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The Effect of Innovation on Employment in Türkiye

Hakkı Kutay BOLKOL[1] Ece Handan GÜLERYÜZ [2]

Abstract

This study examines the impact of innovation on employment in the Turkish labor market between the years 1991-2021, using monthly patent grants and annual R&D expenditure statistics. As for empirical technique, ARDL (autoregressive distributed lag) approach is used. The reason for choosing this approach is that it separates the long-term and short-term results and gives better results in analysis with a lower number of observations than other methods. The difference between the results of this study from the literature is that the analysis was performed in two different time periods, with two different proxy variables, and they gave the same result as proof of the robustness of the results. When the long-run model and the short-run model are investigated separately, it is found that while the effect of innovation on employment is negative in the short-run, it turns out to be positive in the long-run. Thus, during the period 1991-2021 in the Turkish labor market, while innovation might negatively affect employment levels to some extent in the short run, innovation could exert a more structural and sustainable positive impact on employment levels in the long run. In the short-run, the negative effect of innovation on employment can be seen as a kind of creative destruction, but in the long-run, the positive effect of innovation supports the hypothesis that the increase in the education and training levels of workers along with the profit and productivity provided by innovation increases employment by adapting workers to innovation. The aim of this study is to make an inference with macro data sets but, using micro-level, firm data may provide significant results on the effect of innovation on employment.

Keywords: ARDL Approach, Innovation, Patent grants, R&D expenditures, Employment, Türkiye

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Türkiye'de İnovasyonun İstihdama Etkisi

Hakkı Kutay BOLKOL [1]   Ece Handan GÜLERYÜZ [2]

Öz

Bu makale 1991-2021 yılları arasında Türkiye işgücü piyasasında inovasyonun istihdam üzerindeki etkisini aylık patent tescilleri ve yıllık AR-GE harcamaları istatistiklerini kullanılarak incelemektedir. Ampirik teknik olarak ARDL yaklaşımı kullanılmıştır. Bu yaklaşımın tercih edilmesinin nedeni bu yöntemin uzun dönem ve kısa dönem sonuçlarını ayırması ve diğer yöntemlere göre daha az gözlem sayısı ile analizlerde daha iyi sonuçlar vermesidir. Bu çalışmanın sonuçlarının literatürden farklılığı analizin iki farklı zaman diliminde, iki farklı temsili değişken ile yapılması ve sonuçlarının sağlamlılığının kanıtı olarak bunların aynı sonucu vermesidir. Uzun dönem modeli ve kısa dönem modeli ayrı ayrı incelendiğinde inovasyonun istihdam üzerindeki etkisinin kısa dönemde negatif olduğu, uzun dönemde ise pozitif olduğu görülmektedir. Böylece, 1991-2021 döneminde Türkiye işgücü piyasasında inovasyon kısa vadede istihdam düzeylerini bir ölçüde olumsuz etkileyebilirken, uzun vadede inovasyon istihdam düzeyleri üzerinde daha yapısal ve sürdürülebilir bir pozitif etki gösterebilecektir. Kısa dönemde inovasyonun istihdama negatif etkisi bir nevi yaratıcı yıkım gibi karşılanabilir ancak uzun dönemde etkinin pozitife dönmesi inovasyonun sağladığı kar ve verimlilikle birlikte işçilerin eğitim ve öğretim seviyelerindeki artışın onları inovasyona adapte ederek istihdamın arttığı hipotezini desteklemektedir. Bu çalışmanın amacı makro veri setleri ile çıkarım yapmaktır ancak mikro düzeyde firma verileri kullanılarak inovasyonun istihdam üzerindeki etkisine ilişkin önemli sonuçlar elde edilebilir.

Anahtar Kelimeler: ARDL Yaklaşımı, İnovasyon, Patent tescilleri, AR-GE harcamaları, İstihdam, Türkiye

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Introduction

Innovation is broadly acknowledged as one of the main catalyzers for economic growth. Increases in Research and Development (R&D) and different forms of innovation are found to push up countries' technology frontiers, boost up firms' productivity and profits, and increase national aggregate output. Innovation and R&D can help a country get out of an economic rut and middle-income trap, lay the foundation for necessary structural changes, and achieve long run and sustainable economic growth. Therefore, in recent decades innovation and R&D have been crucial especially for emerging economies' development.

Nevertheless, innovation and employment which is also significant and required for economic growth can have a complex nexus. In the related literature, there are studies which find opposing influences of innovation on employment. In some countries, innovation and R&D may have a labor-supporting impact on employment, whereas in other countries innovation and R&D may exert a labor-saving impact on employment, and so disrupt employment levels.

This paper examines the impact of innovation on employment in the Turkish labor market between 1991 and 2021 by using monthly patent grants statistics and annual R&D expenditure statistics. ARDL (autoregressive distributed lag) approach is employed to carry out the empirical analysis.

There are mixed results in the related literature due to the country-specific cases, different time periods, different empirical methodologies, different proxies for innovation etc. In Germany and Italy, respectively, Lachenmaier and Rottmann (2011) and Piva and Vivarelli (2005) find a favorable correlation between innovation and employment. The majority of jobs in the economy are created by innovation followers in the EU, not modest innovators, according to Kancs and Siliverstovs (2020). According to studies, product innovation may not result in job loss but rather a polarization of employment, according to Dosi and Mohnen (2019).

As of 2018, the direct government funding and government tax support for business R&D in Türkiye, as a percentage of GDP was close to the European Union, and a little bit below the OECD averages. Moreover, between 2000 and 2018 the gross domestic expenditure on R&D showed increasing trends in the U.S., China, and European Union's 28 countries. Over the last two decades, the OECD countries' average for gross domestic spending on R&D has been recorded as 2% (OECD, 2021). By 2020, Asia is the leading world region with 66.6% share in patent applications with North America following with only 19.3% (ECLAC, 2022). During 2007-2017 upper middle-income countries maintained 10.2% average annual growth rate in R&D expenditures. According to the Global Innovation Index 2020 report the top three leading countries in innovation are Switzerland, Sweden, and the United States. In the same report Türkiye's ranking is 51, and it is one of the top performers in upper-middle income countries (Soumitra et al., 2020). The study includes the following sections: Literature Review, Data, Methodology, Results, and Conclusion.

Literature Review

Using a Revised Pavitt taxonomy, Bogliacino and Pianta (2010) investigate the relationship between innovation and employment in eight European nations from 1994 to 2004. They discover that technical and cost competitiveness strategies, when combined with demand, pay, and industry dynamics, explain for changes in employee and hour work. Using a large international panel data set from the EU Industrial R&D Investment Scoreboard and flexible semi-parametric approaches - the generalized propensity score - Kancs and Siliverstovs (2020) estimate and decompose the employment effect of innovation by R&D intensity levels. Their findings indicate that small innovators may not create employment and may possibly destroy them by increasing their R&D expenses. The majority of jobs in the economy are produced by innovators: raising innovation by 1% can increase employment by up to 0.7%. The positive employment benefit of innovation peaks when R&D intensity is near 100% of total capital expenditure, after which it falls and becomes statistically insignificant. Innovation leaders do not create jobs by raising their already massive R&D expenses.

Dosi and Mohnen (2019) discuss in a brief related literature survey that there are studies that suggest that product innovation does not lead to job destruction, but rather to job polarization. Furthermore, a significant negative effect of process innovation on employment is frequently absent at the firm level. This does not, however, rule out the possibility of industry-wide labor cuts. Lachenmaier and Rottmann (2011) use a long innovation panel data set of German manufacturing firms spanning more than 20 years to investigate the effect of innovation on employment at the firm level. They can tell the difference between product and process innovations, as well as innovation inputs and outputs. They discover positive effects of innovation on employment using dynamic panel GMM system estimation. This result is resistant to the use of product and process innovations, as well as input and output from innovation.

Crespi and Taisir (2011) examine the relationship between process and product innovation and employment growth in four Latin American countries, using microdata from innovation surveys. They link employment growth to process innovation and separately to sales growth due to innovation and unchanged products. The results demonstrate that compensation effects are widespread, and the adoption of new products is linked to employment growth at the company level. In particular, they find that, for the manufacturing firms in Argentina, the adoption of process innovations only impacts employment growth in the country, whereas in Chile, there is no evidence of displacement due to the adoption of product innovations. The observed compensation effects result in employment growth, even when taking into account replacement of old products.

Piva and Vivarelli (2005) look at whether technological change have a positive impact on jobs at the company level in an environment where intermediate technologies are mainly implemented through gross innovative investments like in Italian manufacturing. They use GMM -SYS to add to the employment equation when it comes to technology and use a special longitudinal dataset from 575 Italian manufacturing companies over the 1992-1997 period. They find a strong - though small - positive correlation between innovation and jobs. Sales and wages have all the signs and are significant, but the job-creating impact of innovation is strong when you factor in time, industry, size, and geographic fixed effects.

Riddel and Schwer (2003) find evidence of endogeneity between employment growth and innovative capacity in a study covering the U.S. states by identifying wages and patenting activity in high-tech industries as leading causes for high-tech labor demand. In a generalized two-stage random effects model, they find out that high-tech workforce size, human capital accumulation, knowledge stock, and industry R&D expenditures significantly affect innovation rate among the U.S. states during the 1990s. In another study done for the U.S. labor market during 1990-1999 Kirchhoff et al. (2007) find out that an increase in university R&D expenditures can lead to a rise in new firm formations which then can cause an increase in employment and economic growth levels within regions. On the contrary, Miguel Benavente (2006) uses a structural model with asymptotic least squares and find that in Chile R&D expenditure and innovation do not significantly impact firms' productivity and innovation sales in the short run.

Bogliacino and Vivarelli (2012) examine R&D expenditures' job creation effect with an over 2000-observations sample for 25 sectors between 1996 and 2005 in 15 European countries. They employ a model of GMM-SYS panel estimations of a demand-for-labor equation augmented with technology. They argue that the R&D expenditure, through supporting product innovation may generate a job-creating effect in the labor market, and this positive influence is observed in both the flow and stock specifications. Evangelista and Savona (2002) find that innovation has a negative effect on employment in the short run in Italy's aggregate service sector by using the 1993-1995 Italian innovation survey. This negative impact which is observed in financial sectors, large firms and capital-intensive industries can be linked to the high usage of Information and Communication Technologies (ICTs) that crowds out low skilled workers. On the other hand, innovation has a positive impact on employment among small firms where there are strong scientific and technological environment.

In another study, Wallsten (2000) uses U.S. firm-level data, OLS, three stage least squares models. He argues that government-industry commercial R&D grants do not appear to show a statistically significant effect on employment. On the other hand, Coccia (2013) finds statistically significant positive influences of public expenditure on education and R&D intensity on employment rate, and a negative influence of general government consolidated gross debt on employment rate by using a dataset covering 27 European countries between 1995 and 2009 and applying multiple regression analysis.

Goel and Nelson (2022) analyze firm level data from 125 countries and argue that both R&D and innovation boost employment growth which indicates that innovation is either capital-saving or labor has strong complementarities with other inputs, and also contracting firms benefit from innovation but not from R&D. Moutinho et al. (2015) find out that governmental R&D employment does not pave the way to wide spread employment, on the other hand it is effective in reducing youth unemployment. University R&D employment and technological capacity enhancement turn out to be important in reducing youth unemployment. In another study focusing on Finland's economy, Aldieri et al. (2021) explore positive employment effects from local innovation activities and knowledge spillovers from other regions only on the demand for high-skilled workers. On the contrary, for low-skilled workers, the employment effects of local innovation activities are significantly negative, while there is no impact from knowledge spillovers from other regions. During 1999-2005 period in German regions Buerger et al. (2012) observe that an increase in patents is associated with subsequent growth of employment in the medical and optical equipment, and electrics and electronics industries. The growth of patents is also associated with subsequent growth of R&D. In a multi-industry work done for Japanese economy, Shah et al. (2022) argue that employment gains are associated with innovation, both at the aggregate level and within groups of major industries, with the positive impact of technological progress being more highlighted in the manufacturing sector.

Pellegrino et al. (2019) and Barbieri et al. (2019) investigate the nexus between innovation and employment for Spanish and Italian firms, respectively. They find a positive relationship between R&D expenditures and employment in high-tech firms, and a negative relationship between embodied technological change and job creation in small and medium enterprises. Destefanis and Rehman (2023), in a study for NUTS 2 European regions, find that the more that European regions shift closer to the world's technology frontier, the more that R&D expenditure, rather than physical capital investment, is capable of generating positive employment externalities. In India's manufacturing sector, Mitra (2020) finds a weakly positive correlation between innovation and employment. In another study on Taiwan's economy, Yang and Lin (2008) argue that innovations, umeasured by R&D investments or patent counts, have a positive impact on employment. Nevertheless, technological innovations are found to be non-neutral in the way that they cause a shift in labor composition in favor of skilled and more educated workers.

It is important to mention the studies on Türkiye to compare the results of our study with them. However, there are very limited studies that investigate the effect of innovation on employment with macro-level data. The Turkish literature on this subject has been increasing recently. In this context, Acar and Sever (2022) discovered that the number of domestic patent applications appears to have a negative impact on employment, while exports of high-tech goods, R&D expenditures, and changes in the number of firms appear to have a positive impact. Doğaner (2022) also investigates the effect of R&D expenditures and number of patents on employment in Türkiye. According to findings of this study, R&D expenditures have a negative impact on employment, patents have a positive effect on employment. Bayar and Öztürk (2021) investigate the effect of technology on employment on Türkiye. According to results of this study, it was stated that both R&D expenditures and patent applications have a positive impact on employment.

There are also some studies that investigate the effect of innovation on economic growth (e.g., see İğdeli 2019; Uçak et. al. 2018; Türedi 2016). This issue is also important since it has indirect effect on employment. İğdeli (2019) analyzed the impact of R&D and education expenditures on economic growth in Türkiye. According to the findings of the analysis, R&D and education expenditures are found to have a positive effect on economic growth. R&D expenditures and economic growth relation on Türkiye was also analyzed by Uçak et al. (2018). According to this study it is found that R&D expenditures have a positive effect on economic growth in the long-run. Türedi (2016), on the other hand, investigates the relationship between R&D expenditures, patent applications and economic growth in OECD countries. According to findings of this study, while there is bi-directional causality between R&D expenditures and economic growth, there is uni-directional causality running from patent applications to economic growth. The effects of both patent applications and R&D expenditure on economic growth is positive.

Apart from R&D expenditures, some studies also use education expenditures on Türkiye (e.g., see Akçacı 2013; Akıncı 2017). Akçacı (2013) found that there is uni-directional causality running from education expenditures to economic growth. Akıncı (2017) also states that education expenditures have a positive impact on economic growth both in the short and the long run.

Data

The data for employment is obtained from TURKSTAT (Turkish Statistical Institute). It is a seasonally adjusted monthly employment rate. Patent grants are used as a proxy for innovation. This data is taken from the Turkish Patent and Trademark Office. This data is also monthly data and only valid for the period between 2009 and 2016. In order to eliminate potential seasonal effects, Seasonal and Trend Decomposition Using Loess (STL) decomposition methodology is applied to the patent grants data. Due to the data limitations on the patent grants side, the time period of this analysis is 2009M01-2016M12.

In order to carry out a more up-to-date alternative analysis on the effects of innovation on employment in Türkiye, R&D expenditure is used in place of patent grants. R&D expenditure data is obtained from TURKSTAT and this yearly data is valid for the period between 1990 and 2021. The employment data is obtained from the World Bank Statistics. This data is only valid for the period between 1991 and 2021. Consequently, the time period of the alternative analysis becomes the years between 1991 and 2021.

The R&D expenditure data is in nominal terms in its original form, so that by dividing it by the GDP deflator obtained from the World Bank Statistics, it is converted into real terms. Using R&D expenditure in place of patent grants is the best alternative since the correlation between them is 0.9755 and when one period lag of R&D expenditure is used the correlation between them remains almost the same, which is 0.9790.

Methodology

ARDL (Autoregressive Distributed Lag) approach is used as the empirical methodology. The first reason for using this approach is that it is more effective in analyzing with a relatively low number of observations. Secondly, with the ability to give different optimal lag lengths for different variables, this approach eliminates the potential endogeneity and autocorrelation problems. The Akaike Information Criterion (AIC) is used in model selection since, according to Liew (2004) when the number of observations is relatively low (less than 120) Akaike information criterion gives the best results according to simulations. After defining the integration order of the variables using the Augmented Dickey Fuller (ADF) and Phillips Perron (PP) unit root tests, a cointegration analysis is done by the ARDL Bound Test. Unlike other cointegration tests, ARDL Bound Test can be applied both to the variables that are integrated of order one and an integrated of order zero, or a mixture of them. However, it is not suitable for use in cases where the variables are second or higher order stationary. Lastly, the ARDL approach produces the long-run and short-run models separately, which can be seen as another advantage of this methodology. This adopted version of the methodology for this study can be reviewed in the results section.

Results

Firstly, monthly patent grants statistics are used as a proxy for innovation so as to analyze the effects of innovation on employment. The time period of this analysis is 2009M01-2016M12.

Since both variables are integrated of order one (see Table 1), the ARDL approach can be applied in this analysis. The variables LEMP and LPAT stand for natural logarithm of the employment rate and natural logarithm of the patent grants, respectively.

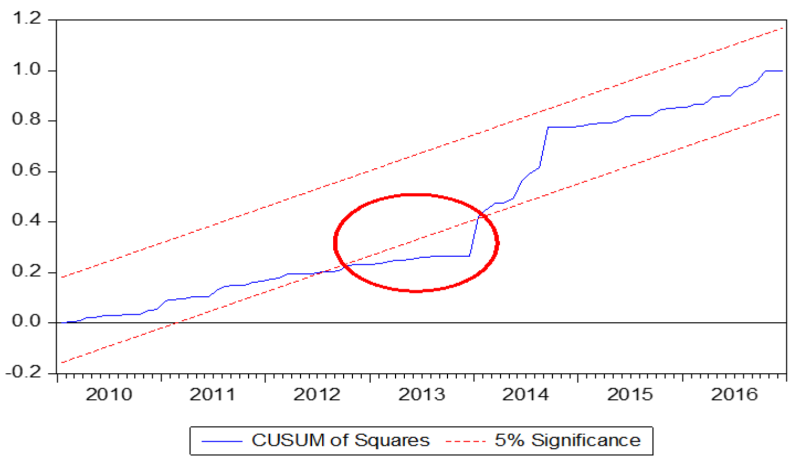
Table 1. Unit Root Tests

Variable Note: D( ) stands for First Difference	**ADF Test Probability Values**			**PP Test Probability Values**			**Decision**
	Intercept	Trend and Intercept	None	Intercept	Trend and Intercept	None	
LEMP	0.1462	0.0256**	0.9967	0.5209	0.3977	0.9968	I (1)
D(LEMP)	0.0001***	0.0002***	0.0001***	0.0000***	0.0000***	0.0000***	
LPAT	0.5876	0.0000***	0.9193	0.0000***	0.0000***	0.7503	I (1)
D(LPAT)	0.0000***	0.0000***	0.0000***	0.0001***	0.0001***	0.0000***	
In the ADF unit root test, the lag length is automatically selected according to the Akaike Information Criterion. In the PP unit root test, the Newey-West Bandwidth is automatically selected using the Barlett Kernel method.							

*** Stationary at 1% significance level, ** Stationary at 5% significance level, * Stationary at 10% statistical significance level.

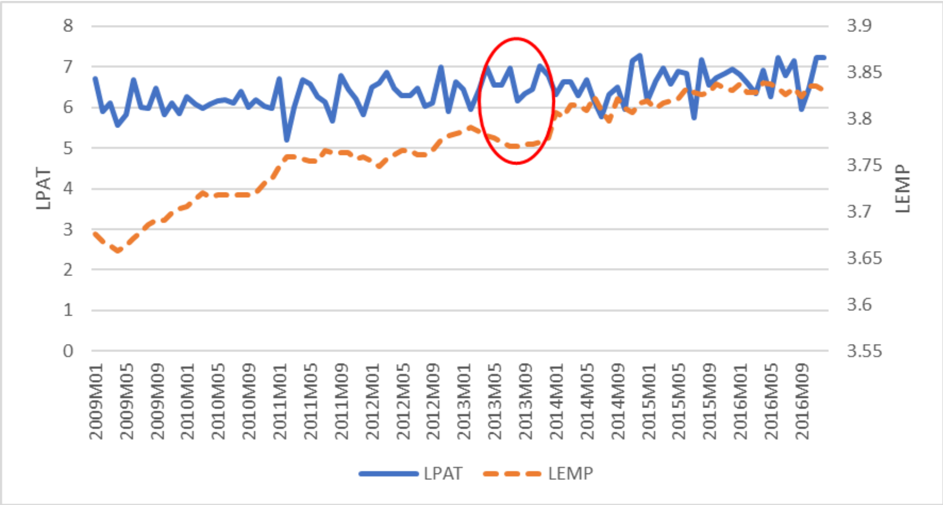
According to the CUSUM (cumulative sum) of squares graph in which the stability of the model parameters is examined, the residuals of the model are not completely within the confidence interval, which is an indication of a structural break during the analysis period (see Figure 1).

Figure 1. CUSUM of Squares



By using a dummy variable for the year 2013 (2013M02 – 2013M11), the break is controlled. When the break period is analyzed (shown in a circle in Figure 2), it is captured that while there is a convergence (in general, it can be captured that the growth rate of LEMP is higher than the growth rate of LPAT) in the trend of these variables, in the break period, this convergence becomes reversed for a while. In other words, while the trend of LPAT is relatively stable, in the break period, there is a kind of V-shaped trend in LEMP.

Figure 2. Analyzing Break Period



According to the ARDL Bound Test equation, which is adapted to this study, the long-term relationship (cointegration relation) is determined in the model by examining the effect of innovation on employment. The equation (ARDL (5,6)) is given below:

$$\Delta LEMP_t = \sum_{i=1}^{5}\beta_{1i}\Delta LEMP_{t-i} + \sum_{i=0}^{6}\beta_{2i}\Delta LPAT_{t-i} + \delta_1 LEMP_{t-1} + \delta_2 LPAT_{t-1} + \gamma_1 dummy + constant + u_t \quad (1)$$

Note: Δ: first difference $H_0: \delta_1 = \delta_2 = 0; H_A: \delta_1 \neq \delta_2 \neq 0$

According to the results, the null hypothesis is rejected and the alternative hypothesis is accepted. This result indicates that the existence of a long-run relationship in the model. In Table 2, the F-stat appears to be bigger than the upper bound, which indicates that the null hypothesis is rejected which means that there is a cointegration relationship.

Table 2. ARDL Bound Test

Critical Values							
		Lower Bound			**Upper Bound**		
F-stat	k	%1	%5	%10	%1	%5	%10
6.098112	1	4.94	3.62	3.02	5.58	4.16	3.51

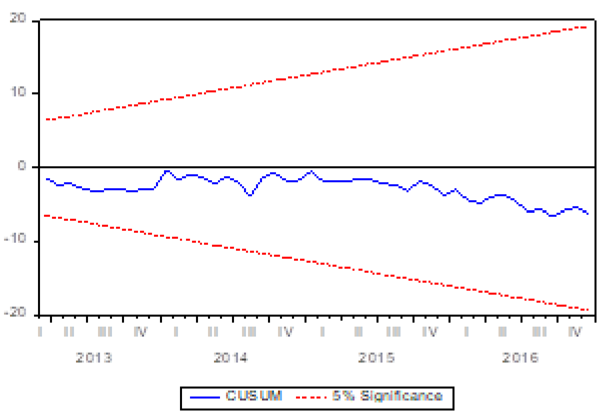
When the long-run model and the short-run model given below are analyzed separately, it is found that while the effect of innovation on employment is negative in the short-run, it turns out to be positive in the long-run.

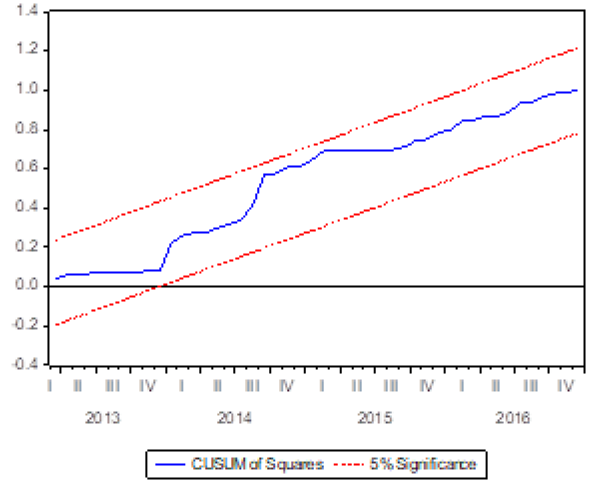
The long-run ARDL model results are given in the table below, along with the diagnostic test results. The model has passed all the diagnostic tests showing that the model is unbiased and consistent. To summarize these results briefly, there is no serial correlation or heteroskedasticity problems in the correctly constructed model (The Ramsey Reset Test results provide the information that the model is correctly constructed. In other words, the model is not misspecified.). Also, according to the CUSUM and CUSUM of Squares (more sensitive than CUSUM) graphs, where the stability of the model parameters is examined, the residuals of the model lie within the confidence interval. It shows that the parameters of the model are stable and that there is no structural break in the model, and that if it exists it is controlled, as in our case. The long-run model and related results are given below.

$$LEMP_t = \sum_{i=1}^{5} \beta_{1i} LEMP_{t-i} + \sum_{i=0}^{6} \beta_{2i} LPAT_{t-i} + \gamma_2\, dummy + \; constant + u_t \qquad (2)$$

Table 3. ARDL Long-run Model Results

Dependent Variable: LEMP		
Variable	**Coefficient**	**Diagnostic Tests**
LEMP(-1)	0.802775*** (0.108297)	**Serial Correlation Test** Breusch-Godfrey LM Test Chi-square (2) Prob. Value: 0.2761
LEMP(-2)	-0.006371 (0.136786)	
LEMP(-3)	0.403958*** (0.133009)	**Heteroskedasticity Test** Breusch-Pagan-Godfrey Chi-square (13) Prob. Value: 0.5555
LEMP(-4)	-0.500563*** (0.144304)	**Regression Specification Error Test (RESET)** Ramsey Reset Test [1] Prob. Value: 0.1342
LEMP(-5)	0.207656** (0.108433)	**Cusum & Cusum of Squares Test**
LPAT	-0.000895 (0.002125)	
LPAT(-1)	0.002144 (0.002034)	
LPAT(-2)	0.004741** (0.002084)	
LPAT(-3)	-0.000471 (0.002094)	
LPAT(-4)	0.003478** (0.002016)	
LPAT(-5)	-0.000828 (0.002023)	
LPAT(-6)	0.005165*** (0.001997)	
DUMMY	-0.004302** (0.002210)	
CONSTANT	0.266625*** (0.084205)	



$R^2 = 0.983109$ $\bar{R}^2 = 0.980219$	

Note: Values in parentheses below the coefficients indicate standard errors. *** indicates statistical significance at 1%, ** at 5%, * at 10% levels.

The long-term coefficient of the patent variable, whose standard errors are calculated using the delta method as in Pesaran and Shin (1998), using the long-term model is given in the Table 4. The long-term coefficients are obtained by dividing the sum of the coefficients of the independent variable to one minus the sum of the coefficients of the dependent variable (Gujarati, 1999: 58). The normally distributed standard errors cannot be obtained due to the presence of non-stationary variables in the model. In this case, the inferences made using t-statistics are not valid. For this reason, the standard error of the long-term coefficient of the patent variable is calculated using the delta method. The specified calculations are made automatically by the EViews 10 program.

Table 4. **ARDL Long-run Coefficients**

Dependent Variable: LEMP	
Variable	**Coefficient**
LPAT	0.144065*** (0.032505)

Note: Values in parentheses below the coefficients indicate standard errors. *** indicates statistical significance at 1%, ** at 5%, * at 10% levels.

As it can be seen in Table 4, patent grants which is used as a proxy for innovation is found to affect employment positively in the long run.

However, according to the short-run model, the impact of innovation on employment appears to be negative in the short-run (see Table 5: D(LPAT(-1)), D(LPAT(-2)), D(LPAT(-3)), D(LPAT(-5)) are statistically significant and negative). The Error Correction Term (ECT) indicates that there is a short-run adjustment to the long-run equilibrium, and it turns out to be statistically significant and negative. This means that any disturbance that causes a deviation from the long-run equilibrium which originates from the employment side (dependent variable side) is corrected by 9% (coefficient value of ECT) in the next period. The short-run model and its results are given below.

$$\Delta LEMP_t = \sum_{i=1}^{5}\beta_{1i}\Delta LEMP_{t-i} + \sum_{i=0}^{6}\beta_{2i}\Delta LPAT_{t-i} + \gamma_2 dummy + \lambda ECT_{t-1} + u_t \qquad (3)$$

Table 5. ARDL Short-run Model Results

Dependent Variable: LEMP	
Variable	**Coefficient**
D(LEMP(-1))	-0.104681 (0.113561)
D(LEMP(-1))	-0.111052 (0.000099)
D(LEMP(-1))	0.292907*** (0.087189)
D(LEMP(-1))	-0.207656** (0.113561)
D(LPAT)	-0.000895 (0.000099)
D(LPAT(-1))	-0.012084*** (0.087189)
D(LPAT(-2))	-0.007343** (0.113561)
D(LPAT(-3))	-0.007815** (0.000099)
D(LPAT(-4))	-0.004337 (0.087189)
D(LPAT(-5))	-0.005165*** (0.113561)
DUMMY	-0.004302** (0.000099)
ECT(-1)	-0.092545*** (0.087189)
$R^2 = 0.357442$ $\overline{R^2} = 0.266825$	

Note: Values in parentheses below the coefficients indicate standard errors. *** indicates statistical significance at 1%, ** at 5%, * at 10% levels.

Secondly, the annual R&D expenditure statistics are used as a proxy for innovation to investigate the effect of innovation on employment. The time period of this analysis is the years between 1991 and 2021.

Since both variables are integrated of order one (see Table 1), the ARDL approach is applicable for this analysis. LEMP stands for natural logarithm of the employment rate, and LRND stands for natural logarithm of the R&D expenditures.

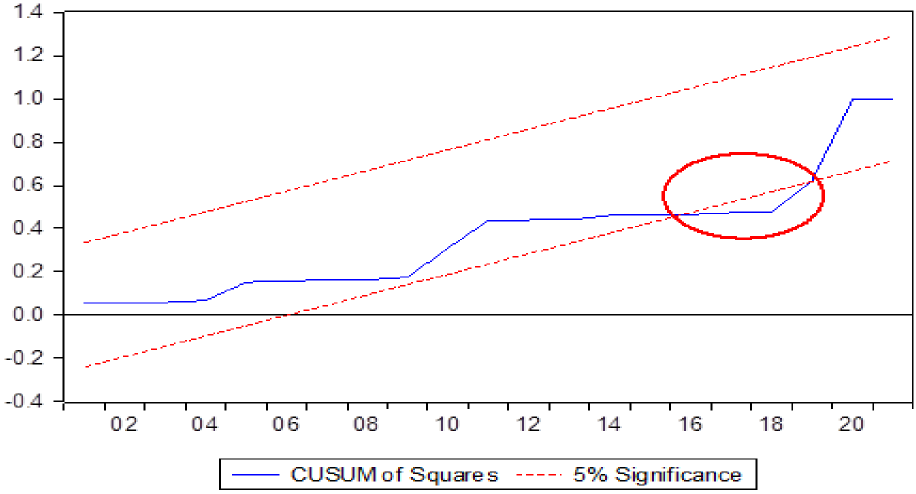
Table 6. Unit Root Tests

Variable Note: D( ) stands for First Difference	**ADF Test Probability Values**			**PP Test Probability Values**			**Decision**
	Intercept	Trend and Intercept	None	Intercept	Trend and Intercept	None	
LEMP	0.0889*	0.0234**	0.3327	0.2951	0.7052	0.2308	I (1)
D(LEMP)	0.0012***	0.0058***	0.0001***	0.0012***	0.0060***	0.0001***	
LRND	0.9899	0.0503**	0.9992	0.9999	0.0007***	0.9999	I (1)
D(LRND)	0.0000***	0.0002***	0.5413	0.0000***	0.0000***	0.0001***	
In the ADF unit root test, the lag length is automatically selected according to the Akaike Information criterion. In the PP unit root test, the Newey-West bandwidth is automatically selected using the Barlett kernel method.							

*** Stationary at 1% significance level, ** Stationary at 5% significance level, * Stationary at 10% statistical significance level.

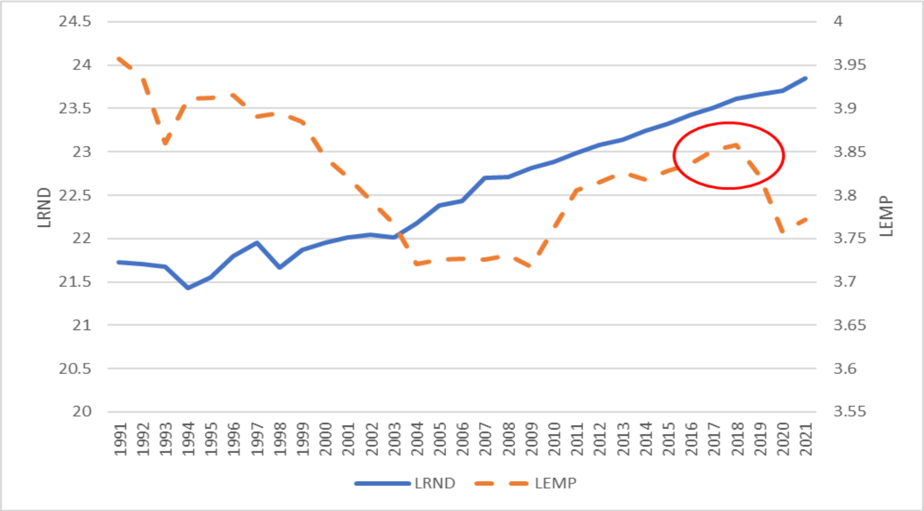
According to the CUSUM (cumulative sum) of squares test result, there is a structural break in the analysis (see Figure 3).

Figure 1. CUSUM of Squares



Using a dummy variable for the indicated break period, 2016-2019, in Figure 3, eliminates the structural break problem in the data. When the break period is analyzed (shown in a circle in Figure 4), it can be captured that, there is a kind of inverted V-shaped trend in LEMP while LRND is relatively stable during that period.

Figure 2. Analyzing Break Period



It is found that the alternative model has a trend as it enters the model statistically significantly. According to the ARDL Bound Test equation, which is adapted to this study, the long-term relationship (cointegration relation) is determined in the model by examining the effect of innovation on employment. The equation (ARDL (1,3)) is given below.

$$\Delta LEMP_t = \sum_{i=1}^{1}\beta_{1i}\Delta LEMP_{t-i} + \sum_{i=0}^{3}\beta_{2i}\Delta LRND_{t-i} + \delta_1 LEMP_{t-1} + \delta_2 LRND_{t-1} + \gamma_1 dummy + constant + trend + u_t \quad (4)$$

Note: Δ: first difference $H_0: \delta_1 = \delta_2 = 0; H_A: \delta_1 \neq \delta_2 \neq 0$

According to the analysis results, the null hypothesis is rejected and the alternative hypothesis is accepted. This result indicates the existence of a long-run relationship in the model. See Table 7, the F-stat is bigger than the upper bound, which indicates that the null hypothesis is rejected which indicates that there is a cointegration relationship.

Table 7. ARDL Bound Test

Critical Values							
		Lower Bound			Upper Bound		
F-stat	k	%1	%5	%10	%1	%5	%10
11.278691	1	8.74	6.56	5.59	9.63	7.3	6.26

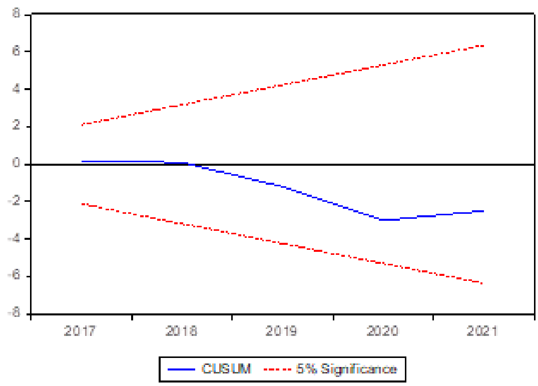
When the long-run model and the short-run model given below are analyzed separately, like the results of the previous analysis, it is found that while the effect of innovation on employment is negative in the short-run, it turns out to be positive in the long-run.

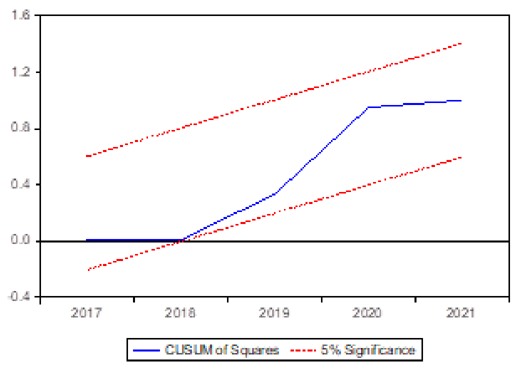
The long-run ARDL model and its results are given in the table below, along with the diagnostic test results. The model has passed all the diagnostic tests showing that the model is unbiased and consistent.

$$LEMP_t = \sum_{i=1}^{1}\beta_{1i} LEMP_{t-i} + \sum_{i=0}^{3}\beta_{2i} LRND_{t-i} + \gamma_2 dummy + constant + trend + u_t \quad (5)$$

Table 8. ARDL Long-run Model Results

Dependent Variable: LEMP		
Variable	**Coefficient**	**Diagnostic Tests**
LEMP(-1)	0.661777*** (0.090915)	**Serial Correlation Test** Breusch-Godfrey LM Test Chi-square (2) Prob. Value: 0.3062
LRND	0.068788 (0.048175)	
LRND(-1)	0.075230 (0.046501)	**Heteroskedasticity Test** Breusch-Pagan-Godfrey Chi-square (7) Prob. Value: 0.3751
LRND(-2)	0.043955 (0.047066)	**Regression Specification Error Test (RESET)** Ramsey Reset Test [1] Prob. Value: 0.5650
LRND(-3)	0.061229 (0.037998)	**Cusum & Cusum of Squares Test**
DUMMY	0.017300 (0.015008)	
CONSTANT	-3.957504*** (1.144994)	
TREND	-0.022646*** (0.005290)	
$R^2 = 0.920604$ $\overline{R^2} = 0.892815$		





Note: Values in parentheses below the coefficients indicate standard errors. *** indicates statistical significance at 1%, ** at 5%, * at 10% levels.

The long-term coefficient of the R&D expenditures is given in Table 9.

Table 9. ARDL Long-run Coefficients

Dependent Variable: LEMP	
Variable	**Coefficient**
LPAT	0.736798*** (0.202189)

Note: Values in parentheses below the coefficients indicate standard errors. *** indicates statistical significance at 1%, ** at 5%, * at 10%.

As it can be captured from Table 9, the R&D expenditures, which is adopted as a proxy for innovation, affects employment positively in the long run.

The short-run model and its results are given below. According to the short-run model, the impact of innovation on employment is negative in the short-run (see table 10: D(LRND(-1) and D(LRND(-2) are statistically significant and negative). As in the previous analysis where patent grants are used, the ECT is statistically significant and negative which indicate that there is a short-run adjustment to the long-run equilibrium. In other words, any deviation from the long-run equilibrium which emerges from the employment side (dependent variable side) will be corrected by approximately 34% in the next period.

$$\Delta LEMP_t = \sum_{i=1}^{1}\beta_{1i}\Delta LEMP_{t-i} + \sum_{i=0}^{3}\beta_{2i}\Delta LRND_{t-i} + \gamma_2 dummy + \lambda ECT_{t-1} + trend + constant + u_t \qquad (6)$$

Table 10. ARDL Short-run Model Results

Dependent Variable: LEMP	
Variable	**Coefficient**
D(LRND)	0.068788 (0.042717)
D(LRND(-1))	-0.105184*** (0.040083)
D(LRND(-2))	-0.061229* (0.036579)
DUMMY	0.017300 (0.013368)
CONSTANT	-3.957504*** (0.812863)
ECT(-1)	-0.338223*** (0.069497)
$R^2 = 0.547786 \quad \overline{R^2} = 0.418582$	

Note: Values in parentheses below the coefficients indicate standard errors. *** indicates statistical significance at 1%, ** at 5%, * at 10% levels.

The results obtained from the second analysis are very consistent with the first analysis, which indicates that although the effect of innovation on employment in the short-run is negative, the long-run impact turns out to be positive.

Conclusion

This study examines the effect of innovation on employment between 1991 and 2021 in the Turkish labor market. ARDL methodology is adopted, and R&D expenditure and patent grants are used as proxy variables for innovation. When the long-run model and the short-run model given above are analyzed separately, it is found that the influence of innovation on employment is negative in the short-run. This outcome is similar to what Evangelista and Savona (2002) find during the period 1993-1995 in Italy's aggregate service sector. In the second part of the analysis, it is found that innovation has a positive effect on employment, and this result is in line with some other studies' findings (Lachenmaier and Rottmann (2011), Piva and Vivarelli (2005), Acar and Sever (2022), Kancs and Siliverstovs (2020), Kirchhoff et al. (2007), Bogliacino and Vivarelli (2012), and Coccia (2013)).

In the short run, R&D and innovation can generate a creative destruction effect, and crowd out low-skilled workers out of the labor market, therefore causing a reduction in the employment level. In the long run, firms' profit and productivity levels increase. Furthermore, the labor force's education and training levels rise, so the workers become sufficiently adapted to the R&D and innovation, and they complement each other. Therefore, during the period 1991-2021 in the Turkish labor market, while innovation might negatively affect employment levels to some extent in the short run, innovation could exert a more structural and sustainable positive impact on employment levels in the long run.

There are very limited empirical studies that investigate the effect of innovation on employment in Türkiye with macro-level data. Generally, this issue is empirically investigated with firm level data. This study also provides a contribution to the literature in this respect. Like Acar and Sever (2022) found, R&D expenditures were found to affect employment positively (in the long run) in the results of this study. However, when it comes to patent data, Acar and Sever (2022) found that patent applications have a negative impact on employment. On the other hand, in this study, patent grants are preferred rather than patent applications in order to use a more certain and accurate proxy for innovation. Like R&D expenditures, it was found that patent grants also affect employment negatively in the short-run but positively in the long-run. Moreover, similar to this study, Doğaner (2022) also found that patents have a positive impact on employment. However, she also found that R&D expenditures have a negative impact on employment. On the other hand, Bayar and Öztürk (2021) found that both patent applications and R&D expenditures have a positive impact on employment in Türkiye. As it can be captured, the results of empirical studies on Türkiye differ. At this point, it is beneficial to state that converting nominal variables into real terms and using both long-term and short-term models give a wider view to this subject. This is actually the main contribution to this study.

The most important limitation of this study is not having large data sets to be used for innovation. This situation has been tried to be solved by using more than one proxy variable for innovation. Furthermore, analyzing the effect of innovation on employment by using firm level micro data sets may provide significant results, yet, it is not in the scope of this study.

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References / Kaynakça

Acar, M., & Sever, E. (2022). The Effect of Innovation on Employment: An ARDL Bounds Testing Approach for Turkey 1. *Sosyoekonomi, 30*(51), 33-52. https://doi.org/10.17233/sosyoekonomi.2022.01.02

Akçacı, T. (2013). Eğitim harcamalarının iktisadi büyümeye etkisi. *Kafkas Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 4*(5), 65-79.

Akıncı, A. (2017). Türkiye'de Eğitim Harcamalarının Ekonomik Büyüme Üzerindeki Etkisi. *Maliye Dergisi*, 173, 387-397.

Aldieri, L., Makkonen, T., & Vinci, C. P. (2021). Spoils of innovation? Employment effects of R&D and knowledge spillovers in Finland. *Economics of Innovation and New Technology*, *30*(4), 356-370. https://doi.org/10.1080/10438599.2019.1703754

Barbieri, L., Piva, M., & Vivarelli, M. (2019). R&D, embodied technological change, and employment: Evidence from Italian microdata. *Industrial and Corporate Change, 28*(1), 203-218. https://doi.org/10.1093/icc/dty001

Bayar, H. T., & Öztürk, M. (2021). Teknolojinin istihdam üzerine etkisi: VAR analizi. *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, *26*(2), 119-127.

Bogliacino, F., & Pianta, M. (2010). Innovation and employment: a reinvestigation using revised Pavitt classes. *Research Policy*, *39*(6), 799-809. https://doi.org/10.1016/j.respol.2010.02.017

Bogliacino, F., & Vivarelli, M. (2012). The job creation effect of R&D expenditures. *Australian Economic Papers*, *51*(2), 96-113. https://doi.org/10.1111/j.1467-8454.2012.00425.x

Buerger, M., Broekel, T., & Coad, A. (2012). Regional dynamics of innovation: Investigating the co-evolution of patents, research and development (R&D), and employment. *Regional Studies*, *46*(5), 565-582. https://doi.org/10.1080/00343404.2010.520693

Coccia, M. (2013). What are the likely interactions among innovation, government debt, and employment?. *Innovation: The European Journal of Social Science Research*, *26*(4), 456-471. https://doi.org/10.1080/13511610.2013.863704

Crespi, G., & Tacsir, E. (2011, September). *Effects of innovation on employment in Latin America*. In 2011 Atlanta conference on science and innovation policy (pp. 1-11). IEEE. https://doi.org/10.1109/ACSIP.2011.6064465

Destefanis, S., & Rehman, N. U. (2023). Investment, innovation activities and employment across European regions. *Structural Change and Economic Dynamics*, 65, 474-490. https://doi.org/10.1016/j.strueco.2023.03.013

Doğaner, A. (2022). The Effect of R&D Expenditures and Number of Patents on Employment in Turkiye: An Evaluation with the ARDL Analysis. *Kırklareli Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 11*(2), 351-365.

Dosi, G., & Mohnen, P. (2019). Innovation and employment: an introduction. *Industrial and Corporate Change, 28*(1), 45-49. https://doi.org/10.1093/icc/dty064

Economic Commission for Latin America and the Caribbean (ECLAC), Innovation for development: the key to a transformative recovery in Latin America and the Caribbean (LC/CCITIC.3/3), Santiago, 2022.

Evangelista, R., & Savona, M. (2002). The impact of innovation on employment in services: Evidence from Italy. *International Review of Applied Economics, 16*(3), 309-318. https://doi.org/10.1080/02692170210136136

Goel, R. K., & Nelson, M. A. (2022). Employment effects of R&D and process innovation: Evidence from small and medium-sized firms in emerging markets. *Eurasian Business Review, 12*(1), 97-123. https://doi.org/10.1007/s40821-022-00203-6

Gujarati, D. (1999). Basic Econometrics, Fourth Edition. *McGrow, Hill.*

İğdeli, A. (2019). AR-GE ve eğitim harcamalarının ekonomik büyüme üzerindeki etkisi: Türkiye örneği. *Manas Sosyal Araştırmalar Dergisi, 8*(3), 2517-2538. https://doi.org/10.33206/mjss.520848

Kancs, D. A., & Siliverstovs, B. (2020). Employment effect of innovation. *Empirical Economics, 59*(3), 1373-1391. https://doi.org/10.1007/s00181-019-01712-6

Kirchhoff, B. A., Newbert, S. L., Hasan, I., & Armington, C. (2007). The influence of university R & D expenditures on new business formations and employment growth. *Entrepreneurship theory and practice, 31*(4), 543-559. https://doi.org/10.1111/j.1540-6520.2007.00187.x

Lachenmaier, S., & Rottmann, H. (2011). Effects of innovation on employment: A dynamic panel analysis. *International journal of industrial organization, 29*(2), 210-220. https://doi.org/10.1016/j.ijindorg.2010.05.004

Liew, V. K. S. (2004), Which lag length selection criteria should we employ?. *Economics bulletin, 3(*33), 1-9.

Miguel Benavente, J. (2006). The role of research and innovation in promoting productivity in Chile. *Economics of innovation and New Technology, 15*(4-5), 301-315. https://doi.org/10.1080/10438590500512794

Mitra, A. (2020). Technological progress, innovation and employment: firm-level evidence from India's manufacturing sector. *Innovation and Development, 10*(3), 451-465. https://doi.org/10.1080/2157930X.2019.1689614

Moutinho, R., Au-Yong-Oliveira, M., Coelho, A., & Manso, J. P. (2015). Beyond the "Innovation's Black-Box": Translating R&D outlays into employment and economic growth. *Socio-Economic Planning Sciences*, *50*, 45-58. https://doi.org/10.1016/j.seps.2015.04.001

Opportunity, O. E. C. D. (2021). OECD Science, Technology and Innovation Outlook 2021.

Pellegrino, G., Piva, M., & Vivarelli, M. (2019). Beyond R&D: the role of embodied technological change in affecting employment. *Journal of Evolutionary Economics*, 29, 1151-1171. https://doi.org/10.1007/s00191-019-00635-w

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters, 58*(1), 17-29. https://doi.org/10.1016/S0165-1765(97)00214-0

Piva, M., & Vivarelli, M. (2005). Innovation and employment: Evidence from Italian microdata. *Journal of economics, 86*(1), 65-83. https://doi.org/10.1007/s00712-005-0140-z

Riddel, M., & Schwer, R. K. (2003). Regional innovative capacity with endogenous employment: empirical evidence from the US. *Review of Regional Studies, 33*(1), 73-84. https://doi.org/10.52324/001c.8414

Shah, I. H., Kollydas, K., Lee, P. Y., Malki, I., & Chu, C. (2022). Does R&D investment drive employment growth? Empirical evidence at industry level from Japan. *International Journal of Finance & Economics*. https://doi.org/10.1002/ijfe.2677

Soumitra, D., Lanvin, B., & Wunsch-Vincent, S. (Eds.). (2020). Global innovation index 2020: who will finance innovation?. WIPO.

Türedi, S. (2016). The relationship between R&D expenditures, patent applications and growth: a dynamic panel causality analysis for OECD countries. *Anadolu Üniversitesi Sosyal Bilimler Dergisi, 16*(1), 39-48.

Wallsten, S. J. (2000). The effects of government-industry R&D programs on private R&D: the case of the Small Business Innovation Research program. *The RAND Journal of Economics*, 82-100. https://doi.org/10.2307/2601030

Uçak, S., Kuvat, Ö., & Aytekin, A. (2018). Türkiye'de Arge Harcamaları- Büyüme ilişkisi: ARDL Yöntemi. *Manisa Celal Bayar Üniversitesi Sosyal Bilimler Dergisi, 16*(2), 129-160.

Yang, C. H., & Lin, C. H. A. (2008). Developing employment effects of innovations: microeconometric evidence from Taiwan. *The Developing Economies, 46*(2), 109-134. https://doi.org/10.1111/j.1746-1049.2008.00059.x