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Characteristics of innovation systems that lead to greater productivity and economic development

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Abstract

The national R&D system is a concept that has gained significant recognition; however, measuring it is challenging and not devoid of difficulties. In this paper the method of composite variables is applied to configure R&D systems and with this examines their characteristics and subsequent impact on fostering greater innovation by studying a group of OECD countries. Starting with many variables, 31 variables were selected for the second step and used in a factor analysis to create composite indicators or unobservable abstract variables. Each variable's assignment to a single factor is clear, allowing the identification of five distinct and interpretable factors. Subsequently, a knowledge production function was estimated, considering the technological outcome of the R&D systems as the dependent variable; another function was configured reflecting scientific output. Finally, an additional model was estimated, using productivity as the dependent variable. In all models, the National R&D Effort and Innovative Firms Factor emerged as the most significant variable, underscoring the importance of reaching certain thresholds in terms of available human and physical resources for carrying out innovative efforts within an R&D system.

Key words: innovation; research policy; r&d intensity; organizations; OECD.

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Características de los sistemas de I+D de países OCDE que conducen a una mayor productividad y desarrollo económico

Resumen

El sistema nacional de I+D es un concepto que ha ganado un reconocimiento significativo; sin embargo, su medición es un desafío y no está exenta de dificultades. En este trabajo se aplica el método de variables compuestas para configuar los sistemas de I+D y con ello se examinan sus características y su posterior impacto en el fomento de una mayor innovación mediante el estudio de un grupo de países de la OCDE. Partiendo de muchas variables, se seleccionaron 31 variables para el segundo paso y se utilizaron en un análisis factorial para crear indicadores compuestos o variables abstractas no observables. La asignación de cada variable a un único factor es clara, lo que permite la identificación de cinco factores distintos e interpretables. Posteriormente, se estimó una función de producción de conocimiento, considerando como variable dependiente un resultado tecnológico de los sistemas de I+D, y se configuró otra función que refleja la producción científica. Finalmente, se estimó un modelo adicional, utilizando como variable dependiente la productividad. En todos los modelos, el factor de esfuerzo nacional en I+D y de empresas innovadoras emergió como la variable más significativa, lo que subraya la importancia de alcanzar ciertos umbrales en términos de recursos humanos y físicos disponibles para llevar a cabo esfuerzos innovadores dentro de un sistema de I+D.

Palabras clave: innovación; política de investigación; intensidad de i+d; organizaciones; OCDE.

1. Introduction

A vast academic literature indicates that one of the most recognised determinants of countries' economic growth is innovation. Authors such as Schumpeter (1939), Solow (1956), Abramovitz (1956), Griliches (1986), Fagerberg (1988), Freeman (1995), Pradhan et al, (2020) and Hausman (2022) recognise innovation as a key factor for development and economic growth.

Innovation is a complex phenomenon and many models and perspectives have been developed to study and attempt to explain it. One of the most widely accepted theoretical frameworks on innovation is the systemic viewpoint, and in particular research and development (R&D) systems (Fagerberg, 2011).

The national R&D system (RDS) is a concept that has gained significant recognition, as evidenced by the numerous scholarly works published on the topic. The RDS embodies division of labour within the realm of innovation, involving a wide array of interconnected agents and institutions. These entities are expected to create synergies or reduce costs through their collaborative efforts. Innovation, being a multifaceted and interdisciplinary endeavour, requires the cooperation of numerous institutions, organisations, and businesses (Gutiérrez, 2018).

However, measuring R&D systems and their results is challenging and not devoid of difficulties. There are different methods such as: analysis with individual variables, network analysis, structural equations, input-output analysis, etc. (Suárez & Natera, 2024).

In this paper we apply the method of composite or synthetic variables to characterise R&D systems. We use this method to identify strengths and weaknesses of different national R&D systems. It follows that this method helps to answer an important question: *What are the characteristics of countries, and more specifically, their national R&D systems, that lead to greater innovation and hence increased productivity and economic growth?*

Such knowledge would clearly be important for public policy that aims to increase innovation activities, and ultimately, increased economic growth.

This paper attempts to answer this question, by studying a group of OECD countries and ascertaining the characteristics and mechanisms in their science, technology and innovation (STI) sectors that are most relevant or have good prospects to be applied as guidelines by emerging economies. This is the contribution to the literature that this paper intends to make.

In addition to this brief introduction, the second section presents a brief overview of R&D systems and the use of composite variables for their measurement; in the third, the theoretical basis for the variables used is explained. In the fourth section the results are shown and in the fifth the conclusions are presented.

2. Methodology: R&D systems and use of composite indicators

There is no doubt that there are clear differences between R&D systems of different countries but speaking of RDS it is implicitly assumed that there is a certain internal homogeneity between the regions that comprise them, although this constitutes an unrealistic abstraction (Lundvall, 1992).

This study subdivides the RDS, following Buesa & Heijs (2016) and Gutiérrez (2018), into four subsystems:

- Firms with their inter-firm relationships and market structures.
- Public interventions regarding innovation and technological development (including the legal and institutional framework and technology policy).
- Public and private infrastructure to support innovation.
- The national environment.

As discussed earlier and supported by Gutierrez et al, (2021), R&D systems and their subsystems are intricate constructs involving numerous participants and varying institutional structures. To accurately represent these systems, it is crucial to use a wide array of diverse variables, many of which are highly interrelated. When developing econometric models that include many correlated variables or indicators, it is necessary to condense the information from the original variables into a smaller set of abstract synthetic variables, referred to as factors using factorial analysis. These factors are identifiable with the components of the R&D subsystems (Gutierrez, 2018; Gutierrez et al, 2021; Alqararah, 2023).

From a conceptual point of view, synthetic variables are important because it is doubtful that individual variables correctly reflect the characteristics of an R&D system and its potential. On the other hand, composite indicators solve econometric problems (such as, among others, multicollinearity and the lack of degrees of freedom in regression models) or methodological problems (they smooth out the existence of 'outliers' or errors in the statistics).

Many individual indicators convey similar concepts and can often be used interchangeably. Despite their high correlation, these individual indicators sometimes present differing perspectives on the same aspect of the R&D system, potentially undermining the simultaneous or holistic nature of innovative behaviour. As Makkonen and Have (2013:251) note, "an individual indicator is only a partial indication of the total innovative effort made by a subject". Thus, composite indicators would more accurately reflect the reality of the R&D system than individual indicators alone.

Despite the advantages of using composite indicators, there are also criticisms regarding their use, their usefulness, and the quality of their preparation (Hollenstein, 1996; Buesa et al, 2006; OECD, 2008; Grupp & Schubert, 2010; Makkonen & Have, 2013). However, these problems are far from being resolved unanimously and by consensus. The creation of composite indicators in the field of R&D systems is still a new phenomenon, and reaching a consensus and standardising the methodological model are both required to formulate the synthetic indices and weight of the variables included in them (Jiménez-Fernández et al, 2022).

2.1. Analysis units and study period for factor analysis

As in all empirical studies, the identification and selection of variables is of special importance in ensuring the quality of the results and their correct interpretation. This task was undertaken based on data compiled from the official statistics of the OECD and the World Bank. It comprises 56 variables, from 25 countries, for the period from 2000 to 2019, limited however by the availability of the data, in addition to being homogeneous and comparable. Finally, the factorial analysis itself led to the study of the R&D systems with 31 variables. These 31 indicators, in turn, can be summarised through principal component factor analysis, into a smaller number of synthetic variables —called factors— of an abstract nature, although identifiable with respect to the elements that make up the indicator.

The use of the statistical technique of factor analysis is very appropriate to render operational the information of the indicators of the R&D system, given its characteristics as a multidimensional reality, by representing it in a limited number of abstract elements. From a statistical perspective, this technique has the following advantages for the type of research carried out here:

- The normality, homoscedasticity and linearity requirements are not required or are applied in a less restrictive way.
- Multicollinearity is a requirement to be able to carry out the analysis, since the objective is to identify a set of related variables that reflect different features of a single aspect.
- The 'factors' somewhat avoid the

problem caused when there are temporary fluctuations in individual variables since each factor is based on a weighted average of several variables.

- Working with factors offers more robust models because it allows the simultaneous inclusion of highly correlated alternative variables.

2.2. Feasibility conditions for factorial analysis

In factorial analysis the variables are not assigned a priori to a factor but rather it is the statistical processing itself that groups them. Therefore, a factor analysis is only useful if the results are unequivocally interpretable from the conceptual framework provided by the theory. This interpretation will be possible if the following conditions hold simultaneously:

- The variables included in a factor belong to the same component or subsystem of the R&D system.
- The variables belonging to a certain subsystem are grouped into a single factor.
- Each factor or hypothetical unobservable variable can be assigned a ‘name’ that without any ambiguity, clearly expresses a concept adjusted to the theory.
- Statistical tests and adequacy measures validate the factorial model obtained.

The variables whose concepts are described in this section, are introduced in the factorial analysis that serves to configure the R&D system of each one of the selected countries, as well as to obtain the inputs for the subsequent analysis of the optimisation process during the study period. These are reflected in Tables 1 - 5 in the results section which also include the basic statistics of each of them. These tables show the use of 31 relative variables to configure five factors that each represent a component of the R&D system: national effort in R&D and innovative firms, national environment, universities and human capital, public administration and degree of economic complexity.

Regarding the statistical tests and adequacy measures that validate the factorial model obtained, the four fundamental aspects that the factorial model must comply with are the following:

- The Kaiser-Meyer-Olkin (KMO) sample adequacy measure which is based on the study of partial correlation coefficients, which must be between 0.6 and 0.8.
- Barlett’s sphericity test which contrasts the null hypothesis that identifies the correlation matrix with the identity matrix.
- The total variance explained by the factors, which reflects the percentage of the initial variance (prior to the factor analysis) explained by the factors, must be greater than 75%.
- The communalities, which are the variables that measure the variability of each of the real indicators used in the factors, must be above 50%.

Finally, the factors are extracted by means of principal component analysis (PCA). This consists of extracting the factorial space and thus obtaining projections of the point clouds on a number of axes in such a way that the resulting factors are mutually perpendicular. It involves going from a set of variables correlated with each other, to a new set of variables, linear combinations of the original ones, that are uncorrelated.

3. Theoretical basis for the variables

As previously mentioned, R&D Systems are intricate entities involving the participation of numerous agents and exhibiting diverse institutional configurations. This complexity necessitates the utilization of multiple variables for effectively representing these systems.

3.1 Input variables of innovation processes

The variables that measure the input or effort of the R&D systems that were included in this analysis are described below, discussing their conceptual importance and their limitations. In this way, in the following pages the suitability of the variables used is discussed in the following order: (1) the effort or innovative ‘input’, (2) the socioeconomic context and (3) human capital. A basic description of the values of the variables is found in Tables 1 - 5. In addition, in section 3.2 the adequacy of the variables related to the results (the output of the R&D systems) is discussed.

Measurement of the effort or ‘input’ of the R&D systems

The input with the highest incidence according to different theoretical approaches is that which represents innovative effort, traditionally measured by spending on R&D (Boeing et al, 2022; Myers & Lanahan, 2022; Dai & Chapman, 2022). Expenditure on R&D includes all the financial means allocated to this activity and includes both current and capital expenses and is calculated as a percentage of Gross Domestic Product. In addition, both funding and execution variables have been incorporated.

The R&D effort variables, in turn, are broken down for each of the three main types of agents in the R&D system, in accordance with the recommendations of the Frascati Manual: firms, higher education (universities) and public administration.

Variables of the socioeconomic context of the R&D Systems

The notion of global environment includes various aspects that indirectly influence the technological capacity of a country, such as the educational system (Junge et al, 2012; Biasi et al, 2022), the level of human capital (Fonseca et al, 2019; Sun et al, 2020), the financial system (venture capital) (Leogrande et al., 2021), the sophistication of consumers of goods and services, the culture, and the standard of living. Thus, various variables have been introduced that reflect the socioeconomic context (Puertas et al, 2020).

The first of these —which is included indirectly— is size. When working with very heterogeneous countries, their size must be considered. For this reason, it is advisable to correct the different variables by population or economic size, which has been done opportunely through the annual average number of inhabitants or the Gross Domestic Product (GDP). In addition, variables have been incorporated that describe the economic reality of the countries. For the above, variables such as GDP per capita and apparent labour productivity have been added.

Another crucial aspect of the environment is the country’s relative wealth and productive capacity, which is represented by two variables. The first variable is GDP per capita, reflecting the standard of living and indirectly indicating the technological sophistication of consumer demand. Higher GDP per capita levels suggest that consumers seek higher quality and more feature-rich products, prompting companies to boost their innovative efforts (demand pull). Additionally, a higher standard of living and higher wages attract new talent and top researchers or inventors. The second variable, which is directly correlated with GDP per capita and related to the innovative capacity of a region or industry, is apparent productivity. This metric tends to rise with the technological advancement of a country or specific industry, being significantly higher in medium and high technology sectors compared to traditional industries (technology push).

As a last aspect of the socioeconomic environment, the degree of commercial openness of the economies was included, particularly exports (Onetti et al, 2012; Filipescu et al, 2013; Yang, 2018).

Human capital indicators

Another very important aspect for innovation is human capital. It is the researchers and engineers —with their talent, experience, and quality— who lead the innovation process and largely determine its level of success and efficiency (Jansen et al, 2016; Meissner & Shmatko, 2019). Measurement of human capital is not easy, and the data tend to be approximations. Nonetheless, the available indicators are generally accepted and can be considered quite accurate. As the OECD states in the Frascati Manual, R&D personnel is not enough to measure the technological performance of a country since it only represents a part of the human input of an R&D system. Scientific and technical personnel equally contribute to technological advancement through their involvement in production, quality control, management, or education.

In addition to using these variables in absolute terms (number of people), relative variables are also provided with respect to the total number of workers in the economy (as a percentage of the labour force). In addition, in the factorial model, another variable that was adequately incorporated in this dimension is the rate of higher education (percentage of the population between 25 and 64 years of age with a university education).

3.2. Output variables of innovation processes

The variables used as output were patents filed with the European Patent Office (EPO), patents filed with the United States Patent Office (USPTO) and scientific papers published.

Business intellectual property (patents)

The use of patents as a measure of output is justified by an extensive literature on the subject that highlights its advantages and disadvantages, establishing a balance in favour of the former. Thus, patents are for the moment the best measure of the national innovative capacity that we have (Hall, 2022; Nguyen et al, 2020).

In short, patents far from being a perfect measure of technological output are for the moment, the best and most complete measure available. Their drawbacks only entail a series of restrictions that must be considered when interpreting the results of the model (Baumert, 2006).

The patents variable has been incorporated into the study using patent applications in Europe via the EPO and in North America via the USPTO, corrected per million inhabitants. The location of the domicile of the inventor (or research group that obtains the patented knowledge) has been considered and not the domicile of the owner of the rights protected by those patents. This makes the use of this statistic the most appropriate for the research presented here.

Results of scientific research (publications)

To address the issue of relative unawareness regarding the significant portion of innovation systems' outputs that include scientific research activities, this study has incorporated statistics on publications in academic journals (Ganga et al, 2016; Castaneda & Cuellar, 2020).

4. Characteristics of I&D systems in OCDE countries: Results and discussions

In this section of results, the composite variables resulting from the factor model are first presented, the statistical robustness of the model is demonstrated, and the result obtained is associated with that indicated by the theory of innovation systems. Then, using the previously obtained factors, the production function of knowledge applied to national R&D systems is estimated.

4.1 Factor analysis results

The factorial model resulting from the application of the CPA technique to the battery of indicators available to describe the R&D systems includes five factors. The following tables show the results for each factor in terms of the variables that constitute the factor.

As can be seen in the tables above, each factor is associated with a subsector of the R&D system. Table 1 indicates the innovative effort made by firms, in addition to grouping the results of the innovation process, publications and patents.

Table 1
National R&D Effort and Innovative Firms

Variable	Mean	Standard Deviation	Maximum	Minimum
Execution of R&D by Firms (% of GDP)	0.0113	0.0073	0.0300	0.0011
Intensity in R&D	0.0180	0.0089	0.0387	0.0036
Funding of R&D by Firms (% of GDP)	0.0099	0.0067	0.0278	0.0007
R&D Workers in Private Sector (% of Workforce)	0.0060	0.0036	0.0141	0.0003
Patents Applied for by Inventor (per million inhabitants)	245.0	231.5	875.3	0.5
Researchers in Private Sector (% of Workforce)	0.0036	0.0025	0.0134	0.0002

Cont... Table 1

Execution of R&D by Firms (% of Total Expenditure on R&D)	0.5702	0.1480	0.7942	0.1686
Funding of R&D by Firms (% of Total Expenditure on R&D)	0.4963	0.1312	0.7906	0.1674
Expenditure R&D per Worker R&D	120,272	46,149	217,955	22,552
R&D Workers (% of Workforce)	0.0060	0.0036	0.0141	0.0003
Researchers (% of Workforce)	0.0076	0.0031	0.0157	0.0028
Publications (per million inhabitants)	1,221	546	2,704	122

Source: Compiled by the authors from OECD data

Table 2 presents indicators that account for the macroeconomic context or the environment for innovation.

Table 2
National Environment

Variable	Mean	Standard Deviation	Maximum	Minimum
Workforce	11,350,223	15,616,485	69,045,529	169,444
GDP (US$ PPP x 1 million)	894,532	1,233,893	5,361,159	11,020
Population	22,690,287	30,524,511	128,083,960	281,200
Investment (US$ PPP x 1 million)	197,484	288,802	1,405,994	1,864
R&D Workers	129,684	199,774	912,202	2,645
Manufacturing (US$ PPP x 1 million)	152,325	234,284	1,123,949	1,682
Researchers	88,465	146,162	684,884	1,719
Expenditure R&D (US$ PPP x 1 million)	19,230	35,104	172,589	123
Exports (US$ PPP x 1 million)	306,826	339,921	2,030,439	3,783

Source: Compiled by the authors from OECD data

Tables 3 and 4 present variables associated with other relevant actors in the national R&D system, universities and public administration.

Table 3
Universities and Human Capital

Variable	Mean	Standard Deviation	Maximum	Minimum
Researchers in Universities (% of Workforce)	0.0030	0.0011	0.0057	0.0011
R&D Workers in Universities (% of Workforce)	0.0038	0.0013	0.0075	0.0014
Higher Education Rate (% Population)	0.3057	0.0984	0.5937	0.0884
Workforce with Higher Education (% of Workforce)	0.6023	0.1767	1.0755	0.1739

Source: Compiled by the authors from OECD data

Table 4
Public Administration

Variable	Mean	Standard Deviation	Maximum	Minimum
R&D Workers in Public Sector (% of Workforce)	0.0014	0.0008	0.0048	0.0002
Researchers in Public Sector (% of Workforce)	0.0008	0.0005	0.0029	0.0001
Execution of R&D by Public Administration (% of GDP)	0.0019	0.0011	0.0069	0.0002

Source: Compiled by the authors from OECD data

Finally, Table 5 presents the variables that account for the level of economic complexity of the country.

Table 5
Economic Complexity

Variable	Mean	Standard Deviation	Maximum	Minimum
GDP per capita (US$ PPP)	39,280	12,398	83,874	12,182
Productivity (US$ PPP/hour)	51.1	16.0	102.3	16.7
Manufacturing (% of GDP)	0.1598	0.0648	0.4344	0.0736

Source: Compiled by the authors from OECD data

Moreover, it is interesting that the variables are saturated in the different factors so that these can be interpreted simply and clearly. This is the purpose pursued by the Varimax rotation, which also maximises the orthogonality of the factors —or minimises their correlation—, thus, avoiding multicollinearity problems when the factors are used to estimate econometric models.

The relevant statistics that validate this model are indicated below:

- The KMO measure is equal to 0.78.
- The null hypothesis of Barlett's sphericity test is rejected with a confidence level of 99%.
- A percentage of 90.3% of the total variance of the sample is preserved.
- All communalities are above 80%, except four.

As can be seen in the Table 6, the communalities (correlation of each variable with respect to the set of other variables that make up that factor) of the variables are relatively high, most of them higher than 0.75 (with the exception of the enrolment rate of workforce in higher education (0.731) and exports (0.733)) which guarantees the reliability of the results and indicates the high degree of conservation of their variance.

Table 6
Communalities

VARIABLES	Initial	Extraction
Population	1.000	.965
GDP	1.000	.982

Cont... Table 6

R&D Workers	1.000	.990
R&D Workers Private (% Total)	1.000	.943
R&D Workers Public (% Total)	1.000	.975
R&D Workers Universities (% Total)	1.000	.820
Researchers	1.000	.967
Researchers Private (% Total)	1.000	.873
Researchers Public (% Total)	1.000	.971
Researchers Universities (% Total)	1.000	.807
Researchers (% Workforce)	1.000	.926
Workforce	1.000	.980
Intensity R&D	1.000	.961
Finance R&D from Firms (%GDP)	1.000	.969
Finance R&D from Firms (% Total)	1.000	.839
Execution R&D Firms (% GDP)	1.000	.978
Execution R&D Firms (% Total)	1.000	.796
Execution R&D Public Administration (% GDP)	1.000	.936
Expenditure R&D	1.000	.966
Expenditure R&D per Worker R&D	1.000	.887
Exports	1.000	.733
Higher Education (% Population)	1.000	.770
Investment	1.000	.976
Manufacturing	1.000	.983
GDP per capita	1.000	.961
Productivity	1.000	.933
Patents Applied Inventor (millions of hab.)	1.000	.835
Publications (millions of hab.)	1.000	.824
Manufacturing (% Total)	1.000	.760
Workforce with Higher Education (% Total)	1.000	.731
R&D Workers (% Total)	1.000	.959

Source: Compiled by the authors from OECD data.

Table 7 shows the result: five factors were extracted by the method of principal component analysis (PCA). Therefore, it is considered that the model with five factors is supported by two facts: firstly, it is the result of objective processing (principal component analysis). Secondly, as will be seen below, the model allows for easy interpretation (since the variables are not saturated in more than one factor); the factors obtained are consistent with the theory of innovation systems, and the model is extremely robust, in addition to maintaining a high percentage of the original variance, as can be seen in Table 7. This shows the total explained variance in three sections: the first indicates the initial eigenvalues, the second indicates the sum of the squared saturations of the extraction, and the third presents the sum of the squared loadings after rotating the factors.

Table 7
Total explained variance

Component	Initial eigenvalues			Sums of Squared Extraction Charges			Sums of squared charges of rotation		
	Total	% of variance	% accumulated	Total	% of variance	% accumulated	Total	% of variance	% accumulated
1	13,728	44,284	44,284	13,728	44,284	44,284	9,185	29,630	29,630
2	7,752	25,005	69,289	7,752	25,005	69,289	9,024	29,111	58,740
3	3,083	9,945	79,234	3,083	9,945	79,234	4,026	12,987	71,727
4	2,146	6,924	86,158	2,146	6,924	86,158	2,969	9,579	81,306
5	1,285	4,145	90,303	1,285	4,145	90,303	2,789	8,997	90,303
6	0,862	2,779	93,082						
7	0,480	1,549	94,631						
8	0,428	1,379	96,010						
9	0,277	0,893	96,904						
10	0,231	0,744	97,648						
11	0,171	0,551	98,199						
12	0,122	0,393	98,592						
13	0,083	0,268	98,859						
14	0,078	0,251	99,110						
15	0,061	0,196	99,306						
16	0,058	0,187	99,493						
17	0,040	0,130	99,623						
18	0,029	0,094	99,717						
19	0,023	0,074	99,791						
20	0,016	0,052	99,844						
21	0,012	0,039	99,883						
22	0,010	0,033	99,916						
23	0,010	0,031	99,947						
24	0,007	0,023	99,970						

Cont... Table 7

25	0,003	0,009	99,978
26	0,002	0,007	99,986
27	0,001	0,005	99,990
28	0,001	0,004	99,994
29	0,001	0,003	99,997
30	0,001	0,002	99,999
31	0,000	0,001	100,000

Source: Compiled by the authors from OECD data.

The initial eigenvalues reflect the percentage of the variance explained by each variable and it is by this value that the system is governed when incorporating variables in the model. Obviously, by including all the variables (each variable would be a factor), 100% of the variance is explained but this would not have achieved the objective of reducing the number of variables with which we worked. The second section shows the percentage of the variance explained by each of the five factors extracted according to the previous specifications as well as the accumulated percentage before the rotation. As can be seen, with five factors the model maintains 90.3% of the variance, that is, when going from 31 variables to five factors, less than 10% of the information is lost.

However, for the purpose of this study, the percentages of variance explained by the factors after rotation are more interesting. As can be seen, the percentage of the variance accumulated by the set of factors remains the same after rotation. However, what is altered is the specific contribution of each factor to the total. Rotation consists of rotating the axes at the origin until reaching a certain position to maximise the load or saturation of the variables in one factor, simultaneously minimising them in the rest, thus allowing a more interpretable solution. There are different rotation procedures —orthogonal rotation and oblique rotation— although in this case only the former was used, since it maintains a 90-degree angle between the axes, thus guaranteeing orthogonality between the factors. Specifically, we carried out a Varimax-type rotation, since the factorial pattern obtained by this procedure tends to be more robust than that obtained by alternative methods.

As shown in Table 7, the assignment of each variable to a single factor is now clear, allowing the identification of five distinct and interpretable factors. These are the following:

1. The national environment.
2. National R&D efforts and innovative firms (including the specific activity of creating technological knowledge).
3. Higher education institutions (universities) and human capital (reflecting the specific generation of scientific knowledge).
4. Public administration.
5. The degree of economic complexity (in a technological sense).

These results from the factor

analysis align closely with the determinants highlighted by the theory.

In summary, the estimated factorial model provides an accurate representation of the R&D systems for the selected sample of countries, meeting all necessary statistical and conceptual criteria. Consequently, the factors derived from this model—which represent the resources, organization, and interrelationships characterizing R&D systems—can be used to analyse the activities related to the creation and dissemination of technological knowledge within these countries.

The adopted solution includes five factors whose name and participation in the variance explained by the model have been represented in Diagram 1.

Diagram 1
The Final Factorial Model (in parentheses the percentage of the total initial variance explained by each resulting factor)

1. **National Effort in R&D and Innovative Firms (29.63%)**
2. **National Environment (29.11%)**
3. **Universities and Human Capital (12.98%)**
4. **Public Administration (9.57%)**
5. **Economic Complexity (8.99%)**

Source: Compiled by the authors from OECD data.

4.2 Estimation of a knowledge production function

As stated in the introduction, finally we identify the determinants of national innovation for the selected countries and their degree of incidence on the technological outcomes of their R&D systems.

The objective consists therefore, in detecting the determinant factors of innovation and their degree of incidence, based on —according to the theoretical assumptions— the hypothesis that all the elements of the R&D system should positively influence its results, albeit with different intensities.

For this, the configuration methodology of the R&D systems explained in the last section is used, considering the factorial scores obtained from a new factorial analysis, this time only including the elements of effort and system environment, discarding the output factors. Technological output (patents per capita) is one of the dependent variables in the regression of the knowledge production function. In addition, another function was configured considering scientific publications per capita as a dependent variable, thus reflecting the scientific output of the R&D systems. Finally, one additional model was estimated, with economic output represented by productivity as the dependent variable.

In this stage of the analysis, the previously calculated ‘synthetic’ variables were used to estimate a knowledge production function from panel data. An additive model was proposed, being common in this type of study, according to the following specification:

$$K_{it} = \beta_0 + \beta_1 NENV_{it} + \beta_2 FIR_{it} + \beta_3 UNI_{it} + \beta_4 ADM_{it} + \beta_5 ECOM_{it} + \varepsilon_{it} + \mu_i + \nu_t$$

(Equation 1)

The output variable refers, on the one hand, to new economically valuable knowledge, both in technological terms (K_{it} = number of patents per capita) and scientific terms (K_{it} = number of scientific publications per capita), and on the other, to national economic performance (K_{it} = productivity) while the explanatory variables are the five factors of effort and environment previously calculated: National environment (NENV), National Effort in R&D and Innovative Firms (FIR), Universities and Human Capital (UNI), Public Administration (ADM) and Economic Complexity (ECOM).[1]

It is important to highlight that the results presented here are intended to identify the relative importance of the determinants of innovation and knowledge through an "explanation" function, rather than to predict future outputs as a "prediction" function. This distinction carries significant methodological implications. Specifically, it means that there is no need for a lag structure between inputs and outputs. Additionally, using regression techniques in combination with other statistical methods like factor analysis is less suitable for forecasting. This is because the resulting (non-standardised) regression coefficients reflect the elasticity of the factor score, which depends on changes in all the variables included in the factor, rather than the elasticity of a single variable.

Moreover, working with diverse national contexts introduces greater errors and non-uniform variance across the regression plane, which are crucial assumptions for predictive regression models. This does not imply that the models have not been thoroughly optimised; appropriate transformations such as robust errors, stationarity tests for panels, and the Hausman test have been applied to ensure their robustness.

The general results are presented in Tables 8 - 11. According to the results of the Hausman test, the fixed effects model corrected for autocorrelations and heteroscedasticity was preferred (Table 8). The global adjustments are acceptable with an R^2 between 30% and 64% in the models.

Table 8
Final Estimation Results for the total sample: Fixed effects corrected for autocorrelation and with standard errors corrected for heteroscedasticity

FACTORS	Patents	Publications	Productivity
National Environment	**55.35** **(0.000)**	-80.88 (0.168)	1.18 (0.098)
National R&D Effort and Innovative Firms	**129.84** **(0.000)**	**213.80** **(0,000)**	**6.72** **(0.000)**

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[1] The global, temporal and individual specific error components are:
ε_{it} = Global error term.
μ_i = Time-invariant individual-specific error component.
ν_t = Time-specific error component invariant to the individual.

Cont... Table 8

Universities and Human Capital	**59.05** **(0.000)**	**228.63** **(0.000)**	**3.89** **(0.000)**
Public Administration	-16.82 (0.018)	-27.32 (0.153)	-0.78 (0.024)
Economic Complexity	**72.14** **(0.000)**	**193.48** **(0.000)**	
Constant	221.04 (0.000)	1166.68 (0.000)	50.74 (0.000)
Rho	0.83	0.94	0.95
Wald Test	382.93 (0.000)	224.73 (0.000)	173.23 (0.000)
R^2	0.39	0.30	0.64

Note: In parentheses the p values. Source: Compiled by the authors from OECD data

In the technological model (patent as output) all the variables positively affect technological production and are statistically significant at 1%, with the exception of the Public Administration variable. In the model whose output is productivity (in this model the 5th factor disappeared developing a new factor model), only two variables are significant with positive signs.

In all models, the National Effort in R&D and Innovative Firms Factor is the most important variable, highlighting the relevance that it would have for a R&D system to reach certain thresholds in terms of the amount of human and physical resources eventually available to execute innovative efforts. Regarding the actors that make the effort, all the models highlight the role of firms (contained in the National Effort in R&D factor) in innovative processes, and Universities as a fundamental subsystem in the configuration of the knowledge base of the R&D system as well as the articulating axis of the transfer of this knowledge to the productive sector.

In the case of Public Administration, its direct role as executor of R&D is not relevant since its coefficient in the models is not significant. In this sense, it is important to understand the role of the public sector in the R&D system, and how to differentiate cases where the State plays a direct role in the effort and execution of R&D, from cases where its role is to promote scientific and technological policies, as a generator of economic structural conditions, especially the formation of human capital (educational system) and/or coordinator of the rest of the actors that make up the system.

Dividing the total sample into 3 subsamples of national R&D systems according to their level of productivity, the results differ among the respective models[2]. In the case of the technological output of patents and the scientific output of publications, the model that best fits the group of emerging R&D systems is fixed effects corrected for heteroscedasticity

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[2] Emerging: Latvia, Slovak R., Poland, Portugal, Lithuania, Greece, Hungary and Estonia. Medium: Italy, Slovenia, Spain, Ireland, Netherlands, Austria, Iceland, Canada and Belgium.
Developed: Norway, United Kingdom, Denmark, Switzerland, Sweden, Finland, Germany and Japan.

but without autocorrelation, unlike the groups of emerging and developed R&D systems that must be corrected for first order autocorrelation.

In the case of the model with technological output (Table 9), among the emerging R&D systems, only the variables of National Effort in R&D and Innovative Firms, plus Universities and Human Capital, are significant. In the case of medium-developed R&D systems, the Economic Complexity variable is added and in the case of developed R&D systems, all are significant, including Public Administration, which enters but with a negative sign.

Table 9
Estimation Results by Clusters, Output: Patents

FACTORS	Emerging N=8	Medium development N=9	Developed N=8
National Environment	-22.50 (0.456)	14.81 (0.625)	**77.92** **(0.000)**
National R&D Effort and Innovative Firms	**21.31** **(0.005)**	**67.61** **(0.001)**	**262.49** **(0.000)**
Universities and Human Capital	**12.03** **(0.001)**	**48.39** **(0.000)**	**86.83** **(0.000)**
Public Administration	2.72 (0.379)	-12.92 (0.230)	**-61.80** **(0.000)**
Economic Complexity	20.42 (0.034)	**49.42** **(0.000)**	**144.67** **(0.000)**
Constant	**51.13** **(0.000)**	**183.28** **(0.000)**	**135.82** **(0.000)**
Sigma u	10.18		
Sigma e	7.08		
Rho	0.674	0.890	0.744
F Test	26.27 (0.000)		
Wald Test		49.40 (0.000)	149.84 (0.000)
R^2			0.183
R^2 within	0.676		
R^2 between	0.334		
R^2 overall	0.497		

Note: In parentheses the p values. Source: Compiled by the authors from OECD data

In the case of the model with scientific output (Table 10), among the emerging R&D systems, only the variables Economic Complexity plus Universities and Human Capital, are significant. In the case of medium-developed R&D systems, the Economic Complexity variable is not significant, but added to the National R&D Effort and Innovative Firms, it is. Finally, in the case of developed R&D systems, all are significant, including National Environment, which enters but with a negative sign, except for the Public Administration variable.

Table 10
Estimations Results by Clusters, Output: Publications

FACTORS	Emerging N=8	Medium development N=9	Developed N=8
National Environment	-930.94 (0.027)	34.90 (0.692)	**-166.41 (0.000)**
National R&D Effort and Innovative Firms	230.05 (0.043)	**150.07 (0.005)**	**175.44 (0.000)**
Universities and Human Capital	**404.47 (0.000)**	**211.39 (0.000)**	**2541.87 (0.000)**
Public Administration	-50.72 (0.359)	-17.90 (0.558)	-72.39 (0.016)
Economic Complexity	**428.99 (0.001)**	47.16 (0.257)	**177.05 (0.000)**
Constant	**1003.32 (0.000)**	**1258.58 (0.000)**	**1393.55 (0.000)**
Sigma u	312.98		
Sigma e	109.39		
Rho	0.891	0.911	**0.878**
F Test	37.41 (0.000)		
Wald Test		55.27 (0.000)	269.11 (0.000)
R^2		0.177	0.707
R^2 within	0.837		
R^2 between	0.171		
R^2 overall	0.409		

Note: In parentheses the p values. Source: Compiled by the authors from OECD data

Finally, as can be seen in Table 11, in the case of productivity, Universities and Human Capital is the only significant variable for all subsamples of R&D systems, thus becoming the subsystem that best explains productivity increases in the long term. The National Effort in R&D and Innovative Firms is a relevant variable for countries with less developed systems, being less important in the case of mature systems, where stationary states are seen both with regard to their growth in productivity as well as in the stagnation of its innovative performance (Park et al, 2023).

These results make it possible to identify those elements of national R&D systems that allow countries to increase both their scientific and technological outputs, as well as their economic performance, guiding the design and implementation of their scientific and technological policies.

Table 11
Estimation Results by Clusters, Output: Productivity

FACTORS	Emerging N=8	Medium development N=9	Developed N=8
National Environment	4.92 (0.049)	5.48 (0.069)	**-3.03 (0.000)**

Cont... Table 11

National R&D Effort and Innovative Firms	**4.92** **(0.000)**	**5.97** **(0.000)**	0.563 (0.604)
Universities and Human Capital	**3.46** **(0.000)**	**3.36** **(0.003)**	**2.13** **(0.000)**
Public Administration	-1.00 (0.049)	-1.23 (0.014)	0.31 (0.655)
Constant	**39.97** **(0.000)**	**57.44** **(0.000)**	**62.03** **(0.000)**
Rho	0.871	0.958	**0.938**
Wald Test	71.80 (0.000)	28.07 (0.000)	35.89 (0.000)
R^2	0.466	0.623	0.85

Note: In parentheses the p values. Source: Compiled by the authors from OECD data

5. Conclusions

In this paper, a configuration of national R&D systems for a sample of 25 OECD countries has been developed by means of the elaboration of composite variables through factor analysis. This allowed us to identify 5 variables that summarise the main characteristics of the R&D sectors, namely: innovative firms, universities, public administration, as well as two variables that identify structural elements of the R&D systems: the socio-economic environment and economic complexity. Using the aforementioned variables, three econometric models were calculated, each measuring different results of these systems: technological output through patents, scientific output through publications and economic productivity.

In all models, the National Effort in R&D and Innovative Firms factor is the most important variable, highlighting the relevance that it would have for a R&D system to reach certain thresholds in terms of the amount of human and physical resources eventually available to execute innovative efforts. Regarding the actors that make the effort, all the models highlight the role of firms (contained in the National Effort in R&D factor) in innovative processes and universities as a fundamental subsystem in the configuration of the knowledge base of the R&D system as well as the articulating axis of the transfer of this knowledge to the productive sector. According to the results obtained, the important thing is to understand that the role of public investment in R&D is varied, and its effectiveness will depend on the structural conditions of the R&D system in question.

The main limitations of this work relate to the sample of countries selected, all developed or emerging countries, which implies that these results cannot be extrapolated to countries that are backward in both economic and technological terms. Furthermore, the lack of publicly available statistical data has prevented the addition of more variables to the configuration of R&D systems. In particular, environmental variables of some importance could not be included due to factors such as the quality of universities, the level of cooperation, etc.

Beyond the characteristics of their R&D systems, countries have recently steadily increased their innovative efforts, especially public spending on R&D. However, given the budgetary and financial restrictions faced by governments, universities and firms, it is important, in addition to a greater innovative drive, to ensure an efficient allocation of resources (public and private), optimising results and minimising costs. For this reason, new research should be aimed at measuring the efficiency of R&D spending, considering the systemic nature of innovation.

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