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The Impact of Technological Growth and Education Spending on Unemployment: Evidence From a Panel ARDL-PMG Approach

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ABSTRACT

Purpose: The aim of this study is to examine the short and long-term effects of technological development variables (R&D expenditures, high technology exports and patent applications) and public education expenditures on unemployment using the ARDL-PMG approach.

Methodology: Panel Ardl model, which is known as an error correction model and allows the diagnosis of short-and long-term relationships, is used. Do technological advances cause the unemployment rate to rise? And Is there a link between technological advances, expenditure on education and employment? In this study, which tries to answer these two questions, ARDL and DH panel causality tests were applied for the European Union.

Findings: According to the Panel ARLD-PMG analysis findings, while R&D spending increases unemployment in the short term, a 1% increase in R&D spending decreases unemployment by 1.42% over the long term. Similarly, a 1% increase in education expenditure decreases unemployment by 0.165% over the long term. Also, R&D spending and high technology exports have bidirectional causation, and bi-directional causality has been identified between unemployment and education expenditures.

Practical Implications: While the widespread use of Industry 4.0 provides significant job savings, it creates pressure on employment. Policymakers should set more careful policies to support employment. The possibility of technological unemployment spreading can cause individual and social instabilities and problems.

Originality: The contribution of the study to the literature allows us to see the effectiveness of public education expenditures while determining the effect of technological developments on unemployment.

Keywords: Technological Unemployment, Industry 4.0, Panel ARDL-Pmg, Panel Causality Test.

JEL Codes: O33, E24, C23.

Teknolojik Büyüme ve Eğitim Harcamalarının İşsizlik Üzerine Etkisi: Panel ARDL-PMG Yaklaşımından Kanıtlar

ÖZ

Amaç: Bu çalışmanın amacı teknolojik gelişme ölçütleri (Ar-Ge harcamaları, yüksek teknoloji ihracatı ve patent başvuruları) ve kamu eğitim harcamalarının işsizlik üzerine kısa ve uzun vadeli etkilerini ARDL-PMG yaklaşımı kullanarak incelemektir.

Metodoloji: Hata düzeltme modeli olarak bilinen, kısa ve uzun dönemli nedensellik ilişkilerinin teşhisine olanak sağlayan Panel Ardl modeli kullanılmaktadır. Teknolojik gelişmeler işsizlik oranının artmasına neden oluyor mu? Teknolojik ilerlemeler, eğitim harcamaları ve istihdam arasında bir bağlantı var mı? Bu iki soruya cevap bulmaya çalışan bu çalışmada, Avrupa Birliği için ARDL ve DH panel nedensellik testleri uygulanmıştır.

Bulgular: Panel ARLD-PMG analiz bulgularına göre Ar-Ge harcamaları kısa dönemde işsizliği artırırken, uzun dönemde Ar-Ge harcamalarındaki %1'lik bir artış işsizliği %1,42 oranında azaltmaktadır. Benzer şekilde, eğitim harcamalarındaki %1'lik bir artış, işsizliği uzun vadede %0,165 oranında azaltmaktadır. Ayrıca, Ar-Ge harcamaları ve yüksek teknoloji ihracatı çift yönlü nedenselliğe sahiptir ve işsizlik ile eğitim harcamaları arasında çift yönlü nedensellik tespit edilmiştir.

Sonuç ve Öneriler: Endüstri 4.0'ın yaygınlaşması önemli iş tasarrufları sağlarken, istihdam üzerinde baskı yaratıyor. Politika yapıcılar, istihdamı desteklemek için daha dikkatli politikalar belirlemelidir. Teknolojik işsizliğin yayılma olasılığı, bireysel ve sosyal istikrarsızlıklara ve sorunlara neden olabilir.

Özgün Değer: Çalışmanın literatüre katkısı, teknolojik gelişmelerin işsizlik üzerindeki etkisini belirlerken kamu eğitim harcamalarının etkinliğini görmemizi sağlamaktadır.

Anahtar kelimeler: Teknolojik İşsizlik, Endüstri 4.0, Panel ARDL-Pmg, Panel Nedensellik Testi.

Jel Sınıflandırması: O33, E24, C23.

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1. Introduction

Technological developments are the greatest driving force that enables change in the modern world (Betz, 2013: 51). These developing technologies may emerge in a new industry or realize new functionalities between existing industries. However, economic developments linked to basic technological innovation may not be successful in increasing employment while providing job opportunities for new industries. Because technological developments are continued by progressing in a way that saves labor power in most industries. Acemoglu (1997a) said on education-employment and technology relationship stated that if the future workforce is uneducated or does not have sufficient education, the profitability of new technologies will decrease.

Technological developments took place in the labor market with mechanization after the industrial revolution. Every innovation that has emerged until today has made it necessary for human beings to adapt to this innovation, that is, to learn new things. Technology and education have become important mechanism that triggers each other. As education increases, innovation increases and technology improves. On the other hand, as technology develops, human has a need to learn increases. However, as a result of scientific developments in recent years, autonomous production and artificial intelligence are changed the current employment structure.

The industrial revolution has enabled people to be employed in the industrial sector rather than in the agricultural sector. However, new technologies are becoming more and more autonomous to produce more products with less labor in order to minimize costs. And besides, technologies that have developed in the last decade are insufficient to create new employment areas. The creative destruction effect of Schumpeter has slowed down with the development of information and communication technologies, autonomization and artificial intelligence. In short, it is seen that people with employment surplus in existing sectors become harder to be employed in a new sector, increasing technological unemployment or causing unemployment for a longer period.

The aim of the study is to examine the labor market impact of technological progress (not seen as a problem for people’s well-being until now) and education spending. Technological developments until the 21st century generally triggered economic growth, reduced unemployment and enabled people with higher education levels to be employed. In short, technological developments have brought society to greater prosperity until recent years. Because the productivity and salaries of the labor force were increasing with technological developments. However, Ford (2015) says "calculations made according to inflation figures in America revealed that the productivity of a production worker increased 107% in 2013 compared to 1973". And despite the increase in productivity, it had been determined that workers' salaries were 13% lower. In short, technological developments have increased productivity in the field of production over the past 40 years, enabling a worker to produce twice as much for fewer wages. This shows that the creative destruction of the Schumpeter is no longer functioning as before, and those technological developments can now lead to an increase in unemployment rates rather than a decrease.

The European Union is an important sample consisting of developed countries. It has been chosen as an ideal country group to work on technological unemployment due to both its technological developments and the investments they have made in education. Figure 1, diverse unemployment rates belonging to the total of the European Union are given. According to this, although unemployment was at its lowest level before the 2008 crisis, it recovered to its previous level only ten years after the crisis. When unemployment is examined by education level, the education level with the highest unemployment is the unemployment level of people with basic education. But, while young people get a better education, they face a high unemployment problem especially in times of economic crisis.

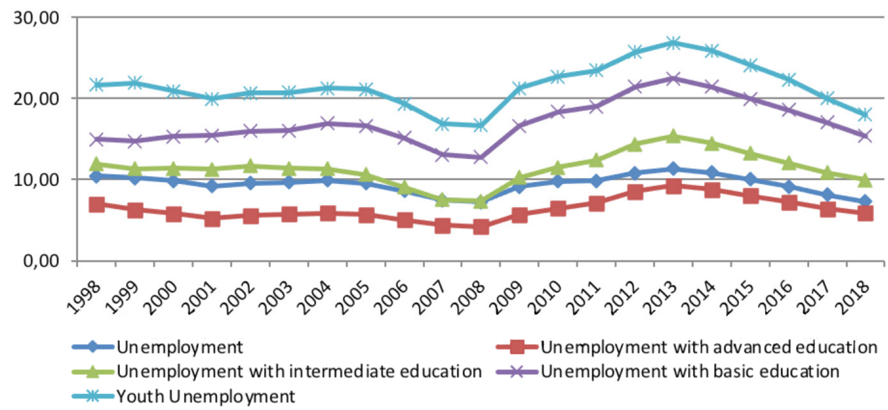

Figure 1. European Union Fundamental Unemployment Rates (1998-2018)
Source: World Bank (https://data.worldbank.org)

Figure 2 shows the EU Patent Applications (1995-2018). According to world bank data, the total number of patents produced in the European Union since 1980 is 3,208,898. Between 1995 and 2018, 2,115,629 and an average of 88,151 patents per year were produced. The number of patents produced by Germany alone is 1,615,012 since 1980 and 1,134,761 since 1995. On average, Germany alone produced half of the total number of patents in the European Union. And in 2018, this number is now 52%.

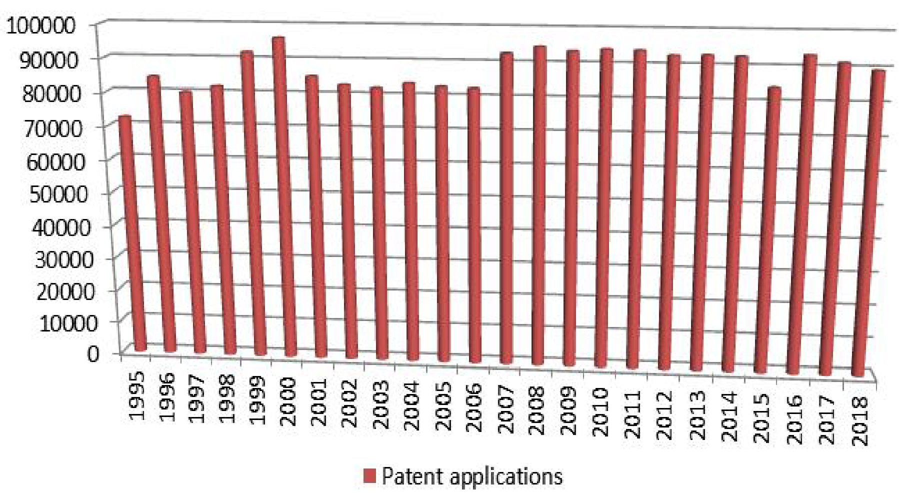

Figure 2. EU Patent Applications (1995-2018)
Source: World Bank (https://data.worldbank.org)

The study is based on the data of 27 EU member countries between 1995 and 2018. In order to reveal the effect of technological development and education expenditures on total unemployment; R&D expenditures, patent applications, high technology exports and education expenditure data have been used. After investigating the theoretical framework in the following sections of the study, a general review of the literature studies examining the association between technological development and unemployment is given in the third section. While the 4th section includes methodology and empirical findings, in the last section, existing theory and empirical findings are evaluated and policy recommendations are made.

2. Literature Review

Technological developments and unemployment issues have popular in economic literature for many years. Technological developments are generally measured by variables such as innovations, R&D spending, patent applications, HTE and ICT spendings. The literature on the studies of the impact of Technological developments on (un)employment has been extensively studied using different methodologies for various time periods and countries.

Technological unemployment, a problem that has been discussed for nearly 200 years, can say started with the attack of textile workers on mechanical looms during the Ludist rebellion that started in 1811 with the concern of people's job loss and low wages. (Brynjolfsson & McAfee, 2014). Say (1821) on this topic, technological development not only leads to processing but to product innovation which inevitably calls for new jobs to be generated. As emphasized later in creative destruction by Schumpeter (1942). Likewise, Ricardo (1821) emphasized that the lowering in costs due to technical developments could result in improved income, provided the prices of commodities do not decline briefly, and that this condition could improve jobs by increasing investment and output. Marx (1963) argued that adequate employment in industries that manufacture is unlikely to be produced, inter alia, newly invented and labor-saving machines. Keynes (2016) defined technological unemployment as unemployment caused by the speed of realization of new discoveries that provide savings in the use of labor, higher than the speed of opening new fields to the workforce. It stated that it is a new disease that will definitely be heard in the coming years in 1930. Acemoglu (1997b) The typical working time of workers may have decreased in advanced countries (the US and the UK e.g.), and this result suggests that the pace of technological progress may have unpredictable consequences.

Current literature research on technological development and (un) employment with differing methodological viewpoints and extent, Fagerberg et al. (1997), Davis (1998), Mortensen and Pissarides (1998), Acemoglu (1997a, 1997b and 2002), Chennels and Van Reenen (2002), Spezia and Vivarelli (2002), Greenan (2003), Bogliacino and Pianta (2010), Lachenmaier and Rottmann (2011), Bogliacino et al. (2012), Evangelista & Vezzani (2012), Ciriaci et al. (2016) and Kim et al. (2017) have been studied.

There are studies in the current literature that determine the effects of technological growth on employment. Greenan and Guellec (2000) have established a positive relation between innovations (product and process) and jobs at the organizational grade, using data from the French manufacturing sector for the period 1986–1990. Postel - Vinay (2002) concludes that faster (slower) technical transformation often has a positive (negative) and theoretically important short-term impact on jobs, leading to a short-term decrease (increase) in work breakdown. Piva and Vivarelli (2004) found proof to suggest a substantial and optimistic effect of innovation on firm-level jobs. Hall et al. (2008) reported that product developments of Italian manufacturing firms generally impact jobs positively and the position of process innovations is unsure. Lachenmaier and Rottmann (2011) indicate that innovation has a gradual positive strong effect on wages, and process innovations have a greater effect than innovation in goods. Evangelista et al. (2014) concluded that digital transformation can accelerate progress in production and welfare and that inclusive policies can successfully serve to bridge the difference between the population's most desired and marginalized parts. Kim et al (2017) aimed to monitor the relative amount of jobs that are or are not sensitive to computerization in the future. The second model, which involves the development of new technological jobs, shows that a substantial share of the total jobs in the future will consist of new jobs that give people employment.

Antonucci and Pianta (2002) showed that technological transition has a negative cumulative effect on jobs in the manufacturing sectors in five European countries where diverse technological strategies are debated. Feldmann (2013) found that rapid technological change temporarily increased unemployment during a transition period. It is concluded that this negative effect lasts for an average of 3 years and then disappears.

Onuoha and Moses (2019) found that spending on infrastructure and education in African countries reduces the unemployment rate. and Pirim at al. (2014) concludes that, in the long run, investment in human capital can play an important role in reducing unemployment rates. In this study, education expenditures are included in the study to see how it has an effect on unemployment in the short and long run. The contribution of the study to the literature allows us to see the effectiveness of public education expenditures while determining the effect of technological developments on unemployment.

Table 1 presents a summary of empirical studies examining the effects of technological developments on employment and unemployment. Studies using different econometric analyzes as methods generally used R&D and innovation as technology variables, and as a result, found results that positively and negatively affected unemployment.

Table 1. Literature review on the nexus between technological development and (un)employment

Author(s)	Time	Methodology	Technology variable	Country group	Findings
Greenan and Guellec (2000)	1986-1990	Regression (OLS)	Innovation	French industry 15,186 firms	Innovating companies and industries generate more jobs than those over the medium term (5 years). Innovation in the process is more about growth in employment than innovation in goods at the enterprise level, although this is true at the market level.The findings of the study help the vision of creative destruction.
Piva and Vivarelli (2004)	1992–1997	Balanced panel GMM-SYS	The value of gross innovative investment	Italian manufacturing firms	The impact of innovation on job creation emerges positively after adjusting for different effects (time, industry, size of the firm and geographically fixed effects).
Mastrostefano and Pianta (2009)	1994-2001	Generalised least squares (GLS) fixed effects panel, ordinary least squares (OLS)	Innovation	10 industrial sectors and 10 countries in Europe	Strong demand and an increase in value-added are essential conditions for new employment. In the long run and in high-innovation sectors, wage rises do not have a negative effect on jobs. Fast-growing industries point to a virtuous cycle of demand and production growth, employment and wages.
Bogliacin and Pianta (2010)	1994-2004	Revised Pavitt classes	Community Innovation Survey data	8 European countries	Efforts to compose new products and markets cause new jobs. On the other hand, discovering labor-saving method advancement contributes to job losses.
Lachenmaier and Rottmann. (2011)	1982–2002	Dynamic panel GMM	Innovation R&D (Product an Process)	German manufacturing firms	Innovation has shown a positive impact on jobs. In addition, innovations display a positive effect on work with a lag and creative methods have a greater impact than product innovations.

Coad and Rao (2011)	1963-2002	Panel Quantile analysis	R&D expenditure Patent applications	US manufacturing industries	Considering the size of the firm, the study shows that innovative activity in large firms results in a more positive increase in employment than small firms.
Bogliacino et al. (2012)	1990–2008	Least Squares Dummy Variable Corrected (LSDVC) estimator	R&D expenditure	677 European companies	It was concluded that the positive effect of R&D spending on jobs is evident in sectors with high product innovation (services and high-tech manufacturing).
Feldmann (2013)	1985-2009	Panel regression	The ratio of triadic patent families to population	21 industrial countries	Rapid technological change causes the unemployment rate to increase. However, it has been determined that the detrimental effect on unemployment lasts for an average of 3 years and then disappears. As a consequence, rapid technological change has been shown to raise unemployment over a transitional period, not permanently.
Harrison et al. (2014)	1998–2000	Panel regression	Innovation	European countries (France, Germany, Spain and the UK) random samples of manufacturing and services (about 20000 companies)	Process innovations do not decrease jobs. Over time observed, certain process advances have eliminated some of the jobs. However, the rise in demand for old goods has been found high enough to compensate for all this. Product innovations are growing the number of workers.
Evangelista et al. (2014)	2004-2008	Dynamic panel	ICT	EU-27 countries	The use of ICT and digital enhancement have significant economic impacts, specially on jobs, even favoring the participation of ‘disadvantaged groups in the labor market. In addition, DE is more important for GDP growth, for employment growth, for growing the employment rate of women and for reducing long-term unemployment.
Kwon et al. (2015)	2009-2011	structural equation modelling (SEM) method	Innovation	532 manufacturing firms in South Korea	The product innovation strategies of companies have positive effects in order to create employment. However, the process innovation strategies of companies have a negative effect on creating new jobs.
Ciriaci et al. (2016)	2002–2009	Panel quantile regression	Innovation R&D	3304 Spanish firms dataset	Innovative firms generate above-average employment. Innovation is also a vehicle for rising jobs and performing well in Spain.
Matuzeviciute et al. (2017)	2000–2012	Panel GMM	Triadic patent families R&D Expenditure	25 European countries	The macro-analysis reveals that technical advances had no impact on unemployment.
Van Roy et al., (2018)	2003–2012.	GMM-SYS estimation	Weighted patents	20,000 European patenting firms	The effect of innovative activities on jobs demonstrates the labor-friendly essence of innovation at the firm stage. However, the positive impact on jobs shows that it is statistically major just in the production sector of high and medium technology.
Yildirim et al. (2020)	1998–2015	Panel threshold analysis	Patent applications	12 EU countries	Technological innovation has been increasing the worklessness proportion for both country groups in all regimes of reform level. But, it has demonstrated to increases unemployment more at the low innovation levels.

In the literature, studies examining the technology-unemployment relationship at micro and macro levels and in various periods and countries have been examined. There are studies that mostly do research with linear models, and most of these studies ignore the time dimension and examine a short time interval. In this study, a single technology variable was not adhered to and 3 basic technology variables were included in the model to see the employment effects of innovation. In addition, due to the increase in educated unemployment in recent years, it was included in the model to examine the effectiveness of public education expenditures. Since long-term data are preferred in this study, and in this case, the ARDL method, which reveals the short-and long-term relationship more clearly, is preferred. In addition, the use of the DH causality test, which takes into account the causal size of the results, provides a better evaluation of the results of the study.

3. Empirical analysis

3.1 Data

The analysis incorporates annual data for European Union covering the period 1995 to 2018[1]. On data availability, countries and time periods are chosen. To find the relationship between technology, unemployment and education spending, all data except the unemployment were used as a proxy variable. Variables used in the model, dependent variable U is total unemployment; The independent variables R&D, Patent, HTE and EE represent R&D expenditures (% GDP), residents' patent applications, high technology exports and government expenditures for education (% GDP), respectively. All variables were obtained from the World Bank-World Development Indicators (WDI) database. All variables are in logarithmic form.

Table 2. Data set - definition and sources

Variable	Definition	Source
LnU	Unemployment	WB
LnPatent	Patent applications, residents	WB
LnR&D	Research and development expenditure	WB
LnHTE	High-technology exports	WB
LnEE	Government expenditure on education	WB

* Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom.

3.2 PMG Method

The purpose of this study is to investigate the short and long-run links between technological development metrics (R&D expenditure, high technology exports and patent applications), public education expenditure and unemployment by using this ARDL-PMG approach, as introduced by Pesaran et al. (1999). The ARDL approach allows for the diagnosis of short- and long-term relationships and can be classed as an error correction model. This approach is preferable because it can test possible long-term relationships irrespective of the integration order of the variables, whether I (1) or mutually integrated (I (0) and I (1)). Also, this approach offers consistent and efficient estimators because it eliminates the problems resulting from endogeneity by the inclusion of lag length for endogenous and exogenous variables. Lastly, the PMG approach supposes heterogeneity of the short-term coefficients, whereas the long-term coefficients are supposed to be identical and homogeneous for all individuals in the panel (Attaoui et al., 2017).

The unrestricted specification for the ARDL(p,q) model of equations for t = 1, 2, …, T, time periods and i =1,…,N countries for the dependent variable Y is:

$$\Delta Y_{it} = \alpha_{1i} + \gamma_{1i}\, Y_{1,it-1} + \sum_{\iota=2}^{k} \gamma_{1i}\, X_{1,it-1} \sum_{j=1}^{p-1} \delta_{ij}\, \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \sum_{\iota=2}^{k} \delta_{ij}\, \Delta X_{i,t-j} + \varepsilon_{it} \qquad (1)$$

In Equation.1, $\boxed{\varepsilon_{it}}$ is the error term, Y is the dependant variable and X is exogenous variable, with *I* = 1,2,3,4. The short-term dynamic relationship is obtained by estimating an error correction model (ECM). The ECM is defined as follows:

$$\Delta Y_{it} = \alpha_{1i} + \sum_{j=1}^{p-1} \beta_{ij}\, \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \sum_{\iota=2}^{k} \beta_{ij}\, \Delta X_{i,t-j} + \mu_{1i} ECT_{1,it-1} + \varepsilon_{it} \qquad (2)$$

In Equation.2, the residuals ε_{it} are independent and normally distributed with zero mean and constant variance, ECT is the error correction term defined by the long-term relationship and μ_i are indicates the speed of adjustment to the equilibrium level. In addition, as unemployment dependent variable, the ARDL-PMG model is defined as follows:

$$\Delta U_{it} = \alpha_{1i} + \gamma_{1i}\, U_{1,it-1} + \gamma_{2i}\, R\&D_{1,it-1} + \gamma_{3i}\, Patent_{1,it-1} + \gamma_{4i}\, HTE_{1,it-1} + \gamma_{5i}\, EE_{1,it-1}$$

$$+ \sum_{j=1}^{p} \beta_i \Delta U_{it-1} + \sum_{i=0}^{q} \beta_{1i} \Delta R\&D_{it-j} + \sum_{i=0}^{q} \beta_{2i} \Delta Patent_{it-j} + \sum_{i=0}^{q} \beta_{3i} \Delta HTE_{it-j}$$

$$+ \sum_{i=0}^{q} \beta_{4i} \Delta EE_{it-j} + \varepsilon_{1it} \qquad (3)$$

In Equation. 3, *i* and *t* indices symbolize countries and time period (t = 1995, …… ..2018) respectively. β1, β2, β3 and β4 are the slope factor for the variables of R&D spending, patent applications, HTE and public education expenditures, respectively. β1 of a 1% change in R&D spending; β2 1% change in patent applications; β3 measures the effect of a 1% change in high technology exports and β4, 1% change in education expenditures on total unemployment.

3.3 Emprical results

The annual data used in the empirical part is derived from Table 2, includes all the variables used in the econometric analysis, organized with brief descriptions and the data sources. Table 3 offers some descriptive statistics and provides a complete overview of the samples used in the study.

Table 3. Descriptive Statistics

Variables	Obs.	Mean	SD	Min	Max
lnU	672	0.904335	0.200904	0.256477	1.438795
lnR&D	672	0.064815	0.268430	-0.696264	0.592601
lnPatent	672	2.612800	1.152192	0.000000	4.713793
lnHTE	672	4.949482	4.984365	0.000000	11.33505
lnEE	672	0.525586	0.309656	0.000000	0.932451

3.3.1. Cross Section Dependency Test

Since panel data discuss the actions of countries, industries and companies over a specific period of time, there may be a correlation relation in these units. For this reason, before determining the causality analysis method to be applied, the presence of cross-section dependency between series should be tested. In the study, the Pesaran (2004) Cross Section Dependence (CD) test, which is one of the cross-section dependency tests frequently used in panel data analysis, was preferred. Table 3 contains CD test results for the variables used in the model for sample countries.

Table 4. CD test results

Variables	EU countries
lnU	22.00***
lnPatent	1.70**
lnR&D	26.67***
lnHTE	95.21***
lnEE	38.18***

** and * denotes 1% and 5% statistically significance levels.

3.3.2. Unit Root Test

Initially, traditional unit root testing includes the low power problem for non-constant data. The primary motive for panel data unit root testing is to use the additional details given by clustered cross-section time series in order to maximize test power as suggested in conventional unit root testing. In table 5, analysis one of the most common unit root test units known as Im, Pesaran and Shin. IPS estimates the t-test for unit roots in heterogeneous panels. Also, it allows for individual effects, time trends, and common time effects (Im et al., 2003). According to Table 5, it has been observed that all variables become stationary at the first difference, and the null hypothesis is rejected at the I(1) level at the 1% significance level.

Table 5. IPS Unit Root Test Results

	Trend	Intercept	Trend	Intercept
	Level		**First Difference**	
lnU	-2.8823[a]	-1.8304 [b]	-6.4815[a]	-3.7870 [a]
lnPatent	0.5021	1.6200	-10.087 [a]	-8.2730 [a]
lnR&D	1.1554	2.3102	-8.5566 [a]	-7.2320 [a]
lnHTE	3.2125	0.9205	-9.7317 [a]	-5.7913 [a]
lnEE	-4.7312 [a]	-0.6667	-16.928 [a]	-16789 [a]

Note: The calculation of optimum lag is based on the Bayesian Knowledge Criterion (SBIC). b and a denotes 5% and 1% statistically significance levels.

3.0.3. Panel Cointegration Test

Panel data unit root analysis showed that all variables in the model were stationary at their first difference. This makes it possible to examine the long-run relationship between the variables. Pedroni (1999, 2004) and Kao (1999) cointegration tests were applied to determine whether the variables act together in the long run. Table 6 shows the results of the panel cointegration test. The findings obtained as a result of these tests indicate that the variables in the system act together in the long run, by rejecting the null hypothesis.

Table 6. Panel Cointegration Results

Pedroni residual test	Statistic	Prob.
Md-pp statistic	5.4470	0.0000
Pp-statistic	3.1564	0.0008
ADF-statistic	3.5227	0.0002
Kao residual test	t statistic	Prob.
ADF-statistic	-5.002	0.000

Note: Estimates include constant terms. The maximum delay length is set to 2 according to the SIC.

3.0.4. Panel ARDL PMG Test

The most suitable ARDL model was selected according to Akaike Information Criteria and Schwartz Bayesian criteria to order the delays for the model. The said results are shown in Figure 3. When the figure is examined, ARDL (2, 2, 2, 2) was determined as the appropriate model for the lags.

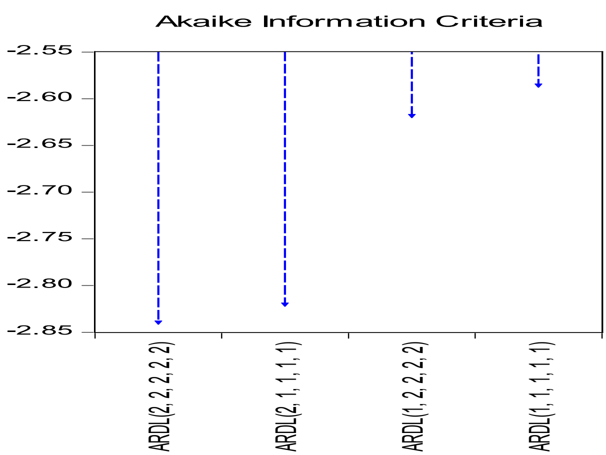

Figure 3. Determining Delay Length

Table 7. PMG Long Run and ECM Estimation (Unemployment is dependent variable)

Long-run Equation			
Variables	**Coefficients**	**t-statistic**	**P-value**
lnPatent	0.6109***	7.8030	0.0000
lnR&D	-1.4250***	-5.1798	0.0000
lnHTE	0.0156***	7.9083	0.0000
lnEE	-0.1650***	-3.7515	0.0002
ECM Equation			
Variables	**Coefficients**	**t-statistic**	**P-value**
ECT(-1)	-0.2199***	-5.1798	0.0000
Δ(U(-1))	0.3874***	7.1884	0.0000
Δ (R&D)	0.2456*	1.7837	0.0753
Δ (R&D (-1))	0.0716	0.5578	0.5773
Δ (Patent)	0.0026	0.0287	0.9771
Δ (Patent(-1))	-0.1470*	-1.6987	0.0902
Δ (HTE)	-0.0087***	-4.3332	0.0000
Δ (HTE(-1))	-0.0065**	-2.5424	0.0114
Δ (EE)	0.0520***	3.3095	0.0010
Δ (EE(-1))	0.0416	1.4379	0.1513
C	-0.1361***	-3.4833	0.0006

Δ is the first difference operator. ***, **, and * indicate significance levels p<0,01, p<0,05, and p<0,10 respectively.

Table 7 shows the short and long-term relationships of the model estimated within the framework of the ARDL method. Accordingly, the coefficient of the variable representing the one-period lagged value of the series of error terms obtained from the long-term relationship, ie the error correction coefficient is between 0 and -1 as expected and is statistically significant. This means that there is long-term cointegration among the variables in model 1, and short-term deviations will approach equilibrium in the long run. Error correction coefficient of -0.2199 was determined in the analysis. Accordingly, approximately 22% of the deviation in the analysis disappears by the end of the first year. The results reveal a significant relationship between technological improvements, education expenditure, and unemployment in both the short- and the long term. When unemployment is the dependent variable, patent and HTE have a negative and significant effect on unemployment over the long term. Although education expenditures and R&D expenditures positively affect unemployment over the long term. According to the analysis findings, while R&D spending increases unemployment in the short term, a 1% increase in R&D spending decreases unemployment by 1.42% over the long term. Similarly, a 1% increase in education expenditure decreases unemployment by 0.165 % over the long term. On the other hand, the patent applications and High tech export increases unemployment in the long term (respectively 0,61% and 0,015%).

4. Panel Causality Test

In order to ascertain the asset of a causal relationship between the series, the causality method established by Dumitrescu and Hurlin (2012) is used. The advantages of this method are that it can take into account both cross-sectional dependency and heterogeneity among countries that make up the panel, the unbalanced panel data yield successful outcomes and the time dimension can be used where the cross-section dimension is greater (or less).

Table 8. DH Panel Causality Test Results

Hypothesis	**U→ R&D**	**U→ Patent**	**U→ HTE**	**U→ EE**	**R&D → Patent**	**R&D → HTE**	**R&D →EE**	**Patent →HTE**	**Patent →EE**	**HTE→ EE**
Z- bar	6.89	2.58***	0.74	1.74*	7.75	2.50**	1.41	2.31**	2.48**	0.28
Decision	NO	**YES**	NO	**YES**	NO	**YES**	NO	**YES**	**YES**	NO
Hypothesis	**R&D → U**	**Patent →U**	**HTE→ U**	**EE→ U**	**Patent → R&D**	**HTE→ R&D**	**EE→ R&D**	**HTE→ Patent**	**EE→ Patent**	**EE→ HTE**
Z- bar	2.71***	1.47	3.48***	1.78*	7.95	12.39***	0.97	6.71	-0.13	29.34***
Decision	**YES**	NO	**YES**	**YES**	NO	**YES**	NO	NO	NO	**YES**

***, ** and * denotes 1%, 5% and 10% statistically significance levels.

Table 8 displays the findings of the causality evaluation of the DH panel in EU countries. As seen in the table, there is a one-way relationship of causality between technical growth and unemployment in EU countries. R&D spending and HTE have been identified as the causes of unemployment. In other words, an increase in these two technology variables increases the unemployment rate. On the other hand, R&D spending and HTE have bidirectional causation. The existence of a system that triggers each other between technological development and technology exports is in line with the theory. The causality result of patent increases affecting the unemployment rate could not be found. However, we can say that this is due to the delayed transformation of patent applications into production. Bi-directional causality has been identified between unemployment and education expenditures. In addition, unidirectional causality has been found from patent applications to education expenditures.

5. Conclusions and policy recommendations

This study examines technological growth and the educational expenditure variables in EU economics, which influence unemployment. For this purpose, R&D spending, patent applications, HTE and public education expenditures variables have been used as arguments. In this study, the 1995-2018 observation period was examined by the Panel ARDL method. In addition, the relationship of causality was investigated.

As the outcomes of ARDL are analyzed, R&D and education investments have an increasing impact on unemployment in the short term and a decreasing effect in the long term. Patent applications and High technology exports increase unemployment in the long-term. Owing to the time and cost issues of patent manufacturing, the impact on jobs is delayed. However, when each new patent is generated in a way that needs fewer labor resources, it raises long-term unemployment. Moreover, since HTE is the result of spending on R&D and patent production, it is a significant variable with a long-term effect. However, the rise in exports of these goods, as an explanation for growing unemployment, suggests that the technology is advanced and that the progress in manufacturing and process is more advanced. In the literature, imports of such items improve production and jobs because they are investment goods. This study's r&d expenditures result is similar to the results of Lachenmaier and Rottmann (2011), Greenan and Guellec (2000) and Piva and Vivarelli (2004), who found that the technology contributing to an increase in employment. However, the results of HTE and patent applications show that these technology variables reduce employment. In addition, as education expenditures increase employment, In addition, our finding that investment in education can play an important role in reducing unemployment rates result is similar to the results of Onuoha and Moses (2019) and Pirim et al. (2014).

As per the findings of the causality panel, there has been a one-way connection of causality between technical growth and unemployment in EU countries. R&D expenditures and high technology exports have been identified as the causes of unemployment. In other words, an increase in these two technology variables increases the unemployment rate. On the other hand, R&D spending and HTE have bidirectional causation. The existence of a system that triggers each other between technological development and technology exports is in line with the theory. the causality result of patent increases affecting the unemployment rate could not be found. However, we can say that this is due to the delayed transformation of patent applications into production. There is a one-sided causality from unemployment to patent applications. In addition, unidirectional causality has been found from patent applications to education expenditures.

There has been identified between unemployment and education expenditures Bi-directional causality. Here, the increase in unemployment affects the increase in human capital expenditures. The causality from unemployment to education expenditure is in accordance with the literature. However, determining the increase in education expenditures as the reason for the increase in unemployment is a serious problem. We can explain this in two ways. First, the reason for the high youth unemployment problem is technological unemployment. Every development, especially in the field of artificial intelligence, causes thousands of workers to lose their jobs or to have no need for new workers. As a second reason, the efficiency of education expenditures may be questioned.

The scientific process progresses exponentially since the industrial revolution. Until the 21st century, technological advances lowered the cost of the basic needs of people, increased disposable incomes, and created new demands and jobs. The advancement of technologies such as automation, digitalization, deep learning, driverless cars, 3 printers, robots, interactive voice response systems, virtual money and banks over the last 20 years has made human life simpler. However, these advances will hamper many jobs, in particular in the industrial and service industries.

The fact that technological developments make human life cheap and easy increases welfare. However, policymakers should set more careful policies to support people's employment. The possibility of technological unemployment to become widespread can cause individual and social instability and problems. Finally, it should be taken into account that as the constructive power of technology increases, its destructive power also increases. Working together instead of struggling with machines will lead to better outcomes. It is getting harder and harder for governments to manage technologies and technology companies every day. There is also a need to define and enforce policies that will better guide the process.

In the future, researchers who will study technological unemployment can access and include micro-innovation data that affect industrial production and increases productivity and can obtain a more comprehensive analysis opportunity. In addition, if informatics variables can be included in the model, the effects of technology on employment can be revealed more clearly. In this context, new analysis methods such as quantile may offer a different and more detailed perspective.

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