Araştırma Makalesi

The Rise of Technology for the Future Labor Force: The Nexus between Technology and Unemployment in OECD Countries

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Abstract: This paper studies the impact of technology on unemployment, focusing on OECD countries. Obviously, there is no consensus in the literature about the future impacts of technological breakthroughs on employment. The clear point is that the current skills will not match the occupations of the future and the companies will need many new skills. Technological advances will create millions of jobs but the other millions of jobs will disappear in this process. The purpose of this paper is to point out the ultimate impact of technology on unemployment at the macro level, which is quite insufficient quantitatively, related to the impact of technology on employment. In this paper, the nexus between technology and unemployment has been analyzed with S-GMM estimator in 33 OECD member countries for the years 2005-2018. According to panel data analysis, it is seen that all the control variables but GDP are statistically significant. The independent variable, IP5 patents representing technology is statistically highly significant and has a negative correlation with the dependent variable. The empirical results show that a 1% increase in technology reduces unemployment by 0.07%.

Keywords: Unemployment, Technological Change, Automation, Innovation, Regional Studies.
JEL Classification: L0, O3, J2.

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Geleceğin İşgücü İçin Teknolojinin Yükselişi: OECD Ülkelerinde Teknoloji ve İşsizlik Arasındaki Bağlantı

Öz: Bu makale, OECD ülkelerine odaklanarak teknolojinin işsizlik üzerindeki etkisini incelemektedir. Literatürde teknolojik atılımların istihdam üzerindeki gelecekteki etkileri hakkında bir fikir birliği olmadığı açıktır. Açık olan nokta, mevcut becerilerin geleceğin meslekleriyle örtüşmeyeceği ve şirketlerin birçok yeni beceriye ihtiyaç duyacağıdır. Teknolojik gelişmeler milyonlarca iş yaratacak ancak yine milyonlarca iş bu süreçte yok olacaktır. Bu çalışmanın amacı, teknolojinin istihdam üzerindeki etkisi ile ilgili olarak, literatürde nicel olarak oldukça yetersiz olan makro düzeyde bir çalışma ile teknolojinin işsizlik üzerindeki nihai etkisine işaret etmektir. Bu çalışmada, 2005-2018 yılları için 33 OECD üyesi ülkede teknoloji ve işsizlik arasındaki ilişki S-GMM tahmincisi ile analiz edilmiştir. Panel veri analizine göre GSYİH dışındaki tüm kontrol değişkenlerinin istatistiksel olarak anlamlı olduğu görülmektedir. Bağımsız değişken, teknolojiyi temsil eden IP5 patentleri istatistiksel olarak oldukça anlamlıdır ve bağımlı değişkenle negatif bir korelasyona sahiptir. Ampirik sonuçlar, teknolojideki %1'lik bir artışın işsizliği %0,07 oranında azalttığını göstermektedir.

Anahtar Kelimeler: İşsizlik, Teknolojik Değişim, Otomasyon, İnovasyon, Bölgesel Çalışmalar.

JEL Sınıflandırması: L0, O3, J2.

Introduction

The increasing number of industrial robots in the production process has raised concerns about its job-saving impact on employment. The age of Industry 4.0 brings smart technologies in every aspect of life, production, trade and services. Robots are getting smarter day by day thanks to machine learning and artificial intelligence. This technological revolution is highly different, profound and faster than the previous ones. Integrated technologies feed each other and electronic devices meet in a common network with the Internet of Things (IoT). In this way, it is possible to operate the heater remotely or to start the washing of the ready-made laundry in the machine before arriving at home. It becomes possible to store the data obtained from the devices connected with the IoT in cloud technologies and to access the information needed with big data. These technologies appear in everyone's daily life in the form of Amazon Prime recommending movies that you will like or Google Academic recommending articles that will interest you or Google Ads recommending products you are considering buying.

The momentum in recent technologies has increased concerns and interest in the impact of innovation on unemployment. However, these concerns about the effects of technology on jobs are not new. The teardown of machines by textile workers in England in 1811 brought about the first debate that technology would replace people in factories. Adam Smith remarked on increasing labor productivity, the effect of the division of labor and specialization (Smith, 1776). Ricardo pointed out the change in skill requirements caused by mechanization, and claimed that this change would cause a mismatch of old skills with new jobs (Ricardo, 1817). In addition to technological unemployment, this case would cause frictional and structural-unemployment as well (Freeman and Soete). Karl Marx took a different approach to mechanization and emphasized how the capitalist system benefited from increasing efficiency in the production process (Bimber, 1990). The renowned economist John Maynard Keynes warned about technological unemployment in 1931 (Schwab, 2016).

Though the belief that machines replace manpower was dominant during the very beginning of the mechanization period (Leontief, 1979), counter-views took a new turn with improving technology. Schumpeter's (1943) creative destruction paradigm is one of the well-known representatives of these views. Simply, in this creative destruction process, while technology is destroying the older ones, it creates the new ones at the same time (Schumpeter, 1943). Schumpeter (1939) pointed out the role of innovation in the production process and described innovation as a change in this production function.

Although there is a wide range of empirical literature, there is no consensus on the relationship between technology and unemployment (Yildirim, Yildirim, Erdogan & Kantarci, 2020). To grasp this, it is vital to determine the two competing effects technology exercises on employment. The first is the destruction effect in which automation substitutes capital for labor and causes unemployment. The second one is creative destruction in which the destruction effect is accompanied by a capitalization effect and the increase in demand for new goods and services leads to the creation of new jobs and industries (Schwab, 2016). To determine the potential impact of technology on employment concerns developing economies in particular to decide their labor strategies and sustainable employment policies (Schwab, 2018). It is claimed that the impact of product innovation on employment is positive while the impact is negative in process innovation in a significant part of the firm-level and sector level studies.

The literature is so limited in the context of macro-level empirical analysis on the relationship between technology and unemployment. This paper contributes new empirical findings to fill the gap in the macro-level empirical literature with a unique dataset covering OECD member countries. Using the count of IP5 patents is also new in the literature dealing with the relationship between technology and unemployment. In this study, S-GMM method is used for a dynamic panel analysis for the period between 2005 and 2018.

This paper consists of four main sections. Section 1 consists of a review of previous empirical literature followed by the estimation methodology framework in Section 2. Section 3 consists of econometric information followed by the econometric results in Section 4, and conclusions and policy recommendations.

Previous Empirical Studies

Most of the empirical studies examining the impact of innovation on employment are at the firm-level and sector-level. The common distinction of the results differentiates based on the type of innovation as product innovation and process innovation. Although there are some exceptions (e.g. Cirillo, Pianta & Nascia 2018), the effect of product innovation on employment is positive in most of the firm-level studies (Dachs & Peters, 2014; Evangelista & Vezzani, 2011; Falk, 2015; Hall, Lotti & Mairesse, 2008; Kwon, Park, Ohm & Yoo, 2015; Lachenmaier & Rottman, 2011; Meriküll, 2008). In other words, product innovation has an increasing effect on employment (Dagli & Kosekahyaoglu, 2021b).

On the contrary, the vast majority of empirical studies at the firm level confirm the negative effect of process innovation on employment (Dachs & Peters, 2014; Falk, 2015; Kwon et al., 2015; Yang & Lin, 2008). The results are likewise at sector-level studies (Aubert-Tarby, Escobar & Rayna, 2017; Bogliacino & Pianta, 2010; Cirillo, Pianta & Nascia, 2018; Greenan & Guellec, 2000; Huo & Feng, 2010; Meriküll, 2008; Peters, 2005; Piva & Vivarelli, 2018).

There are remarkably few studies at the macro level that address the impact of technology on employment. Moreover, in most macro-level studies, the relationship between technology and unemployment is uncertain/unclear (Sinclair, 1981; Simonetti, Taylor & Vivarelli, 2000; Tancioni & Simonetti, 2002). While some studies find the variables as unrelated (Evangelista, Guerrieri & Meliciani, 2014; Matuzeviciute, Butkus & Karaliute, 2017), some of them conclude that technology can affect employment in both directions (e.g. Sinclair, 1981). Vivarelli (1995) found that the employment effect is negative for Italy and positive for the USA. Simonetti, Taylor & Vivarelli (2000) claim that the effect can be compensated in the long term.

The recent literature published for the last three years is also rich for the effects of technology on employment. Recent econometric research of Felice, Lamperti & Piscitello (2021) shows an overall positive relationship between additive manufacturing technologies and employment at the industry level. According to the authors, this effect is caused due to both market expansion and complementarity between labor and additive manufacturing technologies. Avom, Dadegnon, & Igue (2021) revealed that technological development creates more employment than displacements in West African countries. According to Dottori (2021), no harmful impact on total employment was available in Italy caused by the effects of robots from the early 1990s up to 2016. Basol & Yalcin (2021) found that the digital economy and society index (DESI) positively affects labor market indicators and it increases the employment rate and decreases the long-term unemployment rate in EU countries.

The panel threshold model of Yildirim et al. (2020) shows that technological development increases the unemployment rate for the period of 1998–2015 in EU countries. Bordot (2022) found that a 10% increase in the stock of industrial robots is associated with a 0.42-point increase in the unemployment rate in OECD countries between the years 2005 and 2017. The findings of Dauth, Findeisen, Suedekum & Woessner (2021) indicate that automation is related to more stable employment and the new tasks that emerged with automation are of higher quality than the previous ones. According to Katz, Callorda & Jung (2021), the empirical estimates suggest that jobs lost to automation seem to match the jobs being created in Chile. Jongwanich, Kohpaiboon & Obashi (2022) find that the impact of technological progress in Thailand on employment is limited, but it affects the reallocation of workers between skilled and unskilled jobs. Foronda & Beverinotti (2021) find no evidence of a displacement effect due to process innovation in Bolivia.

A study investigating China's labor market based on a panel data of 283 prefectural-level cities from 2010 to 2017 by Du & Wei (2021) shows that massive adoption of robots is a significant driving force raising the unemployment rate while there is a reverse change in the longer period. According to Domini et al. (2021), automation spikes are linked to an increase in firms' contemporaneous net employment growth rate in the French manufacturing industry. Damioli, Van Roy & Vertesy (2021) found that AI technologies generate an extra-positive effect on companies' labor productivity in a wide sample covering 5257 companies. Madese & Wyrwich (2021) examined the relationship between innovation and employment in Nigeria and find a positive relationship between process innovation and employment growth among manufacturing and services firms.

This paper is different from the literature for a few reasons. Firstly, it uses IP5 family patent counts which is very rare in empirical studies, secondly, it covers 33 OECD member countries and lastly it has a very unique and up to date dataset covering 2005 to 2008.

Estimation Method

In this paper, a model with a dynamic panel data, which allows for the inclusion of a lagged dependent as explanatory variables in the econometric analysis has been used. However, in the context of dynamic panel data models, the inclusion of a lagged

dependent would cause heterogeneity. Moreover, the fact that the lagged dependent variable is correlated with unobserved effects in the model would also violate an important assumption in the case of using the random effects model (Baltagi, 2005, p. 135-139). So, using the least-squares method and random-effects models will be out of the alternative since the basic econometric assumptions.
Although it is possible to deal with unobserved heterogeneity by applying the within transformation in fixed-effects models, Nickell (1981) draws attention that it would generate estimates which are inconsistent as the number of "individuals" tends to infinity if the number of periods is kept fixed. Therefore, it is necessary to ensure that the unit and time dimensions of the panel are compatible to avoid Nickell's bias.

There are a few alternative methods to eliminate the effects and the inconsistency caused by the correlation of individual time averages and errors in dynamic models. Anderson & Hsiao (1982) estimator, Arellano & Bond (1991) the generalized method of moments (GMM) estimator, Arellano & Bover (1995)/ Blundell & Bond (1998) the system generalized method of moments estimator (S-GMM), and Keane & Runkle (1992) estimator are common methods which used for dynamic models.

The GMM estimator suggested by Anderson & Hsiao (1981) and Arellano & Bond (1991) uses all of the lagged variables as instrument variables to fulfill all moment conditions. In the GMM method, which consists of two steps, firstly, the first difference model is transformed with instrumental variables, and in the second step, this transformed model is estimated by the generalized least squares method (Tatoglu, 2018, p. 129).

Arellano & Bover (1995) showed that orthogonal deviations give more efficient results as an alternative to taking first differences using the Helmert transform. Arellano & Bover (1995) and Blundell & Bond (1998) improved the original model by making the additional assumption that the first differences of instrumental variables are uncorrelated with fixed effects. The S-GMM method is a two-equation system, original and transformed (Roodman, 2009b, p. 86-87). S-GMM provides increased efficiency by using more instrumental variables.

The classical model for a dynamic model is as follows (Hsiao, 2003, p. 69).

$$y_{it} = \gamma y_{i,t-1} + \beta' x_{it} + \alpha_i^* + \lambda_t + u_{it}, \quad i = 1,\ldots, N, \quad t = 1,\ldots, T, \tag{1}$$

In this model, yit represents dependent variable and $yi,t-1$ represents the lags of it, xit is a K × 1 vector of explanatory variables, β is a K x 1 vector of constants, α_i^* and λt are the (unobserved) individual and time-specific effects, which are assumed to stay constant for given i over t and for given t over i, respectively; and represents the effects of those unobserved variables that vary over i and t.

According to Roodman (2009b, p. 86), S-GMM is designed for situations with

> "1) Small T, large N panels, meaning few time periods and many individuals; 2) a linear functional relationship; 3) one left-hand-side variable that is dynamic, depending on its own past realizations; 4) independent variables that are not strictly exogenous, meaning they are correlated with past and possibly current realizations of the error; 5) fixed individual effects; and 6) heteroskedasticity and autocorrelation within individuals but not across them."

Roodman (2009b, p. 128-129) suggests including time dummies, to use orthogonal deviations in panels with gaps, to mind and report the instrument count in GMM estimator. Asymptotic variance calculations and Monte Carlo simulations have shown that S-GMM provides more efficient results than GMM (Blundell & Bond, 1998, p. 116). Due to N and T dimensions of the dataset of this paper and other econometric assumptions in dynamic panel data, S-GMM has been chosen as the estimation method.

3. Dataset, Variables and Econometric Model

The dataset of this paper covers OECD member countries for the period between 2005 and 2018. Due to the data limitations of data, the coverage of the analysis includes only 33 members of OECD. These OECD member countries are Australia, Austria, Belgium, Canada, Sweden, Chile, Colombia, Czech Republic, Germany, Spain, Finland, France, United Kingdom, Greece, Hungary, Ireland, Iceland, Israel, Italy, Japan, Republic of Korea, Lithuania, Luxembourg, Latvia, Netherlands, Norway, New Zealand, Poland, Portugal, Slovak Republic, Slovenia, Switzerland and the United States of America. The dataset of the variables has been obtained from OECD Data and OECD Stat statistics. The list of the variables and expected correlations are shown in Table 1.

Table 1. Variables and Expected Correlation

Variable		**Source**	**Expected Correlation (+)**	**(-)**
Dependent	Unemployment Rate	OECD Data	X	X
Independent	IP5 Patents	OECD Stat	X	X
Control	GDP (Gross Domestic Product)	OECD Data		X
	Public Unemployment Spending	OECD Data	X	
	Inflation (Consumer Price Index)	OECD Data	X	X
	FDI (Inward)	OECD Data		X
	Long-term Interest Rates	OECD Data	X	

This study follows Feldmann (2013), Matuzeviciute et al. (2017) and Dagli & Kosekahyaoglu (2021a) in determining the variables included in this analysis and creating the model. The empirical model specification is given as:

$$\ln u_{i,t} = \alpha_0 + \beta_1\, lnu_{i,t-1} + \beta_2\, lng_{i,t} + \beta_3\, lns_{i,t} + \beta_4\, lnc_{i,t} + \beta_5\, lnf_{i,t} + \beta_6\, lni_{i,t} + \beta_7\, lnp_{i,t} + \varepsilon_{i,t} \qquad (2)$$

Where lnu is the natural logarithm of the unemployment rate, lng is the natural logarithm of the gross domestic product, US dollars per capita (current PPPs), lns is the natural logarithm of the public unemployment spending in the percentage of GDP, lnc is the natural logarithm of the inflation measured by consumer price index (CPI), lnf is the natural logarithm of the foreign direct investment (FDI) inward flows as a share of GDP, lni is the natural logarithm of the long-term interest rates refer to government bonds maturing in ten years, lnp is the natural logarithm of the count of all IP5 patents by country, and $\varepsilon_{i,t}$ is the error term. Descriptive statistics of the dataset is in Table 2.

Table 2. Descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.
Unemployment Rate	1.940478	0.4571109	0.8183104	3.313883
GDP	10.43139	0.4315707	9.039784	11.66548
Inflation (CPI)	0.6357827	0.9407725	-4.790736	2.793154
Interest Rates	3.77899	2.570749	-0.362	22.4975
FDI (Inward)	0.8715566	1.209196	-5.418353	4.897791
Public Unemployment Spending	-0.6216012	0.9524514	-5.521461	1.275083
IP5 Patents	6.364103	2.248646	1.880914	11.11284

In this study, which analyzes the impact of technology on unemployment, the unemployment rate is used as the dependent variable and the count of IP5 patents is used as the technology variable. In the selection of patent classification, the IP5 patent family has been chosen to provide a comparison with the data of all countries within the scope of the analysis and to be free from technical, geographical or national legislation differences.

> "IP5 patent families refer to patents that have been filed in at least two IP offices worldwide, one of which among the Five IP offices (namely the European Patent Office, the Japan Patent Office, the Korean Intellectual Property Office, the US Patent and Trademark Office and the State Intellectual Property Office of the People Republic of China)" (OECD, 2022).

In the dynamic empirical model of this paper, gross domestic product (GDP), public unemployment spending, consumer price index (CPI), foreign direct investments (FDI) flows (inward), and long-term interest rates are used as control variables.

According to the economics literature, the value of inward direct investments is expected to reduce the unemployment rate (Abor & Harvey, 2008; Chang, 2007; Sharma & Cardenas, 2019). Therefore, a negative correlation between the unemployment rate and FDI is expected in the analysis. Okun's (1962) law predicts the relationship between the unemployment rate and GDP. That predicts a roughly 2% increase in output for every 1% reduction in the unemployment rate. Previous empirical studies confirm the inverse relationship between these variables (Adanu, 2005; Kangasharju, Tavera & Nijkamp, 2012; Lee, 2000; Pierdzioc, Rülke & Stadtmann, 2011; Sögner, 2001; Sögner & Stiassny, 2002).

OECD (2022) defines public unemployment spending as “expenditure on cash benefits for people to compensate for unemployment”. Public unemployment spending is expected to boost unemployment (Fraile & Ferrer, 2005; Nickell, Nunziata & Ochel, 2005). Inflation measured by the consumer price index (CPI) is defined as “the change in the prices of a basket of goods and services that are typically purchased by specific groups of households” (OECD, 2022). The Phillips curve named after William Phillips (1958) is an economic concept stating that corresponding rates of rising in wages have an inverse relationship with unemployment. In a modified version of the Philips curve, Samuelson & Solow (1960) hypothesize an inverse relationship between rates of unemployment and inflation.

Empirical Results

The S-GMM one-step and two-step estimation results are shown in Table 3 which was obtained with the “xtabond2” command developed by Roodman (2009b). In dynamic panel data analysis, uncorrected two-step standard errors are unreliable. For this reason, it is applied finite-sample correction suggested by Windmeijer (2005) to obtain robust standard errors. The standard errors in Table 3 are robust standard errors. In addition, "orthogonal deviations" proposed by Arellano & Bover (1995) are used instead of first differences to reduce data loss caused by the first difference method. In this method, instead of the difference of the previous period from the current period, the difference of the average of all future values of the variable is used (Tatoglu, 2018, p. 136).

Table 3. S-GMM One Step and Two Step Estimation Results

Variable	ONE-STEP S-GMM	TWO-STEP S-GMM	Expected	Result
L.Unemployment	0.705***	0.714***	+/-	✓
GDP	0.274	0.251	-	X
Inflation (CPI)	-0.028***	-0.035***	+/-	✓
Interest Rates	0.020***	0.021***	+	✓
FDI (Inward)	-0.059***	-0.060***	-	✓
Unemp. Spending	0.103***	0.089**	+	✓
IP5 Patents	-0.077***	-0.071***	+/-	✓
Constant	0.827	0.792		
Number of Groups	33	33		
Number of Instruments	31	31		
Year Dummies	Yes	Yes		
F Statistic	8439.33	929.68		
AR (2) p-value	0.052	0.065		
Hansen Statistic p-value	0.311	0.311		

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

According to panel data analysis, it is seen that all the control variables but GDP are statistically significant. The independent variable, IP5 patents representing technology is statistically highly significant (p value= 0,01) and has a negative correlation with the dependent variable. In other words, it is seen that a 1% increase in technology reduces unemployment by 0.07%. This empirical finding shows that, contrary to the general prejudice, technology has a small but positive effect on unemployment.

The relationship of GDP, which is used as a control variable, with unemployment is not statistically significant. The relationship between the CPI, which is used as an inflation indicator, and the unemployment rate is negative and statistically significant at the 1% significance level. According to the findings, a 1% increase in CPI reduces the unemployment rate by 0.035%. The long-term interest rates have the expected sign (+) and are statistically significant at the 1%

significance level, and a 1% increase in the long-term interest rates increase the unemployment rate by 0.021%. The relationship between FDI inflows and the unemployment rate is negative, consistent with the literature, it is statistically significant at the 1% significance level, and a 1% increase in FDI reduces the unemployment rate by 0.06%. Public unemployment expenditure is statistically significant at the 1% significance level, and a 1% increase in public unemployment expenditures increases the unemployment rate by 0.089%.

For the estimators to be accepted as stable and reliable, it is necessary to test the validity of the instrumental variables and the second-order autocorrelation test (Arellano and Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). The Hansen (1982) J and Sargan (1958) tests are commonly recommended for testing over-identifying restrictions (Arellano, 2003, p. 193; Roodman, 2009a, p. 141; 2009b, p. 97). The null hypothesis is not rejected in the Hansen J test. That means over-identifying restrictions are valid and variables are exogenous. In addition, the results are close to the ideal values suggested by Roodman (2009b) in the Hansen J test (p-value: 0.31). There must be no second-order autocorrelation in GMM analysis (Mileva, 2007, p. 7). The autocorrelation test confirms that there is no second-order autocorrelation (AR2 p= 0.07). In addition, the F statistic used in the analysis is also significant and confirms that the econometric model is significant as a whole.

Conclusions and Policy Recommendations

Today, technology is growing faster than ever before and has an exponential effect. The change in production structures and the nature of the business with the impact of technology brings along some concerns. One of the most discussed of these concerns is the impact of technology on unemployment. This debate, which has its roots in the 1930s, has flared up again today with the impact of unique technologies such as artificial intelligence and the internet of things.

On the one hand, the automation process causes robots to replace workers, but on the other hand, more efficient markets emerge with cost reduction due to increased efficiency. However, with the effect of increasing productivity, many new sectors and new jobs are emerging. This contributes to a substantial compensation mechanism for job losses. Thanks to the compensation mechanisms that emerge with the process that Schumpeter calls creative destruction, new job opportunities emerge instead of lost ones. The center of the debate is whether job losses or newly created jobs will dominate. The focus of this discussion will be to point out the ultimate impact of technology on unemployment. Obviously, there is no consensus in the literature about the future impacts of technological breakthroughs on employment. The clear point is that the current skills will not match the occupations of the future and the companies will need many new skills.

Technological advances will create millions of jobs but the other millions of jobs will disappear in this process. New forms of work such as digital labor or remote teleworking diversify the labor life and the labor terminology.

In the empirical part of the study, the data set covering the OECD countries for the years 2005-2018 is used and the relationship between technology and unemployment is analyzed with a dynamic panel data analysis. In the econometric analysis, Arellano & Bover/ Blundell & Bond's "S-GMM" method one-step and two-step estimators are used. The independent variable, IP5 patents representing technology is statistically highly significant and has a negative correlation with the dependent variable. In other words, it is seen that a 1% increase in technology reduces unemployment by 0.07%. This empirical finding shows that, contrary to the general prejudice, technology has a small but positive effect on unemployment.

For now, it seems impossible to predict with certainty the future impact of technology on unemployment. However, history is a good sign which shows that the human workforce adapts to changing conditions and continues to find new jobs in the changing and emerging business world with technology. In the light of the findings of this paper and related literature, it is evaluated that there is no room for great technology-based concern in terms of unemployment. The nature of occupations and business models are changing by automation. Brynjolfsson & McAfee (2014) advise employees to learn to compete with machines instead of competing against machines.

For future studies, it is recommended to analyze the relationship between technology and unemployment with different technology variables. These variables could be a different international patent classification, the number of industrial robots or the global innovation index. In addition, it is also recommended to conduct studies on the social effects of technology in the economy. The empirical studies on skill-biased and routine-biased technological change and job polarization also could make a significant contribution to the literature.

Genişletilmiş Özet

Endüstri 4.0 çağı yaşamın, üretimin, ticaretin ve hizmetlerin her alanında akıllı teknolojileri beraberinde getirmektedir. Makine öğrenimi ve yapay zekâ teknolojileri sayesinde endüstriyel robotlar her geçen gün daha akıllı hale gelmektedir. Günümüzde teknoloji her zamankinden daha hızlı ve üstel bir etkiye sahip olarak büyümektedir.. Teknolojinin etkisiyle üretim yapılarının, işin ve işgücünün doğasının değişmesi ise bazı endişeleri de beraberinde getirmektedir. Bu endişeler içerisinde en çok tartışılanlardan biri teknolojinin işsizlik üzerindeki etkisidir. 1930'lu yıllara dayanan bu tartışma, günümüzde yapay zekâ teknolojileri ve nesnelerin interneti gibi benzersiz teknolojilerin de etkisiyle yeniden alevlenmiş ve farklı boyut almıştır.

Bu çalışma, OECD ülkelerine odaklanarak gelişen teknolojinin işsizlik üzerindeki etkisini incelemektedir. Literatürde teknolojik atılımların istihdam üzerindeki gelecek etkileri hakkında bir fikir birliği olmadığı açıktır. Açık olan nokta ise mevcut becerilerin geleceğin meslekleriyle örtüşmeyeceği ve şirketlerin ve kurumların birçok yeni beceriye ihtiyaç duyacağıdır. Teknolojik gelişmeler milyonlarca iş yaratacak ancak yine milyonlarca iş bu süreçte yok olacaktır. Bu çalışmanın amacı, teknolojinin istihdam üzerindeki etkisi ile ilgili olarak, literatürde nicel olarak oldukça yetersiz olan makro düzeyde bir çalışma ile teknolojinin işsizlik üzerindeki nihai etkisine işaret etmektir. Bu çalışma birkaç nedenden dolayı mevcut literatürden farklıdır. Birincisi, ampirik çalışmalarda çok nadir görülen IP5 ailesi patent sayılarını kullanmakta, ikincisi veri seti 33 OECD üyesi ülkeyi kapsamakta ve son olarak 2005-2008 yıllarını kapsayan özgün ve güncel bir veri seti kullanmaktadır.

Literatürde hali hazırda mevcut çalışmalardan, firma düzeyinde ve sektör düzeyinde yapılan çalışmaların önemli bir bölümünde ürün yeniliğinin istihdam üzerindeki etkisinin olumlu, süreç yeniliğinin etkisinin ise olumsuz olduğu görülmektedir. Literatür, teknoloji ve işsizlik arasındaki ilişki üzerine makro düzeyde ampirik analiz bağlamında ise çok sınırlıdır. Bu makale, OECD üye ülkelerini kapsayan benzersiz bir veri seti ile makro düzeyde ampirik literatürdeki bu boşluğu doldurmak için yeni ampirik bulgulara katkı sunmayı amaçlamaktadır.

Bu çalışmada, ekonometrik analize açıklayıcı değişkenler olarak gecikmeli bir bağımlının dahil edilmesini sağlayan dinamik panel veri içeren bir model kullanılmıştır. Çalışmanın ampirik kısmında 2005-2018 yılları için OECD ülkelerini kapsayan veri seti kullanılmış ve teknoloji ile işsizlik arasındaki ilişki dinamik panel veri ile analiz edilmiştir. Ekonometrik analizde Arellano & Bover/ Blundell & Bond'un "S-GMM" yöntemi bir aşamalı ve iki aşamalı tahmin edicileri kullanılmıştır.

Verilerin sınırlılıkları nedeniyle, analizin kapsamı OECD'nin tüm üyelerini değil, sadece 33 üyesini içermektedir. Çalışmaya dahil edilen OECD üyesi ülkeler: Avustralya, Avusturya, Belçika, Kanada, İsveç, Şili, Kolombiya, Çek Cumhuriyeti, Almanya, İspanya, Finlandiya, Fransa, Birleşik Krallık, Yunanistan, Macaristan, İrlanda, İzlanda, İsrail, İtalya, Japonya, Kore Cumhuriyeti, Litvanya, Lüksemburg, Letonya, Hollanda, Norveç, Yeni Zelanda, Polonya, Portekiz, Slovak Cumhuriyeti, Slovenya, İsviçre ve Amerika Birleşik Devletleri'dir. Değişkenlerin veri seti OECD Data ve OECD Statistics veri bankasından elde edilmiştir.

Teknolojinin işsizlik üzerindeki etkisinin analiz edildiği bu çalışmada, bağımlı değişken olarak işsizlik oranı, teknoloji değişkeni olarak ise IP5 patent sayıları kullanılmıştır. Patent sınıflandırmasının seçiminde IP5 patent ailesi, analiz kapsamındaki tüm ülkelerin verileriyle karşılaştırma sağlayacak ve teknik, coğrafi ve/ veya ulusal mevzuat farklılıklarından uzak olacak şekilde seçilmiştir. Bağımsız değişken olan ve teknolojiyi temsil eden IP5 patent sayıları istatistiksel olarak oldukça anlamlı ve bağımlı değişken ile negatif bir korelasyona sahip olarak görülmektedir. Diğer bir deyişle, teknolojideki %1'lik bir artışın işsizliği %0,07 oranında azalttığı görülmektedir. Bu ampirik bulgu, genel önyargının aksine teknolojinin işsizlik üzerinde küçük ama olumlu bir etkisi olduğunu göstermektedir.

Otomasyon süreci bir yandan robotların insan işçilerin yerini almasına neden olurken diğer yandan artan verimlilik nedeniyle maliyetlerin düşmesiyle daha verimli pazarlar ortaya çıkmaktadır. Artan verimliliğin de etkisiyle birçok yeni sektör ve yeni işler ortaya çıkmaktadır. Bu durum özünde iş kayıpları için önemli bir telafi mekanizmasına katkıda bulunmaktadır. Schumpeter'in yaratıcı yıkım dediği süreçle birlikte ortaya çıkan telafi mekanizmaları sayesinde kaybedilenler yerine yeni iş fırsatları ortaya çıkmaktadır. Teknolojik gelişmeler milyonlarca iş yaratacak ama yine milyonlarca iş de bu süreçte yok olacaktır. Tartışmanın merkezi ise, bu süreçte iş kayıplarının mı yoksa yeni yaratılan işlerin mi hâkim olacağına ilişkindir. Bu tartışmanın odak noktası da teknolojinin işsizlik üzerindeki nihai etkisine işaret etmek olacaktır. Mevcut literatürde teknolojik yeniliklerin işgücü üzerindeki etkileri hakkında bir fikir birliği oluşmamıştır.

Mevcut imkanlar dahilinde teknolojinin işsizlik üzerindeki gelecek etkisini kesin olarak tahmin etmek imkânsız görünmektedir. Ancak yakın tarihimiz insan işgücünün değişen koşullara uyum sağladığını ve teknoloji ile birlikte değişen ve gelişen iş dünyasında yeni işler bulmaya devam ettiğini gösteren iyi bir işaret olarak karşımıza çıkmaktadır. Bu makalenin bulguları ve ilgili literatür ışığında teknolojik yenilikler kaynaklı işsizlik yönünden büyük kaygılara yer olmadığı değerlendirilmektedir. Bu makale dört ana bölümden oluşmaktadır. Bölüm 1, önceki ampirik literatürün gözden geçirilmesini ve ardından Bölüm 2'deki tahmin metodolojisi çerçevesini içermektedir. Bölüm 3, ekonometrik bilgileri, ardından Bölüm 4 ekonometrik sonuçlardan ve takiben sonuç ve politika önerilerinden oluşmaktadır.

Beyan

"The Rise of Technology for the Future Labor Force: The Nexus between Technology and Unemployment in OECD Countries" başlığıyla derginize gönderdiğim ve yayına kabul edilen çalışmamın yazım sürecinde herhangi bir kurum ya da kişi ile çıkar çatışmam olmamıştır.

REFERENCES:

Abor, J., & Harvey, S. K. (2008). Foreign direct investment and employment: Host country experience. *Macroeconomics and Finance in Emerging Market Economies, 1*(2), 213–225.

Adanu, K. (2005). A cross-province comparison of Okun's coefficient for Canada. *Applied Economics, 37*(5), 561-570.

Anderson, T. W., & Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association*, 76, 598-606.

Anderson, T. W., & Hsiao, C. (1982). Formulation and estimation of dynamic models u-using panel data. *Journal of Econometrics,* 18, 47-82.

Arellano, M. (2003). *Panel data econometrics*. Oxford: Oxford University Press.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: monte carlo evidence and an application to employment equations. *Review of Economic Studies*, 58, 277-297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variables estimation of error component models. *Journal of Econometrics,* 68, 29-51.

Aubert-Tarby, C., Escobar, O. R., & Rayna, T. (2017). The impact of technological change on employment: the case of press digitisation. *Technological Forecasting & Social Change*, 128, 36-45.

Avom, D., Dadegnon, A. K., & Igue, C. B. (2021). Does digitalization promote net job creation? Empirical evidence from WAEMU countries. *Telecommunications Policy, 45*(8), 102215.

Baltagi, B. H. (2005). *Econometric analysis of panel data*. New York, NY: John Wiley & Sons Inc.

Başol, O., & Yalçın, E. C. (2021). How does the digital economy and society index (DESI) affect labor market indicators in EU countries? *Human Systems Management, 40*(4), 503-512.

Bimber, B. (1990). Karl Marx and the three faces of technological determinism, *Social Studies of Science*, *20*(2), 333-351.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87, 115-143.

Bogliacino, F., & Pianta, M. (2010). Innovation and employment: A reinvestigation using revised Pavitt classes. *Research Policy*, 39, 799-809.

Bordot, F. (2022). Artificial intelligence, robots and unemployment: Evidence from OECD countries. *Journal of Innovation Economics Management, 37*(1), 117-138.

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. New York, NY: W.W. Norton.

Chang, S. C. (2007). The interactions among foreign direct investment, economic growth, degree of openness and unemployment in Taiwan. *Applied Economics*, *39*(13), 1647-1661.

Cirillo, V., Pianta, M., & Nascia, L. (2018). Technology and occupations in business cycles. *Sustainability, 10*(463), 1-25. doi.org/10.3390/su10020463

Dachs, B., & Peters, B. (2014). Innovation, employment growth, and foreign ownership of firms. *Research Policy, 43*(1), 214-232.

Dağlı, İ., & Kösekahyaoğlu, L. (2021a). Bilim ve teknoloji politikalari bağlaminda teknoloji-işsizlik ilişkisi: Ampirik bir inceleme. *Yaşar Üniversitesi E-Dergisi, 16*(63), 1237-1255. doi: 10.19168/jyasar.911828

Dağlı, İ., & Kösekahyaoğlu, L. (2021b). Will destructive destruction beat creative destruction? Does the rising of technology favor the future of humanity? In B. Selçuk, S. Ünal, Y. L. Mert (Ed.), *Academic Studies in Social Sciences* (pp. 231-253), İzmir: Duvar Yayınevi.

Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review, 11*(1), 1-25.

Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association, 19*(6), 3104-3153.

Domini, G., Grazzi, M., Moschella, D., & Treibich, T. (2021). Threats and opportunities in the digital era: automation spikes and employment dynamics. *Research Policy, 50*(7), 104137.

Dottori, D. (2021). Robots and employment: evidence from Italy. *Economia Politica, 38*(2), 739-795.

Du, Y., & Wei, X. (2021). Technological change and unemployment: evidence from China. *Applied Economics Letters*, DOI: 10.1080/13504851.2021.1896666.

Evangelista, R., & Vezzani, A. (2011). The impact of technological and organizational innovations on employment in European firms. *Industrial and Corporate Change, 21*(4), 871-899.

Evangelista, R., Guerrieri, P., & Meliciani, V. (2014). The economic impact of digital technologies in Europe. *Economics of Innovation and New Technology, 23*(8), 802–824.

Falk, M. (2015). Employment effects of technological and organizational innovations: evidence based on linked firm-level data for Austria. *Jahrbücher Für Nationalökonomie Und Statistik, 235*(3), 268-285

Feldmann, H. (2013). Technological unemployment in industrial countries. *Journal of Evolutionary Economics*, 23, 1099-1126.

Felice, G., Lamperti, F., & Piscitello, L. (2021). The employment implications of additive manufacturing. *Industry and Innovation*, https://doi.org/10.1080/13662716.2021.1967730

Foronda, C., & Beverinotti, J. (2021). Effects of innovation on employment: An analysis at the firm level in Bolivia (No. 11626). Inter-American Development Bank.

Fraile, M., & Ferrer, M. (2005). Explaining the determinants of public support for cuts in unemployment benefits spending across OECD countries. *International Sociology, 20*(4), 459-481.

Freeman, C. & Soete, L. (1997). *The economics of industrial revolution*, MIT Press.

Greenan, N., & Guellec, D. (2000). Technological Innovation and Employment Reallocation. *Labor, 14*(4), 547-590.

Hall, B. H., Lotti, F., & Mairesse, J. (2008). Employment, innovation, and productivity: evidence from Italian microdata. *Industrial and Corporate Change, 17*(4), 813-839.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50, 1029-1054.

Hsiao, C. (2003). *Analysis of panel data*, Cambridge: Cambridge University Press.

Huo, J., & Feng, H. (2010). The political economy of technological innovation and employment. *Comparative Political Studies, 43*(3), 329-352.

Jongwanich, J., Kohpaiboon, A., & Obashi, A. (2022). Technological advancement, import penetration and labor markets: Evidence from Thailand. *World Development*, 151, 105746.

Kangasharju, A., Tavera, C., & Nijkamp, P. (2012). Regional growth and unemployment: The validity of Okun's law for the Finnish regions. *Spatial Economic Analysis, 7*(3), 381-395.

Katz, R., Callorda, F., & Jung, J. (2021). The impact of automation on employment and its social implications: evidence from Chile. *Economics of Innovation and New Technology*, DOI: 10.1080/10438599.2021.1991798.

Keane, M. P., & Runkle, D. E. (1992). On the estimation of panel-data models with serial correlation when instruments are not strictly exogenous. *Journal of Business and Economic Statistics,* 10, 1-9.

Kwon, S. J., Park, E., Ohm, J. Y., & Yoo, K. (2015). Innovation activities and the creation of new employment: An empirical assessment of South Korea's manufacturing industry. *Social Science Information, 54*(3), 354-368.

Lachenmaier, S., & Rottmann H. (2011). Effects of innovation on employment: A dynamic panel analysis. *International Journal of Industrial Organization*, 29, 210–220.

Lee, J. (2000). The robustness of Okun's law: Evidence from OECD countries. *Journal of Macroeconomics, 22*(2), 331-356.

Leontief, W. (1979). Is technological unemployment inevitable?, *Challenge*, *22*(4), 48-50.

Matuzeviciute, K., Butkus, M., & Karaliute, A. (2017). Do technological innovations affect unemployment? Some empirical evidence from European countries. *Economies, 5*(48), 1-19.

Medase, S. K., & Wyrwich, M. (2021). The role of innovation for employment growth among firms in developing countries: Evidence from Nigeria. *African Journal of Science, Technology, Innovation and Development*, 1-10.

Meriküll, J. (2008). The impact of innovation on employment: Firm- and industry-level evidence from Estonia. *Eesti Pank Bank of Estonia*, Working Paper Series, 1/2008.

Mileva, E. (2007). *Using Arellano-Bond dynamic panel GMM estimators in Stata*, New York: Fordham University.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, 49, 1417-1426.

Nickell, S., Nunziata, L., & Ochel, W. (2005). Unemployment in the OECD since the 1960s. What do we know? *The Economic Journal*, 115 (500), 1-27.

OECD (2022). Patents by technology. https://stats.oecd.org/Index.aspx?DataSetCode=PATS_IPC (retrieved November 11, 2021).

Okun, A. (1962). Potential GNP: Its measurement and significance. *Proceedings of the Business and Economic Statistics Section of the American Statistical Association, 7*(1), 89-104.

Peters, B. (2005). Employment effects of different innovation activities: Microeconometric evidence. *ZEW-Centre for European Economic Research*, Discussion Paper 04-073.

Phillips, A. W. (1958). The relationship between unemployment and the rate of change of money wage rates in the United Kingdom 1861–1957. *Economica*, 25, 283–299.

Pierdzioch, C., Rülke, J.C., & Stadtmann, G. (2011). Do professional economists' forecasts reflect Okun's law? Some evidence for the G7 countries. *Applied Economics, 43*(11), 1365-1373.

Piva, M., & Vivarelli, M. (2018). Is innovation destroying jobs? Firm-level evidence from the EU. *Sustainability, 10*(1279), 1-16.

Ricardo, D. (1817). *The principles of political economy & taxation*, Kitchener, 3rd.Edition, 1821, Canada: Batoche Books

Roodman, D. M. (2009a). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71, 135–158.

Roodman, D. M. (2009b). How to do xtabond2: An introduction to "Difference" and "System" GMM in Stata. *The Stata Journal, 9*(1), 86-136.

Samuelson, P. A., & Solow R. M. (1960). Analytical aspects of anti-inflation policy. *American Economic Review*, 50, 177–94.

Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica,* 26, 393-415.

Schumpeter, J. A. (1943). *Capitalism, socialism and democracy*, 2003, New York: Harper Collins. ISBN 0-203-26611-0

Schumpeter, J.A. (1939). *Business cycles: A theoretical, historical, and statistical analysis of the capitalist process*, (Ed.Rendigs Fels) ,New York and London : McGraw-Hill, 1964.

Schwab, K. (2016). *The fourth industrial revolution*. Currency. Switzerland: World Economic Forum.

Schwab, K. (2018). *Shaping the future of the fourth industrial revolution*. New York: World Economic Forum.

Sharma, A., & Cardenas, O. (2019). The labor market effects of FDI: A panel data evidence from Mexico. *International Economic Journal*, 1–17.

Simonetti, R., Taylor, K., & Vivarelli, M. (2000). *Modelling the employment impact of innovation.* In M. Pianta and M. Vivarelli (Eds.), The employment impact of innovation: evidence and policy (pp. 26-46), Routledge.

Sinclair, P. J. N. (1981). When will technical progress destroy jobs? *Oxf. Econ. Pap.*, 31, 1–18.

Smith, A. (1776). *An inquiry into the nature and causes of the wealth of nations*, (Edited with an Introduction, Notes, Marginal Summary and an Enlarged Index by Edwin Cannan), London: Methuen. 1904.

Sögner, L. (2001). Okun's law does the Austrian unemployment–GDP relationship exhibit structural breaks? *Empirical Economics,* 26, 553-564.

Sögner, L., & Stiassny, A. (2002). An analysis on the structural stability of Okun's law-a cross-country study. *Applied Economics, 34*(14), 1775-1787.

Tancioni, M., & Simonetti, R. (2002). A macroeconometric model for the analysis of the impact of technological change and trade on employment. *Journal of Interdisciplinary Economics*, 13, 185–221.

Tatoğlu, Y. F. (2018). *İleri panel veri ekonometrisi: Stata uygulamalı*. İstanbul: Beta Yayıncılık.

Vivarelli, M. (1995). *The economics of technology and employment: Theory and empirical evidence*, Lyme: Edward Elgar.

Windmeijer, F. (2005). A Finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, 126, 25–51.

Yang, C-H., & Lin, C-H.A. (2008). Developing employment effects of innovations: microeconometric evidence from Taiwan. *Developing Economies*, 46, 109-134.

Yildirim, D. Ç., Yildirim, S., Erdogan, S., & Kantarci, T. (2020). Innovation-unemployment nexus: The case of EU countries. *International Journal of Finance & Economics*. https://doi.org/10.1002/ijfe.2209