The Effect of information and Communication Technologies on Unemployment: the Case of Selected OECD Countries[1]

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ABSTRACT

With the acceleration of technological advances since the 1970s, Information and Communication Technologies (ICT) have begun to play an active and significant role in the global economy. Today, it is widely accepted that ICT directly or indirectly affects economic structures as well as social life. It is seen that ICT, together with globalization, has important consequences on macroeconomic indicators such as growth, development and unemployment. The effects of ICT, countries and specific economic variables are progressing with various academic studies. In this study, it was aimed to question the causality relationship between two variables in a sample of countries selected from the OECD with similar ICT and unemployment rates in order to reduce the overall variance in the model. This is seen in the most similar countries with Türkiye, the rate of internet access and rate ratio representing ICT development, the bootstrap panel causality analysis presented by Emirmahmutoğlu & Kose (2011) was completed for the period covering the years 2005-2021. As a result, although the countries show similar characteristics in the selection criterion rates, it is understood that there are differences between the unemployment rate and the rate of internet access representing ICT according to the shape of the causality relationship. A direct causality relationship was found in Brazil, which has similar characteristics to Türkiye, in terms of ICT exits, while a reverse causality relationship was found in Latvia and Lithuania.

Key words: *Information and Communication Technologies, Unemployment, OECD, Causality, Time Series*

JEL Codes: B22, D83, J21, C23

1. INTRODUCTION

The term ‘information and communication technologies’ has been used since the mid-1980s to refer to various telecommunication and information technologies used in the field of transport. ICTs include a large number of technologies and systems in various stages of development,

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from research prototypes to commercially available products and applications (Giannopoulos, 2004, p. 302).

The economic structure resulting from the structural change in information and communication technology and globalisation is called the ‘New Economy’ (Pohjola, 2002, p. 134). This structural transformation in the economy is also referred to as ‘Information Society’, ‘Post-Industrial Society’, ‘Innovation Economy’, ‘Knowledge Economy’, ‘Weightless Economy’, ‘Digital Economy’, ‘Network Economy’ and ‘e-Economy’ (Cohen et al., 2000, p. 7).

D. Ricardo (1821) argued that, as long as there is no sudden fall in commodity prices, the reduction in costs due to technological progress leads to an increase in profits, which in turn can lead to an increase in investment and production and thus increase employment. According to 19th century economist T.R. Malthus, process innovation can lead to technological unemployment, which can be both significant and permanent. This is because there may be a reduction in the demand of workers who lose their jobs as a result of technological innovation. When there is a technological innovation, entrepreneurs will primarily invest in capital-intensive technologies. In this case, it may not lead to an increase in profits. Lack of profit increase may lead to a decrease in wages, and a decrease in wages may encourage employers to employ fewer workers. K. Marx argued that it is not possible to create enough jobs in industries that produce newly invented labour-saving machines (Feldmann, 2013, p. 1101).

J.A. Schumpeter is one of the first economists to pioneer the importance of innovations and technological change in economic growth. In the Schumpeterian approach, knowledge was seen as a key component, and it was emphasized that developments and fluctuations in the economy emerged through technological innovations. In this context, although innovations were accepted as the basic component of development, it was implied that significant and long-lasting frictions arose in the labor market due to creative destruction, and this brought unemployment. According to Schumpeter, technological unemployment is the most important type of unemployment.

Since the birth of economics, the effects of technological change on the labor market have been discussed. For example, according to J.B. Say (1971, p. 87), process innovations increase labor demand in industries using newly invented machines and create new employment opportunities. In addition, Say stated that process innovations reduce unit costs of production and thus lower prices, which in turn increases product demand and employment. If the relationship between ICT and unemployment is evaluated from this perspective, it can be stated that technology expands the economy and creates new job opportunities.

Beginning in the mid-1990s, various studies were conducted to explain the rapid pace of productivity growth in the United States of America (USA). One of these studies was conducted by Van Ark et al. (2003), who stated that the developments in ICT are the basis for the much faster productivity growth in the USA compared to the European Union (EU).

According to Autor et al. (2003), how computerization is related to labor input was investigated in the period between 1960-1998 among industries, occupations and education groups. For these categories, the widespread use of computers was associated with a decrease in labor input for manual and routine cognitive tasks, while on the other hand, it was associated with an increase in labor input for cognitive tasks that do not involve routine processes. In occupations where computer use became widespread with job changes within the industry, the input of routine cognitive tasks decreased and the input of non-routine cognitive tasks increased.

Acemoglu and Restrepo (2019) stated in their study on technology and labor demand that automation eliminates routine jobs in particular and may lead to unemployment for low-skilled workers. However, they stated that new jobs and tasks created by new technologies will create different new job opportunities, especially for more highly skilled workers. As a result of the empirical study they conducted based on the methodology they constructed, the process of creating new jobs has slowed down, especially with the acceleration of automation in manufacturing, and an understandable stagnation has emerged in labor demand. In addition, with such a phenomenon, which is probably in the composition of technological progress, the economy has experienced a significant slowdown in productivity growth and has paved the way for stagnation in labor demand.

In order to close the ICT gap with the USA, the EU has also implemented a number of initiatives in the field of ICT starting from the end of the 1990s (Alper, 2017, p. 48). These initiatives in the EU, the USA and the leading countries of the world have had a number of effects on the economy, especially on the labour force.

In the literature, studies on employment, economic growth and labor productivity with ICT are encountered intensively, but studies on unemployment are partly rare. With the perception that studies emphasizing a relationship between ICT and unemployment in panel causality tests are rare, it was desired to present a study on a country group including Türkiye. In addition, it was seen that studies were generally conducted on country groups established within a certain economic integration scope, and a group of countries similar to Türkiye was formed.

In this study, the effects of ICT on unemployment in OECD countries are analysed by using the Panel bootstrap causality method developed by Emirmahmutoğlu and Köse (2011) for the period covering 2005-2021. Firstly, a literature review on the subject has been made. Then, information about the data set and methodology is given and the empirical results are discussed.

2. LITERATURE REVIEW

Entorf et al. (1999) estimated the effect of ICT on firms' employment in France by using a Logit model. According to the results of the study, it is emphasised that the use of ICT has a negative effect on firms' employment in the short run but not in the long run.

Diaz and Tomas (2002) analysed the relationship between technological innovation and employment within the framework of Spain. By examining the period between 1980-1990, they investigated the effect of technological advances on employment and concluded that the quality of labour force increased as a result of technological advances.

Matteucci and Sterlachini (2003) analysed the effect of ICT on employment in the period between 1997-2000 in their study on the Italian industry. In the study where regression analysis was performed, they also found a positive relationship between employment in Italian industries and investments in ICT. The regression results show that employment growth in both secondary and service sectors in the relevant period was positively affected by changes in production (or demand), while it was negatively affected by changes in labour costs. According to the research findings, the intensity of ICT investment has a negative impact on employment changes in secondary industries, while it is positively and significantly related to employment growth in service industries.

Oulton and Srinivasan (2005) investigated the role of ICT in productivity increases in the UK for the period between 1970-2000. In this study of 34 sectors, they found that ICT is the most important determinant in the increase in labour productivity. Some indirect inferences can be made from this study regarding the ICT and Unemployment Relationship as follows: First, one of the main findings of the study is that ICT increases productivity at the industrial level. Productivity increase generally affects labor demand. If productivity increase occurs in a way that reduces the demand for labor (due to automation etc.), this may increase the unemployment rate. Secondly, in an environment where ICT leads to the emergence of new business lines and sectors with increased productivity, positive effects on the unemployment rate may also be observed (increase in labor demand).

O'Mahony et al. (2008) examined the impact of ICT on the employment of skilled labour in the US, the UK and France using panel data analysis techniques. As a result of the research, the authors found that the employment of skilled labour increased with the inclusion of ICT in the production process and the interaction between ICT and skilled labour was higher in the USA than in the UK and France.

Harrison et al. (2008) investigated the impact of ICT on employment using micro data from firms in Germany, France, England and Spain between 1998-2000. In the study, a dynamic panel data model was estimated with the GMM estimator, taking employment as a dependent variable. Different innovation processes were added to the model independently, and although the ICT effect was not directly included in the model, it can be assumed that innovation processes (especially technological improvements in production processes) include the use of ICT. It is understood that ICT can reduce labor demand in the short term through process innovations, but can create new job opportunities through product innovations. As a result, it has been observed that while the use of ICT can reduce employment and increase unemployment rates through the automation effect on production processes, technological innovations can expand labor demand and employment in the long term.

Türedi (2013), The effect of ICT on economic growth was estimated by panel data method for the period 1995-2008 with the data of 53 countries including Türkiye. Using fixed and random effects panel data method, the author analysed GDP per capita, physical capital, human capital, number of personal computers, number of mobile phone and fixed line subscribers, number of internet users and number of telephone lines installed. According to the results of the analyses, the effect of ICT on growth has a positive effect on economic growth in developed and developing countries and this effect is higher in developed countries.

Artan et al. (2014) examined the relationship between ICT and economic growth for transition economies. In the study where static panel data analysis technique was used, the period 1994-2011 was analysed and as a result, it was emphasised that developments in ICT positively affected economic growth in transition economies.

In the study conducted by Meçik (2015), the effects of ICT on labour productivity in OECD member countries with data covering the period 1990-2012 were investigated by panel data method. In addition to the countries' expenditures on ICT infrastructure, especially with components such as communication technologies and computer use, household internet usage rate, fixed capital and R&D investments were used as independent variables. In addition to the countries' expenditures on ICT infrastructure, especially with components such as communication technologies and computer use, household internet usage rate, fixed capital and R&D investments were used as independent variables. The main finding of working with fixed and random effect panel data models is that ICT investments and fixed capital formation increase labor productivity. The integration of ICT into business processes significantly increases productivity, contributing to more output per worker.

Bahrini and Qaffas (2019) analyzed the impact of information and communication technology (ICT) on economic growth using the GMM panel data model on selected developing countries from the Middle East and North Africa (MENA) region and Sub-Saharan Africa (SSA) region during the period 2007-2016. According to the results obtained by the panel data analysis, the main drivers of economic growth in MENA and SSA developing countries are other information and communication technologies such as mobile phones, Internet use and broadband adoption, apart from fixed-line telephones. In addition, the findings reveal the superiority of MENA countries over SSA countries in terms of Internet use and broadband adoption. From a policy perspective, the results indicate that authorities in MENA and SSA countries should increase their investments in ICT infrastructure.

Mike and Mahjoub Laleh (2016) investigated the relationship between ICT and employment in a panel data analysis study. Two different groups were formed within the G-20 country group and two different groups were taken as developed countries (DC-7) and developing countries (EC-13) and the results of two different periods, before and after 1999, were evaluated. In the analysis, the ratio of employment to population is taken as the dependent variable and the number of internet users (ICT index), real GDP and real wage rate variables are taken as independent variables by using the panel EGLS method (Cross-section weights) and estimations are made for two sub-periods. According to the results, the ICT variable has a positive and weak effect on employment in percentage terms before 1999 and a relatively higher but negative effect after 1999. Real GDP has an approximately similar positive effect on employment in both periods, while the real wage rate has an approximately similar but negative effect.

Alper (2017), it focuses on the effects of ICTs on economic growth and unemployment. FGLS panel data analysis was carried out on 23 European Union (EU) countries and Türkiye by using annual data for the period 1996-2016 as a sample. It is concluded that ICTs have a positive effect on economic growth and reduce unemployment.

Karabulut and Shahinpour (2017), the effects of ICTs on unemployment are discussed and exemplified through the Iranian economy. In the sample, they analysed the relationship between ICT and unemployment by using the ARDL method with variables such as GDP per capita, ICT expenditures, capital stock change per labour force together with the unemployment variable using annual Iranian data for the period 1980-2015. It was concluded that the advances in ICT in the Iranian economy have a negative impact on the unemployment rate in the short and long run. In terms of coefficient and sign, a 1% increase in the number of telephone subscribers decreases the unemployment rate by 0.4%.

Garcia-Murillo et al. (2018) The concept of technology-induced unemployment and the effects of ICTs on business life have been analysed by the authors. The authors reveal the effects of ICTs on structural change in existing industries and the emergence of new industries, the workplace, the role of education and labour laws in the USA. In this context, three models are presented and one model is discussed. As a result of the research, it was concluded that a significant portion of the US population will be negatively affected by technology.

Dağlı and Kosekahyaoğlu (2021) The authors analysed the relationship between technological development and unemployment for 22 European Union countries and the Turkish economy for the period 2005-2018 using the System Generalised Moments estimator method. Authors using unemployment, GDP, inflation, real exchange rate, real interest rate, wage bargaining, foreign direct capital inflows and outflows, unemployment expenditure, unionisation and patent variables as a result of the analysis, the authors found that technology does not have a negative effect on employment.

In the study of Çebişli (2021), the data of the G-7 countries obtained from the World Bank for the years 2004-2018 on ICT, Unemployment, GDP and inflation variables were analyzed using panel data methods. The variables were determined to be stationary with panel unit root tests and then fixed effects and random effects models were estimated. According to the results obtained from the two models of the research, the ICT variable had a positive effect on GDP and was found to be statistically significant.

Cheng et al. (2021) in the study, a dynamic GMM estimation model was obtained by using the panel data method with 72 country data for the period 2000-2015. As a result of the estimations, it is revealed that, regardless of the level of national income, increases in financial development are generally negative on economic growth, but this effect is more pronounced in high-income economies, while ICT diffusion can increase economic growth, especially in high-income countries. It is also reported that the interaction between ICT and the financial sphere can overcome the negativities related to financial development, but the related results are important only for high-income countries.

Ünlü (2022) investigated the effects of ICT use on labor productivity and employment in his study. For this purpose, ARDL Cointegration and Toda Yamamoto causality analyses were performed using the data from the World Bank Development indicators for Türkiye between 2001-2020, taking the percentage of internet usage rate in the total population for the ICT usage variable. According to the results, it was suggested that there is a two-way causality relationship between ICT use and labor productivity. A similar two-way causality relationship was found between labor force and employment, but no relationship was found between ICT and employment. In addition, it was determined that the effects of ICT use on labor productivity and employment were negative but quite weak with the ARDL model.

Ece and Çetin (2022) used annual data from 35 OECD countries between 2010-2019 in order to examine the relationship between ICT use, employment and economic growth. According to the two different models established, they used the employment-to-population ratio as dependent variables, representing GDP per capita and employment, respectively. In both models, the number of individual internet users, fixed broadband subscriptions and active mobile broadband subscriptions representing ICT use were taken as independent variables. It was reported that only the number of active mobile broadband subscriptions (per 100 people) had a significant effect on GDP per capita and employment.

Harman and Abdioğlu (2023) used Toda and Yamamoto (1995) causality analysis to examine the causality relationship between the number of mobile phone subscribers and GDP for Brazil, Indonesia, South Africa, India and Türkiye. As a result of the study, while there is a unidirectional causality relationship from economic growth to ICT utilisation for Brazil and South Africa, there is a bidirectional causality relationship between the series for Indonesia and Türkiye. For India, they found that there is no causality relationship between economic growth and ICT utilisation.

According to the general findings obtained from the literature, different results are seen according to the countries. Different variables can be used as representatives within the scope of ICT usage. It is known that the concept of unemployment is directly related to the employment variable and the GDP variable in economic science theories. Because the increase in GDP and employment will indirectly lead to a decrease in unemployment. Since the focus of this study is on the unemployment variable, examples of different types of models in which the closely related GDP and employment variables are associated with ICT use have been evaluated. It was aimed to draw attention to the relationship between the concept of unemployment and the use of ICT, with the approach that it has a different interaction from the variables of GDP and employment.

3. THEORETICAL MODEL

ICT affects an economy in terms of both supply and demand. It affects producers in terms of supply and consumers in terms of demand. Equation 1 shows the production function of a firm with ICT capital, labour and physical capital factors (Karabulut ve Shahinpour, 2017, s.246);

$$Q_t = A_t f(C_t, L_t, K_t) \tag{3.1}$$

Where; Qt is the total value added arising from the level of production, Ct, Lt, Kt are ICT capital, labour force and physical capital respectively. ICT is both used as a factor of production and affects the productivity of factors of production through the technology symbol At (Karabulut et al., 2019, p. 1189). According to this equation, ICT goods and services constitute a part of the total value added in the economy. On the other hand, an increase in the rate of economic growth can be achieved by utilising ICT capital. In addition, ICT can increase the rate of economic growth by providing technological development in all other sectors (Pohjola, 2002, p.382). ICT includes computer-telephone hardware, programmes and web page software products. On the other hand, in the labour market, ICT creates employment for qualified or unqualified labour in distribution and after-sales services (Karabulut et al., 2019, p. 1189).

The relationship between the increase in the rate of ICT (Information and Communication Technologies) usage and the employment rate is a subject that is constantly debated in the literature. According to economic theory, these discussions proceed on two different axes of view. According to one view, the existence of a positive relationship between ICT usage and production and employment will lead to an increase in innovations. According to the other view, it is claimed that although productivity increases and product process innovations are experienced through ICT, this will occur with decreases in the volume of labor. The issue of how ICT usage affects employment may also be related to differences in firm, industry and macroeconomic conditions. For example, when ICT is considered as an investment element in production, it may lead to a need for labor in some sectors while it may create labor savings in others (Koellinger, 2006: 5).

Based on the sources in the theoretical literature, Information and Communication Technologies (ICT) contribute to the acceleration of the production process, the increase in production and in total factor productivity. In this context, the increase in production volume will lead to the expectation that employment will also increase based on the economic connection between them. Although it brings to mind the possibility that the increase in employment will also reduce unemployment, the fact that the use of ICT can also save employment is one of the topics discussed today. The dominance of sectors with a strong tendency to save employment through ICT in the economy will lead to an increase in unemployment as production increases. As a result of the study, it will be revealed in which countries this tendency is stronger.

4. DATA SET AND MODEL

In order to support the theoretical framework of the study, the countries included in the empirical analysis are those that are statistically similar to Türkiye in terms of the variable representing information and communication technologies. Accordingly, the panel data set related to the OECD countries group was used. From this group of countries, a data set consisting of a total of 272 observations covering the years between 2005 and 2021 on the variables Households with Internet Access at Home (%) and Rate of Unemployment as % of Labour Force was used for 16 countries that have similarities with Türkiye. Since it is possible to obtain data sets for different years in current countries, the process of identifying countries based on similarity is summarized below.

The date range for the countries in the study was chosen based on the availability of data for each country and the Emirmahmutoğlu and Köse (2011) bootstrap causality method was used. In studies with econometric panel data analysis, countries defined as a political group are generally used. However, the similarity of such studies according to diagnostic statistical data cannot be guaranteed. In this study, countries that are close to Türkiye according to two different variables were taken and panel data causality analysis was applied to this group of countries. It was expected that the variance of the economic models created in this way would be low and the model consistency would be generally high.

In order to include a large group of countries in the selection of the Internet Access rate variable, the similarities of OECD countries with Türkiye were examined by using 18-year observations covering the years 2005-2022, and the distance calculation method for variables generally used for this purpose in statistics was applied. Accordingly, first, since the unemployment rate data set is available until 2021, the average internet access rate for each OECD country for 17 years (2005-21) was obtained. Based on these country averages, the mean ($X_{i,\ mean} = 71.44$) and standard deviation (std = 14.906) values for the OECD were calculated. We then searched for countries that were within 1 standard deviation of Türkiye's average ($X_{turkiye,\ mean} = 59.78$) (i.e. with values between 44.88 and 74.69). In addition, among the BRICS countries, Brazil was included due to its high similarity in terms of internet access.

In the unemployment rate (Unemp_Rate) variable, a 22-year observation set covering the years 2000-2021 was obtained in order to create the largest country group, but data from 2005 onwards were used for the compatibility of the panel data set with the internet access rate variable. For the unemployment rate variable, countries similar to Türkiye in terms of internet access rate were included in the country selection, but the Costa Rica data set was canceled since it started in 2011. In addition, the missing values for Türkiye 2005 and Brazil 2010 were estimated by interpolation method. In this way, 16 countries with the most similarities with Türkiye and the largest data set were identified out of 43 countries whose data could be obtained for both variables, and their annual data for 17 years were used.

These countries are the Czech Republic, Estonia, Greece, Hungary, Israel, Italy, Latvia, Lithuania, Poland, Portugal, Slovak Republic, Slovenia, Slovenia, Spain, Türkiye and Brazil. Finally, the panel data set was created by adjusting the data for two different variables. The process of obtaining data on the variables used in the research is summarized in Table 4.1.

Variable	Description	Source	Country and Year
Int_access	Households' access to the Internet Access Rate	Data.worldbank.org	16 count., 18 year
Unemp_rate	Unemployment Rate	Data.worldbank.org	16 count., 18 year

Table 4.1. Observation Acquisition Information for the Variables Used in the Model

The diagnostic statistics associated with the data set determined in accordance with the objectives of the study are as follows:

Country	Min-Max.	Mean	Median	Std.Dev.	Skewness	Curtosis
15	4.845-95.918	64.3664	69.126	20.4098	-0.7380	2.7762
Türkiye	7.659-91.975	55.6792	56.814	27.3398	-0.1675	1.7318

Table 4.2a. Diagnostic Statistics for **Y:** Households' access to the Internet Access Rate (%)

In the Table 4.2a, It can be seen that the average values of the variable of "household internet access rate" for Türkiye are lower than the averages of the other 15 countries. The other hand, the standard deviation values of the same variable for Türkiye fluctuate in a wider range.

Country	Min-Max.	Mean	Median	Std.Dev.	Skewness	Curtosis
15	2.014-27.468	9.6929	8.425	4.8223	1.3511	5.008
Türkiye	8.167-13.667	10.3772	10.246	1.6798	0.52558	2.185

Table 4.2b. Diagnostic Statistics for **X:** Unemployment Rate (%)

As the Table 4.2b, For the unemployment rate variable, the mean values are slightly higher than in other countries, while the standard deviation value fluctuates within a narrower range.
The equations in which the relationships between the variables determined within the framework of the research are modeled through the causality test are as follows:

$$\textbf{Int\_Access}_{i,t} = \alpha_0 + \alpha_1 \textbf{Unemp\_Rate}_{i,t} + u_{i,t} \tag{4.1}$$
$$\textbf{Unemp\_Rate}_{i,t} = \beta_0 + \beta_1 \textbf{Int\_Access}_{i,t} + e_{i,t} \tag{4.2}$$

In equation (4.1), α_0 represents the constant term parameter, α_1 represents the degree to which the change in Unemp_Rate (independent) variable affects Int_Access (dependent) variable in terms of direction and magnitude, and $u_{i,t}$ represents the residual term of the estimation. In equation (4.2), β_0 represents the constant term parameter, β_1 represents the degree to which the change in the Int_Access (independent) variable affects the Unemp_Rate (dependent) variable in terms of direction and magnitude, and $e_{i,t}$ represents the residual term of the estimation of the second equation. In equations (4.1) and (4.2), the index i represents the country information in the panel and t represents the time information of the panel. The variables in these equations are used at their level values as shown in Table 4.1.

4.1. Methodology and Findings

Granger-type causality works by estimating a variable with its own lagged symbols and the lagged symbols of the other variable in a model structure with more than one equation and variable. In this way, we can see how effective a variable with a structured set of lagged values is in estimating the other variable. In the panel-type data set, two features that should had in the data should be determined firstly, and then it should be investigated whether there is Granger causality (Ajovin-Puente and Navarro-Sanso, 2015, p. 68). Accordingly, in this study, the existence of cross-sectional dependence and heterogeneity conditions among these two features were questioned and determined. Based on the results obtained, the direction of the relationships was then investigated by using the panel Fisher bootstrap causality test developed by Emirmahmutoğlu and Köse (2011), which is appropriate for the panel data set.

In order to test the causality relationship between the rate of households' access to the Internet and the unemployment rate, it is first necessary to question the cross-sectional dependence and homogeneity properties.

4.2. Cross-Sectional Dependence Test

One type of test that determines which generation of analysis to use in panel data models is "cross-sectional dependence". The existence of this dependence is understood when a shock in one of the cross-sections (units) in the model affects the other cross-sections as well. Within the framework of the variables in the data set, different methods have been defined in the literature to test whether there is dependence between cross-sections (units). Among these, the LM test was developed by Breusch and Pagan (1980) and can be used when the time dimension is larger than the cross-section dimension, i.e. (T > N). The LM_{adj} test was developed by Pesaran (2004) and it is reported that it can be used in the case of (T > N) but the difference should be close. Thirdly, the CD test was developed by Pesaran (2004) and is a test statistic recommended when the cross-sectional dimension is larger than the time dimension (N > T) (Ozer and Kocaman, 2019, p. 243).

The cross-sectional dependence (LM) test was developed by Breusch and Pagan (1980, pp. 246-247) and the following panel equation should be established in the system established to obtain SUR (Seemingly Unrelated Regression) model estimation:

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it}; \quad i = 1, 2, \dots, N; \quad t = 1, 2, \dots, T \qquad (4.3)$$

According to Equation (4.3), the symbol x_{it} represents the k × 1 vector of independent variables in the model, while α_i and β_i represent the constant term and the slope coefficient, respectively.

Null hypothesis under the LM test is that:

H_0: $Cov(u_{it}, u_{jt}) = 0; \qquad \forall_{t,\,i} \neq j.$

Based on the LM test, the null hypothesis (H_0) states that there is no cross-sectional dependence (CD) among the error terms, while the alternative hypothesis (H_1) states that there is CD among the error terms. The LM statistic is asymptotically chi-square (χ^2) distributed with N (N - 1)/2 degrees of freedom. To test the null hypothesis H_0, the calculation of the test statistic in equation (5) below is used:

$$LM = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\, \hat{\rho}_{ij}^2 \rightarrow \chi^2 \qquad (4.4)$$

The meaning of the term $\hat{\rho}_{ij}^2$ in this equation (4.4) is that the residual terms were calculated for each country in the sample by means of equations (4.1 and 4.2), from which two-way correlations were obtained. Moreover, for all (i, j) cases, the test statistic is asymptotically distributed in the χ^2 pattern with the property that T_ij → ∞ when N is constant:

$$\hat{\rho}_{ij} = \hat{\rho}_{ij} = \sum_{t=1}^{T} e_{it} e_{jt} \Big/ \left(\sum_{t=1}^{T} e_{it}^2\right)^{0.5} \left(\sum_{t=1}^{T} e_{jt}^2\right)^{0.5} \tag{4.5}$$

In equation (4.5), the correlation relationship between the error term e_{it} and e_{jt} obtained by the OLS (least squares) method between two different cross-sections is calculated.

The null hypothesis in the CD-type cross-sectional dependence (CD) test is "H_0: There is no CD between cross-sections, ($T \rightarrow \infty$ and $N \rightarrow \infty$)" and the statistic of this test is calculated from equation (4.6):

$$CD = \left({}^{2T}\!/_{N * (N-1)}\right)^{0.5} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij} \hat{\rho}_{ij} \rightarrow \mathrm{N}\ (0,\ 1) \tag{4.6}$$

In this equation, the CD statistic is predicted to have an asymptotically standard normal distribution due to the property that $T_{ij} \rightarrow \infty$ and $N \rightarrow \infty$ for each time and cross-sectional dimension.

The BP LM statistic, another CD test, is known to be used when the difference between N and T is not very large, preferably when N>T. Pesaran (2004) developed a modified version of this LM test as in equation (4.7) by adding the mean and variance of the relevant variable to the test statistic (Kar et al., 2011, p. 691).

$$LM_{adj} = \left({}^{1}\!/_{N * (N-1)}\right)^{0.5} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T_{ij} \hat{\rho}_{ij}^2 - 1) \rightarrow \mathrm{N}\ (0,\ 1) \tag{4.7}$$

For the LM_{adj} test, based on the assumptions that $T_{ij} \rightarrow \infty$ and $N \rightarrow \infty$ for time and cross-sectional dimensions, it is predicted that the statistical values are asymptotically normally distributed.

The null hypothesis (H_0) can be rejected at the 5% significance level if the probability value obtained after obtaining different statistical values within cross-sectional dependence (CD) is less than 0.05. Therefore, the null hypothesis that "there is no cross-sectional CD" in the panel data set is not accepted and the existence of CD is inferred.

In the Emirmahmutoğlu and Köse (2011) type symmetric bootstrap causality test, the results of which can be seen in Table 4.3, the first step is to determine the presence of cross-sectional dependence.

Equation No	**CD Test Type:**	**Test Statistic**	**Prob**
For Equation	LM (Breusch & Pagan 1980)	1655.428	0.000
(1)	CD lm (Pesaran 2004)	106.990	0.000
Unemp_rate =>	CD (Pesaran 2004)	40.633	0.000
Int_access	LM_{adj}	0.853	0.197
For Equation	LM (Breusch & Pagan 1980)	1324.143	0.000
(2)	CD lm (Pesaran 2004)	84.129	0.000
Int_access =>	CD (Pesaran 2004)	12.839	0.000
Unemp_rate	LM_{adj}	0.506	0.306

Table 4.3. Cross-Sectional Dependence Test Results

Since the time dimension (T=17) is larger than the cross-sectional dimension (N=16), the LM test introduced in Breusch and Pagan (1980) and the CD and LM_{adj} tests introduced in Pesaran (2004) are used to conclude the existence of the cross-sectional dependence (CD) phenomenon for the countries studied.

The results of the LM tests for equations (1) and (2) are shown in Table 4.3. According to the results, the null hypothesis "H_0: There is no cross-sectional dependence" can be rejected among the selected countries that make up the panel, since the p-likelihood values are less than 5% for the first three tests focused on. It is therefore concluded that there is cross-sectional dependence among the countries concerned. This means that a shock that has occurred or will occur in one of the countries included in the study will have an impact on other countries.

4.3. Homogeneity Test

In the bootstrap causality test of Emirmahmutoğlu and Köse (2011), the next step after detecting the existence of CD is to obtain different equation estimates depending on these cross sections (countries) and to test whether the slope coefficients are homogeneous or heterogeneous. When the time dimension is large (T > N), the Wald test is the most suitable option to determine the existence of homogeneity. In the homogeneity test, the null hypothesis is "all slope coefficients are equal" (H_0) and the alternative hypothesis is "at least one slope coefficient is different from the others" (H_1). Swamy (1970) stated that it is necessary to identify heterogeneity across countries in panel studies, which can be done using the following equation (Altınok and Akça, 2021, p. 263):

$$\tilde{S} = \sum_{i=1}^{N} \left(\left(\widehat{\beta_\iota} - \widetilde{\beta_{WFE}} \right) \right)' \frac{x_i' M_\tau x_i}{\hat{\sigma}_i^2} \left(\widehat{\beta_\iota} - \widetilde{\beta_{WFE}} \right) \tag{4.8}$$

In equation (4.8), $\hat{\beta}_\iota$ is the estimated panel OLS (pooled model) estimator, $\widetilde{\beta_{WFE}}$ is the value calculated based on the weighted model estimator (fixed effect model), M_τ is a defined matrix, and $\hat{\sigma}_i^2$ in the denominator is the estimator of σ_i^2, which is the variance for cross-sections. The equation shown in Pesaran and Yamagata (2008, p. 57), which differentiates the Swamy equation above to produce the delta test ($\tilde{\Delta}$) in equation (4.9), is given by:

$$\tilde{\Delta} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}} \right) \tag{4.9}$$

In this calculation, N represents the number of cross-sections in the panel dataset, k denotes the number of independent variables in the model, and $\tilde{S}$ stands for the Swamy test statistic. While the delta test statistic in equation (4.9) above is employed by Pesaran and Yamagata (2008, p. 57) particularly for small samples, for larger samples they propose the adjusted delta test ($\tilde{\Delta}_{adj}$). The adjusted delta test statistic, denoted by $\tilde{\Delta}_{adj}$, is derived from the following equation (4.10):

$$\tilde{\Delta}_{adj} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - E(\widetilde{z_{\iota t}})}{\sqrt{var(\widetilde{z_{\iota t}})}} \right) \tag{4.10}$$

The symbol $E(\widetilde{z_{\iota t}})$ in this equation represents the mean value (or k) of Z_{it} and the variance value of Z_{it} is formulated with the calculation of $var(\widetilde{z_{\iota t}}) = 2k\,(T - k - 1)/(T + 1)$. The homogeneity test results shown in Table 4.4 are calculated for the countries in the sample based on equations (4.1) and (4.2) above.

	Method	Test Stat.	Prob. (p)	Wfe Estimation
For (1st)	$\tilde{\Delta}$ Test	10.458 ***	0.000	**b2_wfe (k2) =**
Equation	$\tilde{\Delta}_{adj}$ Test	11.456 ***	0.000	- 0.1125
For (2nd)	$\tilde{\Delta}$ Test	10.532 ***	0.000	**b2_wfe (k2) =**
Equation	$\tilde{\Delta}_{adj}$ Test	11.537 ***	0.000	0.0063

Table 4.4. Homogeneity Test (Delta) Results;
Notes: 1) b_wfe(k2): The values of the weighted fixed effects estimates of the k2 slope coefficients obtained through the tests. 2) For $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ test statistics, see Pesaran and Yamagata (2008: 50-93).

Interpreting the results from Table 4.4 in light of the study by Pesaran and Yamagata (2008), the null hypothesis "H_0: There is homogeneity in the slope coefficients of the cross-sectional model ($\beta_i = \beta$)" is rejected at the 5% significance level. Consequently, given that the slope coefficients vary across countries in accordance with hypothesis H_1, it can be concluded that there is heterogeneity in the units ($\beta_i \neq \beta$) and the units exhibit different slope parameter behaviour.

4.4. Panel Bootstrap Causality Test

Emirmahmutoğlu and Köse (2011) adapted the Toda-Yamamoto (1995, pp. 225-250) test approach to the widely used Granger causality test in time series and developed a causality test with certain advantages. The first advantage of this test, which is also referred to as the panel bootstrap causality test, is that it is possible to use the test without applying unit root and cointegration tests on the variables in connection with the T&Y test. Therefore, all variables can be used directly in the model with their level values or with different degrees of stationarity without looking for stationarity. If the variables are used in any model in different forms other than their level values, dynamics such as trends that may be included in their original values may be lost. Another advantage of the test is that it permits the existence of simultaneous correlation between variables called cross-sectional dependence and can be used in heterogeneous panels (Emirmahmutoğlu and Köse, 2011, pp. 870-876; Koçdemir and Gölpek, 2021, pp. 31-32; Chang et al., 2015, pp. 1405-1412).

In the Emirmahmutoğlu and Köse (2011) causality test, the bivariate VAR model is first estimated by constructing the following form (12a, b):

$$x_{i,t} = \mu_i^x + \sum_{j=1}^{k_i+dmax_i} A_{11,ij}x_{i,t-j} + \sum_{j=1}^{k_i+dmax_i} A_{12,ij}y_{i,t-j} + \mu_{i,t}^x \tag{4.11a}$$

$$y_{i,t} = \mu_i^y + \sum_{j=1}^{k_i+dmax_i} A_{21,ij}x_{i,t-j} + \sum_{j=1}^{k_i+dmax_i} A_{22,ij}y_{i,t-j} + \mu_{i,t}^y \tag{4.11b}$$

In this system of equations, i (i= 1,2,...N) denotes each cross-section, t (t=1,2,...T) denotes each period, and $dmax_i$ denotes the maximum level of integration for each. μ_i^x and μ_i^y are two vectors of fixed effects, μ_{it}^x and μ_{it}^y are column vectors of error terms, and k_i is the lag structure assumed to be known and differing across cross-sectional units.

In this approach, causality is common to all units. When applying this for heterogeneous panels, we use the test statistic obtained by combining the unit statistics with the meta-analysis approach proposed by Fisher (1932). In this causality analysis developed by Emirmahmutoğlu ve Köse (2011), Granger causality is calculated through the following equation:

(Emirmahmutoğlu, 2011, pp. 99-104; Chang et al., 2015, pp. 1405-1412; Çelik and Paksoy, 2021, pp. 740-748).

$$y_{i,t}^{*} = \hat{\mu}_i^{y} + \sum_{j=1}^{k_i+dmax_i} \hat{A}_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i+dmax_i} \hat{A}_{22,ij} y_{i,t-j}^{*} + u_{i,t}^{*} \qquad (4.12)$$

The Wald statistics for each cross-section is a general tool for testing restrictions on the VAR model. For each i = 1, 2, 3.... N, $\alpha_i = [A_{ij}]$ denotes the vector of coefficients in the VAR process. To test the null hypothesis of non-causality, y it is replaced by y_{it}^{*} in equation (12b) and estimated without parameter restrictions.

Individual p-values are calculated using individual Wald statistics with asymptotic chi-square distribution with chi-degrees of freedom. In order to determine the presence of causality in heterogeneous panels, the Fisher test statistic (λ) calculated with these p (pi) values is formulated as follows:

$$\lambda = -2\sum_{i=1}^{N} \ln(\pi_i) \ ; \ i = 1, 2, \ldots, N. \qquad (4.13)$$

The hypotheses of this test are as follows:

H_0 : There is no causality between the variables in the model.
H_1 : There is a causal relationship.

The null hypothesis (H_0) indicates that there is no causal relationship between the variables, while the alternative hypothesis H_1 indicates that there is a causal relationship. When the H_0 hypothesis is rejected, it is understood that there is a causal relationship between the relevant variables.

4.5. Empirical Findings

Tables 4.3 and 4.4, which were employed as a pretest, indicate that heterogeneity exists across cross-sections in terms of slope coefficients and dependence across cross-sections. Consequently, it is possible to apply the panel bootstrap causality test, which yields causality results for each country separately, to panel data (Emirmahmutoğlu and Köse, 2011, pp. 870-876). This approach posits that in order to apply Granger causality to panel data, bootstrap critical values for each country are generated with the assistance of software. The results of the causality relationship between the series forming the model are presented in Tables 5a and 5b. Upon analysis of the Tables, it is observed that causality from the unemployment rate to the household internet access rate in Table 4.5a and vice versa in Table 4.5b is reported at different significance levels for the panel as a whole. Both the Akaike and Schwarz information criteria results can be observed concurrently on any given Table.

Countries	Lags	AIC, dmax= 3 lags Wald Stat. and Prob.		Lags	SIC, dmax=3 lags Wald Stat. and Prob.	
1. Czech Republic	3	1.115	0.773	3	1.115	0.773
2. Estonia	3	0.543	0.909	1	0.061	0.806
3. Greece	3	0.377	0.945	3	0.377	0.945
4. Hungary	3	5.773	0.123	3	5.773	0.123
5. Israel	1	1.724	0.189	1	1.724	0.189
6. Italy	3	1.133	0.769	2	4.920	0.085 *
7. Latvia	3	13.159	0.004 ***	3	13.159	0.004 ***

8. Lithuania	3	24.568	0.000 ***	3	24.568	0.000 ***
9. Poland	3	23.219	0.000 ***	3	23.219	0.000 ***
10. Portugal	3	3.597	0.166	2	3.597	0.166
11. Slovak Republic	2	1.021	0.796	3	1.021	0.796
12. Slovenia	3	6.038	0.110	3	6.038	0.110
13. Spain	3	3.726	0.293	3	3.726	0.293
14. Türkiye	3	5.353	0.148	3	5.353	0.148
15. Brazil	3	5.445	0.142	3	5.445	0.142
Maximum Lag: 3 Information Criteria: Akaike		Panel Fisher 80.601 Asymptotic p-val. 0.000			Panel Fisher 85.237 Asymptotic p-val. 0.000	

Table 4.5a. Emirmahmutoğlu and Köse (2011) Causality Test Results (H0: UNEMP._RATE ≠> INT_ACCESS); *Note:* AIC: Akaike Information Criteria, SIC: Schwarz Information Criteria. *, ** and *** denote significance at the 10, 5 and 1 percent (%) level, respectively. Critical values are calculated with 1,000 bootstrap cycles.

Table 4.5a indicates that, according to the information criteria (IC) of AIC and SIC, there is a causal relationship from the unemployment rate to the internet access rate. According to the results of the Fisher test statistic and asymptotic p-value for the overall panel, the null hypothesis H_0 can be rejected unidirectionally at 5% (0.05) significance level. This result implies that there is a statistically strong and significant causality relationship between ICT (Information and Communication Technologies) and unemployment rate. The country-specific screening revealed that Latvia, Lithuania, and Poland were the examples that were significant at the 0.05 (%5) level according to both information criteria. Italy is significant only according to the Schwarz IC. In these countries, fluctuations in the unemployment rate result in discrepancies in the rate of Internet access. Consequently, fluctuations in the unemployment rate may result in alterations to the circumstances surrounding households' internet usage.

Table 4.5b shows that there is a causality from the Internet access rate to the unemployment rate according to the AIC and SIC information criteria (IC). In general, according to the Fisher test results of the panel model, H_0 hypothesis can be rejected unidirectionally at 5% significance level, it means that there is a statistically strong and significant causality relationship. At the same level of significance, Poland, Türkiye and Brazil are particularly significant according to both information criteria. Italy is found significant only according to Akaike IC. In these countries, variations in the rate of internet access cause changes in the unemployment rate. Therefore, service development practices for households' internet usage may reveal the desired results regarding policy management on the unemployment rate.

		AIC: Akaike Inf. Crt.			SIC: Schwarz Inf. Crt.	
Countries	**Lags**	**Wald Stat.**	**and Prob.**	**Lags**	**Wald Stat.**	**and Prob.**
1. Czech Republic	3	1.567	0.667	3	1.567	0.667
2. Estonia	3	0.178	0.981	1	0.222	0.638
3. Greece	3	4.591	0.204	3	4.591	0.204
4. Hungary	3	1.071	0.784	3	1.071	0.784
5. Israel	1	0.114	0.736	1	0.114	0.736
6. Italy	3	13.844	0.003 ***	2	3.686	0.158
7. Latvia	3	1.343	0.719	3	1.343	0.719
8. Lithuania	3	3.461	0.326	3	3.461	0.326
9. Poland	3	11.447	0.010 ***	3	11.447	0.010 ***
10. Portugal	2	1.309	0.520	2	1.309	0.520
11. Slovak Republic	3	4.270	0.234	3	4.270	0.234

12. Slovenia	3	3.246	0.355	3	3.246	0.355
13. Spain	3	2.787	0.426	3	2.787	0.426
14. Türkiye	3	8.934	0.030 ***	3	8.934	0.030 ***
15. Brazil	3	22.595	0.000 ***	3	22.595	0.000 ***
Maximum Lag: 3 Information Criteria: Akaike		Panel Fisher Asymptotic p-val.	63.709 0.000		Panel Fisher Asymptotic p-val.	56.720 0.002

Table 4.5b. Emirmahmutoğlu and Köse (2011) Causality Test Results (H0: INT_ACCESS => UNEMP._RATE); *Note:* AIC: Akaike Information Criteria, SIC: Schwarz Information Criteria. *, ** and *** denote significance at the 10, 5 and 1 percent (%) level, respectively. Critical values are calculated with 1,000 bootstrap cycles.

When the causality results of the Emirmahmutoğlu and Köse (2011) type seen in Tables 4.5a and 4.5b are analysed together, the causality flow between which countries is summarized in Table 4.6.

The direction of Effect	Countries
Unemp_Rate <=> Int_Access	Italy, Poland
Unemp_Rate => Int_Access	Latvia, Lithuania
Int_Access => Unemp_Rate	Türkiye, Brazil

Table 4.6. Causality Flow

According to Table 4.6, examples of bi-directional causality were found for Italy and Poland, i.e. the existence of an interaction between unemployment and Internet access. According to the other finding, evidence of unidirectional causality, i.e. from the unemployment rate to the Internet access rate, was found for Latvia and Lithuania. In these cases, developments in unemployment have an impact on internet access. Evidence for a unidirectional relationship where the Internet access rate affects the unemployment rate is found in the cases of Türkiye and Brazil. For these cases, developments in internet access also have an impact on the unemployment rate.

5. CONCLUSION

With the increasing contribution of endogenous growth models to the economic literature, the meaning and importance of technological developments in growth have become more emphasized. The meeting of technological developments with computer technologies after the 2000s has given a new impetus to growth. The diverse applications of information technologies have initiated a shift in endogenous growth dynamics for both capital and labour factors. This has subsequently influenced a broader range of variables within the context of economic systems.

It is evident that some of these effects are manifested in terms of unemployment and economic growth. On the one hand, the advent of information and communication technologies (ICTs) has the potential to significantly enhance production and growth. However, on the other hand, it can also have a detrimental impact on the unemployment rate. The primary rationale for this phenomenon is the gradual transfer of physical and mental labour from the labour force to automation and artificial intelligence technologies, which has the effect of reducing the employment requirement. This interaction has been the subject of constant debate in the academic literature.

Regarding the impact of the unemployment rate on IT, it is expected that a higher employment rate will correspond to a higher level of IT use. This is because people with jobs are more likely to use by having access the latest technological developments and amenities. Furthermore, access to and use of ICT also contributes to increased employment opportunities and overall economic growth.

This study also wanted to draw attention to the relationship between the information technology variable and the unemployment rate. In this context, the first variable is the rate of household access to the Internet. The reason for this is that the rate of household access to the Internet is increasing as an indicator of the development of information technologies.
In order to limit the dataset, countries with a high similarity to Türkiye in terms of Internet access rates are included. With such an implementation, it is aimed to work with a group of countries where the variance is quite low and consistent in model estimation. In this context, some OECD countries in general and Brazil which has a close contact with OECD were included in the study due to its high degree of similarity. The dataset is prepared as a panel data set for 15 countries and 17 years (2005-2021).

The bootstrap causality test proposed by Emirmahmutoğlu and Köse (2011) is used to investigate the causality relationship between Internet access rate and unemployment rate. Since this test works by taking into account the cross-sectional dependency, the existence of the relevant situation was questioned and it was understood that the dependency was present. In addition, homogeneity among panel cross-sections was also investigated and results supporting the existence of heterogeneity were obtained.

When the bootstrap causality results of Emirmahmutoğlu and Köse (2011) are analyzed as a country group, it is understood that there is a bidirectional causality relationship between ICT and unemployment. In this context, the Fisher test result can be strongly rejected based on statistical values. In other words, it can be said that ICT affects unemployment and vice versa.

Finally, as these causality tests allow us to obtain results on a country-by-country basis, we examined the results of the bidirectional causality analysis between the unemployment rate and the Internet access rate variables. While causality from the unemployment rate to the Internet access rate is found in Latvia and Lithuania, reverse causality is found in Brazil and Türkiye. Bi-directional causality is found in Italy and Poland.

As a policy recommendation, the unemployment variable is a variable that is generally considered in the context of outcomes. It is important for economies to manage unemployment by increasing access to and use of the Internet in areas of employment that are increasingly dependent on information and computing technologies. Therefore, policy implementation on the household internet rate, which represents information and computing technologies, is particularly especially important in countries such as Latvia, Lithuania, Türkiye and Brazil, which are seen to have effects on the unemployment rate. For the first two countries, changes in unemployment rates may have an impact on internet access, but in the event of unemployment, directing internet access to productive human capital growth will contribute to growth. In Türkiye and Brazil, depending on the finding that changes in internet access rates cause unemployment, the preparation of an employment structure that is resistant to problems that may lead to further increases in unemployment in the future should be ensured by the economic administration.

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