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DETERMINANTS OF INNOVATION THROUGH PATENTS: AN ANALYSIS USING PANEL DATA

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Abstract

Innovation is a key driver of economic growth and competitiveness, yet its determinants remain difficult to assess. This study examines factors associated with technological innovation using patents as a proxy. A panel dataset of 58 countries and 1,207 annual observations (2000–2021) from the World Bank is analyzed. Explanatory variables include R&D expenditure, education expenditure, economic openness, per capita income, and government effectiveness. The empirical strategy combines clustered ordinary least squares and panel data estimators. Diagnostic tests support a two-way fixed-effects model with country and year effects and country-clustered robust standard errors. Results identify R&D expenditure as the most robust determinant of patent activity, showing a positive and significant effect across all specifications. Per capita income is also positively associated with innovation, whereas evidence for education expenditure, openness, and government effectiveness is inconclusive. Findings highlight the importance of sustained investment in R&D to strengthen national innovative capacity.

Keywords: Innovation, Patents, R&D expenditure, Panel data, Economic development, Technological innovation.

1. Introduction

The degree of innovation has traditionally been considered one of the most reliable indicators for defining a country's level of competitiveness, its degree of sustained economic growth, and its level of well-being. In an economic model marked by increasing globalization and based on knowledge, the degree of innovation has become one of the fundamental determinants for measuring the level of development and productive transformation (OECD, 2025). The ability of any country or geographic area to develop and incorporate new technologies into its productive capacity largely determines its development potential and its ability to adapt to global crises and risks (Alqararah, 2023). For this reason, the measurement of innovative activity has become a fundamental subject of study in economic theory and one of the most important factors in defining a country's economic context and, consequently, for the definition, design, and evaluation of its corresponding public policies (Geissler et al., 2024; Barrichello et al., 2020).

Since the degree of innovation is not an independent variable, its study must be conducted from a multifaceted perspective that takes into account the multiple dimensions that comprise it (Ciccarelli et al., 2026). Therefore, although there is broad consensus on the need to study and understand the degree of innovation in a country, the academic literature has not yet reached agreement on how to measure and explain the variables that determine innovation (Bate et al., 2023; Lee & Zhao, 2025). This is why finding the model that best captures the variables determining the exact degree of innovation remains a significant empirical and conceptual challenge in academia (Ji et al., 2022).

Thus, it is common in the academic literature to study the variables that influence and determine the degree of innovation in a given country. Authors such as Bhattacharya and Bloch (2004) studied the independent variables influencing this level of innovation at the beginning of the century, focusing their research on the types of existing firms. There are also frequent academic studies aimed at measuring not only a specific innovation index for a given country, but also for a group of countries or geographic areas that share

common characteristics or belong to specific organizations or structures (Abdelhamid, 2025; Lee & Zhao, 2025; Novillo-Villegas et al., 2025). Thus, there are academic studies on the degree of innovation in OECD member countries (Kirikkaleli & Ozun, 2019), in the so-called BRICS countries—Brazil, Russia, India, China, and South Africa—(Bate 2021), and in the countries of the Gulf Cooperation Council —Saudi Arabia, UAE, Bahrain, Kuwait, Oman, and Qatar (Chun-Yao, 2014), the so-called MENA region—Middle East and North Africa—(Morrar, 2018), specific continents such as Africa or Asia (Okrah & Hajduk-Stelmachowicz, 2020; Malik, 2020) or markets such as the European Union (Dima et al., 2018).

Given the variables that determine a country's level of innovation, it seems clear that, as the academic literature amply demonstrates, the greater the effort and investment in R&D&I (research, development, and innovation), the higher the level of innovation measured at the national level (Barrichello et al., 2020; Chletsos & Sintos, 2024; Abdelhamid, 2025). Traditionally, this indicator—measured as a percentage of each country's gross domestic product (GDP)—has been accepted as one of the most reliable and robust measures of a country's innovative performance (Nasir & Zhang, 2024). In this regard, more traditional studies have limited themselves to linking the degree of innovation solely through partial indicators such as aggregate R&D&I expenditure or the number of patents, assuming that a limited number of variables are sufficient to define the degree of innovation in a country or a specific geographic area (Lema et al., 2021; Archibugi & Iammarino, 2002; Gault, 2013). However, more recent studies have highlighted the need to examine innovation from a multidimensional perspective, given that its definition depends on a multitude of technological, economic, human, and institutional factors and variables (Hadhri et al., 2016).

This is why the academic literature has established that linking the degree of innovation exclusively to direct research and development efforts is inadequate; rather, it results from the interaction of a greater number of variables and factors (Castellacci & Natera, 2013). Otherwise, there is a risk of excluding from the scope of study factors that influence the varying degrees of innovation among different countries, by relying solely on isolated indicators or fixed indices (Uyar et al., 2024). Therefore, as inferred in this study, there appears to be a certain consensus within the academic community that a country's innovative capacity is defined by the relationship between a number of disparate variables (MacGregor et al., 2025; Aghion & Howitt, 2023). Among these multifactorial variables, analyses vary depending on the perspective of different authors. Thus, (Chletsos & Sintos 2024) link the degree of innovation to factors as diverse as the availability of skilled human capital, demographic structure, level of economic development, quality of the institutional environment, and per capita spending on education. (Novillo-Villegas 2022) emphasizes that innovation is the result of a complex process influenced by technological, human, and organizational factors.

1.1. Measuring the number of patents as a dependent variable

Innovation has become a complex and multifaceted phenomenon, and it is necessary to define the variables that best determine and influence a country's level of innovation (Novillo-Villegas et al., 2025). It seems clear that one of the most direct relationships determining innovative capacity is the ability to generate measurable knowledge. The generation of technological knowledge clearly reflects a country's innovative performance, and within these measurements, the number of patents developed tends to be considered one of the most significant indicators (Koo & Cho, 2021). In various studies, the number of patents granted has emerged as one of the most widely accepted final indicators for measuring a country's level of technological innovation (Bakhtiar et al., 2021; Liebman & Reynolds, 2019).

The number of patents not only reflects the final volume of successfully implemented innovations but also reflects market validation of that process and the capacity to apply knowledge to productive reality (Novillo-Villegas et al., 2025; Hook Law et al., 2020). As indicated by the World Intellectual Property Organization (WIPO) in its *Global Innovation Index 2025*, patent applications serve as a direct barometer of the degree of innovation, demonstrating that economies leading in the number of patents also lead in the production of technological knowledge (WIPO, 2025). In particular, the number of patents per resident reflects each country's endogenous capacity to generate new knowledge and transform R&D&I efforts into innovative outcomes (Ciccarelli et al., 2026; MacGregor et al., 2025).

It is important to note that studying patents by country in absolute terms can distort reality due to sample size. For this reason, the academic literature has highlighted the need to avoid relying solely on absolute patent indicators, as they may introduce biases stemming from population size (Mendoza-Silva, 2021). For

this reason, as done in the present study, the number of patents in the total population must be normalized using measures such as the number of patents per capita. This methodology will allow for an accurate measurement of actual innovative capacity and will enable more robust and consistent comparisons between different countries (Chen & Song, 2024).

The dependent variables selected to determine the level of innovation are research and development expenditure, education expenditure, per capita income, economic openness, and government effectiveness. The use of this set of variables as a basis for studying the number of patents—and, consequently, innovation capacity—is widely supported in the academic literature. As previously noted, it appears clear that the volume of R&D&I expenditure as a percentage of gross domestic product (GDP) is clearly identified as one of the most robust determinants of the degree of innovation across different countries (Barrichello et al., 2020; Chletsos & Sintos, 2024). This variable represents the direct financial effort made by the public and private sectors to expand knowledge and create the appropriate ecosystem for innovation (Abdelhamid, 2025; Nasir & Zhang, 2024). However, the innovative effect is particularly strong when this research and development spending is combined with robust educational systems characterized by significant spending on education (Krishna, 2019). Various authors have empirically demonstrated the relationship between spending on education and improvements in innovation indices (Cudic et al., 2022; Correa, 2014). It is also true that not only is the presence of education spending necessary, but so is its efficiency (Shi et al., 2021). The European Commission itself has emphasized the relationship between improving human capital formation and converting knowledge into tangible results (European Commission, 2020).

These effects tend to be amplified in economies with higher per capita income, directly contributing to higher spending on R&D&I and higher spending on education—both measured as a percentage of GDP—(Jeon et al., 2022). It seems clear that greater availability of financial resources allows for increased funding of knowledge-intensive activities and a greater allocation of resources to the education sector (Fan & Jackson, 2025; MacGregor et al., 2025).

Economic openness, which is more difficult to measure, also plays an important role in the outcomes of the innovation process (Novillo-Villegas et al., 2025; Malik, 2020). This economic openness, measured as the capacity for integration into global markets, in principle promotes competitiveness from an international perspective, which, ultimately, would be related to increased technological and productive capacity (Coelli et al., 2022; Khan et al., 2023). In other words, competition creates incentives for the country's firms and institutions to innovate in order to maintain their competitiveness (Jeon et al., 2022). However, this point generates some controversy in the academic literature, as it is noted that the benefits of trade openness are neither automatic nor uniform across countries, but rather depend directly on the institutional framework (Uyar et al., 2024). Some authors point out that trade openness makes it easier to import technology than to develop it domestically, which would suggest a negative correlation between trade openness and patent generation (Hakimi et al., 2024).

Government effectiveness—understood as the public sector's capacity to create the appropriate ecosystem for knowledge generation—has also been studied as a variable determining a country's level of innovation (Acemoglu, D., & Robinson, 2012). In this regard, an effective institutional environment that reduces uncertainty and guarantees legal certainty strengthens the confidence of economic agents and encourages investment in long-term activities, such as research, technological development, and innovation (Clausen et al., 2020; Danta, & Rath, 2024).

Despite the extensive existing literature, there remain limitations in the study and understanding of the factors that interact to determine a country's level of innovation. This limitation is even more pronounced when attempting to study a large and heterogeneous sample of countries over an extended period of time. The inclusion in this study of institutional variables alongside technological, educational, and economic indicators to measure the degree of innovation reflects the broad consensus in the academic community (Lee & Zhao, 2025). It seems clear that the study of a country's innovative capacity must be conducted using a multidisciplinary approach and framed within a multivariate framework (Vasin & Timokhina, 2024). In line with this consensus, this study presents an empirical approach to analyze the degree of innovation in different countries based on a coherent set of measurable and quantifiable variables, such as resident patents, patents per capita, R&D and education spending as a percentage of GDP, economic openness, per capita income, and government effectiveness. Unlike other studies that incorporate only technological variables or predefined indices, this study breaks down the degree of innovation into a series

of structural determinants, offering a robust and novel perspective, grounded in rigorous scientific methodology, on the existing differences in measuring innovative performance.

In this way, the article contributes to improving the existing literature on innovation and economic growth by providing a multivariate framework that integrates different dimensions, using exclusively official and internationally comparable data. The expected results will advance the theoretical understanding of the factors that explain innovation at the country level and provide relevant tools for the design of public policies aimed at strengthening innovation.

2. Materials and Methodology

2.1. Materials

The empirical analysis is based on an international panel dataset comprising 58 countries and annual observations for the period 2000–2021 (see Dataset). The dataset was generated using World Bank data; after cleaning the database and excluding records with incomplete information on the variables included in the estimation, the final sample consisted of 1,207 observations. This resulted in a panel with a time span ranging from 19 to 21 years per country. The dependent variable of the study is the number of patents, while the set of explanatory variables consists of spending on research and development, spending on education, economic openness, per capita income, and government effectiveness. The unbalanced structure of the panel is due to the presence of missing values. Specifically, there are missing observations in the patent variable, in R&D spending and education spending, as well as in economic openness and government effectiveness, while per capita income has complete data coverage for the period analyzed.

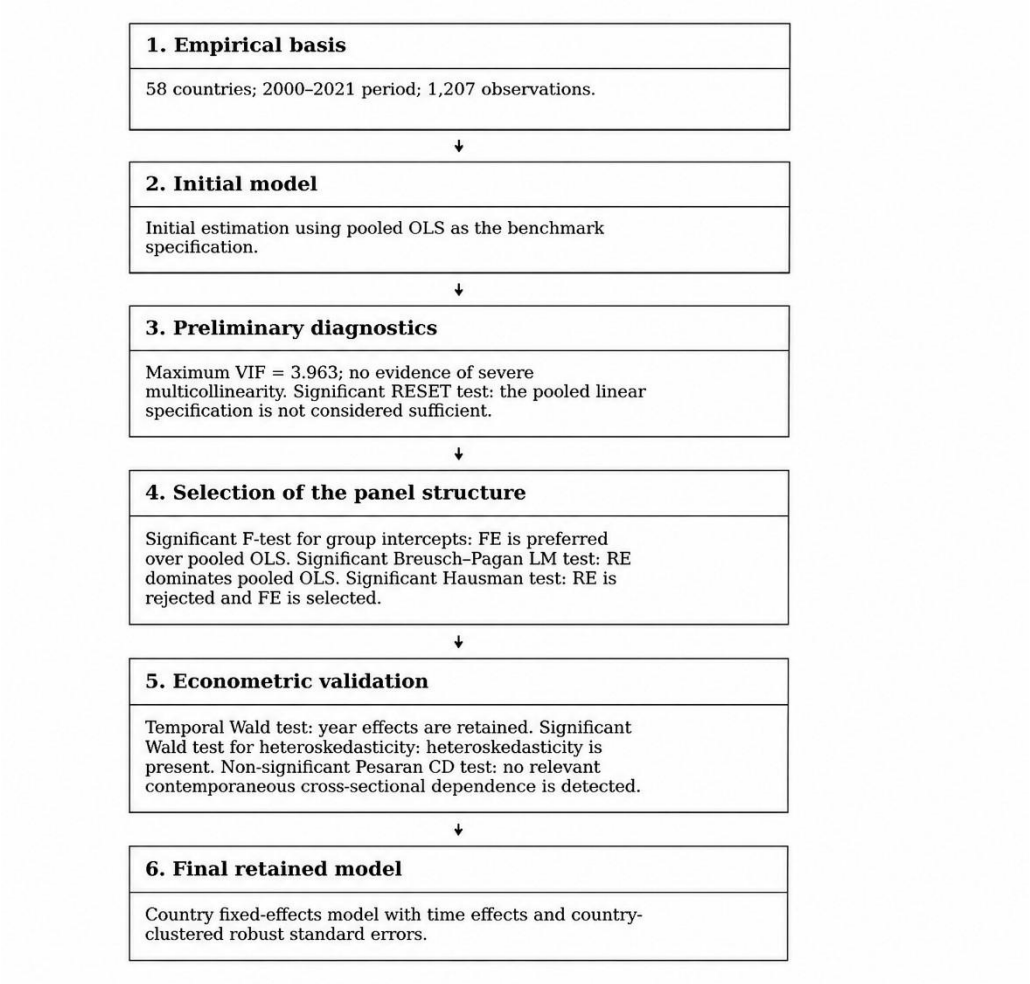
2.2. Methodology

The methodological strategy is based on a panel data approach aimed at identifying the relationship between patenting activity and a set of economic and institutional determinants, while simultaneously controlling for country-specific unobserved heterogeneity and for common effects associated with the time dimension. This follows the approach taken in previous studies such as those by Cincera (1997); Meliciani (2000); Allred & Park (2007); Roper & Hewitt-Dundas (2015); Lee & Lee (2019); or Konstantakis et al. (2025).

As a starting point, a clustered model was estimated using ordinary least squares, serving as the baseline specification against which subsequent diagnostic and selection tests were conducted, following previous authors such as Bottazzi & Peri (2003); Madrid-Guijarro et al. (2013); or Berkes et al. (2022). Thus, in a first stage, the internal consistency of the initial specification was evaluated using multicollinearity analysis based on variance inflation factors. Next, RESET specification tests were applied. Subsequently, estimator selection was carried out using the standard sequence of tests for panel models. The Breusch-Pagan LM test was also applied, following authors such as Tosunoğlu (2024) or Zhu (2025). The choice between the two formulations was resolved using the Hausman test, as done by Ramirez-Hernandez & Isaza-Castro (2019) in their study. The significant result of the test revealed a correlation between country-specific unobserved effects and the explanatory variables, thus justifying the adoption of a fixed-effects model. Once the basic structure of the model was selected, the appropriateness of incorporating common time effects was analyzed. However, the model ultimately applied incorporates both country-specific fixed effects and year effects. The econometric validation of the final specification was completed by examining the residual structure, using the Wald heteroscedasticity test following (Appendix Table 2). (Alstadsæter et al., 2018); and Pesaran's CD test as done by Mabrouki (2022).

The final inference was performed using robust standard errors clustered by country. Consequently, the main specification of the study was defined as a country-fixed-effects model with time effects and robust standard errors clustered by cross-sectional observation unit. This allows the coefficients to be interpreted strictly within-country: the estimates capture how the number of patents varies within a given country over time when the explanatory variables change, after controlling for both the unobservable and constant characteristics of each economy and the common disturbances affecting all countries in each period. Figure 1 summarizes the methodology used in this research.

Figure 1. Applied Methodology**.** *Source* Own elaboration



Note: FE = fixed effects; RE = random effects; pooled OLS = pooled ordinary least squares. The figure summarizes the methodological sequence documented in the study, from the initial pooled estimation to the final specification with fixed effects, time effects, and robust inference.

The final estimated equation of the two-way fixed-effects econometric model is:

$$Patents_{ij} = \alpha_i + \lambda_t + \beta_1 * R\&D\ Expenditures_{it} + \beta_2 * Education\ Spending_{it} + \beta_3 * Economic\ openness_{it} + \beta_4 * Per\ capita\ income_{it} + \beta_5 * Government\ effectiveness_{it} + \varepsilon_{it}$$

where:

- i: identifies the country
- t: identifies the year
- α_i: captures the country-specific fixed effect
- λ_t: captures the time-specific effect common to all countries in each year
- ε_{it}: is the idiosyncratic error term

3. Results

The main results of the study are shown in the following table (Table 1)

Table 1. Results of the patent model estimates under alternative specifications. *Source* Own elaboration

Variables	**(1) Pooled OLS**	**(2) FE**	**(3) FE + time effects**	**(4) Robust FE + time effects**	**(5) Robust FE without time effects**
R&D Expenditures	0.328469***	0.122018***	0.149382***	0.149382*	0.122018
	(0.0155544)	(0.0119362)	(0.0121466)	(0.0860055)	(0.0821783)
Education spending	-0.108786***	0.00592362	0.0123574**	0.0123574	0.00592362
	(0.00905476)	(0.00544415)	(0.00550239)	(0.0107845)	(0.00896614)
Economic openness	-0.000676990***	-0.000377569**	-0.000301714	-0.000301714	-0.000377569
	(0.000192339)	(0.000190527)	(0.000195018)	(0.000445368)	(0.000457415)
Per capita income	-1.10101e-06	8.91603e-07	6.08247e-06***	6.08247e-06***	8.91603e-07
	(8.57017e-07)	(6.73150e-07)	(9.45709e-07)	(2.24043e-06)	(1.12730e-06)
Government effectiveness	-0.0506893**	0.0662880***	0.0509336***	0.0509336	0.0662880
	(0.0229446)	(0.0162117)	(0.0161949)	(0.0642867)	(0.0663040)
Constant	0.417420***	-0.0412590	-0.223597***	-0.223597	-0.0412590
	(0.0451523)	(0.0391322)	(0.0462069)	(0.205802)	(0.179300)
Fixed effects by country	No	Yes	Yes	Yes	Yes
Temporary effects	No	No	Yes	Yes	No
Robust errors grouped by country	No	No	No	Yes	Yes
Remarks	1207	1207	1207	1207	1207
Countries	58	58	58	58	58
Intra-R^2	—	0.121916	0.175266	0.175266	0.121916
AIC	994.8734	-2151.736	-2,187.393	-2,187.393	-2151.736
Set of regressors test (p-value)	2.5e-120	2.25883e-30	6.14059e-44	0.0682489	0.728317

Note: Dependent variable: Patents. Standard errors in parentheses. In columns (4) and (5), standard errors are robust and grouped by country. Temporal dummy variables were included in columns (3) and (4), but are not reported individually for brevity. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 1 shows the results of the estimates using the different model specifications. R&D expenditure exhibits positive and significant coefficients in all models, both in the ordinary least squares (OLS) model and in the various fixed-effects (FE) models, indicating that higher levels of research and development expenditure are positively correlated with a greater number of patents. The same conclusion is reached when examining Appendix Figure 2 (see appendices), which reflects the dispersion among the variables. The relationship is positive, and a strong concentration is observed at low levels, implying that countries that spend little on R&D obtain very few patents. However, this relationship is not linear, as considerable

dispersion in the data is observed at high levels. This variable has the strongest positive correlation with patent production, as shown in Appendix Figure 2, which depicts a bivariate correlation matrix. In turn, there is also a high positive correlation between R&D spending and other independent variables, such as per capita income or government effectiveness.

Spending on education does not show a robust statistical effect. In the first model, an inverse relationship is observed between spending on education and patent development, although in the subsequent models, from 2 to 5, the results are positive but very close to zero. It is true that in models 3 and 4, some robustness is observed in the coefficients, but this is lost in the final fixed-effects model without time effects. This result can also be seen in Appendix Figure 2. Although a greater concentration at low levels is also apparent, the scatter is much more dispersed, so a strong relationship between the variables cannot be established. In fact, Appendix Figure 4 shows a complete absence of a relationship between the two variables.

The Table shows that economic openness has a negative coefficient in all models, although it certainly lacks strong statistical significance, which prevents definitive conclusions from being drawn. The scatter plot in Appendix Figure 2 shows high dispersion and a slight decreasing relationship between the variables. Regarding the impact of per capita income levels on patent production, the results are mixed. On the one hand, an inverse relationship is observed in the OLS model, followed by a change in sign—showing a positive correlation—in the various fixed-effects models where statistically significant results are obtained. This change may be due to a bias in the OLS model caused by the effect of unobserved heterogeneity in the model. Appendix Figure 2 reflects a nonlinear positive relationship between the variables characterized by a "fan-shaped" pattern, where, as with R&D spending, there is greater dispersion at high levels, implying the presence of heteroscedasticity.

The final variable to be analyzed is government effectiveness, which is an indicator of the quality of a country's institutions. Once again, a change in sign is observed in the first model compared to the others, ultimately showing a positive but not significant relationship, as also reflected in Appendix Figure 2, which shows a high degree of dispersion. The last two variables mentioned—per capita income and government effectiveness—exhibit a strong correlation with each other, as seen in Appendix Figure 1.

In the following section, where the results will be discussed in light of the existing academic literature on the subject, various analyses will be presented to help explain these effects.

The most consistent finding of the model—due to its robustness and stability across all models—is that higher levels of R&D spending lead to greater technological innovation, as measured by the number of patents. A robust result was also obtained for per capita income, but only in the FE models, which yield the most reliable results. However, the study's data do not provide conclusive results for the variables of economic openness, education spending, and government effectiveness. In the FE models with time effects (models 3 and 4), an R^2 of 0.175 was achieved, which offers adequate explanatory power for this type ofstudy using panel data. It should be noted that innovation is a highly complex phenomenon, so there are unobserved factors that limit and moderate this explanatory power, as shown in Figure 2:

Figure 2. Estimated coefficients and confidence intervals for the main model specifications. *Source* Own elaboration

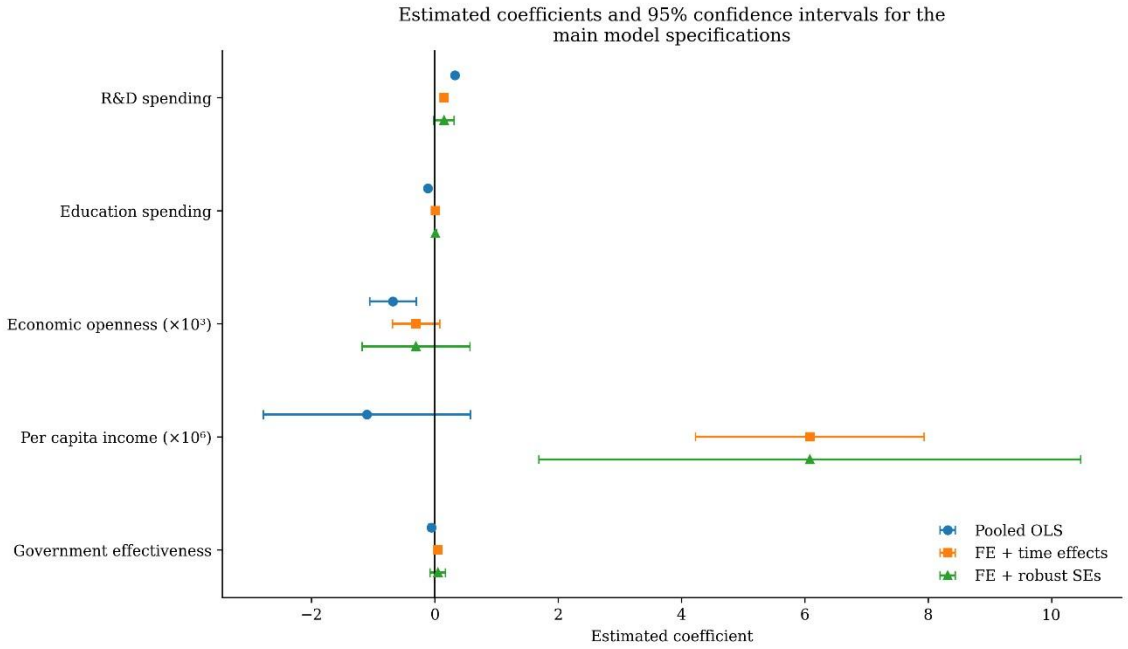
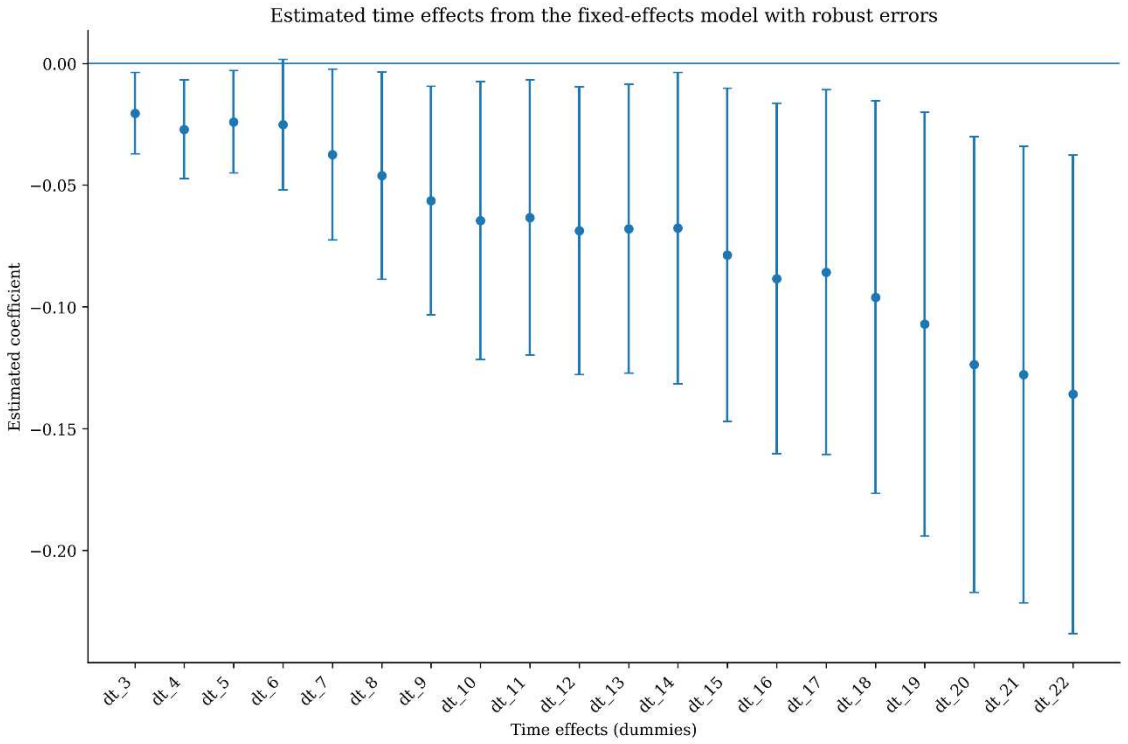


Figure 2 shows the estimated coefficients of the different variables in relation to three models (the OLS model and two FE models, with time effects and time-robust) and provides a visual illustration of the results in Table 1. The vertical zero line indicates that there is no correlation between the variables, and if the results are close to zero, the effect is not very significant. The most disparate results are found in the per capita income variable, which, due to the unit of measurement (in millions of international dollars), exhibits higher coefficients. As noted earlier, the negative coefficients of some variables in the pooled OLS model (blue) are primarily due to model specification issues rather than a real causal relationship between the dependent variable—the number of patents—and the corresponding explanatory variable (economic openness, per capita income, education spending, or government effectiveness). In this regard, the choice of model becomes relevant, with fixed-effects models being more reliable and consistent, as shown in Figure 3:

Figure 3. Estimated time effects of the fixed-effects model with robust errors. *Source* Own elaboration



Note: The figure shows the estimated coefficients of the time-specific dummy variables from the fixed-effects model with time effects and robust standard errors, grouped by country, along with their 95 percent confidence intervals. The labels dt_3 to dt_22 follow the nomenclature of the original econometric output. Since the omitted reference period cannot be identified with complete certainty in the available data, the figure retains this coding and does not assign the dummies to specific years.

Figure 3 shows the results of the fixed-effects model with time effects and robust errors, and it can be seen that all coefficients are negative and become more negative as the periods progress. This indicates that the time effect has a downward trend, as Appendix Table 3 also shows. More specifically, the average value of the coefficient indicates the change in the dependent variable (number of patents) in a given period relative to the reference period; although, as noted in the footnote, the reference period is unknown and cannot be associated with specific years, the time trend can still be examined. Therefore, compared to the base period, there is a decline in technological innovation, as measured by the number of patents, over the period.

Appendix Figure 4 (see appendices) shows the aggregate time series of all variables in the study. The horizontal axis represents the number of observations, while the vertical axis uses different scales for each variable. In the case of patents, low values are observed for the set of observations, although with certain peaks of great magnitude, which shows significant inequality in innovative activity through patents, with a high concentration of data in a few countries that patent extensively. It can also be seen that the education variable is fairly stable, while others, such as economic openness and per capita income, exhibit significant fluctuations with the presence of certain sharp peaks.

Appendix Table 1 (see appendices) shows the descriptive statistics for the variables. The dependent variable exhibits very low mean values with a high maximum value, indicating high skewness, with few countries obtaining many patents, as already observed in Appendix Figure 4. Education spending is fairly homogeneous, with a mean similar to the median—a pattern somewhat similar, though to a lesser extent, to that of R&D spending, which shows moderate skewness. Economic openness exhibits a high standard deviation and a significant difference between the mean and the median. Per capita income data show strong inequality among countries, with a large gap between the minimum and maximum values. On the other hand, government effectiveness also reflects great diversity, with some countries having government institutions that promote innovation and others having very deficient institutions.

To conclude, Appendix Figure shows the box plots for the variables. Appendix Table 4 shows the explained variance for each component and, finally, Appendix Table 5 details the factor loadings for the components.

4. Discussion

Several studies analyze the determinants of innovation through patent applications (Archibugi & Iammarino, 2002; Gault, 2013). Although there are different ways to measure a country's level of innovation, patents are a relevant and easily accessible indicator.

Academic evidence shows a strong correlation between R&D spending and patent acquisition. (Ciccarelli et al., 2026) examine the impact of R&D spending and patent acquisition in different regions of Italy, distinguishing between various types of spending: public sector, business sector, and university research. The results show that research in higher education yields positive long-term effects, while the other types of spending have no statistically significant effects. (MacGregor *et al*., 2025) analyze the European Union (EU) program for the protection of innovation known as the Unitary Patent System and show that in the first twenty months of the program's operation, it was a viable option that helped boost research spending and per capita income in most EU member states, although these variables are considered essential prerequisites. In fact, a disparity is observed among them regarding the production of unitary patents due to initial differences in these two variables, particularly between northern countries, which have more patents per capita, and southern countries, which perform worse.

Falk (2004) uses panel data for the countries of the Organization for Economic Cooperation and Development (OECD) and finds that R&D spending is the most decisive factor in patent applications. These results are therefore similar to those of the present study.

According to various authors (Fan & Jackson, 2025; MacGregor *et al.,* 2025), the relationship between per capita income and the number of patents is also positive. This is because a higher level of income is associated with better infrastructure, broader financial markets, and larger firms that can undertake the substantial initial investments required. The aforementioned studies suggest a bidirectional relationship between these variables, as innovation also drives long-term economic growth (Romer, 1990; Grossman & Helpman, 1993), often leading to significant technological disruptions that trigger a process of creative destruction (Mokyr, 2023; Aghion & Howitt, 2023)

The quality of institutions is also another important factor for the development of innovation. There are inclusive government institutions, which foster economic growth and development and thus innovation, and extractive institutions, which hinder the generation of ideas and material progress (Acemoglu, D., & Robinson, 2012). Among the former, respect for private property, the separation of powers, efficient public spending, and low levels of corruption stand out. Countries with authoritarian systems of government and high levels of corruption have extractive institutions that generally benefit only the ruling elites and businesspeople connected to political power.

(Danta & Rath, 2024) analyze 39 Asian countries from 2000 to 2021 and find that human capital and institutional quality are the main drivers of innovation. The authors distinguish between patent applications filed by residents and non-residents and find similar results in both groups. Having strong governance institutions allows for better protection of rights, long-term planning, and access to better financing conditions. (Lu et al., 2024) study the impact of economic openness and the institutional environment on technological innovation in different regions of China using panel data from 2008 to 2017. Although results vary by region, they find that trade openness does not contribute to innovation, whereas foreign direct investment and a better institutional environment foster it in the long term. (Borsekova *et al.,* 2026) use decision trees for more than 200 EU regions and 15 indicators of institutional quality. The results show high performance in Western and Northern Europe, with strong government institutions and strong innovation performance, while areas in Central and Eastern Europe, although they have great potential for innovation, are hampered by governance deficiencies. However, this variable is often considered more of a necessary, though not sufficient, condition for innovation and economic growth.

Spending on education is another variable that can contribute to improving innovation through better training of researchers, but its contribution is more indirect and long-term, and more difficult to measure, especially over short periods of time. (Diakodimitriou et al., 2025) find, in a study of several European countries, that educational spending, particularly that related to research and development, positively influences per capita income. (Yue, 2023) analyzes the impact of university expansion in China during the

1990s and its positive effect on innovation and patent generation. (Ma et al., 2024) show that university education spending in China has a positive impact on technological innovation related to renewable energy through the acquisition of "green patents." Although these results confirm human capital theory (Becker, 2009), this variable exhibits time lags (Correa, 2014) and does not account for the quality of educational spending, which can yield statistically insignificant results, as occurs in this study with the various fixed-effects models. Thus, several authors (Pritchett & Filmer, 1999; Hanushek, 2002; Afonso, 2004) show that inefficiency in educational spending generates negative effects on innovation and economic development. (Rubilar-Torrealba *et al.,* 2022) also fail to find a clear correlation between education spending and patents in a study of over 90 countries, in which they detect multicollinearity among the study variables (education spending, R&D spending, scientific publications, etc.), which contributes to the variable losing significance.

Economic openness is undoubtedly the most ambiguous variable to analyze. Some authors (Sachs et al., 1995; Coelli *et al*., 2022; Khan et al., 2023) show that competition and trade openness foster innovation and that a high degree of protectionism discourages domestic firms from developing advanced technology because they have a captive market due to tariffs or other trade barriers. Other authors (Sakakibara & Cho, 2002; Chang, 2004) argue that domestic industries must be protected and that countries that adopted trade openness through economic liberalization did so only after having previously implemented protectionist measures. (Sakakibara & Cho, 2002) show that developed countries such as Japan and South Korea protected their industries for decades and only later opened up to international trade. There is, therefore, a controversy between more liberal authors and those who advocate for state intervention to promote innovation in a dirigiste manner. (Mazzucato, 2011) maintains that the state has played an entrepreneurial role in countries such as the U.S. or China and that many inventions, such as GPS or the internet, were driven by the public sector (Mazzucato, 2015). Some authors point out that trade openness makes it easier to import technology than to develop it domestically, so there may be, as is the case in this study, a negative correlation between trade openness and patent generation. (Hakimi et al., 2024) analyze this effect in African countries. (Phuc Canh *et al*., 2019) use GMM estimators with panel data for a set of 84 countries and find an inverse relationship between trade openness and patent development.

A more nuanced result is obtained by (Liebman & Reynolds, 2019), who review the academic literature on innovation and show that the U.S. fostered technological development during the 1980s through tariffs and protectionist policies, but that high levels of innovation were also achieved in the 1990s in a different context characterized by trade openness. According to the theory of absorptive capacity, economic openness yields positive results in terms of innovation if there is a prior foundation of research and development and a robust system for training researchers (Cohen & Levinthal, 1990).

5. Conclusions

Innovation emerges as an essential component in promoting economic growth, productive transformation, and the international competitiveness of nations. This study analyzes innovation using an empirical approach based on patents, which are considered a relevant indicator of the capacity to generate technological knowledge. To this end, an exhaustive analysis was conducted of a panel database comprising 58 countries for the period from 2000 to 2021. In this regard, various relevant factors were examined, such as the effects of research and development spending, education spending, economic openness, per capita income, and government effectiveness on the number of patents. The empirical findings from the study support a multi-causal interpretation of the innovation phenomenon. However, it has been observed that not all factors considered have the same impact or the same empirical clarity.

First, R&D spending emerges as the most robust, consistent, and coherent determinant of technological innovation, as measured through patent analysis. The results obtained show a positive and statistically significant impact that holds across the various estimated specifications, which strengthens the hypothesis that investment in research and development constitutes the main pillar of a country's innovative capacity. This finding is consistent with the reviewed literature and confirms that the generation of applicable knowledge depends, to a large extent, on the existence of a sufficient base of resources allocated to knowledge-intensive activities.

Second, per capita income also shows a positive association with patent production in the fixed-effects models, which provide the most appropriate specification for the analysis conducted. This result suggests that a higher level of economic development fosters the availability of resources, infrastructure, and capabilities necessary to sustain innovation processes over time. In contrast, spending on education, government effectiveness, and economic openness do not yield conclusive results in terms of statistical robustness. In the educational context, this finding does not suggest an absence of a relationship with innovation, but rather the possibility that its effect may manifest indirectly, cumulatively, or depend on the quality and efficiency of spending—aspects not fully captured in the estimation. Similarly, government effectiveness emerges as a significant, though not exclusive, environmental factor in explaining variations in patenting activity within the countries studied.

With regard to economic openness, a negative correlation is evident in the estimates, although it does not reach statistical significance. This result calls for a cautious interpretation and suggests that the relationship between openness and innovation is not unambiguous, but likely depends on additional structural factors, such as technological absorption capacity, the prior level of development, or the strength of the institutional framework. Consequently, the study's findings do not allow us to assert that greater trade openness leads, in and of itself, to an increase in technological innovation as measured by patents.

The analysis conducted leads to the conclusion that policies aimed at strengthening investment in R&D constitute the clearest path to boosting countries' innovative capacity and, thereby, fostering sustained processes of economic development.

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References

Abdelhamid, M. (2025). Proposal of a model to measure national innovation capacity: a cross-country comparative analysis. *Journal of Innovation and Entrepreneurship*, 14:115– https://doi.org/10.1186/s13731-025-00544-2

Acemoglu, D., & Robinson, J. A. (2012). *Why nations fail: The origins of power, prosperity, and poverty*. Profile Books.

Afonso, A., & St. Aubyn, M. (2004). Non-parametric approaches to education and health expenditure efficiency in OECD countries. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.498383

Aghion, P., & Howitt, P. (2023). Conclusion: The promise of the creative destruction paradigm. In *The Economics of Creative Destruction* (pp. 736–752). Harvard University Press. https://doi.org/10.4159/9780674293052-029

Alqararah, K. (2023). Assessing the robustness of composite indicators: the case of the Global Innovation Index. *Journal of Innovation and Entrepreneurship*, 12, 61. https://doi.org/10.1186/s13731-023-00332-w

Allred, B. B., & Park, W. G. (2007). Patent rights and innovative activity: Evidence from national and firm-level data. *Journal of International Business Studies*, *38*(6), 878–900. https://doi.org/10.1057/palgrave.jibs.8400306

Alstadsæter, A., Barrios, S., Nicodeme, G., Skonieczna, A. M., & Vezzani, A. (2018). Patent boxes design, patents location, and local R&D. *Economic Policy*, *33*(93), 131–177. https://doi.org/10.1093/epolic/eix021

Archibugi, D., & Iammarino, S. (2002). The globalization of technological innovation: Definition and evidence. *Review of International Political Economy*, *9*(1), 98–122. https://doi.org/10.1080/09692290110101126

Bakhtiar, A., Ghazinoory, S., Alireza, A., & Mafi, V. (2021). Efficiency-effectiveness assessment of national innovation systems: comparative analysis. *Journal of Science and Technology Policy Management,* 13(3). https://doi.org/10.1108/JSTPM-03-2021-0044

Bate, A. F.; Wachira, E. W. & Danka, S. (2023). The determinants of innovation performance: An income-based cross-country comparative analysis using the Global Innovation Index (GII). *Journal of Innovation and Entrepreneurship*, 12 (1), 1-27. https://doi.org/10.1186/s13731-023-00283-2

Barrichello, A., Paulo, S., De Política, E. P., Negócios, E., & Morano, R. S. (2020). Determinant and priority factors of innovation for the development of nations. *Innovation & Management Review*, 17(3), 307–320. https://doi.org/10.1108/ INMR-04-2019-0040

Bhattacharya, M. & Bloch, H. (2004) Determinants of Innovation. *Small Business Economics* 22, 155–162. https://doi.org/10.1023/B:SBEJ.0000014453.94445.de

Becker, G. S. (2009). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press.

Berkes, E., Manysheva, K., & Mestieri, M. (2022). *Global innovation spillovers and productivity: Evidence from 100 years of world patent data*. Federal Reserve Bank of Chicago. https://doi.org/10.21033/wp-2022-15

Borsekova, K., Korony, S., Rodríguez-Pose, A., Styk, M., & Westlund, H. (2026). Decoding regional dynamics: Institutions, innovation, and regional development in the EU. *Papers in Regional Science*, *105*(1), 100133. https://doi.org/10.1016/j.pirs.2025.100133

Bottazzi, L., & Peri, G. (2003). Innovation and spillovers in regions: Evidence from European patent data. *European Economic Review*, *47*(4), 687–710. https://doi.org/10.1016/s0014-2921(02)00307-0

Castellacci, F. & Natera, J.M. (2013). The dynamics of national innovation systems: A panel cointegration analysis of the coevolution between innovative capability and absorptive capacity. *Research Policy*, 42 (3), 579-594. https://doi.org/10.1016/j.respol.2012.10.006

Chang, H.-J. (2004). *Pulling Up the Ladder: The Strategy of Development in Historical Perspective*. Catarata Books.

Chen, W. & Song, H. (2024). National innovation system: Measurement of overall effectiveness and analysis of influencing factors. *Technology in Society*, 77. 102514. https://doi.org/10.1016/j.techsoc.2024.102514

Chletsos, M., & Sintos, A. (2024). Political stability and financial development: An empirical investigation. *The Quarterly Review of Economics and Finance,* 94, 252–266. https://doi.org/10.1016/j.qref.2024.02.003

Chun-Yao, T. (2014). Technological innovation capability, knowledge sourcing and collaborative innovation in Gulf Cooperation Council countries. Innovation, 16(2), 212–223. https://doi.org/10.1080/14479338.2014.11081983

Ciccarelli, A., De Dominicis, A., & Torquati, G. (2026). R&D expenditure and regional innovation in Italy: Evidence from a panel data analysis. *Rivista Italiana Di Economia Demografia e Statistica*, 403–414. https://doi.org/10.71014/sieds.v80i4.562

Cincera, M. (1997). PATENTS, R&D, AND TECHNOLOGICAL SPILLOVERS AT THE FIRM LEVEL: SOME EVIDENCE FROM ECONOMETRIC COUNT MODELS FOR PANEL DATA. *Journal of Applied Econometrics*, *12*(3), 265–280. https://doi.org/10.1002/(sici)1099-1255(199705)12:3<265::aid-jae439>3.0.co;2-j

Clausen, T. H., Demircioglu, M. A., & Alsos, G. A. (2020). Intensity of innovation in public sector organizations: The role of push and pull factors. *Public administration*, *98*(1), 159-176. https://doi.org/10.1111/padm.12617

Coelli, F., Moxnes, A., & Ulltveit-Moe, K. H. (2022). Better, faster, stronger: Global innovation and trade liberalization. *The Review of Economics and Statistics*, *104*(2), 205–216. https://doi.org/10.1162/rest_a_00951

Cohen, W., & Levinthal, D. (1990). Absorptive capacity: A new perspective on learning and innovation. In *Strategic Learning in a Knowledge Economy* (pp. 57–86). Routledge. https://doi.org/10.4324/9780080517889-9

Correa, P. (2014). *Public Expenditure Reviews in Science, Technology, and Innovation: A Guidance Note*. World Bank Publications—Reports 21064. The World Bank Group.

Ćudić, B., Alešnik, P., & Hazemali, D. (2022). Factors impacting university–industry collaboration in European countries. Journal of Innovation and Entrepreneurship, 11(1), 33. https://doi.org/10.1186/s13731-022-00226-3

Danta, S., & Rath, B. N. (2024). Do institutional quality and human capital matter for innovation in the Asian region? *Innovation and Green Development*, *3*(3), 100141. https://doi.org/10.1016/j.igd.2024.100141

Diakodimitriou, D., Tsioutsios, A., & Papageorgiou, T. (2025). Education Expenditures and Growth: Is R&D the link? *Journal of Policy Modeling*, *47*(2), 322–337. https://doi.org/10.1016/j.jpolmod.2025.01.003

Dima, A. M., Begu, L., Vasilescu, M. D., & Maassen, M. A. (2018). The relationship between the knowledge economy and global competitiveness in the European Union. Sustainability (Switzerland), 10(6), 1706. https://doi.org/10.3390/ su10061706

European Commission. (2020). Internal market, industry, entrepreneurship, and SMEs. Retrieved January 20, 2022, from https://ec.europa.eu/growth/smes/sme-definition_en

Falk, M. (2004). *What determines patents per capita in OECD countries?* (WIFO Working Papers No. 242). Austrian Institute of Economic Research (WIFO).

Fan, Y., & Jackson, A. (2025). The relationship between technological innovation, human capital and civil liberties in advancing economic complexity and sustainable growth. *Frontiers in Environmental Science*, *13*. https://doi.org/10.3389/fenvs.2025.1567322

Gault, F. (2013). Innovation indicators and measurement: An overview. In *Handbook of Innovation Indicators and Measurement*. Edward Elgar Publishing. https://doi.org/10.4337/9780857933652.00008

Geissler A., Gorodkin J., & Seemann S. (2024). Patent data-driven analysis of literature associations with changing innovation trends. *Frontiers in Research Metrics and Analytics*, 9. https://doi.org/10.3389/frma.2024.1432673

Grossman, G. M., & Helpman, E. (1993). *Innovation and growth in the global economy*. MIT Press.

Hadhri, W., Arvanitis, R., & M'Henni, H. (2016). Determinants of innovation activities in small and open economies: The Lebanese business sector. Journal of Innovation Economics, 21(3), 77. https://doi.org/10.3917/jie.021.0077

Hakimi, A., Hamdi, H., & Inglesi-Lotz, R. (2024). To innovate or to import innovation? Evidence from African countries. *Regional Science Policy & Practice*, *16*(3), 12594. https://doi.org/10.1111/rsp3.12594

Hanushek, E. (2002). *The failure of input-based schooling policies*. National Bureau of Economic Research. https://doi.org/10.3386/w9040

Hook Law, S., Naseem, N.A.M., Theng Lau, W., & Trinugroho, I. (2020). Can innovation improve income inequality? Evidence from panel data. *Economic Systems*, 44, 4. https://doi.org/10.1016/j.ecosys.2020.100815.

Jeon, J., Geetha, S., Kang, D., & Narayanamoorthy, S. (2022). Development of the evaluation model for national innovation capability. *Technology Analysis & Strategic Management*, *34*(3), 335–348. https://doi.org/10.1080/09537325.2021.1900561

Ji, Y., Yu, X., Sun, M., & Zhang, B. (2022). Exploring the Evolution and Determinants of Open Innovation: A Perspective from Patent Citations. *Sustainability*, *14*(3), 1618. https://doi.org/10.3390/su14031618

Khan, M. N., Jan, A. A., Asif, M., Lai, F.-W., Shad, M. K., & Shadab, S. (2023). Do domestic innovations promote trade openness? Empirical evidence from emerging economies. *Heliyon*, *9*(12), e22848.

Kirikkaleli, D., & Ozun, A. (2019). Innovation capacity, business sophistication, and macroeconomic stability: Empirical evidence from OECD countries. Journal of Business Economics and Management, 20(2), 351–367. https://doi.org/10. 3846/jbem.2019.9602

Krishna, V.V. (2019). Universities in the National Innovation Systems: Emerging Innovation Landscapes in Asia-Pacific. *Journal of Open Innovation: Technology, Market, and Complexity*, 5 (3), 43. https://doi.org/10.3390/joitmc5030043

Konstantakis, K. N., Michaelides, P. G., Papadakis, T.-E., Stamos, D. L., & Tsitsou, V. C. (2025). Do patents drive economic growth: dynamic panel data evidence from selected economies. *Journal of the Knowledge Economy*. https://doi.org/10.1007/s13132-025-02854-y

Koo, Y., & Cho, K. (2021). The Relationship between Patents, Technology Transfer and Absorptive Capacity in Korean Universities. *Sustainability*, *13*(9), 5253. https://doi.org/10.3390/su13095253

Lee, K., & Lee, J. (2019). National innovation systems, economic complexity, and economic growth: Country panel analysis using the US patent data. In *Economic Complexity and Evolution* (pp. 113–151). Springer International Publishing. https://doi.org/10.1007/978-3-030-84931-3_6

Lee, C.C., & Zhao, Y.N. (2025). What affects national innovative capacity? The role of economic growth and trade openness. *Economic Analysis and Policy,* 86, 1099-1118. https://doi.org/10.1016/j.eap.2025.04.022

Lema, R., Kraemer-Mbula, E., & Rakas, M. (2021). Innovation in developing countries: examining two decades of research. *Innovation and Development*, *11*(2–3), 189–210. https://doi.org/10.1080/2157930X.2021.1989647

Liebman, B. H., & Reynolds, K. M. (2019). Competitive pressure, innovation, and trade protection: Evidence from US patent data. *The World Economy*, *42*(6), 1695–1712. https://doi.org/10.1111/twec.12765

Lu, H., Feng, Z., & Wang, S. (2024). The impact of economic openness and institutional environment on technological innovation: Evidence from China's provincial patent application data. *Sage Open*, *14*(2). https://doi.org/10.1177/21582440241240528

Ma, C., Ma, Y., & Wu, W. (2024). A pathway to sustainable development in China: The impact of local higher education expenditure on green total factor productivity. *Heliyon*, *10*(15), e34415. https://doi.org/10.1016/j.heliyon.2024.e34415

Mabrouki, M. (2022). Patent, education, human capital, and economic growth in Scandinavian countries: A dynamic panel CS-ARDL analysis. *Journal of the Knowledge Economy*, *14*(3), 3028–3043. https://doi.org/10.1007/s13132-022-01001-1

MacGregor Pelikánová, R., Hála, M., & Beneš, M. (2025). Unitary Patent System and innovation Dynamics in the European Union: The role of economic resources and R&D investments. *Journal of Entrepreneurship, Management and Innovation*, *21*(2), 98–115. https://doi.org/10.7341/20252126

Madrid-Guijarro, A., García-Pérez-de-Lema, D., & Van Auken, H. (2013). An investigation of Spanish SME innovation during different economic conditions. *Journal of Small Business Management*, *51*(4), 578–601. https://doi.org/10.1111/jsbm.12004

Malik, S. (2020). Macroeconomic determinants of innovation: Evidence from Asian countries. *Global Business Review,* 24 (1). https://doi.org/10.1177/0972150919885494

Mazzucato, M. (2011). The entrepreneurial state. *Soundings*, *49*(49), 131–142. https://doi.org/10.3898/136266211798411183

Mazzucato, M. (2015). Building the entrepreneurial state: A new framework for envisioning and evaluating a mission-oriented public sector. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2544707

Meliciani, V. (2000). The relationship between R&D, investment, and patents: A panel data analysis. *Applied Economics*, *32*(11), 1429–1437. https://doi.org/10.1080/00036840050151502

Mendoza-Silva A. (2021). Innovation capability: a systematic literature review. *European Journal of Innovation Management*, 24 (3), 707–734, doi: https://doi.org/10.1108/EJIM-09-2019-0263

Mokyr, J. (2023). Creative destruction or destructive creation? In *The Economics of Creative Destruction* (pp. 714–735). Harvard University Press. https://doi.org/10.2307/jj.4820341.30

Morrar, R. (2018). Innovation in the MENA Region. *Economy & Territory. IED Mediterranean Yearbook*
https://www.researchgate.net/publication/337158652_Economic_Innovation_MENA_Region_Rabeh_Morrar_IEMed_MedYearbook2019#fullTextFileContent

Nasir, M.H. & Zhang, S. (2024). Evaluating innovative factors of the global innovation index: A panel data approach. *Innovation and Green Development*, 3 (1). https://doi.org/10.1016/j.igd.2023.100096.

Novillo-Villegas, S., Tulcanaza-Prieto, A. B., Chantera, A. X., & Chimbo, C. (2025). Exploring a Sustainable Pathway Towards Enhancing National Innovation Capacity from an Empirical Analysis. *Sustainability*, 17(15), 6922. https://doi.org/10.3390/su17156922

Novillo-Villegas, S., Acosta-Vargas, P., Cruz-Boada, C., Garzon, M., Marin-Dett, A., & Anzules-Falcones, W. (2022). Sustaining the Path for Innovation Capability from a Developing Country Perspective: A Conceptual Framework. *Sustainability*, *14*(19), 12807. https://doi.org/10.3390/su141912807

Okrah, J., & Hajduk-Stelmachowicz, M. (2020). Political stability and innovation in Africa. Journal of International Studies, 13(1), 234–246. https://doi.org/10.14254/2071-8330.2020/13-1/15

Phuc Canh, N., Schinckus, C., & Thanh, S. D. (2019). Do economic openness and institutional quality influence patents? Evidence from GMM systems estimates. *International Economics*, *157*, 134–169. https://doi.org/10.1016/j.inteco.2018.10.002

Ramirez-Hernandez, L. F., & Isaza-Castro, J. G. (2019). When size matters: Trends in innovation and patents in Latin American universities. *Journal of Technology Management & Innovation*, *14*(3), 44–56. https://doi.org/10.4067/s0718-27242019000300044

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5, Part 2), S71–S102. https://doi.org/10.1086/261725

Roper, S., & Hewitt-Dundas, N. (2015). Knowledge stocks, knowledge flows and innovation: Evidence from matched patents and innovation panel data. *Research Policy*, *44*(7), 1327–1340. https://doi.org/10.1016/j.respol.2015.03.003

Rubilar-Torrealba, R., Chahuán-Jiménez, K., & de la Fuente-Mella, H. (2022). Analysis of the growth in the number of patents granted and its effect on the level of growth of the countries: An

econometric estimation of the mixed model approach. *Sustainability*, *14*(4), 2384. https://doi.org/10.3390/su14042384

Sachs, J. D., Warner, A., Åslund, A., & Fischer, S. (1995). Economic reform and the process of global integration. *Brookings Papers on Economic Activity*, *1995*(1), 1–118.

Sakakibara, M., & Cho, D.-S. (2002). Cooperative R&D in Japan and Korea: A comparison of industrial policy. *Research Policy*, *31*(5), 673–692. https://doi.org/10.1016/s0048-7333(01)00150-0

Shi X, Lu L, Zhang W, Zhang Q (2021), "Managing open innovation from a knowledge flow perspective: the roles of embeddedness and network inertia in collaboration networks". *European Journal of Innovation Management*, 24 (3) https://doi.org/10.1108/EJIM-07-2019-0200

Tosunoğlu, M. (2024). The relationship between technological innovation and economic growth in EU countries: A system GMM approach. *Verimlilik Dergisi*, *58*(4), 651–662. https://doi.org/10.51551/verimlilik.1440264

Uyar, A., Gerged, A.M., Kuzey, C., & Karaman, A.S. (2024). Corporate innovation capacity, national innovation environment, and renewable energy use. *Technological Forecasting and Social Change*, 205, 123459. https://doi.org/10.1016/j.techfore.2024.123459

Vasin, S. M., & Timokhina, D. M. (2024). Specific Effect of Innovation Factors on Socioeconomic Development of Countries in View of the Global Crisis. *Economies*, *12*(8), 190. https://doi.org/10.3390/economies12080190

World Intellectual Property Organization, WIPO (2025). *Global Innovation Index 2025: Innovation at a Crossroads*. Geneva: WIPO. https://doi.org/10.34667/tind.58864

Yue, W. (2023). Human capital and firm innovation: Evidence from China's higher education expansion in the late 1990s. *Emerging Markets Finance and Trade*, *60*(3), 500–518. https://doi.org/10.1080/1540496x.2023.2242568

Zhu, M. (2025). The impact of China's national independent innovation demonstration zone policy on provincial-level innovation. *Procedia Computer Science*, *266*, 731–738. https://doi.org/10.1016/j.procs.2025.08.092

Appendix

Appendix Table 1. Descriptive statistics of the variables included in the model. *Source* Own elaboration

Variable	Mean	Median	Minimum	Maximum

Patents	0.20158	0.057682	0.00000	3.5976
RD_Expenditures	1.3271	0.98581	0.016970	5.7968
Education_spending	4.7445	4.7670	0.96440	9.5098
Economic_openness	94.021	74,363	19,560	442.62
Per capita income	35,787.	30,464.	3,099.5	1.3868e+005
Government_effectiveness	0.74836	0.80183	-1.2246	2.4697
Variable	Standard Dev.	C.V.	Skewness	Kurtosis
Patents	0.48086	2.3854	4.6722	22.911
RD_Expenditures	1.0699	0.80619	0.96505	0.33132
Education_spending	1.3037	0.27479	0.33524	0.14874
Economic_openness	69.424	0.73839	2.6131	7.8602
Per capita income	24,555.	0.68615	1.3146	2.5178
Government_effectiveness	0.89206	1.1920	-0.15066	-1.1359
Variable	5%	95% percentile	IQ range	No observations
Patents	0.0020818	0.76465	0.16065	0
iD_consumption	0.12195	3.2995	1.5793	0
Education_expenditure	2.7718	7.2463	1.6384	0
Economic_openness	30.490	243.53	56,231	10
Per capita income	6,836.7	78,152	35,274.	0
Government_efficiency	-0.69202	1.9874	1.6086	59

Appendix Table 2. Selection, functional specification, and residual diagnostic tests for the econometric model. *Source* Own elaboration using SPSS v. 31

Block	Contrast	Null hypothesis	Statistic	p-value	Decision

Estimator selection	Joint significance of intercepts by group (FE vs. pooled)	Countries share a common intercept	F (57,1144) = 278.992	0.0000	Pooled is rejected; FE is justified
Selection of the estimator	Breusch-Pagan LM (RE vs. pooled)	No random effects	LM = 8249.9	0.0000	Pooled is rejected in favor of RE
Estimator selection	Hausman (FE vs RE)	RE is consistent	H = 19.9849	0.00125789	RE is rejected; FE is preferred
Functional specification	RESET (squares and cubes)	The specification is adequate	F = 180.754843	2.45e-69	The initial linear specification is rejected
Functional specification	RESET (squares)	The specification is adequate	F = 253.428483	6.49e-52	The initial linear specification is rejected
Functional specification	RESET (cubes)	The specification is adequate	F = 114.677913	1.27e-25	The initial linear specification is rejected
Preliminary diagnosis	Maximum VIF	No problematic collinearity	3.963	—	No severe collinearity detected
Selection of time effects	Wald joint test on time dummies (non-robust)	No time effects	Chi² (20) = 72.7094	6.5374e-08	Temporal effects are justified
Residual diagnosis	Wald heteroscedasticity	Homoscedasticity	Chi² (58) = 196,936	0.0000	There is heteroscedasticity
Residual diagnosis	Pesaran CD	Cross-sectional independence	z = 0.624525	0.5320	Transverse independence is not rejected
Validation of the final model	Wald test on time dummies (robust)	No time effects	Chi²(20) = 30.2356	0.0661248	Marginal evidence in favor of retaining them
Validation of the final model	Robust comparison of intercepts by group	Common intercept across countries	Welch F (57,395.9) = 95.6007	8.68201e-198	Fixed effects are retained

Appendix Table 3. Coefficients of the time effects in the final model. *Source* Own elaboration using SPSS v. 31

Temporal effect	Coefficient	Robust standard error	t-statistic	p-value	Significance
dt_3	-0.0204887	0.00853204	-2.401	0.0196	**
dt_4	-0.0270770	0.0102972	-2.630	0.0110	**
dt_5	-0.0240014	0.0107413	-2.234	0.0294	**
dt_6	-0.0251883	0.0136831	-1.841	0.0709	*
dt_7	-0.0374859	0.0178905	-2.095	0.0406	**
dt_8	-0.0461589	0.0217280	-2.124	0.0380	**
dt_9	-0.0564511	0.0239664	-2.355	0.0220	**
dt_10	-0.0645429	0.0291536	-2.214	0.0309	**
dt_11	-0.0633322	0.0288172	-2.198	0.0320	**
dt_12	-0.0686510	0.0301576	-2.276	0.0266	**
dt_13	-0.0678800	0.0302626	-2.243	0.0288	**
dt_14	-0.0676828	0.0326337	-2.074	0.0426	**
dt_15	-0.0786496	0.0349097	-2.253	0.0281	**
dt_16	-0.0883660	0.0367371	-2.405	0.0194	**
dt_17	-0.0857620	0.0382110	-2.244	0.0287	**
dt_18	-0.0960531	0.0411215	-2.336	0.0230	**
dt_19	-0.1070820	0.0444022	-2.412	0.0191	**
dt_20	-0.1237030	0.0477540	-2.590	0.0121	**
dt_21	-0.1278370	0.0478544	-2.671	0.0098	***
dt_22	-0.1359080	0.0501544	-2.710	0.0089	***

Note: Coefficients corresponding to the final fixed-effects model by country with time effects and robust standard errors grouped by country. The labels dt_3 to dt_22 follow the nomenclature of the original econometric output. Since the omitted base period is not clearly identified in the available data, it is advisable to retain this coding or verify the time reference in Gretl before substituting it with specific years. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Appendix Table 4. Principal component analysis: variance explained by component. *Source* Own elaboration using SPSS v. 31

Component	Eigenvalue	Proportion	Cumulative
1	2.8981	0.4830	0.4830
2	1.3148	0.2191	0.7021
3	1.0189	0.1698	0.8720
4	0.4111	0.0685	0.9405
5	0.2005	0.0334	0.9739
6	0.1566	0.0261	1.0000

Note: Principal component analysis was performed on 1,207 complete observations, after excluding 91 incomplete observations. The table presents the eigenvalues of the correlation matrix, the proportion of variance explained by each component, and the cumulative variance. The first three components account for 87.20 percent of the total variance.

Appendix Table 5. Factor loadings of the principal components. *Source* Own elaboration using SPSS v. 31

Variable	PC1	PC2	PC3	PC4	PC5	PC6
Patents	0.243	0.528	-0.591	0.461	0.312	-0.066
R&D Expenditures	0.506	0.310	-0.023	-0.100	-0.779	0.174
Education spending	0.288	0.180	0.769	0.515	0.155	-0.065
Economic openness	0.210	-0.716	-0.240	0.546	-0.247	-0.160
Per capita income	0.520	-0.269	-0.033	-0.186	0.407	0.675
Government effectiveness	0.536	-0.086	0.002	-0.424	0.213	-0.693

Appendix Figure 1. Matrix of bivariate correlations between the model variables. *Source* Own elaboration using SPSS v. 31

Note: Missing values were ignored. Critical value at 5% (two-tailed) = 0.0564 for n = 1207.

Appendix Figure 2. Scatter plots between patents and the explanatory variables. *Source* Own elaboration using SPSS v. 31

Appendix Figure 3. Box plots of the main variables in the model. *Source* Own elaboration using SPSS v. 31

Appendix Figure 4. Aggregate time series of the model variables in the sample. *Source* Own elaboration using SPSS v. 31

Note: This graph is presented for descriptive purposes and uses the available data for the series under consideration while maintaining the panel structure. Consequently, the sample used in the graph may differ from that used in the model's estimation, which is determined by the simultaneous availability of data for the dependent variable and all the explanatory variables included in the final specification.

Supplementary Files

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- AppendixFigure1.jpg
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- AppendixFigure3.jpg
- AppendixFigure4.jpg