneously reducing jobs [5]. Figure 1 shows historical global data on certain indicators related to technology and unemployment. It can be seen that unemployment rose significantly during the recent coronavirus pandemic and has returned to its previous level. It is also noticeable that, unlike the two technology-related indicators, which have a clear upward trend (indicating the acceleration of human technological development), the unemployment rate has shown different trends in different periods. After all, this indicator is primarily determined by economic factors, such as the economic cycle, labor supply, etc.

Unemployment is a social and economic situation in a society in which a part of active working-age citizens cannot find work that they are capable of performing [7]. In economic science, there are different types of unemployment: frictional (short-term dismissal from a job to find another, as well as seasonal work), cyclical (caused by a decline in production), and structural (caused by technological progress, these workers will not be able to find a job without retraining or moving to another area) [8]. Frictional and structural unemployment constitute the natural rate of unemployment [9]. Progress changes the technology of production and, accordingly, the structure of demand for labor. Demand for new professions is growing, while demand for some other types of labor is declining. As a result of technological progress, there is a category of workers whose skills and practical experience are outdated and not needed, and therefore cannot be sold [10]. The main aspect of the research in this article is structural unemployment as a consequence of technological progress.

The hypothesis of the research is that countries with a higher level of technology development have a lower level of structural unemployment. To test this hypothesis, it is necessary to first distinguish structural unemployment from the total unemployment rate.

Empirically, it is difficult to separate structural unemployment from the other two main types of unemployment (cyclical and frictional). Many economists have developed methods to distinguish structural unemployment. In particular, Jackman and Roper and Osberg and Lin measured structural unemployment in the UK and Canada in the late twentieth century [9]. In practice, structural unemployment is often measured by passing total unemployment through smoothing filters. However, the most common way to measure structural unemployment is the non-accelerating inflation rate of unemployment (NAIRU) (although its use is also not without criticism and does not provide a completely accurate estimate, any estimate has some uncertainty) [9; 11].

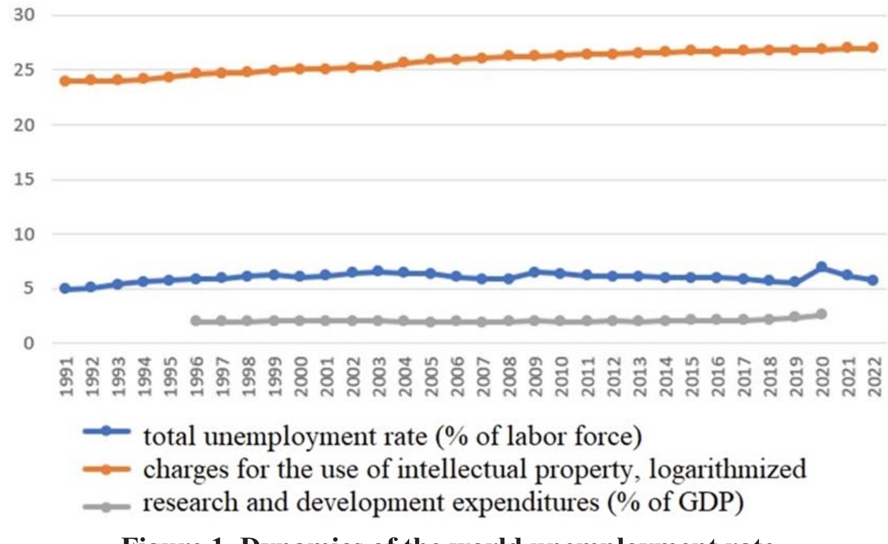

Figure 1. Dynamics of the world unemployment rate and some indicators of technological development

Source: calculated by the authors based on data from [6]

NAIRU is the lowest unemployment rate that can be maintained without causing wage growth and inflation. It is a concept that helps to estimate how much "spare capacity" is available in the economy [11]. There are various ways to determine NAIRU using statistical models and transformations.

International organizations, in particular the OECD, deal with the issue of determining structural unemployment. Scientists working with the OECD have developed the NAIRU estimation methodology and are constantly improving it [12].

Thus, among the methods of estimating structural unemployment, it is advisable to choose NAIRU as the most common and researched method, namely NAIRU according to the OECD methodology, since this organization has the best developed NAIRU estimation methodology. In addition, the OECD member countries considered in this research are technologically advanced countries, so they can track the latest trends in the impact of technology on the level of structural unemployment.

In Figure 2 shows the value of this indicator in some countries. There are no sharp jumps or constant changes in its dynamics, as structural unemployment is characterized by gradual changes, and the factors that affect it usually form trends for decades (birth rates, labor market structure) and do not change as quickly as the economic factors that affect cyclical unemployment. In particular, the pandemic has had no impact on the unemployment rate.

When comparing the NAIRU estimate with the overall unemployment rate, it can be concluded that there is indeed no economic cycle influence and, accordingly, no cyclical unemployment in NAIRU. Therefore, the analysis of the impact of technology on NAIRU should give an adequate result. It is also noticeable that, as a result of smoothing, the natural rate of unemployment may be higher than the real rate for periods.

To find out the level of dependence between the level of technology development and the NAIRU indicator, an analysis was conducted in MS Excel.

Thus, the sample includes 9 OECD member countries (Canada, Japan, Israel, Australia, Norway, Lithuania, Czech Republic, Ireland, and the Republic of Korea). These countries are also developed economies according to the IMF classification. These countries were chosen because NAIRU assessment in them is carried out according to a single methodology and is available for analysis.

Indicators of technological progress were chosen as factors influencing NAIRU (since progress is the main determinant of structural unemployment, and factors influencing frictional unemployment, which is also at least partially present in NAIRU, are difficult to analyze numerically). Among the indicators characterizing the level of technological development, the following were selected.

– Research and development expenditures (% of GDP) – RDE – show how interested a country is in creating innovations. The higher the R&D expenditures, the more innovations will be created in the country.

– Charges for the use of intellectual property – CIP – show the level of involvement of modern technologies in the country.

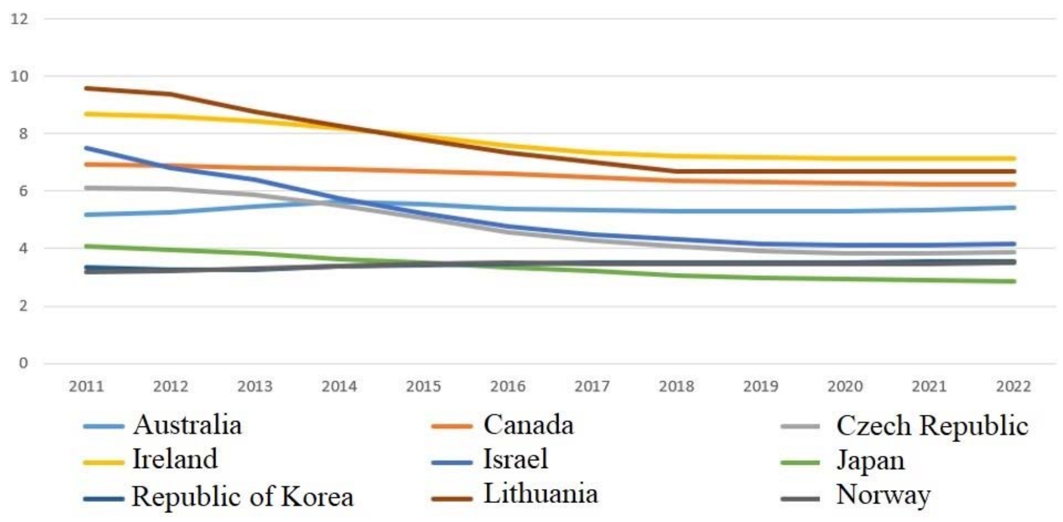

Figure 2. NAIRU indicator dynamics in some countries

Source: calculated by the authors based on data from [13]

– The share of high-tech exports in total exports – HTE – shows how effectively the technologies created in the country are used and how successful they are, since only a truly competitive technological product can enter the international market.

– Global Innovation Index – GII, which is calculated annually by the World Intellectual Property Organization.

The statistics characterizing these indicators were taken from the World Bank database [6] and the World Intellectual Property Organization [14].

In addition, for better coverage of the dynamics by the model, annual data starting from 2011 were included in the analysis and a sample of 99 observations was formed (9 OECD countries, data for 2011–2021).

The study's hypothesis will be proved by the existence of an inverse relationship between the indicators of technological progress and the level of structural unemployment. If a direct relationship is found, the positive impact of technology on unemployment will be refuted, which will require additional research into the causes of this phenomenon.

Since one of the independent variables is an absolute number, it was pro-logarithmized to improve the model (charges for the use of intellectual property CIP).

A brief description of the sample is given in Table 1.

Table 1

Descriptive statistics of the sample

	NAIRU	*HTE*	*GII*	*LN CIP*	*RDE*
Mean	5,306	20,59	52,28	21,92	2,425
Standard Error	0,179	0,603	0,488	0,203	0,126
Median	5,293	19,55	53,3	22,02	1,917
Mode	3,48	25,52	53,1	#N/D	1,829
Standard Deviation	1,783	6	4,854	2,019	1,25
Sample Variance	3,179	36	23,56	4,078	1,56
Kurtosis	-0,929	0,072	1,036	-0,3	-0,48
Skewness	0,427	0,66	-1,21	-0,44	0,84
Range	6,685	25,78	20,8	8,263	4,714
Minimum	2,886	10,61	38,5	17,35	0,842
Maximum	9,571	36,39	59,3	25,61	5,557
Sum	525,3	2039	5176	2169	240,1
Count	99	99	99	99	99
Confidence Level(95,0%)	0,356	1,197	0,968	0,403	0,249

Source: calculated by the authors

The next step is to test the factors for multicollinearity by forming a correlation matrix (Table 2). The correlation between the high-tech exports indicator and two other variables (the Global Innovation Index and R&D expenditure) was found. There is also a relationship between the Global Innovation Index and charges for the use of intellectual property. Therefore, it was decided to exclude HTE and LN CIP from the model. An additional reason for this is the absence of a relationship between LN CIP and NAIRU. It is noteworthy that the correlation coefficients of all factors with NAIRU are negative, indicating an inverse relationship. At the same time, the relationship between R&D investment and NAIRU is greater than 0.5.

Table 2

Correlation matrix of the sample

	NAIRU	*HTE*	*GII*	*LN CIP*	*RDE*
NAIRU	1				
HTE	-0,369	1			
GII	-0,283	0,622	1		
LN CIP	-0,11	0,487	0,746	1	
RDE	-0,576	0,536	0,455	0,192	1

Source: calculated by the authors

After checking for multicollinearity, a regression with an R-square value of 0.33 was formed (Table 3).

Table 3

Linear regression results

Regression Statistics						
Multiple R	0,577					
R Square	0,333					
Adjusted R Square	0,319					
Standard Error	1,471					
Observations	99					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	2	103,67	51,833	23,933	3,69E-09	
Residual	96	207,91	2,166			
Total	98	311,58				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	7,769	1,682	4,618	1,2E-05	4,43	11,1
GII	-0,01	0,034	-0,28	0,777	-0,08	0,06
RDE	-0,805	0,134	-6,03	3,1E-08	-1,07	-0,54

Source: calculated by the authors

When creating the model, it was found that the coefficient on GII was statistically insignificant. After re-including LN CIP and HTE in the model and excluding RDE (multicollinearity) and GII (insignificant level of relationship and insignificant coefficient in the previous version of the model), another version of the regression was formed (Table 4).

Table 4

Linear regression results (2)

Regression Statistics						
Multiple R	0,377					
R Square	0,14					
Adjusted R Square	0,12					
Standard Error	1,67					
Observations	99					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	2	44,37	22,19	7,97	6,20E-04	
Residual	96	267,2	2,78			
Total	98	311,6				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	6,06	1,87	3,24	1,60E-03	2,34	9,77
LN CIP	0,08	0,09	0,85	0,4	-0,11	0,27
HTE	-0,12	0,032	-3,82	2,30E-04	-0,19	-0,06

Source: calculated by the authors

This model is characterized by a low R-squared value (0.14). Also, the coefficient on LN CIP is statistically insignificant. Thus, given the results of the first regression, as well as the significant relationship between R&D investment and NAIRU, it is advisable to identify a one-factor model of NAIRU dependence on R&D investment (Figure 3).

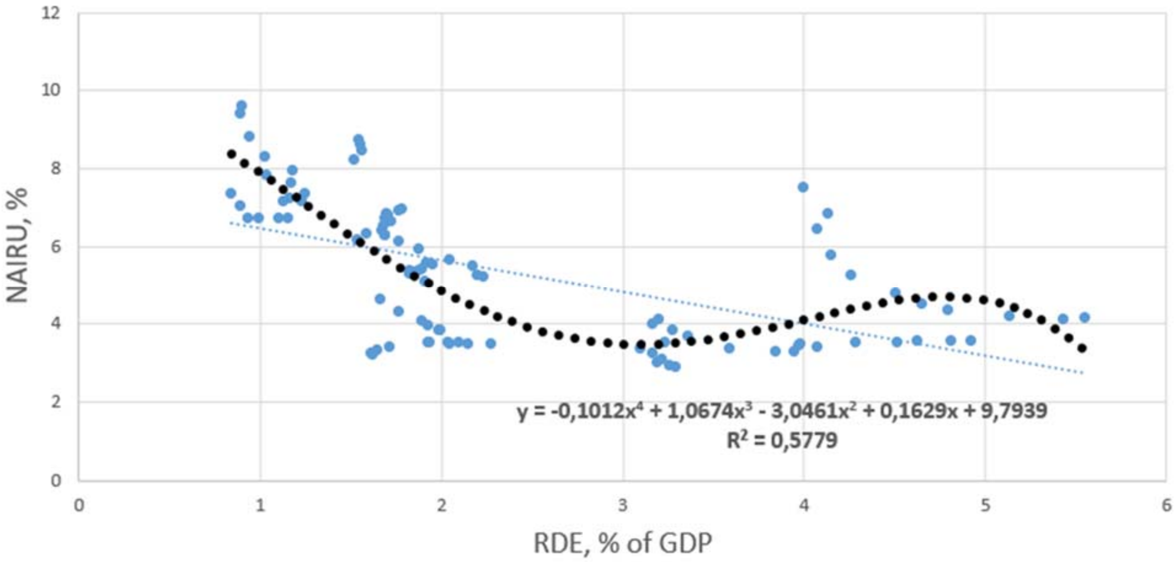

Figure 3. A one-factor model showing the relationship between R&D expenditures and structural unemployment

Source: calculated by the authors

The relationship in this sample is best represented by a 4th degree polynomial trend line. There is a sufficient relationship between R&D investment and NAIRU, and the relationship is mostly inverse, as evidenced by the direction of the trend line. When constructing a linear one-factor model, the strength of the relationship is lower (the coefficient of determination is 0.33), the coefficient at RDE is -0.82 and is statistically significant, which further indicates an inverse relationship between the variables.

In general, it can be concluded, on the one hand, that some indicators of the level of technology development do not have a strong impact on the NAIRU indicator. On the other hand, there is a significant level of correlation with such an indicator as R&D expenditures, and this relationship is inverse. The reason for this result may be the presence of frictional unemployed, which are not excluded by the NAIRU estimate. A significant number of people in developed countries pay attention to self-development and self-realization, so the labor force is more likely to voluntarily change jobs for better prospects or opportunities, as work is not only a means of subsistence, but also a means of self-realization to some extent. Further researches can also select other developed countries or apply other methods of analysis. It is also relevant to analyze the impact of technology on unemployment in developing countries, as some recent studies have found that the relationship between unemployment and the spread of the digital economy is stronger in this group of countries, which may be due to the higher share of frictional unemployed in developed countries [15]. However, it should be noted that there is no direct link between technological factors and structural unemployment.

Scientists also point out that it is almost impossible to completely separate structural unemployment from the overall unemployment rate, so the NAIRU estimate, which is constantly being improved, also does not give a completely accurate result [9; 12]. However, even the available estimates show an inverse relationship with the level of technology. Given these circumstances, part of the hypothesis about the positive, i.e. inverse, impact of technology on structural unemployment can be considered proven.

Additionally, for the analysis to be complete, another aspect of unemployment was identified. Structural unemployment, unlike frictional and cyclical unemployment, is characterized by its long duration. After all, workers who lost their jobs due to the development of technology cannot find a job without retraining and retraining, which takes a long time. Therefore, it can be assumed that the higher the share of unemployed who cannot find a job for a long period of time, the higher the structural unemployment. Thus, the existence of an inverse relationship between the share of long-term unemployed and the level of technology development would be an additional argument to support the hypothesis that technology has a positive impact on structural unemployment.

To prove or disprove this, according to the data of the OECD [16], the share of unemployed workers who have not worked for more than a year was calculated for 35 OECD member countries over 11 years and a correlation matrix was formed between this indicator and indicators of technological development

(Table 5). The share of workers who have been unemployed for more than a year excludes the impact of seasonal, short-term frictional, and to some extent cyclical unemployment. The hypothesis of the model is that there is a significant and inverse relationship between the indicators of technology and the share of long-term unemployment.

Table 5

Correlation matrix of the sample

	CIP LN	*HTE*	*GII*	*RDE*	*% long*
CIP LN	1				
HTE	0,328	1			
GII	0,469	0,462	1		
RDE	0,324	0,415	0,682	1	
%long	-0,199	-0,296	-0,325	-0,34	1

Source: calculated by the authors

There was no sufficient correlation with any of the indicators of technological development, and the model revealed insignificance of the coefficients for SIR and GII. Also, the R-square value is 0.15. This is too low to consider the model as explaining the relationship between the variables.

The reasons for this result are the presence of a component of cyclical unemployment in the share of the long-term unemployed, as well as the social policies of developed countries with high long-term unemployment payments. Such policies often contribute to the presence of a part of the labor force that does not voluntarily want to get a job and lives off social payments for a long time. Therefore, the impact of technological progress explains only 15% of the change in the long-term unemployment rate. Thus, the attempt to distinguish structural unemployment by its duration has not been successful in this group of countries with their social and economic policies aimed at protecting and providing for the unemployed.

Conclusions. The research confirmed the hypothesis of a positive, i.e. inverse, impact of technology on the level of structural unemployment. This means that, despite the fears of some scientists about the growth of unemployment due to the introduction of modern technologies, and artificial intelligence in particular, at the present stage, progress creates more new jobs than it eliminates. At the same time, no connection has been found between the duration of unemployment and the level of technology development. This is primarily due to the social policy of states, which contributes to the emergence of a share of the labor force that is not employed and lives off unemployment payments. It was also found that it is inexpedient to single out structural unemployment due to its duration.

It is worth noting that although the impact of technology on structural unemployment is clearly inverse at the present stage, as evidenced by negative correlation coefficients and negative statistically significant coefficients on variables in econometric models, this impact is often not significant or even decisive. Although technological change is currently contributing more to job creation than job elimination, technology is causing only minor changes in the unemployment rate. Most of the change in unemployment is attributable to factors such as government social policy, education, and social benefits. An empirical test of the impact of these factors on unemployment, including structural unemployment, is a promising area of research.

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Lidiya Yemelyanova, Candidate of Economic Sciences, Associate Professor at the Department of International Economic Analysis and Finance. **Semen Mlynko**, Master's Student, Ivan Franko National University of Lviv. **Analysis of the impact of technological factors on structural unemployment in developed countries**.

The article analyzes the impact of technological factors on the labor market, namely on unemployment. Structural unemployment is singled out as the one that is most affected by modern technologies. The ways of empirical identification of structural unemployment are analyzed. An econometric model is formed that reflects the impact of technology on structural unemployment in some developed countries over the past 11 years. It is found that this impact is inverse and that not all indicators of technological development have an impact on unemployment. The reason for this is frictional unemployment, as well as the social policy of developed countries. The author also calculated the share of the unemployed who have not worked for more than a year and formed a correlation matrix, which, however, did not reveal a correlation between this indicator and indicators of the level of technological development. Thus, it is not appropriate to distinguish structural unemployment due to its duration. Conclusions are drawn about the impact of technological factors on structural unemployment. This influence is inverse, which proves the hypothesis that technology creates more jobs than it eliminates. However, technology is not recognized as a determining factor affecting the unemployment rate.

Keywords: structural unemployment, technology, labor market, frictional unemployment, R&D, social policy.

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У статті досліджено вплив технологічних факторів на ринок праці, а саме на безробіття. Окреслено основні форми безробіття та їх причини. Виділено структурне безробіття як таке, яке піддається найбільшому впливу сучасних технологій. Проаналізовано способи емпіричного виокремлення структурного безробіття серед інших його видів та обрано показник рівня безробіття, що не прискорюється інфляцією як такий, що найкраще підходить для аналізу. Також вибрано показники, які найкраще відображають технологічні фактори та слугують індикаторами рівня технологічного розвитку. Аналіз зосереджено на економічно та технологічно розвинутих країнах, в яких можливе формування нових трендів на ринку праці. Сформовано економетричну модель, яка відображає вплив технологій на структурне безробіття в деяких розвинутих країнах протягом останніх 11 років. Виявлено, що цей вплив є оберненим а також що серед обраних індикаторів найбільший вплив на структурне безробіття в обраній групі країн за аналізований період чинять інвестиції в НДДКР (% від ВВП). Також було з’ясовано, що не всі обрані показники технологічного розвитку чинять вплив на безробіття в обраній групі розвинутих країн. Причиною цього названо фрикційне безробіття, яке не може бути повністю відокремлене від структурного, а також соціальну політику розвинутих країн. Також доречним визнано аналіз впливу технологій на безробіття в інших розвинутих країнах, а також в країнах, що розвиваються, оскільки в цих країнах менша кількість фрикційних безробітних, які добровільно не влаштовуються на роботу. Після проведеного аналізу було розраховано частку безробітних, які не працюють понад рік та з допомогою цього показника було сформовано кореляційну матрицю, яка, проте, не виявила зв’язку між часткою безробітних, які не працюють понад рік, та індикаторами рівня технологічного розвитку. Отже, виокремлення структурного безробіття через його тривалість не є доцільним, оскільки, хоча таким способом вдається виключити фрикційних безробітних, які були такими короткий час, водночас велика частка фрикційних безробітних, які довший час не працюють, залишається в значенні цього показника, а розвинуті країни через свою соціальну політику характеризуються досить значною кількість саме таких безробітних. Насамкінець зроблено висновки щодо впливу технологічних факторів на структурне безробіття. Цей вплив є оберненим, що доводить гіпотезу про те, що на даний час, як і впродовж історії, технології створюють більшу кількість робочих місць, ніж усувають. Проте технології визнано не визначальним фактором, який впливає на рівень безробіття.

Ключові слова: структурне безробіття, технології, ринок праці, фрикційне безробіття, НДДКР, соціальна політика.