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The Impact of Technological Achievement on Economic Growth: Evidence from a Panel ARDL Approach

Teknolojik Başarının Ekonomik Büyüme Üzerindeki Etkisi: Panel ARDL Yaklaşımından Kanıt

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Abstract: In recent times, technological innovations among nations are the most powerful instrument for higher economic growth rates and development. A higher level of achievement in the diffusion/adoption of technology can create more effective economic growth. Given this motivation, the study aims to examine the impact of technological achievements on economic growth, gross capital formation, medium and high-tech exports, and employment in chosen 72 countries over the period of 1990 - 2020. The unit root tests of the cross-section augmented Im-Pesaran-Shin (CIPS) test of Pesaran and also covariate Augmented Dickey-Fuller (CADF) test of Hansen, the Pedroni cointegration test, and then Pesaran ARDL model has been applied in the analysis of the data. The ARDL model results reveal a statistically significant causality and positive relationships between the technology achievement index and GDP growth, gross capital formation, medium and high-tech exports, and employment significance at 1 percent level in the long run according to Pooled Mean Group (PMG) estimator. Consequently, technological innovations are linked with economic growth and macroeconomic factors, that is to say, to get higher growth needs to grow up adaptation of technology and also to produce and trade technology-specific products.

Keywords: Technology Achievement Index, Economic Growth, Technological Innovation, Technology Adoption, ARDL Methodology

JEL Classification: O11, O31, O33

Öz: Son zamanlarda, uluslararasındaki teknolojik yenilikler, daha yüksek ekonomik büyüme oranları ve kalkınma için en güçlü araçtır. Teknolojinin yayılmasında/kabul edilmesinde daha yüksek bir başarı düzeyi, daha etkili ekonomik büyüme yaratabilir. Bu motivasyon göz önüne alındığında, çalışma, 1990 - 2020 döneminde seçilen 72 ülkede teknolojik başarıların ekonomik büyüme, brüt sermaye oluşumu, orta ve yüksek teknoloji ihracatı ve istihdam üzerindeki etkisini incelemeyi amaçlamaktadır. Verilerin analizinde Pesaran'ın kesit artırılmış Im-Pesaran-Shin (CIPS) testi ve ayrıca Hansen'in ortak değişkenli Augmented Dickey-Fuller (CADF) birim kök testleri, Pedroni eşbütünleşme testi ve ardından Pesaran ARDL modeli uygulanmıştır. ARDL modeli sonuçları, Havuzlanmış Ortalama Grup tahmincisine göre uzun vadede teknoloji başarı endeksi ile GSYİH, brüt sermaye oluşumu, orta ve yüksek teknoloji ihracatı ve istihdam anlamlılığı arasında yüzde 1 düzeyinde istatistiksel olarak anlamlı bir nedensellik ve pozitif ilişkiler ortaya koymaktadır. Sonuç olarak, teknolojik yenilikler ekonomik büyüme ve makroekonomik faktörlerle bağlantılıdır, yani daha yüksek büyüme elde etmek için teknolojiye adapte olmak ve ayrıca teknolojiye özgü ürünler üretmek ve ticaretini yapmak gerekir.

Anahtar Sözcükler: Teknoloji Başarı Endeksi, Ekonomik Büyüme, Teknolojik Yenilik, Teknolojinin Benimsenmesi, ARDL Metodolojisi

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1. Introduction

A plethora of economists have long researched the drivers of economic growth. At first, they focused on labor and capital as factors, but they couldn't explain the growth phenomena of various countries due to some of the failures of both. After the 1980s, they focused on technology improvements. Hence, technological innovation has become a factor of endogenous economic growth. The advantages of technological achievement in increasing economic growth have received much attention in the process of development. This type of advantage could derive from the rising returns and endogenous technological progress that influence the standards of living (Lucas, 1988; Frankel and Romer, 1999). Technological progress can also create new investment opportunities, divisions of labor, and employment. Moreover, the other advantage of technological achievements is that they also help to encourage international trade and create a comparative advantage in exports among nations. Accordingly, it can be concluded that higher achievement levels of diffusion and adoption of technology are the more efficient factors for economic growth. Within this perspective, this study aims to investigate the impact of technological achievements on economic growth, gross capital formation, medium and high-tech exports, and employment in selected 72 countries over the period from 1990 to 2020. Thus, this paper contributes to the literature on economic growth by technology innovation.

Unlike previous studies, the Technology Achievement Index (TAI) helps to analyze countries' reviews of the level of their technological performance relative to macroeconomic factors. A number of current studies reveal a relationship between the technology achievement index and economic growth and openness to trade and investment among countries. For example, Gani (2009) used the GLS estimation to examine the links between the level of technology achievement in countries and economic growth and high technology export data for 45 countries. The findings in this study show that economic growth and high-technology have a significant positive impact on the growth of the technology leader category of countries, whereas the category of potential leader countries has a positive relationship but is statistically insignificant. Another example is by Ali et al. (2015) who calculated the values of TAI in both the Organization of Islamic Cooperation (OIC) member countries and OECD countries. Their findings show that the performance of OIC countries has different development of technological capabilities than OECD countries.

In this context, the selected 72 countries in the study can be divided into upper-income, middle-income, and lower-income nations, as the World Bank classified them. These classified countries have undergone substantial economic growth between 1990 and 2020. While upper-income countries have GDP growth of an average of 4.85% in the periods covered, middle-income countries have GDP growth of an average of 4.71%. Additionally, lower-income countries have GDP growth of an average of 4.35%. The economic growth of countries depends on the share of all activities that affect the economy in certain sectors. One of those is based on technological progress. That is to say, understanding the drivers of technological achievement is an important and necessary beginning since the ranks of technological achievements among nations can be changeable under different conditions, which are based on economic development, openness to trade, and investment, and also employment. Consequently, the purpose of the study is to deal with the relationship and substantial drivers of technological achievements in all countries' economic growth.

In this respect, this paper has focused on empirically analyzing whether or not high-level employment, foreign direct investments, and exports have become decisive factors for economic growth per capita in nations with higher levels of technological achievement. The paper provides a new perspective with the method of the autoregressive distributed lag (ARDL) approach to the current literature on technological performance and economic development of nations by calculating their technology achievement indices and comparing these with macro-economic indicators.

The ARDL model (Pesaran, 2008) is employed to estimate the causal relationship in the long-run and short-run and the effect of the technology achievement index on economic growth, gross capital formation, medium- and high-tech exports, and employment. This model has used three different estimations as Pooled Mean Group (PMG), Mean Group (MG), and Dynamic Fixed Effects (DFE) estimations. The results of the study show that there are positive links between the technology achievement index and GDP growth, gross capital formation, medium and high-tech exports, and employment across 72 countries in the long-run and short-run estimates.

Following the introduction, the arrangement of the paper is as follows: In section 2 presents the literature review while section 3 indicates data representation and methodology. Additionally, section 4 represents empirical results and finally, section 5 is composed of the concluding remarks and policy.

2. Literature Review

This study has an extensive range of connections for technology achievement across countries and a time-varying analysis of the real world. It provides evidence for assessing technological progress and its economic determinants. A growing body of literature has concentrated on determinants that affect the achievement and diffusion of technology. The relation of technical change and aggregate products increase simultaneously in the economy (Solow, 1957). Technical change is the most important driving force in economic competitiveness. Therefore, this paper aims to examine the links between macro indicators and determinants of technology achievement in selected countries. Based on the literature focusing on there are several relationships between factors of demand and supply-side and technology achievement.

There are similarities between the effects of technological innovation and economic growth. Ulku (2007) examines whether innovation raises per capita output for 41 OECD and non-OECD countries using the method of difference Generalized Methods of Moments (GMM) estimation over the period of 1981-1997. The findings show a positive correlation among innovation and labor GDP in all non-OECD countries, but excluding lower-income countries. Similarly, Kirchhoff et al. (2007) focus on the causal links between R&D expenditures and employment growth in the U.S. labor market through 1990- 1999. The study finds that R & D expenditures have a positive indirect relation to economic growth. Fan (2011) also examines the impact of technological innovation on China and India’s GDP growth throughout 1981- 2004. This study obtains the R&D expenditure is the main contributor to economic development for both countries.

On the other hand, Bujari and Martínez (2016) use the GMM estimation to investigate the interactions between technological innovation and economic performance of countries in Latin America over the period 1996-2008. Their results imply significant and positive linkages between economic development and technological innovation in these countries. Therefore, the main contributor to economic growth is encouraging technological innovations in Latin American economies. Another study uses panel cointegration tests for 49 European countries period from 1961 to 2014 by Pradhan et al. (2018) to investigate the links among financial performance, technological innovation, and economic development. Results obtained from a vector error-correction model show the economic performance in 49 European countries has a positive causality with regard to financial development and technological innovation. Likewise, Maradana et al. (2019) used the vector autoregressive method during 1989–2014 to analyze multi-directional causality between innovation and economic growth. Findings of the study show the long-run cointegration and both bidirectional and unidirectional causality among technological achievement and economic development in some nations.

Considering some of the studies on technology achievements and economic growth in recent years, Wang et al. (2021) use a Maki Cointegration method to investigate the links between green growth and its determinants such as GDP, technological innovation, human capital, globalization, and R&D expenditures from 1990 through 2018 in China. The findings imply a long-run relationship and a positive effect of technological innovation on green growth. Another study by Pradhan et al. (2020) examines the links between global competitiveness and the level of technology and entrepreneurial development, which are key drivers of economic development. They used the Granger causality method in Eurozone countries over the period 2001–2016. Their findings show that, in the long run, both innovation and entrepreneurship encourage economic growth. However, Gyedu et al. (2021) analyze the impact of technological innovation on economic growth during the period 2000-2017 in the G7 and BRICS countries, using the GMM panel VAR estimator. According to their empirical findings, the main determinants of innovation, such as patents, R&D expenditure, and trademarks, have a positive relationship with economic growth in G7 and BRICS countries.

Another method is used by Chien et al. (2021) called the quantile autoregressive distributed lag (QARDL) method to analyze the links between carbon neutrality targets and green growth in the USA over the period from 1970 to 2015. The results of the study show a statistically significant and negative impact of green growth in determining CO2 emissions. Shen et al. (2021) also examine the links between green technology innovation and economic growth in China over the period from 2004 to 2016. Their findings conclude that economic growth targets affect green technology innovation through foreign investment. The study by Li and Solaymani (2021) also analyzes, by using an ARDL model and a dynamic ordinary least squares (DOLS) method for the period of 1978-2018 in the short-run and long-run economic growth, finds feedback on technological performance increases energy productivity.

The literature on the relationship between technological innovation and economic growth evaluates with multiple factors and gives mixed results. Santacreu (2015) utilizes the annual data during the 1996–2007 period and examines the links between innovation, output, and trade. The findings indicate how growth rates and levels of income change if countries face limitations on the adoption of foreign technologies. On the one hand, Ahmad et al. (2021) employ Westerlund panel co-integration model annual data from 1980 to 2016 in G7 countries. Their findings provide the links between urbanization, eco-innovation, financial globalization, and economic growth. Another study by Li and Wei (2021) examines the non-linear linkages between carbon emissions, financial development, trade, technological innovation, and GDP growth of 30 cities in China over the period from 1987 to 2017. The results reveal that carbon emissions have been reduced by the impact of technology performance on economic growth.

There are similarities between the effects of foreign direct investment and technological innovation. Holland and Pain (1998) utilized a panel dataset over the period 1992-1996 in eleven Central and Eastern European countries to examine the role of technological innovation in economic development through aggregate FDI. Empirical results indicate that significant impact on the level of investment. Another related study by Blind and Jungmittag (2004) employs probit estimation using data from German service firms to examine the impact of foreign direct investment and imports on technological innovation. Their empirical findings conclude that both factors have significant positive impacts on the innovation process. In addition, Pradhan et al. (2018) use the granger causality data with technological innovation, venture capital investment, economic growth, and financial development from 1989 through 2015 for 23 European countries. Empirical results obtained from analyzing three variables contribute to long-term economic performance. Later, Khan et al. (2021) use the dynamic GMM estimators in 69 countries throughout 2000-2014 to analyze the effects of technological innovation and foreign direct investment (FDI) on the variables of CO_2 emissions, renewable energy, and non-renewable energy. Empirical findings show a significantly positive relationship between technological innovation, FDI, and GDP growth and also show a two-way causality between renewable energy and technological innovation.

There are also similarities between the effects of exports and technological innovation. Fu (2005) employs a panel of 26 manufacturing industries in China date from 1990 to 1997 to investigate the links between export, productivity growth, and technical progress. As a result, we have come to the conclusion that exports have an important and positive impact on China's technological progress. However, Gani (2009) used the GLS estimation to examine the links between the level of technology achievement in countries and economic growth and high technology export data for 45 countries during the period from 1996 to 2004. Empirical findings in this study show that economic growth and high-technology have a statistically significant and positive impact on the development of the technological leader category of countries, whereas the category of potential leader countries has a positive link but is statistically insignificant. Similarly, Palangkaraya (2012) use the data of firms from Australia to examine the links between causality between export market participation and innovation, findings conclude that export is a highly significant and positive causal relationship with technological innovation. The result is in line with the findings of Aghion et al. (2018), technological innovation effort increases to all firms export activities. The panel cointegration methods and findings are consistent with Ustabaş and Ersin (2016) analyzed the links among GDP growth and high technology exports in Turkey and South Korea from 1989 through 2014. Comparative results show investments in human capital and R&D should encourage in Turkey in long run to support economic performance.

Besides, Wu et al. (2017) focus on the technological innovation productivity of 80 countries over the period 1981–2010. The results imply that exports and foreign direct investment make significant contributions to the development of new technologies. The GMM model is applied by Sultanuzzaman et al. (2019) over the period from 2000 to 2016 to study the effects of technology and exports on the economic development of emerging Asian countries. They find that technology and exports have long-term positive effects on the economies of the countries that use them. The finding is consistent with Cassiman et al. (2010), their findings also imply the positive links between exports and innovation activities in firms. Lastly, Hammar and Belarbi (2021) use panel data for 36 countries from 2002 through 2014 to examine the nonlinear linkages between technological innovation, productivity, expenditures for R&D, and high-tech export products. Their empirical findings show that there is a single threshold (two regimes) in the relationship between technological innovation, R&D expenditures, and productivity.

The current literature also includes the other indexes that are used to compare the technology achievement index (TAI) with the other indexes. For instance, Ali (2017), finds that the impact of technological progress accounts for approximately 13.2% of long-run economic development using yearly data from the TAI, HDI, and Gross Capital Formation (GCF) from 1995 to 2015. Likewise, Ali et al. (2015) have calculated TAI values for both the Organization of Islamic Cooperation (OIC) member countries and OECD countries during the period of 2008–2013. Their analysis shows that the performance of OIC countries differs greatly from that of OECD countries. These differences show that education, R&D, innovation, socioeconomic growth, and industrial development are important for a country.

In general, the results of these studies show that technological innovation and technology adaptation are growing in parallel with economic performance and its determinants in a country. That is to say, technological achievements among nations could contribute to economic growth and human well-being. On the other hand, the technological achievements of countries are related to economic geography, high mobility, and more competition among nations.

3. Data Representation and Methodology

3.1. Data

There are several factors that affect a country's technological progress and achievements, besides many methods for measuring this success. Technology Achievement Index (TAI) is one of these methods. A pioneering study by Desai et al. (2002) is used to calculate the TAI. The calculation of TAI is composed of four major dimensions and eight sub-indicators of these dimensions, the dimensions of the indicators are averaged according to the selected variables. The final indicator of TAI, dimensions are taken a quarter of the weight. Furthermore, TAI is derived as an index related to the minimum and maximum values observed by all the countries with data are chosen as indicators for each variable in these dimensions. The performance of each indicator is calculated separately the following general formula is applied.

$$TAI = \frac{(actual\ value - observed\ minimum\ value)}{(observed\ maximum\ value - observed\ minimum\ value)}$$

According to the TAI formula, the output of each country index is expressed as a value between 0 and 1. Therefore, the TAI summarizes the technological achievements of society and allows countries to make the level of technology and innovation comparable. If the value of a country's index approaches 1, this situation makes it reach a more leading position among others.

Time series and annual datasets have been taken from the World Bank Development Indicators Database in the period of 1990 - 2020 and used to analyze this study. The variables comprise GDP PPP per capita, gross capital formation (% of GDP), medium and high-tech exports (% manufactured exports), employment to population ratio, 15+, total (%). A summary description of the dataset is presented in Table 1.

Table 1. Summary Table of Variables

Variables	Proxy	Symbols
Technology achievement index	average of four sub-indices; old and recent innovations, creation of technology, and human skills	tai
Economic growth	GDP PPP (Current $)	gdp
Investment-GDP ratio	Gross capital formation (% of GDP)	inv
Exports	Medium and high-tech exports (% manufactured exports)	exp
Employment	Employment to population ratio, 15+, total (%)	emp

Source: Description of Data taken from World Bank Database.

Likewise, the descriptive statistics are in Table 2 and the pair-wise correlation matrix is also in Table 3 are all shown.

Table 2. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
lntai	2,232	0.408193	0.118996	0.132671	0.83134
lngdp	2,232	9.534996	1.032351	6.052875	12.10275
lninv	2,232	3.124571	0.259276	0.146137	4.063038
lnexp	2,232	3.528144	0.792448	1.179322	4.447210
lnemp	2,232	4.001591	0.151982	3.583797	4.345881

Source: Calculated by author on STATA program.

The descriptive statistics of the technology achievement index (lntai), economic growth (lngdp), gross capital formation (lninv), medium and high-tech exports (lnexp), and employment (lnemp) are represented in Table 2 above. Dependent and independent variables are defined in natural logarithms.

The mean of lntai (0.40) is calculated low, which implies that for the period under study, the lntai of selected countries on average is nearly little. The maximum and the minimum values of lntai are 0.831 and 0.132 respectively. The mean of lngdp (9.53) is low among selected countries. Also, lngdp has the maximum and the minimum value of 12.10 and 6.05 respectively. Additionally, the mean, maximum, and standard deviation of variables of lniv, lnexp and lnemp are close to each other and have a small variability over time.

In table 3, the correlations among the dependent and independent variables are presented in the table of the correlation matrix result below. There is a positive correlation between lntai and all independent variables at a 10% significance level. Also, it is expected that independent variables like GDP, investments, employment, and exports are positively correlated among themselves.

Table 3. Pair-wise Correlation

Correlation	lntai	lngdp	lninv	lnexp	lnemp
lntai	1				
lngdp	0.7672*	1			
lninv	0.1109*	0.0451**	1		
lnexp	0.6870*	0.4985*	0.0860**	1	
lnemp	0.1073*	0.1074*	0.1212*	0.1102*	1

*Note: ***, ** and * indicate 1%, 5% and 10% level of significance, respectively.*

3.2. Model Specification

This paper assessed the linkages between the technological achievement index, economic growth, gross capital formation, medium and high-tech exports, and employment in a selected 72 countries. The dependent variable is the technology achievement index, while the independent variables are GDP per capita, gross capital formation, medium and high-tech exports, and employment. In the literature, some of these variables have been used by Gani, 2009, Cassiman et al., 2010, Li and Solaymani, 2021, and Li and Wei, 2021.

$$\text{tai} = \text{f (gdp, inv, exp, emp)}$$

By applying natural logarithm, the standard form of the model is mentioned below:

$$\text{lntai} = q_0 + q_1\text{lngdp} + q_2\text{lninv} + q_3\text{lnexp} + q_4\text{lnemp} + e_t$$

Following the standard form of the model, the nature of the data is analyzed with some estimation techniques. Moreover, the effect of the provisional dimension of the panel under consideration appears to increase the probability of likely long-run links between the variables and the occurring causal relationships. Therefore, in order to analyze the long-run causality among variables in selected countries, this study applied an ARDL model. The ARDL modeling proposed by Pesaran et al. (1996, 2001) analyzes the variables that integrated I(0) and I(1) and works as an error correction model. Furthermore, ARDL modeling maintains efficient and consistent estimators by removing endogeneity issues and adding lag length in both exogenous and endogenous variables.

After estimating the presence of co-integration in the data, the long-run and short-run causal impacts of lntai on lngdp, lniv, lnemp, and lnexp are evaluated. The ARDL model works as an error correction model by analyzing the variables that are integrated of I(0) and I(1). Furthermore, ARDL modeling maintains efficient and consistent estimators by removing endogeneity issues and adding lag length in both exogenous and endogenous variables. The following equation indicates the ARDL (p,q,q,...,q) model for long-run estimates of the study:

$$\ln tai_{it} = \mu_i + \sum_{j=1}^{p-1} \beta_{1it}\, lngdp_{it-j} + \sum_{j=0}^{q-1} \beta_{2it}\, lninv_{it-j} + \sum_{j=0}^{q-1} \beta_{3it} lnexp_{it-j} + \sum_{j=0}^{q-1} \beta_{4it} lnemp_{it-j} + v_{it}$$

This equation is reformulated by Pesaran et al. as follows:

$$\Delta lntai_{it} = \mu_i + \gamma_{1i} lngdp_{it-1} + \gamma_{2i} lninv_{it-1} + \gamma_{3i} lninv_{it-1} + \gamma_{4i} lnexp_{it-1} + \gamma_{5i} lnemp_{it-1} + \sum_{j=1}^{p-1} \delta_{1ij}\, \Delta lngdp_{it-j} + \sum_{j=0}^{q-1} \delta_{2ij}\, \Delta lninv_{it-j} + \sum_{j=0}^{q-1} \delta_{3ij} \Delta lnexp_{it-j} + \sum_{j=0}^{q-1} \delta_{4ij}\, \Delta lnemp_{it-j} + \varepsilon_{it}$$

where terms in level display long-run dynamics, whereas terms in first difference display short-run effects. Δ expresses the first difference operator and εit is the error term. Besides, the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) supports assigning the choice the optimal lag length of variables (p,q).

3.3. Estimation Techniques

This study employs different test methods to analyze the correlation and long-run relationship between technology achievement index (lntai), economic growth (lngdp), gross capital formation (lninv), medium and high-tech exports (lnexp), and employment (lnemp). Some of the researchers neglected the problem of cross-sectional dependence among variables and also assumed homogenous slopes in their panel research. As a starting point, the cross-sectional dependence (CD) test analysis permits examining the cross-sectional dependency and heterogeneous slopes. The CD test developed by Pesaran (2004) is appropriate for data sets with N > T. N is the cross-section unit and T is the time. After the analysis continues to present the series for all variables containing second-generation unit root tests, it has proceeded to an analysis of panel cointegration tests to check whether there are long-run links among variables. These findings from Table 4 and Table 5 show that cross-sectional dependence exists in the panel and slope heterogeneity should be taken into account in the following steps.

Table 4. Cross-section Dependency Test Results

Variables	CD Test	*p*-value
lntai	165.07***	0.000
lngdp	268.58***	0.000
lninv	18.37***	0.000
lnexp	38.701***	0.000
lnemp	14.59***	0.000

Note: (***) denotes statistically at 1% the significance level.

The cross-sectional dependence test (Pesaran, 2004; De Hoyos and Sarafidis, 2006) was first performed to determine cross-section dependency across the countries at all significance levels. According to the findings of the cross-sectional dependence in Table 4, the null hypothesis of no cross-section dependency across the countries is rejected at all significance levels. Therefore, findings show the existence of cross section dependency among nations which means that due to the advanced integration and globalization across countries, the shock that emerged in one of these 72 countries appears to have spread to other countries. The unit root and cointegration test to be used can be selected depending on the results of the cross-section dependency analysis. Due to an existing cross-section dependency, the second-generation unit root test can be used to make more efficient and robust estimations.

Table 5. Homogeneity of Slope Test Result

Test	LM statistics	*p*-value
$\tilde{\Delta}_{HAC}$	41.484***	0.000
$\tilde{\Delta}_{adj,\,HAC}$	46.195***	0.000

Note: (***) denotes statistically at 1% the significance level.

Table 5 also indicates the slope homogeneity (Pesaran and Yamagata, 2008) which implies strongly rejecting the null hypothesis of slope homogeneity across countries at all significance levels. As a result, the slope is expected to change by country, and the direction of the causal relationship among variables in 72 countries seems to be heterogeneous. Following, the existence of cross-sectional dependence and slope heterogeneity across countries provides evidence to use the unit root test, which is a second-generation approach.

The panel data method that should be used depends on the stationarity of the data. Hence, testing for unit roots before proceeding is important to the estimation of empirical relationships. Table 6 shows the second-generation panel unit root results at the level and first difference.

Table 6. Panel Unit Root Tests Results

	CIPS Test Statistic		CADF Test Statistic	
	Level	First difference	Level	First difference
tai	-1.389	-4.712***	-1.761	-3.330***
gdp	-1.618	-3.680***	-1.830	-2.885***
inv	-2.010	-4.702***	-2.010	-3.700***
exp	-2.040*	-3.418***	-1.937	-3.732***
emp	-1.010	-4.960***	-1.434	-2.690***

*Note: The critical values for CIPS test and CADF test at the 1%, 5%, and 10% levels of significance are 2.17, 2.08, and 2.02, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.*

For the second generation unit root tests that allow cross-sectional dependency, the study uses the cross-section augmented Im-Peseran-Shin (CIPS) test of Pesaran (2007) and also covariate augmented Dickey-Fuller (CADF) test of Hansen (1995) which is in the standard Dickey-Fuller framework. Some modifications are developed for CADF and CIPS test statistics by Westerlund and Hosseinkouchack (2016). Both test results indicate that all the variables are not stationary at 1% significance in the level, except exp which is also stationary at 10% significance in the level in CIPS test. At first difference, however, all the time series are stationary at 1% significance level.

4. Empirical Results

The results of the second-generation panel unit root tests when the cross-section dependency is taken into account show that at certain levels, the whole variables show a unit root. However, when taking the first difference, it is stationary. This means that the whole variables being analyzed are integrated orders of I(1); therefore, the Pedroni (2004) cointegration test is used. The Pedroni cointegration analysis emphasizes the heterogeneity across countries and time factors as well. As can be observed in Table 7, we used the Pedroni cointegration test to analyze the long-run relations among the variables in the study. The Pedroni cointegration test with seven statistics is separated into sections within and between dimensions. The outcome of the test shows no strong evidence of long-run relations among the variables. Due to missing several important properties such as heteroskedasticity, serial correlation, cross-section dependency, and structural breaks among the nations in the Pedroni cointegration test, it may use the other cointegration tests.

Table 7. Pedroni (2004) Cointegration Test Result

	t-stat	Prob.	Weighted-stat.	Prob.
H1: common coefficients (within dimensions)				
V-stat	-1.5502	0.802	-1.6014	0.922
Rho-stat	0.9239	0.177	0.9824	0.244
PP-stat	-3.5907	0.000*	-4.5282	0.000*
ADF-stat	-2.7271	0.003*	-4.0217	0.004*
H1: individual coefficients (between dimensions)				
Rho-stat	1.5472	0.060		
PP-stat	-6.4293	0.000*		
ADF-stat	-5.3930	0.000*		

Note: (*) and (**) refer to the rejection of the null hypothesis at 1% and 5% significance level, respectively.

An advanced cointegration test was developed by Westerlund and Edgerton (2007), adding some of the properties like structural breaks and cross-sectional dependence that were mentioned above. Westerlund also provided two types of tests using the ECM model: group mean statistics (Gt, Ga) and panel statistics (Pt, Pa). Hence, the results of Westerlund cointegration test are more reliable for long-run relations between the variables. Table 8 reports the results of the Westerlund (2007) ECM panel cointegration test, which shows that all the panel cointegration statistics reject the null hypothesis, which refers to no cointegration being rejected at the 5% level of significance in both the asymptotic standard distribution and in the bootstrap method, except for Ga. Overall, with the rejection of the null hypothesis of no cointegration verified the variables are cointegrated and there is a long-run relationship among the variables. That is to say, there exists a statistically significant cointegration relation among the variables. When cointegration has been found, the next step is to figure out which variables have long-term connections to each other.

Table 8. Westerlund ECM Panel Cointegration Test Result

Statistic	Value	Z -value	P-value	Robust P-value
Gt	-1.8780	0.8360	0.009**	0.006**
Ga	-3.8170	7.2330	0.9997	0.8590
Pt	-17.1060	-12.6740	0.004**	0.020**
Pa	-13.0490	-11.0850	0.039**	0.004**

Notes: (**) indicates cointegration at 5% the significance level.

After making sure that the variables are cointegrated among all countries, it is also important to estimate long run and short run estimates and use the panel ARDL model (Pesaran, 2008) to investigate the causal relationship with the Pooled Mean Group (PMG), Mean Group (MG), and Dynamic Fixed Effects Estimation (DFE) estimator. The panel ARDL method has various significant advantages in that it is used to examine the different lengths and short-run and long-run effects of the dependent and independent variables and helps to reduce endogeneity problem. Possibly, the biggest advantage of the ARDL method is that it assumes different degrees of cointegrated variables like I (0) and I (1). Therefore, ARDL methodology is employed in this study to examine the long-run and short-run causal relationship and impact of technology achievement index on economic growth, gross capital formation, medium and high-tech exports, and employment. This study used the technology achievement index as a dependent variable in the equation with GDP, gross capital formation, medium and high-tech exports, employment as the explanatory variables. In this model, the chosen ARDL model is ARDL (1, 1, 1, 1, 1) with respect to the Akaike info criterion for lag selection. This model has been analyzed appear with a Log-likelihood of 3703.772 and a standard deviation of 0.0403.

The findings of the ARDL model in Table 9 confirm with three estimators. According to PMG and DFE estimators, lntai has a positive effect on lngdp, lniv, lnemp and lnexp in long-term and also short-term (except for lninv) at 1%, 5% significance level. Whereas, MG estimator provides that there is no significant effect of lntai on lniv and lnemp in long-run and short-run and significant and positive impact on lngdp and lnexp. Therefore, PMG and DFE estimators approve of the existence of long-term and short-term causality between the variables.

Additionally, when we utilize the Hausman test to investigate the efficiency and consistency among the PMG, MG, and DFE estimators. Results of the Hausman test show impossible to reject the homogenous constraint in long-run variables at 1% level of significance, hence concluding the PMG is looking a consistent and efficient estimator than MG and DFE. As can be seen, the PMG is the most efficient estimator for the model. Moreover, the PMG method not only estimates the long-run links among cointegration variables but also provides error correction terms that prove the presence of long-run links. Hence, the study is pointed out the interpretation of this estimator.

Table 9. ARDL Model Results
(Dependent Variable: Dlntai)

Tests	**Pooled Mean Group**			**Mean Group**			**Dynamic Fixed Effects**		
Variables	Coeff.	Std. Error	Prob.	Coeff.	Std. Error	Prob.	Coeff.	Std. Error	Prob.
Long-run coefficients									
lngdp	0.0765447	0.01517	0.000*	0.054761	0.0254	0.000*	0.122236	0.0188	0.000*
lninv	0.079008	0.02939	0.007*	0.018753	0.0314	0.111	0.062448	0.0377	0.008*
lnexp	0.3472174	0.02863	0.000*	0.245875	0.0221	0.044**	0.151932	0.0254	0.000*
lnemp	1.224937	0.10549	0.000*	-0.54785	0.1277	0.254	0.288911	0.1400	0.039**
Short-run coefficients									
∆ECT	-0.1726521	0.02408	0.000*	-0.27584	0.0257	0.000*	-0.21618	0.0142	0.000*
∆lngdpt-1	0.1640275	0.06434	0.011**	0.41574	0.0874	0.024**	0.129493	0.0337	0.000*
∆lninvt-1	-0.0379138	0.03122	0.225	-0.08451	0.0521	0.145	-0.012	0.0113	0.289
∆lnexpt-1	0.0384766	0.05799	0.007**	0.189925	0.0049	0.002*	0.060605	0.0076	0.000*
∆lnempt-1	0.6179258	0.19304	0.001*	0.084815	0.0016	0.112	0.250401	0.0772	0.001*
Hausman test				2.13[a] (0.3817)			2.68[b] (0.3244)		

*Notes: ***, ** and * indicate 1%, 5% and 10% level of significance; ECT is error correction term. [a] Under the null hypothesis, PMG is more efficient estimation than MG. [b] PMG is more efficient estimation than DFE under the null hypothesis.*

As seen in table 9 also, the PMG estimator indicates that a statistically significant causality and positive links among lntai and lngdp, lninv, lnexp and lnemp at 1% significance level in long-term. There is also significant and a positive causality between lntai and lngdp, lnexp and lnemp, except for lninv which is found statistically insignificant in short run.

5. Concluding Remark and Policy

Technological achievements of countries have a substantial role in economic growth. This study investigates and estimates the links between technology achievement index and GDP PPP per capita, Gross capital formation, Medium and high-tech exports, Employment to population ratio for 72 countries. In the first step of this study, CD (Pesaran, 2004) test is applied to investigate the cross-section interdependence among the variables that present the null hypothesis is rejected of no cross-section dependency at all significance levels across the countries. Next, the slope heterogeneity across countries is found, this shows to use the second-generation unit root test approach with the existence of cross-section dependency evidence. The second step of this study utilizes the cross section augmented Im-Peseran-Shin (CIPS) test of Pesaran (2007) and also covariate augmented Dickey-Fuller (CADF) test of Hansen (1995). Both test results indicate that all the variables are not stationary at 1% significance in the level. Thus, this study could apply the co-integration test to indicate that there is a long-term or non-relationship between technology achievement index and GDP, gross capital formation, medium and high-tech exports, and employment. The third step introduces after finding all variables have unit root and those are first-order integrated, the Pedroni (2004) cointegration test is applied for long-run relations between the variables. Furthermore, the consequences of the cointegration test results displays the null hypothesis rejection that is mentioned to no cointegration is verified the variable are cointegrated and the presence of a long-run linkages among the variables.

In the final stage of this study, modeling of the ARDL method (Pesaran, 2008) is employed to determine both long-run and short-run causality and the impact of the technology achievement index on economic growth, gross capital formation, medium and high-tech exports, and employment. This method is based on three different estimations, such as PMG, MG, and DFE estimations. The findings of the ARDL method show a statistically significant causality and positive links between the technology achievement index and GDP, gross capital formation, medium and high-tech exports, and employment at 1% significance level in the long run with respect to the PMG estimator. Besides, strong evidence has revealed that the PMG estimator is more fruitful in analyzing than the MG and DFE estimators.

Overall, empirical results of this study have shown that there is a positive link between the technology achievement index and economic growth among 72 countries, both in the long-run and the short-run. In addition, in the long run, there is a strong connection between the technology achievement index and gross capital formation between countries. Moreover, the findings show significant and positive links between the technology achievement index and medium and high-tech exports in long-run and short-run estimations. However, there is also an important and positive link between the technology achievement index and employment for selected countries.

The technological achievement rankings of countries have been greatly influenced by their economic and business scenarios. Besides, the diffusion of technology can be associated with some specific terms: population, communication, education, democracy, equality in society, poverty, geography. For instance, high-income countries have considerable technological diffusion and achievements when all effective factors are considered. The policy recommendation of the study is that countries aiming for high growth need to increase their adaptation of technology and also produce and trade technology-specific products. Therefore, countries should have and improve their technological capabilities in the fields of creation of technology, human skills, diffusion of old technologies, and diffusion of new technologies. These major fields consist of many alternatives such as investments in R&D, increase schooling ratio, human capital formation, developing new technological products, and open technology trading. Particularly, research and development department in new products and technologies need to be part of the process of technology adaptation of countries. Furthermore, governments and policymakers should encourage producers and create new opportunities for individuals to produce and trade technological products on a global scale. In this way, it could be possible to upgrade economic growth and human well-being. Therefore, policymakers should carefully assess whether macroeconomic conditions are likely to produce a rebound effect or a lock-in mechanism on the technological achievements.

REFERENCES

Aghion, P., Bergeaud, A., Lequien, M., & Melitz, M. J. (2018). The Impact of Exports on Innovation: Theory and Evidence. *SSRN Electronic Journal*, 1–33. https://doi.org/10.2139/ssrn.3171084

Ahmad, M., Jiang, P., Murshed, M., Shehzad, K., Akram, R., Cui, L., & Khan, Z. (2021). Modelling the dynamic linkages between eco-innovation, urbanization, economic growth and ecological footprints for G7 countries: Does financial globalization matter? *Sustainable Cities and Society*, *70*(October 2020), 102881. https://doi.org/10.1016/j.scs.2021.102881

Ali, T. M. (2017). Technological Achievements and Economic Development : The Significance of Technological Achievement Gap in Selected East and South Asian Countries. *STI Policy Review*, *8*(August), 113–156.

Ali, T. M., Bashir, T., & Kiani, A. K. (2015). Assessment of Technological Capabilities of OIC Countries. *Science, Technology and Society*, *20*(1), 114–131. https://doi.org/10.1177/0971721814561394

Blind, K., & Jungmittag, A. (2004). Foreign Direct Investment, Imports and Innovations in the Service Industry. *Review of Industrial Organization*, *25*(2), 205–227. https://doi.org/10.1007/s11151-004-3537-x

Bujari, A. A., & Venegas-Martínez, F. (2016). Technological Innovation and Economic Growth in Latin America Procesos de Innovación Tecnológica y Crecimiento Económico en América Latina. *Remef - The Mexican Journal of Economics and Finance*, *11*(2), 77–89.

Cassiman, B., Golovko, E., & Martínez-Ros, E. (2010). Innovation, exports and productivity. *International Journal of Industrial Organization*, *28*(4), 372–376. https://doi.org/10.1016/j.ijindorg.2010.03.005

Chien, F., Ananzeh, M., Mirza, F., Bakar, A., Vu, H. M., & Ngo, T. Q. (2021). The effects of green growth, environmental-related tax, and eco-innovation towards carbon neutrality target in the US economy. *Journal of Environmental Management*, *299*(September), 113633. https://doi.org/10.1016/j.jenvman.2021.113633

De Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. *Stata Journal*, *6*(4), 482–496. https://doi.org/10.1177/1536867x0600600403

Fan, P. (2011). Innovation capacity and economic development: China and India. *Economic Change and Restructuring*, *44*(1–2), 49–73. https://doi.org/10.1007/s10644-010-9088-2

Frankel, J. A., & Romer, D. (1999). Does trade cause growth? *American Economic Review*, *89*(3), 379–399. https://doi.org/10.1257/aer.89.3.379

Fu, X. (2005). Exports, technical progress and productivity growth in a transition economy: A non-parametric approach for China. *Applied Economics*, *37*(7), 725–739. https://doi.org/10.1080/00036840500049041

Gani, A. (2009). Technological Achievement, High Technology Exports and Growth. *Journal of Comparative International Management*, *12*(2), 31.

Gyedu, S., Heng, T., Ntarmah, A. H., He, Y., & Frimppong, E. (2021). The impact of innovation on economic growth among G7 and BRICS countries: A GMM style panel vector autoregressive approach. *Technological Forecasting and Social Change*, *173*(September), 121169. https://doi.org/10.1016/j.techfore.2021.121169

Hammar, N., and Belarbi, Y. (2021). R&D, innovation and productivity relationships: Evidence from threshold panel model. *International Journal of Innovation Studies*, *5*(3), 113–126. https://doi.org/10.1016/j.ijis.2021.06.002

Hansen, B. E. (1995). Rethinking the univariate approach to unit root testing: Using covariates to increase power. *Econometric Theory*, *11*(5), 1148–1171. https://doi.org/10.1017/S0266466600009993

Hashem Pesaran, M. (2007). A pair-wise approach to testing for output and growth convergence. *Journal of Econometrics*, *138*(1), 312–355. https://doi.org/10.1016/j.jeconom.2006.05.024

Hashem Pesaran, M., and Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, *142*(1), 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010

Holland, D., and Pain, N. (1998). The Diffusion Of Innovations In Central And Eastern Europe: A Study Of The Determinants And Impact Of Foreign Direct Investment. *National Institute of Economic and Social Research*, 1–48. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.156.9930&rep=rep1&type=pdf

Khan, A., Chenggang, Y., Hussain, J., and Kui, Z. (2021). Impact of technological innovation, financial development and foreign direct investment on renewable energy, non-renewable energy and the environment in belt & Road Initiative countries. *Renewable Energy*, *171*, 479–491. https://doi.org/10.1016/j.renene.2021.02.075

Kirchhoff, B. A., Newbert, S. L., Hasan, I., and Armington, C. (2007). The Influence of University R & D Expenditures on New Business Formations and Employment Growth. *Baylor University*, *979*, 1000.

Li, G., and Wei, W. (2021). Financial development, openness, innovation, carbon emissions, and economic growth in China. *Energy Economics*, *97*, 105194. https://doi.org/10.1016/j.eneco.2021.105194

Li, Y., and Solaymani, S. (2021). Energy consumption, technology innovation and economic growth nexuses in Malaysian. *Energy*, *232*, 121040. https://doi.org/10.1016/j.energy.2021.121040

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, *22*(1), 3–42.

https://doi.org/10.1016/0304-3932(88)90168-7

Maradana, R. P., Pradhan, R. P., Dash, S., Zaki, D. B., Gaurav, K., Jayakumar, M., & Sarangi, A. K. (2019). Innovation and economic growth in European Economic Area countries: The Granger causality approach. *IIMB Management Review*, *31*(3), 268–282. https://doi.org/10.1016/j.iimb.2019.03.002

Palangkaraya, A. (2012). The Link between Innovation and Export: Evidence from Australia's Small and Medium Enterprises. *ERIA Discussion Paper Series*.

Pedroni, P. (2004). Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econometric Theory*, *20*(3), 597–625. https://doi.org/10.1017/S0266466604203073

Pesaran, M. Hashem. (2008). An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis. *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*, 371–413. https://doi.org/10.1017/ccol0521633230.011

Pesaran, M.H. (2004). General Diagnostic tests for Cross Section dependence in Panels:Cambridge working Paper in Economics. *IZA Discussion Paper*, *1240*.

Pradhan, R. P., Arvin, M. B., and Bahmani, S. (2018). Are innovation and financial development causative factors in economic growth? Evidence from a panel granger causality test. *Technological Forecasting and Social Change*, *132*(February), 130–142. https://doi.org/10.1016/j.techfore.2018.01.024

Pradhan, R. P., Arvin, M. B., Nair, M., and Bennett, S. E. (2020). The dynamics among entrepreneurship, innovation, and economic growth in the Eurozone countries. *Journal of Policy Modeling*, *42*(5), 1106–1122. https://doi.org/10.1016/j.jpolmod.2020.01.004

Pradhan, R. P., Arvin, M. B., Nair, M., Bennett, S. E., Bahmani, S., and Hall, J. H. (2018). Endogenous dynamics between innovation, financial markets, venture capital and economic growth: Evidence from Europe. *Journal of Multinational Financial Management*, *45*, 15–34. https://doi.org/10.1016/j.mulfin.2018.01.002

Santacreu, A. M. (2015). Innovation, diffusion, and trade: Theory and measurement. *Journal of Monetary Economics*, *75*, 1–20. https://doi.org/10.1016/j.jmoneco.2015.06.008

Shen, F., Liu, B., Luo, F., Wu, C., Chen, H., and Wei, W. (2021). The effect of economic growth target constraints on green technology innovation. *Journal of Environmental Management*, *292*(April), 112765. https://doi.org/10.1016/j.jenvman.2021.112765

Solow, R. M. (1957). Technical Change and the Aggregate Production Function. *The MIT Press*, *39*(3), 312–320.

Sultanuzzaman, M. R., Fan, H., Mohamued, E. A., Hossain, M. I., and Islam, M. A. (2019). Effects of export and technology on economic growth: Selected emerging Asian economies. In *Economic Research-Ekonomska Istrazivanja*, 32 (1), 2515–2531. https://doi.org/10.1080/1331677X.2019.1650656

Ulku, H. (2007). R&D, innovation and output: Evidence from OECD and nonOECD countries. *Applied Economics*, *39*(3), 291–307. https://doi.org/10.1080/00036840500439002

Ustabaş, A., and Ersin, Ö. Ö. (2016). The Effects of R&D and High Technology Exports on Economic Growth: A Comparative Cointegration Analysis for Turkey and South Korea. *International Conference on Eurasian Economies 2016*, *August*, 44–55. https://doi.org/10.36880/c07.01475

Wang, K. H., Umar, M., Akram, R., and Caglar, E. (2021). Is technological innovation making world "Greener"? An evidence from changing growth story of China. *Technological Forecasting and Social Change*, *165*(July 2020), 120516. https://doi.org/10.1016/j.techfore.2020.120516

Westerlund, J., and Edgerton, D. L. (2007). A panel bootstrap cointegration test. *Economics Letters*, *97*(3), 185–190. https://doi.org/10.1016/j.econlet.2007.03.003

Westerlund, J., and Hosseinkouchack, M. (2016). Modified CADF and CIPS Panel Unit Root Statistics with Standard Chi-squared and Normal Limiting Distributions. *Oxford Bulletin of Economics and Statistics*, *78*(3), 347–364. https://doi.org/10.1111/obes.12127

Wu, J., Ma, Z., and Zhuo, S. (2017). Enhancing national innovative capacity: The impact of high-tech international trade and inward foreign direct investment. *International Business Review*, *26*(3), 502–514. https://doi.org/10.1016/j.ibusrev.2016.11.001