# The Effect of Technological and Scientific Knowledge on Economic Growth in Turkey (1980 - 2015)

Teknolojik ve Bilimsel Bilginin Türkiye'de Ekonomik Büyümeye Etkisi (1980 - 2015)

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## Abstract

In this study, we analyze the relationships among science, technology, and economic growth in Turkey for the period 1980 - 2015. We fitted linear regression and ARDL models by using scientific articles and patents as representatives for the scientific and technological outputs, respectively. The results obtained from the fitted models reveal that there is no significant statistical evidence showing a strong relation between science, technology, and economic growth. There are two possible interpretations of the results. First, the ties between university and industry are weak in Turkey. Second scientific papers of Turkey do not impact the productive sectors of Turkish economy directly.

***Keywords:*** economic growth, patents, scientific articles, time-series models, Turkey

***JEL codes:*** C32, O14, O25, O33, O53

## Öz

Bu çalışma, Türkiye'de 1980 - 2015 döneminde bilim, teknoloji ve ekonomik büyüme arasındaki ilişkileri analiz etmektedir. Bilimsel yayınlar ve patent verileri sırasıyla bilimsel ve teknolojik çıktıları temsil etmektedir. Çalışmada doğrusal regresyon ve ARDL modelleri kullanılmıştır. Uygulanan modellerden elde edilen sonuçlar, bilim, teknoloji ve ekonomik büyüme arasında güçlü bir ilişki olduğunu gösteren önemli bir istatistiksel kanıt olmadığını ortaya koymaktadır. Çalışmanın sonuçlarına bağlı olarak, iki temel çıkarıma ulaşmak mümkün olabilmektedir. Birincisi, Türkiye'de üniversite ile sanayi arasında bulunan bağlar zayıftır. İkincisi ise, bilimsel makaleler, Türkiye ekonomisinin üretken sektörlerini doğrudan etkilememektedir.

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***Anahtar Kelimeler:*** ekonomik büyüme, patent, bilimsel makaleler, zaman serisi modelleri, Türkiye

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## Introduction

Before the Second World War; per capita incomes of five East Asia countries or territories, namely South Korea, Taiwan, Singapore, Japan, and Hong Kong, were between 10 to 40 percent of U.S.A. But, after the Second World War, these 5 East Asia countries successfully caught up the developed countries. These countries which joined the rich countries during 1950 - 1990 period, were also the only states that succeeded to catch up in this period (Popov and Jomo, 2018: 39). Although there is no consensus about what kind of policies are more important to explain this success (Popov and Jomo, 2018: 39), the effective use of science and technology policies of these countries is considered to be one of the most leading explanations.

In the 1960s and 1970s, East Asia countries had less advanced economies than Latin America countries. However, this situation changed over time. East Asia countries left behind Latin America countries and catch up the rich countries. Differences between technology and science policies of Latin America and East Asia countries could explain this success. In Latin America, science policies were given more emphasis than technology policies. As a result of this policy choice, science policy is isolated from the technology sector. Thus, the co-evolution between science and technology policies could not be achieved. In contrast to Latin America, the co-evolution between technology and science policies succeeded in the East Asia countries. In fact, companies in the East Asian countries have invested heavily in R & D activities. This situation increased the demand of national firms to applied science. Therefore, the co-evolution between science and technology policies could be accomplished in the East Asia countries (Lee and Kim, 2018: 78 - 79).

Another development which increases the significance of science and technology policies in developing countries, relates to growth expectations. Although emerging economies achieved high growth rates in the period between 2000 and 2012; it is expected that developing countries will not sustain these growth rates in the following period. Particularly, the end of credit and commodity booms which occurred during the 2000 and 2012 period and financial fragility of developing countries is defined as important facts which cause expectation of growth slowdown in emerging economies (Åslund, 2013: 16 - 17).

Therefore, it could be concluded that, developing countries need to design new policies including science and technology policies in order to sustain high growth rates.

The determination of the state of correlations between science and technology policies and economic growth is important to design new policies for developing countries. Turkey is one of the developing countries which, like for Latin America and East Asia countries, involved the globalization of economies which started in 1980s. The objective of our study is to assess the relationship among economic growth, science, and technology in Turkey for the period between 1980 and 2015 by using scientific articles and patents as representatives for the technological and scientific outputs, under a linear regression and Autoregressive Distributed Lag (ARDL) models.

The methodology followed through the paper has the aim of detecting significant determinants of growth of GDP. And in that framework the paper focuses on the role of knowledge variables which are represented by articles and patents. The first estimation is used under a classical linear regression model where the growth of GDP is dependent variable. As a result of the analysis of the time series of Turkey, we could not observe any significant effect of growth of knowledge variables to the growth of GDP. The second estimation is the ARDL model of Paseran et al. (2001). The main results based on the time series of Turkey reveal that, patents have a long-run but weak contribution to GDP, but articles have no significant impact on GDP neither in long- nor in short-run. To our knowledge, such results for Turkey has not been documented in the existing literature.

The structure of the study is as follows: The existing empirical literature on the relationships between output level (or economic growth), scientific articles, and patents is summarized in Section 1. In Section 2, linear regression analysis is presented, whereas the ARDL analysis is given in Section 3. The last section includes our concluding remarks.

## 1. Literature Review

One of the main contributions related with the literature on scientific and technological knowledge, is the study of Narin, Hamilton, and Olivastro (1997) in which the authors investigate the relationship between patents and scientific articles. Although this paper does not use an econometric model, they show the link between public science and U.S.A. technology empirically. Dosi, Llerna, and Labini (2006) examines the relation between science and technology for European countries. Their analyses, which do not employ an econometric model, indicate that both European system of scientific research and European industry lag behind U.S.A. Jeff (1989) investigates the correlation between university research and commercial innovation for states of U.S.A. by the help of OLS method. Given that strong relation between innovation and scientific research in drugs and electronic sectors is detected.

Furman and Hayes (2004) explore the relations among patents, GDP per capita, and patents by utilizing an econometric model. Furman and Hayes (2004) base their econometric analysis with the same framework which developed by Furman, Porter, and Stern (2002). In their econometric model, patents are used as dependent variable. GDP per capita is one of the independent variables which has an impact on patents. Their analysis comprises 29 countries for the period of 1978 - 1999. They obtain strong correlation between patents and GDP per capita. Lee et al. (2011) and Tunalı (2016) are among the current studies which analyze the impact of scientific research papers on GDP per capita. Tunalı (2016) use ARDL methodology to cointegration in order to show the impact of scientific product on GDP per capita for 15 countries in the European Union between 1981 and 2011. The results of this study indicate that scientific products impact GDP per capita significantly only for Sweden and France. Whereas Lee et al. (2011) analyse the correlation of GDP with scientific publications. In this study, VAR analysis in order to find out causality between scientific publications and economic productivity for the period 1982 -2007 has been used. The results indicate that the link between research and economic growth is strong.

Although some studies in the existing empirical literature investigate the pairwise relations between scientific knowledge, technological knowledge, and economic growth; there is no widespread studies which analyze these three variables under a single framework. Because of that reason, the results of the important studies which examine the links between patents, scientific papers, and GDP, are elaborately explained below.

Bernardes and Albuquerque (2003) examine the relationships between GNP per capita, patents, and scientific papers in 120 countries. They use United States Patent and Trademark Office (USPTO) data for patents, and ISI data for scientific papers. In 120 countries for the year 1998, they detect strong relationships between GNP per capita, patents, and scientific papers. They conclude that scientific and technological productions are correlated to GNP per capita. They also investigate the relationship between patents and scientific papers in 120 countries in the years of 1974, 1982, 1990, and 1998, respectively. Given that two important results have been found out. First, they identify a threshold level in scientific production. When scientific production goes beyond this threshold level (for the year 1998, it is approximately 150 scientific papers per million inhabitants), technological sector use scientific output more efficiently. Second, it is demonstrated that this threshold level changes in time. For instance, while the threshold level for the year of 1982 is approximately 28 scientific papers per million inhabitants, this threshold level rises 60 scientific papers per million inhabitants in 1990.

Chaves and Moro (2007) examine the relation between technology and science. For the years of 1981, 1991, and 2001, panel data analysis has been applied in order to determine this relationship. In their analysis, scientific production is measured by the log of scientific articles per capita for all scientific areas and technological production is represented by the log of patents per capita. Their investigation includes 59, 60, and 81 countries for the years 1981, 1991, and 2001, respectively. In their first panel data analysis, scientific production is a dependent variable, whereas gross national income and technological production are independent variables. They find out strong relationship between the scientific production and the independent variables. In their second panel data analysis, technological production is a dependent variable, gross national income and scientific production are independent variables. A significant relationship between technological production and with both gross national income and scientific production is detected.

Fagerberg, Srholec, and Knell (2007) examine the competitiveness of 90 countries during the period of 1980 - 2002. They use a factor analysis in order to define demand competitiveness, price competitiveness, capacity competitiveness, and technology competitiveness variables. USPTO patent grants and articles in scientific and engineering journals are among the indicators which are used to compose technology competitiveness variable. In their econometric model, the dependent variable is the growth of GDP and the independent variables are defined as demand, price, capacity, and technology competitiveness. It is shown that the interrelation between growth of GDP and the competitiveness variables is significant.

Fagerberg and Scholec (2008) investigate the influence of capabilities in economic development. Their empirical study is based on 115 countries. They use 25 indicators which include USPTO patents and scientific articles. By the help of factor analysis, four sets of capabilities from 25 indicators has been defined. These sets of capabilities are innovation system, governance, political system, and openness. In their empirical investigation, they try to find out a relationship between these four set of capabilities and annual growth of GDP which is a dependent variable in their model. Fagerberg and Scholec (2008) reach three important results from their econometric investigation. First, they show that there is a strong statistical relationship between GDP per capita and innovation system set which is highly correlated with USPTO patents and scientific articles. Second, the authors find that good governance is also important for the economic development.

Third, their study indicates that there is no significant relationship between the openness and annual growth of GDP.

Castellaci (2008) analyzes growth trajectories of different country groups. For this purpose, the effect of innovative ability and absorptive capacity on economic growth of 70 different countries is investigated for the period of 1970 - 2000. In the econometric model, dependent variables are separated into two groups. While the first group is classified as innovative ability variables, the second group is called as absorptive capacity variables. Independent variable of the econometric model is defined as the growth rate of GDP. The innovative ability variables are given as patents and scientific articles per capita. The dynamic panel methodology is used in order to assess relationships of variables. The patents variable has a positive correlation with the growth rate of GDP. The same result is obtained for the scientific articles per capita variable, although data of scientific articles is available only for the period 1985 - 2000.

Castellaci and Natera (2013) try to estimate the determinants of technological output by using panel cointegration analysis. Their research comprises 87 countries for the period of 1980 - 2007. The dependent variable in their econometric model is technological output which is represented by the number of patents, which are registered at the US Patent and Trademark Office, per million people. They find out significant relationships between technological output and independent variables which are GDP and innovative input. But interestingly, they do not detect any relationship between technological output and scientific output which is represented by the number of scientific and technical journal articles per million people.

Kim and Lee (2015) use a cross country panel data analysis in order to investigate the effect of technological knowledge and scientific knowledge measures on the knowledge production functions and on the GDP growth. The technological knowledge measure is quantified by the number of corporate patents per million people. SCI journal articles per million people represents the scientific knowledge. In the econometric analysis, data from the period of 1960 and 2005 which belong to East Asia and Latin American countries are used. The article empirically shows that impact of basic scientific knowledge on economic growth is weak. Although the article finds that the ties among technological knowledge and economic growth is strong. Therefore, it could be suggested that technological knowledge is found to be one of the leading determinants of economic growth.

Fagerberg and Scholec (2017) assess the impact of technological and social capabilities on life expectancy at birth, adjusted net national income per capita, GDP, and GDP per capita in 114 countries over the period of 1995 - 2003. A factor analysis is implemented on 11 different indicators in order to quantify social and technological capabilities. Scientific and engineering articles and USPTO patent applications are among the indicators which are used in the factor analysis. By the help of iteratively reweighted least squares method, Fagerberg and Scholec show that both technological and social capabilities play an important role in the economic development.

In summary, although there are important studies in the empirical literature that concentrate on the relationships among scientific articles, economic growth or GDP and patents; these studies in general use a panel data methodology to make a comparison among countries, and up to our knowledge, there is no detailed study which investigates these relationships for a specific country by exploring time series properties. In this study, based on these facts, it is aimed to fill this gap in the given literature by focusing on Turkey's case as one of the leading developing countries. In this paper, the ties among economic growth, scientific publications, and patents in Turkey for the period of 1980 - 2015 would be investigated by using a time series analysis.

## 2. A Linear Regression Model for Determination of Effects of Technological and Scientific Knowledge on Economic Growth (1980 - 2015)

As it is underlined in the literature review section, the impact of technological and scientific knowledge on economic growth is not analysed particularly for Turkey. In this section the model proposed by Kim and Lee (2015) for investigation of the effect of technological and scientific knowledge measures on GDP growth rate would be used. This paper uses an ordinary least squares (OLS) analysis for the dataset of a single country that is similar to Kim and Lee's country-panel econometric analysis.

Our study considers the time span of 1980 - 2015. We used the statistical software R for our regression analysis (R Core Team, 2019). In the regression analysis, GDP per capita which is expressed in constant 2010 US dollars, is defined as the dependent variable. The GDP per capita data is excerpted from the World Development Indicators of the World Bank Database. In our article, first independent variable is capital formation, which is represented by gross capital formation as percentage of GDP. In the regression analysis, second independent variable is total population growth. The third independent variable in our study is the rate of secondary school enrollment, which is represented as a percentage of GDP. The data for these specific variables is excerpted from the World Development Indicators as well. We used the imputation method in the R package "imputeTS" in order to fill missing values in the data (Moritz and Bartz-Beielstein, 2017). In the regression analysis, the knowledge is represented by two dependent variables. The first dependent variable is scientific knowledge which is given by the number of articles per million people, which are published in science citation index (SCI) journals. The data for the SCI journal articles is taken from the ISI Web of Knowledge. The second dependent variable which represents knowledge, is corporate patent intensity, which is a proxy for the technological knowledge. The corporate patent intensity is represented by the number of corporate patents granted by the United States Patent and trademark Office (USPTO) per million people. The source of the corporate patent intensity data is the web site of USPTO. The number of patents in some years is zero. It is observed that, this situation causes a problem when we take the natural logarithm of the time series. Therefore, we used imputation method in the R package "imputeTS" in order to fill the data entries which have zero values.

**Table 1: Descriptive statistics**

| Variables | Average | Std.dev. | Max | Min |
|---|---|---|---|---|
| GDP per capita (constant 2010 USD) | 8267 | 2456 | 13899 | 4987 |
| Growth Rate of GDP | 0.027 | 0.041 | 0.090 | -0.076 |
| Corporate patents intensity ( per million) | 0.234 | 0.339 | 1.482 | 0.018 |
| Growth Rate of Corporate patents intensity | 0.119 | 0.680 | 2.282 | -1.223 |
| SCI journal articles intensity (per million) | 126.3 | 131.9 | 430.3 | 6.3 |
| Growth Rate of SCI journal articles intensity | 0.116 | 0.094 | 0.388 | -0.151 |
| Population Growth | 0.017 | 0.003 | 0.023 | 0.012 |
| Investment to GDP ratio | 23.77 | 4.29 | 31.26 | 16.18 |
| Enrollment of secondary education | 67.87 | 20.98 | 103.05 | 37.56 |

Table 1 shows the descriptive statistics of variables. For period of 1980 - 2015, the mean value, standard deviation, maximum and minimum values are reported. Table 2 presents the correlations between growth rate of GDP, growth rate of SCI journal article intensity, and growth of corporate patent intensity. As it could be seen from Table 2, all the correlations are found to be weak.

**Table 2: Correlations between variables**

| Variable | Growth Rate of GDP | Growth Rate of SCI | Growth Rate of CPI |
|---|---|---|---|
| GDP Growth Rate | 1 | | |
| SCI Growth Rate | -0.06926391 | 1 | |
| CPIGrowth Rate | -0.07332147 | -0.05018548 | 1 |

Although the analysis of correlations gives a rough idea about the strength of the relationships among the analyzed variables, our main aim in this study is to perform a more delicate analysis of the relationships under a well-defined economic production function. As Solow model uses Cobb–Douglas type production function in order to forecast the output of an economy. This production function is described by Equation (1). In this equation, Y stands for the output, K denotes the physical capital input, L stands for labour input, and the technical efficiency is denoted by A (Solow, 1957: 312).

$$Y= f(K,L,A). \quad (1)$$

Cobb–Douglas type production function is expanded by Lucas (1988) and Romer (1990). They added human capital H to the production function (Lucas,1988: 18 and Romer, 1990: 80).

$$Y = f(K,L,A,H). \quad (2)$$

An empirical verification of production function in Equation (2) is presented by Mankiw, Romer, and Weil (1992). In the same line with Lucas (1988) and Romer (1990), Kim and Lee (2015) used Equation (2) in order to show the relationship between GDP and knowledge. In our regression analysis, we use an equation similar to that of Kim and Lee (2015). Equation (3) below is the model which we used to estimate the effect of technological knowledge and scientific knowledge on GDP.

$$\Delta \ln(y_t) = \alpha + \varphi \Delta \ln(SCI_t) + \omega \Delta \ln(CPI_t) + \tau \ln(K_t) + \varrho \ln(P_t) + \text{Ϛ} \ln(SSE_t) + \epsilon_t \quad (3)$$

where $\Delta \ln(y_t) = \ln(y_t) - \ln(y_{t-1})$, $\Delta \ln SCI_t = \ln(SCI_t) - \ln(SCI_{t-1})$, and $\Delta \ln CPI_t = \ln(CPI_t) - \ln(CPI_{t-1})$.

The variables in Equation (3) are explained below:

$y_t$: Gross domestic product (GDP) per capita in year t for Turkey

$SCI_t$: Number of SCI articles per million people in year t for Turkey

$CPI_t$: Corporate patents per million people in year t for Turkey which are granted by the United States Patent and trademark Office (USPTO)

$K_t$: Gross capital formation as fraction of GDP in year t for Turkey

$P_t$: Total population growth in year t for Turkey

$SSE_t$ : The secondary school enrollment rate in year t for Turkey

In the regression equation, the human capital is quantified by the enrollment rate of secondary schools. The physical capital input is defined by the gross capital formation as percentage of GDP. Total population growth represents the labour input. In regression analysis, the technical efficiency is represented by the corporate patent granted by (USPTO) per million people and SCI articles per million residents.

In the regression analysis, $y_t$, $SCI_t$ and $CPI_t$ are in growth form, whereas $K_t$, $P_t$ and $SSE_t$ are in logarithmic form.

Table 3 shows regression results for the Equation (3). The results are obtained by the OLS method. The most important outcome of the regression analysis is that there is no significant statistical evidence showing a relation between GDP growth rate and growths of corporate patents per million residents and number of SCI articles per million people. On the other hand, formation of gross capital and increase of total population influence GDP growth rate in a positive way. The secondary school enrollment rate's impact on GDP growth rate is insignificant.

**Table 3: Results of regression for equation (3)**

| | Estimates | Std. Errors | t Values | Pr(>\|t\|) |
|---|---|---|---|---|
| Intercept | 0.033406 | 0.181468 | 0.184 | 0.85523 |
| $\ln(SSE_t)$ | 0.003474 | 0.041861 | 0.083 | 0.93443 |
| $\ln(K_t)$ | 0.173774 | 0.053123 | 3.271 | 0.00277** |
| $\ln(P_t)$ | 0.138198 | 0.075286 | 1.836 | 0.07669 . |
| $\Delta\ln(CPI_t)$ | 0.001589 | 0.010011 | 0.159 | 0.87500 |
| $\Delta\ln(SCI_t)$ | 0.015499 | 0.072224 | 0.215 | 0.83158 |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Standard error of residuals: 0.03803on 29 degrees of freedom
Multiple $R^2$: 0.3041, Adjusted R-squared: 0.1841
F-statistic: 2.534 on 5 and 29 DF, p-value: 0.0508

### 3. The Relationships Between Scientific Knowledge, Technological Knowledge, and GDP: ARDL Analysis (1980-2015)

In this part of the study, we will try to determine the relationships between scientific knowledge, technological knowledge, and GDP in Turkey for the years of 1980 - 2015. For this purpose, autoregressive-distributed lag (ARDL) methodology which was first introduced by (Pesaran et al., 2001), is used.

#### 3.1. The ARDL Methodology

The (ARDL) approach has three steps (Paseran, 2015: 526). To explain the method, let's assume that there are three variables, $y_t$, $x_{1,t}$ , and $x_{2,t}$ , to be analyzed.

The first step is to estimate the error correction model:

$$\Delta y_t = a_0 + \sum_{i=1}^{p} \psi_i \Delta y_{t-i} + \sum_{i=0}^{p} \phi_{i1} \Delta x_{1,t-i} + \sum_{i=0}^{p} \phi_{i2} \Delta x_{2,t-i}$$
$$+\delta_1 y_{t-1+} \delta_2 x_{1,t-1+} \delta_3 x_{2,t-1+} u_t, \qquad (4)$$

where $u_t$ denotes a zero-mean white noise process.

The second step is the computation of Wald- or F-statistics. The null hypothesis is $H_0$: $\delta_1 = \delta_2 = \delta_3 = 0$. The critical value bounds of the test statistics are calculated by Pesaran, Shin, and Smith (2001).

The third step is comparison of the Wald- or F -statistics which are calculated in Step 2, with the upper and lower critical value bounds. $F_U$ and

$F_L$ represent the upper and lower critical value bounds for a given significance level, respectively.

If $F > F_U$, $H_0$ hypothesis is rejected. Hence, it could be concluded that there is a long run relationship among the variables.

If $F < F_L$, $H_0$ hypothesis is not rejected. Then, it could be inferred that there does not appear to exist a long run relationship among the variables.

If $F_L < F < F_U$, then the test is inconclusive.

**3.2. The Model Setting, Unit Root Tests, and Determination of Lag Length of Variables**

We use the ARDL methodology in order to investigate the long- and short-run effects of knowledge variables to GDP. The regression analysis in Section 2 which was performed by using differenced time series of knowledge variables and GDP, was not capable of showing the significance of the effects of level variables under the long-run equilibrium.

Under the assumption that knowledge variables contribute to national production process, one can construct a production function such as $y_t = f(K_{C,t}, H_t, SCI_t, CPI_t)$, where:

$K_{C,t}$: Capital stock at current PPPs (in million 2011 USD) in year t.

$H_t$: Human capital augmented employment which is the product of number of persons engaged (in millions) in year t and index of human capital per person, based on years of schooling and returns to education, in year t.

In our study, the times series data of two variables $K_{C,t}$ and $H_t$ are taken from Penn Table 9 (Feenstra et al. 2015) in the R package "pwt9" of Zelias (2019).

Our ARDL model will be based on the presumed cointegration relationship implied by above production function in the log-linear form. But before starting the ARDL analysis, two steps need to be carried out. Firstly, the stationarity of the variables which are used in the ARDL model, should be checked. Second lag length of the variables has to be determined. Therefore, in this part of the article, first of all, the stationarity tests will be conducted, and lag length of variables will be determined. After that the ARDL analysis will be conducted. All these steps would be estimated by using the R package "ardl" for our analysis (Barbi, 2016).

For testing hypotheses or to investigate the statistical significance of the coefficients, variates in the ARDL model have to be I(0) or I(1) (Pesaran et al., 2001: 291). To identify the order of integration of variables, the unit root tests are employed. In the literature, unit root test of (Dikey and Fuller,

1979) and (Dikey and Fuller, 1981), which is called Augmented Dickey–Fuller (ADF) unit root test, is mostly used. But ADF test depends on the restrictive assumption that error terms are white noise (Enders, 2015: 200). On the other hand, Phillips–Perron (PP) unit root test (Phillips and Perron 1988) relaxes the white noise error terms assumption of ADF test, and therefore allows to test unit roots under the more general situation that error terms are autocorrelated and have nonconstant variance. The null hypothesis of ADF and PP tests is that the analyzed time series is a unit root process. On the other hand, in the KPSS test of Kwiatkowski, Phillips, Schmidt, and Shin (1992), the null hypothesis of stationarity is tested against the alternative of a unit root.

The ADF and PP unit root tests and the KPSS stationarity test are performed for the variables, which are used in the ARDL model, to figure out whether they are I(0) or I(1). Also, the same tests are applied to the first-differences of time series to show that the series are not I(2).

Table 4 which can be seen below, shows the results of the tests. We observed that all the analyzed series seem to be unit root processes and their first differences are stationarity. In other words, none of the series are found to be I(2). This result allows us to construct an ARDL model.

**Table 4: Unit root results.**

| Variables | ADF | PP | KPSS |
|---|---|---|---|
| $\ln y_t$ | 0.3684 | 0.4433 | 0.9863 |
| $\ln CPI_t$ | 1.3491 | 0.7781 | 0.8770 |
| $\ln SCI_t$ | 1.0621 | 0.2382 | 0.9874 |
| $\ln K_{C,t}$ | 1.6488 | 1.8401 | 0.8243 |
| $\ln H_t$ | 4.1426* | 0.7535 | 0.9924 |
| $\Delta \ln y_t$ | 4.2148* | 6.1702* | 0.1141* |
| $\Delta \ln CPI_t$ | 6.0377* | 10.0288* | 0.1367* |
| $\Delta \ln SCI_t$ | 3.5467* | 4.8981* | 0.1919* |
| $\Delta \ln K_{C,t}$ | 2.3713* | 3.2308* | 0.0594* |
| $\Delta \ln H_t$ | 3.2499* | 5.0265* | 0.2219* |

Rejection of unit root hypothesis and failure of rejection of stationarity hypothesis with a significance level5%are showed with an asterisk.Δindicates first difference. All the test statistics are expressed in absolute value.

The lag length of the ARDL models could be determined by using the information criteria such as Akaike information criterion (AIC) and Bayesian information criterion (BIC). However, since we have a very limited amount of data (36 years), we prefer to fix the maximum lag length to two for all variables, as in Narayan (2005).

### 3.3. Analysis of the Results of ARDL Model

The equation that we estimate is given by

$$\Delta y_t = a_0 + \psi \Delta y_{t-1} + \sum_{i=0}^{p} \phi_{i1} \Delta \ln K_{C,t-i}$$
$$+ \sum_{i=0}^{p} \phi_{i2} \Delta \ln H_{t-i} \sum_{i=0}^{p} \phi_{i3} \Delta \ln SCI_{t-i} + \sum_{i=0}^{p} \phi_{i4} \Delta \ln CPI_{,t-i}$$
$$+ \delta_1 y_{t-1} + \delta_2 \ln K_{C,t-1} + \delta_3 \ln H_{t-1} + \delta_4 \ln SCI_{t-1}$$
$$+ \delta_5 \ln CPI_{t-1} + u_t \tag{5}$$

The bound test is performed for the null hypothesis that $H_0 : \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$. The results of the test are shown in Table 5. As it can be observed there seem to exist a cointegration relationship between the variables.

**Table 5: Bound test for cointegration.**

| F statistic | 5.513767 | |
|---|---|---|
| Critical Values | I(0) | I(1) |
| 10% | 2.45 | 3.52 |
| 5% | 2.86 | 4.01 |
| 2.5% | 3.25 | 4.49 |
| 1% | 3.74 | 5.06 |
| I(0)and I(1) are lower and upper levels of bound test. If F statistic is above the upper level, then $H_0$ hypothesis is rejected. If F statistic is below the lower level, then $H_0$ hypothesis is not rejected.If F statistic is between lower and upper levels, then test hypothesis is inconslusive. | | |

In Equation (6), the lagged level variables of Equation (5) is replaced by the error correction term $EC_{t-1}$:

$$\Delta y_t = a_0 + \psi \Delta y_{t-1} + \sum_{i=0}^{p} \phi_{i1} \Delta \ln K_{C,t-i}$$
$$+ \sum_{i=0}^{p} \phi_{i2} \Delta \ln H_{t-i} \sum_{i=0}^{p} \phi_{i3} \Delta \ln SCI_{t-i} + \sum_{i=0}^{p} \phi_{i4} \Delta \ln CPI_{,t-i}$$
$$+ \lambda EC_{t-1} + u_t \tag{6}$$

where $\lambda$ is the speed of adjustment parameter. A significantly negative $\lambda$ indicates the reversion of dependent variable to the long-run equlibirium.

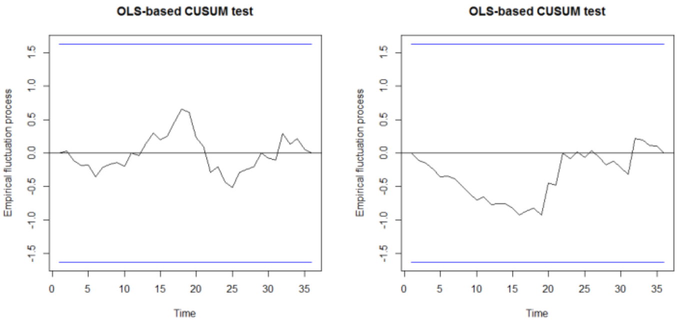
**Table 6: ARDL cointegration findings for growth equation.**

| Panel A: Long-run results. Dependent variable: $lny_t$ | | | | |
|---|---|---|---|---|
| Regressors | Estimate | Std.Err | Z value | Pr(>z) |
| $lnCPI_t$ | 0.015647 | 0.008212 | 1.905 | 0.0567 · |
| $lnSCI_t$ | 0.002595 | 0.013573 | 0.191 | 0.8484 |
| $lnK_{C,t}$ | 0.035691 | 0.020151 | 1.771 | 0.0765 · |
| $lnH_t$ | 0.829128 | 0.027992 | 34.697 | <2e-16*** |
| | | | | |
| Panel A: Short-run results. Dependent variable: $\Delta lny_t$ | | | | |
| Regressors | Estimate | Std.Err | Z value | Pr(>z) |
| Intercept | 4.582283 | 0.801033 | 5.720 | 1.06e-08 *** |
| $\Delta lny_{t-1}$ | 0.022950 | 0.140317 | 0.164 | 0.870 |
| $\Delta lnCPI_t$ | -0.007998 | 0.007500 | -1.066 | 0.286 |
| $\Delta lnSCI_t$ | -0.003978 | 0.064988 | -0.061 | 0.951 |
| $\Delta lnK_{C,t}$ | 0.289332 | 0.059452 | 4.867 | 1.14e-06 *** |
| $\Delta lnH_t$ | -0.001392 | 0.223390 | -0.006 | 0.995 |
| $EC_{t-1}$ | -0.783696 | 0.137819 | -5.686 | 1.30e-08 *** |
| Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 | | | | |

Table 6 reports the short- and long-run coefficients which are computed based on Equation (6). In Panel A of Table 6, the long run elasticity of GDP with respect to human capital augmented employment is observed to be the most significant. On the other hand, CPI and K have less pronounced long-run effects on GDP. Also, all the coefficients are found to be positive and so these three variables positively contribute to the GDP. Moreover, according to the reported ARDL results, the SCI variable does not have a significant contribution to the GDP.

In Panel B of Table 6, the estimation results for the short-run coefficients are reported. We observe that none of the variables have a significant short-run effect on GDP except for the capital stock K and the error correction term EC. The speed of adjustment parameter $\lambda$ is found to be -0.78. This implies that one-unit deviation from the long-run equilibrium in one year is corrected by 78% change in the next year. In addition, the stability of the error correction model is verified by CUSUM plots obtained by using R package "strucchange" of Zeileis et al. (2002). As it can be seen from Figure 1, there exists no structural break and so that it could be stated that the model is stable.

**Figure 1. The CUSUM plots of the residuals (left) and the squared residuals (right) of the ARDL model.**




In summary, our conclusion about the impact of knowledge variables to GDP is that patents have a long-run but weak contribution to GDP, but articles have no significant impact on GDP neither in long nor in short-run.

## Conclusion

In this study, we investigated the relations among SCI, CPI, and GDP in Turkey from 1980 to 2015. First, we conducted a linear regression analysis in order to determine the effects of growths of technological and scientific knowledge variables on the growth rate of GDP. The regression results exhibited no statistical evidence for the relation among the GDP growth rate and knowledge variables growth rates.

As it is a well-known fact that, the linear regression model is not able to capture the long run and short run relations between variables. Therefore, we make use of an ARDL model for a more comprehensive analysis. Our main finding regarding the knowledge variables is that patents have a long-run but weak contribution to GDP, but articles have no significant impact on GDP neither in long nor in short-run.

The results, which were obtained from our empirical analysis, can be interpreted in two different ways. First although there is a relationship between patents and GDP, this relationship is weak in case of Turkey for the given period. This result could be due to fact that conversion of patents to commercial products is not widespread. Second scientific papers of Turkey do not impact the productive sectors of Turkish economy directly. These findings suggest that Turkey should follow a more aggressive strategy to strengthen the ties between universities and firms to incentive research and development activities that can contribute to the economic growth.

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