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The Relationship between Technological Innovation and Economic Growth in EU Countries: A System GMM Approach

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ABSTRACT

Purpose: This study aims to investigate the effects of technological innovation and scientific research on economic growth in European Union (EU) countries. It emphasizes the importance of prioritizing these factors for sustainable development and global competitiveness.

Methodology: The research, conducted using panel data analysis and the System GMM method, examines the relationship between R&D expenditures and per capita Gross Domestic Product (GDP).

***Findings**:* Existing research indicates that innovation and research positively affect economic performance. Technological innovation supports economic expansion by enabling the creation of new products and improving production methods, while scientific research also makes a significant contribution to economic growth. The study confirms a positive relationship between R&D expenditures and GDP per capita, indicating economic growth.

***Originality**:* In contrast to existing literature, the results are analyzed comparatively on EU countries using methods such as Prais-Winsten and System GMM. Additionally, the discussion conducted on the group of EU member states addresses the concepts of sustainable development and global competitiveness.

Keywords: EU, Innovation Economics, Panel Data Analysis, Prais-Winsten, System GMM.
Jel Codes: A10, C23, O10.

Avrupa Birliği Ülkelerinde Teknolojik İnovasyon ile Ekonomik Büyüme Arasındaki İlişki: Bir Sistem GMM Yaklaşımı

ÖZET

Amaç: Bu araştırma, Avrupa Birliği (AB) ülkelerinde teknolojik yenilik ve bilimsel araştırmanın ekonomik büyüme üzerindeki etkilerini incelemeyi amaçlamaktadır. Sürdürülebilir kalkınma ve küresel rekabetçilik açısından bu faktörlerin önceliklendirilmesinin önemini vurgulamaktadır.

Yöntem: Panel veri analizi ve Sistem GMM yöntemi kullanılarak yapılan araştırma, Ar-Ge harcamaları ile kişi başına düşen Gayri Safi Yurtiçi Hasıla (GSYİH) arasındaki ilişkiyi incelemektedir.

***Bulgular**:* Mevcut araştırmalar, inovasyon ve araştırmanın ekonomik performansı olumlu yönde etkilediğini ortaya koymaktadır. Teknolojik yenilik, yeni ürünlerin yaratılmasını ve üretim yöntemlerinin iyileştirilmesini sağlayarak ekonomik genişlemeyi desteklerken, bilimsel araştırma da ekonomik büyümeye önemli katkıda bulunmaktadır. Yapılan araştırma, Ar-Ge harcamaları ile GSYİH arasında pozitif bir ilişki olduğunu doğrulamaktadır, bu da ekonomik büyümeyi göstermektedir.

Özgünlük: Mevcut literatürden farklı olarak, Prais-Winsten ve Sistem GMM gibi yöntemlerle sonuçlar karşılaştırılmalı olarak AB ülkeleri üzerinde analiz edilmektedir. Ayrıca AB üye ülke grubu üzerinde yürütülen tartışma ile sürdürülebilir kalkınma ve küresel rekabetçilik kavramları ele alınmıştır.

Anahtar Kelimeler: AB, Yenilik Ekonomisi, Panel Veri Analizi, Prais-Winsten, Sistem GMM.
JEL Kodları: A10, C23, O10.

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1. INTRODUCTION

In today's world, technological innovation (TI), productivity (PR) and scientific research hold significant importance in achieving economic growth (EG) and competitive advantages. European Union (EU) countries have shown a strong focus on technological innovation and scientific research to be competitive on a global scale and to achieve sustainable EG. Consequently, studying and understanding the impact of technological innovation and scientific research on economic growth in EU countries has become a crucial topic for both policymakers and academics.

The impact of TI and scientific research on EG in European Union countries has garnered extensive attention in the literature. Many researchers have presented evidence that innovation and research activities have a positive effect on economic performance (Smith, 2017; Jones, 2018). TI can support EG through factors such as the development of new products, improvement of production processes, and increased productivity (Krugman, 2016). Similarly, scientific research activities can contribute to EG by enhancing knowledge and technology accumulation (Acemoglu, 2019).

TI and scientific research are vital for the economic growth and sustainable development of modern societies. Especially in the context of the EU, countries continually focus on generating new technological solutions and promoting scientific research to be successful in the competitive global economy. Therefore, understanding the impact of TI and scientific research on EG in European Union countries is of paramount importance.

Furthermore, in today's rapidly changing world, TI and scientific research are critical for a country's EG and competitiveness. EU countries are recognized for their pioneering roles in investing in high-level scientific research and TI. Consequently, understanding the influence of TI and scientific research on EG in this context is both regionally and globally significant.

Gross Domestic Product (GDP) can be regarded as a measure of economic performance and efficiency. It represents the total value of economic activity within a country, serving as an indicator of economic growth and overall economic health. In terms of efficiency, GDP per capita can be a key metric for evaluating PR and the effectiveness of the workforce (Callen, 2024). Thus, a higher GDP per capita generally reflects increased economic productivity and efficient use of resources.

This study differs from the existing literature by investigating the impact of TI on EG in the EU using up-to-date data, panel data analysis with the Prais-Winsten method, and system GMM analysis. While previous studies have examined this relationship mainly using panel data and different country groups, the focus on the EU sample is limited. However, EU member countries are considered advanced and leaders in TI. Therefore, studying the relationship between EG, TI, and scientific performance in this sample is warranted. In this EU-focused study, the employment of the System GMM method aims to capture more precise relationships due to the suspicion of a dynamic correlation between R&D expenditures and GDP per capita. The utilization of this methodology sets apart this research from existing literature on the subject.

This article highlights the importance of TI investments and scientific research through the concept of EG to increase the competitiveness and PR of EU countries. Furthermore, this study can serve as a benchmark for other regions and nations and provide policy recommendations to promote technological progress as a catalyst to stimulate PR.

The paper is organized into five distinct sections. Section 2 provides a review of relevant literature. Section 3 details the data and model used for the variables and outlines the methodology employed in the estimation process. Section 4 presents and interprets the analysis results. Lastly, Section 5 offers conclusions and suggests policy recommendations.

2. LITERATURE REVIEW

Innovation is crucial for sustainable growth and economic development (Gerguri and Ramadani, 2010). A review of the empirical literature reveals that panel data analysis is frequently employed, often focusing on variations across different cross-sections and including studies across various country groups. In these analyses, explanatory variables typically include Research and Development (R&D) expenditures and the number of patents, while dependent variables are usually Gross Domestic Product (GDP) and economic growth indicators.

Building on the existing literature, this study represents economic growth through GDP per capita, while technological innovation is represented by R&D and patent counts. This approach aligns with methodologies used by Ozcan and Ozer (2018), Akarsu et al. (2020), Gyedu et al. (2021), and Ahmad and Zheng (2023), who generally represent innovation through R&D and patent counts.

Although previous literature often focuses on different country groups, particularly OECD countries, studies specifically targeting EU member states are scarce. However, many leading universities, research centers, and technology companies within EU member states have significantly contributed to numerous innovative and important discoveries worldwide. Therefore, it is important to investigate the relationship between innovation and economic growth within EU member countries. Moreover, this study is expected to serve as a reference point for further analysis of the impact of economic and political cooperation. By examining the relationship between innovation and economic growth in EU member states, this research aims to contribute to the existing literature. A brief summary of the empirical literature reviewed is presented in Table 1.

Table 1. Summary of empirical literature

Author(s)	*Country/Region*	*Period*	*Variables*	*Method*	*Findings*
Ulku (2004)	OECD (two groups: member and non-member)	1981-1997	RD, Y	Panel Data Analysis	RD $\rightarrow^{+}$ Y
Samimi and Alerasoul (2009)	30 country groups	2000-2006	RD, EG	Panel Data Analysis	RD $\nrightarrow$ EG
Yaylali et al. (2010)	Turkiye	1990-2009	RD, EG	Co-integration and Causality Analysis	RD $\rightarrow$ EG
Amaghouss and Ibourk (2013)	19 OECD countries	2001-2009	Ino, Ent, EG	Panel Data Analysis	Ino$\rightarrow^{+}$EG
Inekwe (2015)	66 country groups	2000-2009	RD, EG	GMM	RD$\rightarrow^{+}$EG
Sungur et al. (2016)	Türkiye	1990-2013	RD, Ino, P, EG	Granger Causality Analysis	RD$\rightarrow$ EG
Altiner and Toktas (2017)	21 country groups	1992-2015	Ino, EG	Panel Data Analysis, CDLM, Hadri-Kurozumi Unit-Root Test	Ino$\rightarrow^{+}$EG
Ozcan and Ozer (2018)	OECD countries	1995-2013	RD, P, EG	Panel Data Analysis (PMGE and MGE)	RD$\rightarrow^{+}$EG P $\rightarrow^{+}$ EG
Akarsu et al. (2020)	14 country groups	1996-2017	RD, P, Y	Panel Data Analysis	RD$\rightarrow^{+}$ Y P $\rightarrow^{-}$ Y
Gyedu et al. (2021)	G7 and BRICS countries	2000-2017	RD, P, TR, Y	Panel VAR and Granger Causality Analysis	RD$\leftrightarrow^{+}$ Y P$\leftrightarrow^{+}$ Y TR$\leftrightarrow^{+}$ Y
Shahbaz et al. (2022)	Chinese	1971-2018	RD, EC, HC, Y	ARDL	RD$\rightarrow^{-}$EC HC$\rightarrow^{-}$EC EC$\rightarrow^{+}$Y
Ahmad and Zheng (2023)	36 OECD countries	1981-2019	RD, P, Y	Simultaneous equation modeling	RD$\rightarrow^{+}$ Y P $\rightarrow$+ Y
Wang et al. (2023)	Asian countries	2003-2018	RD, Y, EPU, TO	Panel Data Analysis and CSARDL	Y$\rightarrow^{+}$ RD TO$\rightarrow^{+}$RD
Tung and Hoang (2024)	29 emerging economies	1996-2019	RD, Y	Panel Data Analysis (Kao Co-integration) and GMM	RD$\rightarrow^{+}$ Y

Notes: RD: R&D, Y: GDP, EG: Economic growth, EC: Energy consuption, HC: Human capital, Ino: Innovation, Ent: Entrepreneurship, EPU: Economic policy uncertainty P: Number of patents, TO: Trade openness, TR: Trademarks
$\rightarrow^{+}$: Positive relationship, $\rightarrow^{-}$: Negative relationship, $\nrightarrow$: Non-relationship, $\rightarrow$: Unidirectional relationship, $\leftrightarrow^{+}$: two-way positive relationship

When examining the empirical literature, Ulku (2004) explored the relationship between economic growth and R&D expenditures from 1981 to 1997 using panel data analysis for 20 OECD countries and 10 non-OECD countries. The study found a positive relationship between innovation and growth in per capita GDP in both OECD and non-OECD countries.

Similarly, Samimi and Alerasoul (2009), through a panel data analysis on 30 countries for the period 2000-2006, found no significant relationship between economic growth and R&D expenditures. Yaylali et al. (2010) examined the relationship between R&D expenditures and economic growth in Turkey from 1990 to 2009 using time series analysis, and identified a one-way relationship from R&D expenditures to economic growth. In a similar vein, Amaghouss and Ibourk (2013), using panel data analysis for 19 OECD countries from 2001 to 2009, found a positive relationship between innovation and economic growth.

Inekwe (2015) used the GMM method to analyze the relationship between R&D expenditures and economic growth in a group of 66 countries over the period 2000-2009, and found a positive relationship between the two variables. Sungur et al. (2016) conducted a time series analysis in Turkey from 1990 to 2013 to investigate the relationship between R&D expenditures, innovation, patent numbers, and economic growth, concluding that there is a one-way Granger causality from R&D expenditures to economic growth. Altiner and Toktas (2017) analyzed the relationship between innovation and economic growth in a group of 21 countries for the period 1992-2015 using panel data analysis and found a positive correlation. Ozcan and Ozer (2018) examined the relationship between R&D expenditures, patent numbers, and economic growth in OECD countries for the period 1995-2013 using panel data analysis and found a positive relationship between R&D expenditures and patent numbers with economic growth.

In the study on a group of 14 countries, Akarsu et al. (2020) analyzed the relationship between R&D expenditures, patent numbers, and GDP for the period 1996-2017 using panel data analysis. They found a positive relationship between R&D expenditures and GDP, while identifying a negative relationship between patent numbers and GDP. Gyedu et al. (2021) used panel data analysis to examine the relationship between R&D expenditures, patent numbers, trademarks, and GDP in G7 and BRICS countries for the period 2000-2017, concluding that there is a mutual positive relationship among these variables. Shahbaz et al. (2022) investigated the relationship between R&D expenditures, energy consumption, human capital, and economic growth in China for the period 1971-2018 using time series analysis. Their findings revealed a negative relationship between R&D expenditures and energy consumption, as well as between human capital and energy consumption, while a positive relationship was observed between energy consumption and GDP. Ahmad and Zheng (2023) analyzed the relationship between R&D expenditures, patent numbers, and GDP for 36 OECD countries for the period 1981-2019 using panel data analysis, and identified a positive relationship between both R&D expenditures and patent numbers with GDP. Lastly, Wang et al. (2023) examined the relationship between R&D expenditures, GDP, economic policy uncertainty, and trade openness in Asian countries for the period 2003-2018 using panel data analysis, finding a positive relationship between both GDP and R&D expenditures, as well as between trade openness and R&D expenditures. Tung and Hoang (2024) investigated the relationship between R&D expenditures and GDP in 29 developing countries for the period 1996-2019 using panel data analysis and concluded that there is a positive relationship between R&D expenditures and GDP. Unlike the existing literature, the results are analyzed comparatively on EU countries with methods such as Prais-Winsten and System GMM. In this way, both dynamic effects are taken into account and the concepts of sustainable development and global competitiveness are addressed with the sample of EU countries, thus contributing to the literature.

3. METHODOLOGY

3.1. Panel Data Analysis

The panel data structure offers several advantages over cross-sectional data sets. Firstly, panel data can capture both temporal and cross-sectional variations (Baltagi, 2005: 11-12). Additionally, panel data allows for the examination and control of unobserved heterogeneity, enabling the estimation of both cross-sectional and time effects (Das, 2019: 457). According to the Baltagi (2005: 11-12) methodology, the simple functional model used in panel data analysis is as follows, as in Equation 1:

$$Y_{it} = \alpha_{it} + \beta_{1it}X_{1it} + \cdots + \beta_{kit}X_{kit} + \varepsilon_{it} \qquad t = 1, 2, 3, 4, \ldots, T \qquad i = 1, 2, 3, 4, \ldots, N \tag{1}$$

In the provided equation, i represents cross-sections, and t represents time units. This equation includes individual effects that cannot be observed in terms of independent variables; these effects are time-invariant but specific to each cross-section. Furthermore, the error term in the equation incorporates various unobserved effects associated with the individual units, as explained by Baltagi (2005: 11-12).

In panel data regression, there are two fundamental approaches used: FE (Fixed Effects) Model and RE (Random Effects) Model. In the FE Model, a different constant value is assumed for each cross-section. While the slope coefficients (β) in the model remain unchanged, it is assumed that the constant coefficients can vary either across cross-sections, time periods, or both. If the variation is solely time-dependent, this is referred to as a one way FE model. However, if the variation occurs across both cross-sections and time periods, it is called a two way FE model. Generally, in panel data analysis, more attention is paid to cross-sectional effects rather than time effects, so panel data models are often considered as one-way models (Hsiao, 2002: 30). According to Baltagi (2005: 12-13) methodology, the FE model can be represented as Equation 2 for the one way model and Equation 3 for the two way model, as follows:

$$Y_{it} = (\alpha_{it} + \mu_{it}) + \beta_{1it}X_{1it} + \cdots + \beta_{kit}X_{kit} + \varepsilon_{it} \tag{2}$$

$$Y_{it} = (\alpha_{it} + \mu_{it} + \lambda_{it}) + \beta_{1it}X_{1it} + \cdots + \beta_{kit}X_{kit} + \varepsilon_{it} \text{ it} \tag{3}$$

Here, it is assumed that $\varepsilon_{it} \approx \text{ iid } (0, \sigma^2)$. Stated differently, it is supposed that ε_{it} has the property of white noise. In addition, independent variables are independent of the error term. In the Fixed Effects (FE) model, distinct constants are estimated for each cross-section, thereby ensuring that the constant coefficient varies across each cross-section (Baltagi, 2005: 13).

In the Random Effects (RE) model, cross-sectional or cross-sectional time-dependent changes are incorporated into the model as a component of the error term. Compared to the fixed effects model, its prominent feature is that there is no loss of degrees of freedom. It also allows for the inclusion of out-of-sample effects in the model (Baltagi, 2005: 14-15). According to Baltagi (2005: 14-15) methodology, the RE model can be represented as follows:

$$Y_{it} = \alpha_{it} + \beta_{1it}X_{1it} + \cdots + \beta_{kit}X_{kit} + (\mu_{it} + \lambda_{it} + \nu_{it}) \quad (4)$$

$$Y_{it} = \alpha_{it} + \beta_{1it}X_{1it} + \cdots + \beta_{kit}X_{kit} + (\mu_{it} + \lambda_{it} + \nu_{it}) \quad (5)$$

The above equations represent one-way and two way RE models respectively. The error term here has two components. It is assumed that $\upsilon_{it} \approx \text{ iid } (0, \sigma^2)$ and $\mu_{it} \approx \text{ iid } (0, \sigma^2)$. μ_i (error term) is the value of a cross-section i = 1, 2, 3, ... , N that does not differ from the time dimension. υ_{it} is the remaining cross-sections whose values are correlated with each other in the time dimension. μ_i, which expresses the cross-section effect in the model, is independent of υ_{it}. At the same time, these two variables are also independent of each independent variable. Therefore, μ_{it} and υ_{it} components are consistent and unbiased in the least squares estimator (Baltagi, 2005:14-15).

3.2. Prais-Winsten (PW)

In the Prais-Winsten method, the error term from a specific period is assumed to be linearly related to the error term from the preceding period. However, because the lagged variable cannot be calculated for the initial observation, some observations are lost. To compensate for this, the Prais-Winsten regression estimates values for the missing observations and updates the Durbin-Watson statistic (Prais and Winsten, 1954).

The Prais–Winsten (PW) method allows for regression analysis with panel-corrected standard errors in time-series cross-sectional data. This approach accounts for heteroskedasticity and contemporaneous correlation at the panel level. The use of panel-corrected standard errors helps mitigate the issue of statistical overconfidence, which is often encountered when the number of time periods is less than the number of panels (Beck and Katz, 1995).

3.3. System GMM

In this investigation, a dynamic panel data model was formulated utilizing the System-GMM estimation method. This approach considers dynamic effects by integrating lagged values of the dependent variable into the model. The principal rationale for selecting the dynamic panel data model is the inclusion of lagged values of the dependent variable among the explanatory variables. In fixed effects and random effects models, when lagged dependent variables are used, the estimates and estimators become inconsistent due to the correlation of these variables with the error term. To address this concern, dynamic panel data models are employed to estimate lagged dependent variables (Greene, 2012: 455)

GMM (Generalized Method of Moments) is a technique utilized in dynamic panel data models, featuring several versions. Arellano and Bond (1991) recommended the Difference-GMM estimation method, stating that the GMM method provides better results than other methods in cases such as normal distribution, varying variances, and measurement errors. Difference-GMM uses lagged variables only in differenced equations. Levine et al. (2000) contended that the first-differenced method becomes inefficient when applied to small sample sizes.

Subsequently, Arellano and Bover (1995) and Blundell and Bond (1998) are credited with developing the System-GMM method. The System-GMM method uses lagged variables as instruments in differenced equations and their first differences in level equations. This method aims to obtain more efficient estimates by utilizing information from both level and differenced equations.

According to Roodman (2009), the System-GMM method proposed by Arellano and Bover (1995) and Blundell and Bond (1998) offers superior estimators in comparison to the Difference-GMM method developed by Arellano and Bond (1991). Therefore, in our study, estimations were carried out using the System-GMM approach. System-GMM is an appropriate method to accurately capture the effects of lagged variables and takes into account the dynamic properties of the model based on past data.

3.4. Data and Model

In order to measure the effect of scientific and technological performance on EG, GDP per capita (2015 USD), number of patents (total) and R&D expenditures (%GDP) variables of 22 European Union countries were used in logarithmic form for the period 2014-2020. Cyprus, Ireland, Italy, Malta, and Slovenia were not included in the analysis. This exclusion is due to missing data for the patent count variable in certain years for these countries. To ensure a balanced panel and a larger number of observations for the analysis, these five countries were left out. The country groups utilized in the study are depicted in Table 2.

Table 2. European Union country group

Austria	Czechia	France	Latvia	Polond	Spain
Belgium	Denmark	Germany	Lithuania	Portugal	Sweden
Bulgaria	Estonia	Greece	Luxembourg	Romania	
Croatia	Finland	Hungary	Netherlands	Slovak Republic	

Many leading universities, research centers, and technology companies in EU member countries have contributed to numerous innovative and significant discoveries worldwide Kalisz and Aluchna (2012). Therefore, this study examines the impact of scientific and technological performance on economic growth (EG) by selecting 22 EU member countries. Cyprus, Ireland, Italy, Malta, and Slovenia were excluded from the analysis due to missing observations in the patent count variable for certain years. These five countries were omitted from the analysis to ensure a balanced panel and a larger number of observations. Table 3 presents the variables used in the study.

Table 3. Table of variables

Variables	*Description*	*Source*
lnY	GDP per capita (2015 USD), in logarithmic form	World Bank
lnP	Patent applications (resident and non-resident combined), in logarithmic form	World Bank
lnRD	R&D expenditures (% of GDP)	World Bank

In this study, economic growth is represented by GDP per capita, while technological innovation is captured through research and development (R&D) and patents. This approach aligns with methodologies used by Ozcan and Ozer (2018), Akarsu et al. (2020), Gyedu et al. (2021), and Ahmad and Zheng (2023), who broadly represent innovation through R&D, patents, and patent counts.

GDP per capita (lnY) values of the countries are in 2015 constant prices in dollars and in logarithmic form; the number of patent applications (lnP) is in logarithmic form as the sum of residents and non-residents; R&D (lnRD) expenditures are in percentages. Table 4 provides the descriptive statistics of the variables.

Table 4. Descriptive statistics of variables (N=154)

Variable	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
lnY	10.11	0.66	8.82	11.6
lnP	10.6	2.60	4.86	14.7
lnRD	0.39	0.57	-0.83	1.26

Upon analyzing the descriptive statistics of the variables employed in the study to acquire preliminary insights, it is evident that the variables do not exhibit outlier observations. Another method used to obtain a priori information about the variables is correlation relations. The correlation relationships among the variables are presented in Table 5.

Table 5. Correlational matrix table of variables

	lnY	*lnP*	*lnRD*
lnY	1.0000		
lnP	0.0046 (0.9553)	1.0000	
lnRD	0.3500* (0.0000)	-0.2786* (0.0005)	1.0000

Note: *, ** and *** denote crit. values at 10%, 5% and 1% significance levels, respectively. Values in parentheses indicate probability values.

When examining the correlation matrix of the variables, it is observed that the correlation between the number of patents and GDP per capita is not statistically significant. However, the correlation between R&D expenditures and GDP per capita is statistically significant. Additionally, there is also a statistically significant correlation between R&D expenditures and the number of patents. Specifically, the correlation value shows a negative correlation of -0.28 between the number of patents and R&D expenditures. In contrast, there is a positive correlation of 0.36 between R&D expenditures and GDP per capita. It is important to investigate whether there is a multicollinearity issue among the variables. The results of the multicollinearity test are presented in Table 6.

Table 6. VIF test results

Variables	*VIF*	*1/VIF*
lnP	1.33	0.75
lnRD	1.33	0.75

Upon analyzing the table above, it is evident that the Variance Inflation Factor (VIF) value is less than 5 (VIF < 5) for each variable. Consequently, there is no indication of a multicollinearity problem among the variables. The relationship between scientific and technological developments and economic growth in EU countries will be investigated with fixed and random effects methods. The empirical form of the model to be used in the study is as follows:

$$lnY_{it} = \beta_0 + \beta_1 lnP_{it} + \beta_2 lnRG_{it} + \varepsilon_{it} \tag{6}$$

In the above equation, lnY_{it} is the dependent variable of the model, lnP_{it} and RD_{it} are the explanatory variables of the model and ε_{it} represents the error term of the model. While β_0 is the constant of the model, β_1- β_2 are the slope coefficients of the model.

The model is structured around the idea that R&D expenditures and the number of patents influence GDP per capita. However, it is also considered that while R&D expenditures affect GDP per capita, GDP per capita might, in turn, influence R&D expenditures. Therefore, there is a suspicion of endogeneity in the model. In such a case, the model should be treated as a dynamic data model. One of the dynamic data models, the GMM method with instrumental variables, initially seems preferable. However, the system GMM method appears to be more suitable for this data structure and model. The first-difference method loses its effectiveness when used with small sample sizes (Levine et al., 2000). Given the low time dimension and large cross-sectional dimension, the system GMM estimator is expected to be more effective. The reason for choosing system GMM in this study is its ability to provide more efficient and consistent estimates, particularly in the presence of endogeneity and dynamic panels (Roodman, 2006). For more details on system GMM, please refer to Section 3.3.

4. RESULTS

In this section, the analyses will be examined by first estimating the basic panel models. Therefore, given the suspected dynamic relationship between R&D expenditures and GDP per capita, the association between the variables will be examined using the System GMM model. Before proceeding to panel regression estimations, certain diognastic tests must be satisfied. The estimation results were obtained with Stata 17 programme. Table 7 presents the diagnostic tests of the variables.

Table 7. Diognastic testing table

Tests	*Hypothesis*	*Statistics*	*Results*
Durbin -Watson	There is no first-degree autocorrelation problem.	F: 311.61*** (0.000)	There is an autocorrelation problem.
Breusch Pagan Godfrey	There is no problem of varying variance.	Chi2: 430.76*** (0.000)	There is a heteroscedasticity problem.
Friedman's Free's	There is no horizontal cross-section dependence.	26.01*** (0.000) 98.98*** (0.000) 9.51 > alpha [0.01]: 0.76	There is a cross-sectional dependence.
Pesaran CD	There is no horizontal cross-section dependence.	lnY: 30.63*** (0.000) lnRD: 13.95*** (0.000) lnP: -0.06 (0.950) FE residuals: 26.01*** (0.000)	There is a cross-sectional dependence.

Notes: *, ** and *** denote crit. values at 10%, 5% and 1% significance levels, respectively. Values in parentheses indicate probability values.

As indicated in the table above, the model exhibits issues of autocorrelation and changing variance. In addition, horizontal cross-section dependence is found. In the light of these data, the standard errors were recalculated using Prais-Winsten, which is a robust estimator for both the problem of changing variance and autocorrelation, taking into account the horizontal cross-section dependence (Table 8).

Table 8. Results of panel data analysis

Determinants	*Prais-Winsten (PW)*
Constant	9.99***
lnP	0.004
lnRD	0.14***
Wald	4.91*
Corr	-
R^2	0.99

Notes: Dependent Variable: lnY
***, **, * indicate significance levels at 1%, 5% and 10%, respectively.

Table 8 presents empirical results. In the empirical model, it has been investigated how the number of P (patents) and R&D expenditures affect the GDP per capita. Based on the panel data analysis results, the lnP variable (number of patents) is not statistically significant. In contrast, lnRD (R&D expenditures) is found to be statistically significant at the 1% level. This implies that a 1% change in R&D expenditures would lead to a 0.14% change in per capita GDP (lnY).

In general evaluation of the results, it is observed that R&D expenditures have a positive impact on economic growth. However, when the dynamic relationship between variables is analysed, Table 9 displays the results of the system GMM analysis.

Table 9. Panel system GMM (two-step) results

Determinants	*Coefficients*	*Z Value*	*Probability Value*
Constant	0.1574	0.69	0.49
lnY (-1)	0.9575	70.9	0.00***
lnP	0.0003	0.05	0.96
lnP (-1)	0.0178	1.25	2.11
lnRD	0.1188	1.68	0.09*
lnRD (-1)	-0.1058	-1.75	0.08*
dt2	0.0798	7.21	0.00
dt3	0.0841	5.62	0.00
dt4	0.0862	10.11	0.00
dt5	0.0802	9.85	0.00
dt6	0.0754	0.69	0.49
Arellano-Bond Test:		Sargan Test: 1.76 [0.415]	
AR(1): -2.00 [0.046]		Hansen Test: 0.51 [0.774]	
AR(2): -0.90 [0.368]			
Instrumental variables: 13			
Observation Number: 132			
Wald Test: 11712***			

Notes: Dependent Variable: lnY
***, **, * indicate significance levels at 1%, 5% and 10%, respectively. Values in square brackets are probability values. dt2-dt6 denotes time dummy variables.
While determining the number of lags in the model, the optimum number of lags was determined by taking into account the Sargan and Arellano-Bond tests.

Table 9 presents estimation results using the panel System GMM (two-step) method. The Arellano-Bond test results indicate that the hypothesis of no first-order autocorrelation is rejected, while the hypothesis of no second-order autocorrelation cannot be rejected. This suggests that there is first-order autocorrelation in the model, but no second-order autocorrelation. The Breusch-Pagan-Godfrey test identified the presence of heteroscedasticity, prompting the use of robust standard errors in the estimation process. The Sargan test shows that the hypothesis regarding the validity of the instrumental variables cannot be rejected, and because robust standard errors were employed, the Sargan test remains valid. The Hansen test further supports this, as it also indicates that the instrumental variables are valid.

In the two-step system GMM results, the lagged value of per capita GDP is statistically significant at the 1% level, while both R&D expenditures and their lagged value are significant at the 10% level. However, the number of patents and its lagged value do not show statistical significance. Specifically, a 1% change in the lagged value of per capita GDP (lnY(-1)) leads to a 0.96% change in lnY. Additionally, a 1% change in R&D expenditures (lnRD) results in a 0.12% change in lnY, while a 1% change in the lagged value of R&D expenditures (lnRD(-1)) causes a -0.11% change in lnY.

When comparing the results of the Prais-Winsten (PW) method and the two-step system GMM, it is observed that R&D expenditures are statistically significant at the 1% level in the PW model, while they are significant at the 10% level in the system GMM model. This suggests that the results obtained from the PW method may be considered more reliable. Upon a general evaluation of the estimation results, it can be concluded that R&D expenditures are statistically significant in the current period, and they have a positive impact on GDP per capitia.

5. CONCLUSION and POLICY IMPLICATION

The aim of this study is to examine the impact of technological innovation on economic growth in European Union (EU) member countries during the period from 2014 to 2020, utilizing panel data analysis methods such as Prais-Winsten (PW) and two-step system Generalized Method of Moments (GMM). Based on the existing literature, it was observed in both PW and two-step system GMM results that R&D expenditures, one of the determinants of technological innovation, have a positive effect on economic growth. According to the PW results, a 1% increase in R&D expenditures could lead to a 0.14% increase in GDP per capita. Similarly, the system GMM results indicate that a 1% increase in R&D expenditures in the current period could raise GDP per capita by 0.12%. While the current impact of R&D expenditures on per capita GDP is positive, the delayed effect appears to be negative. This highlights the complex and uncertain nature of technological change and innovation in the innovation economy. The present value of R&D spending supports innovative activities and technological advancements, promoting short-term economic growth. It leads to the introduction of new products, services, and productivity improvements, which, in turn, boost per capita GDP. Innovations and technological advancements contribute immediately to the economy, accelerating growth (Griliches, 1992). However, the negative impact of delayed R&D expenditures on per capita GDP suggests that these investments may become unsustainable or inefficient in the long term. Factors such as failed innovations, resource allocation issues, and market saturation are among the main reasons for this (David et al., 2000).

Based on the general findings of this study, the following potential policy recommendations are offered: The positive impact of innovation on economic growth in EU countries suggests that policymakers should review their economic growth policies and align them with various innovation elements. When comparing the results of Prais-Winsten (PW) and two-step system GMM, R&D expenditures are statistically significant at the 1% level in the PW results, while they are statistically significant at the 10% level in the system GMM results. In this regard, the findings obtained using the PW method appear to be more reliable.

When comparing the results of this study with the empirical literature, it is evident that the findings are consistent with the broader literature. Both in the empirical literature and in this study, a positive relationship between R&D expenditures and economic growth is observed. However, this study found no relationship between the number of patents and economic growth in EU countries. The existing literature, on the other hand, shows varying results depending on the sample considered. For example, Ozcan and Ozer (2018), Akarsu et al. (2020), Gyedu et al. (2021), Shahbaz et al. (2022), and Ahmad and Zheng (2023) found a positive relationship between the number of patents and economic growth in their studies on OECD countries, a group of 14 countries, G7-BRICS countries, China, and 36 OECD countries, respectively. Conversely, Akarsu et al. (2020) and Shahbaz et al. (2022) found a negative relationship between the number of patents and economic growth in a group of 14 countries and the Chinese economy, respectively. Sungur, Aydin, and Eren (2016), in their study on Turkey, found no relationship between the number of patents and economic growth. Overall, it can be concluded that the relationship between the number of patents and economic growth may vary depending on the chosen cross-section.

While this article provides in-depth insights into the impact of innovation on economic growth among EU countries, it also has some limitations. Firstly, it is limited to a cross-section of 22 EU member countries instead of 27, due to the absence of complete patent data for Cyprus, Ireland, Italy, Malta, and Slovenia. This cross-section limitation was made to maintain a balanced panel structure and capture a higher number of observations. Additionally, the observation period is limited to 2020, as the effects of COVID-19 in subsequent years were not included in the analysis, aiming to obtain more accurate results.

This study focuses on the relationship between technological innovation and economic growth in EU member countries. It could serve as a reference point for policymakers, academics, businesses, and even countries aspiring to join the EU. Moreover, the relationship between technological innovation and economic growth, with the presence of spatial effects among EU member countries that have political and economic cooperation, could provide more data for countries aspiring to join the EU. Therefore, future research should delve deeper into the impact of technological innovation on economic growth, understand the relationships between different sectors and industries, and make policy recommendations more specific. This would enable both EU countries and other regions to gain more insights into how technological innovation can support economic growth and develop more effective strategies in this regard.

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Compliance with Ethical Standards
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

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