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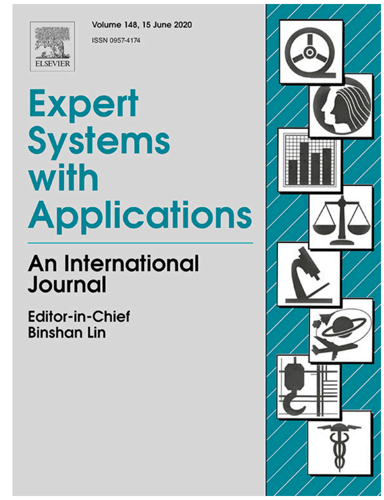

R&D&I Efficiency AS one OF the Sustainable Development Goals (SDGS) In Europe: Application of A Dynamic Model With Network Structure and Cumulative Divisional Malmquist Index (CDMI)

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R&D&I EFFICIENCY AS ONE OF THE SUSTAINABLE DEVELOPMENT GOALS (SDGS) IN EUROPE: APPLICATION OF A DYNAMIC MODEL WITH NETWORK STRUCTURE AND CUMULATIVE DIVISIONAL MALMQUIST INDEX (CDMI).

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TITLE: **R&D&I efficiency as one of the sustainable development goals (SDGs) in Europe: Application of a Dynamic model with Network structure and Cumulative Divisional Malmquist Index (CDMI).**

ABSTRACT

In European countries the measurement of the efficiency of Research, Development and Innovation (R&D&I) is a problematic issue for politicians and the general population. For this reason, the United Nations (UN) 2030 Agenda on Sustainable Development Goals (SDGs) signed by UN Member States in 2015 includes SDG 9 for Industry, Innovation and Infrastructure. The objective of this study is to assess whether European countries efficiently manage their R&D&I resources. To meet this objective, the output-oriented Dynamic DEA with Network structure based on SBM framework (DNSBM) is used under constant returns in order to first, verify how European countries are positioned in their contribution to realizing SDG 9, considering the dynamic relationships between the resources allocated to R&D&I and their results; and, second, define the long-term relationships between them by applying the Cumulative Divisional Malmquist Index (CDMI) model. This work contributes to the advancement of the research via: (1) development of a framework for the analysis of R&D&I efficiency based on a dynamic network optimization model, where the analyzed periods present interdependence based on the relationships between the inputs and outputs of the R&D&I of SDG 9 and (2) development of a new conceptual model to measure efficiency in the management of R&D&I in a sample of European countries.

Keywords: DEA DNSBM; Divisional Malmquist Index; SDG Innovation; R&D&I; European countries

1. Introduction.

The measurement of efficiency in Research, Development and Innovation (R+D+I) at the European level is an issue that concerns politicians and citizens. The investments made in R&D by the countries of the European Union (EU), and the results obtained, have been of particular importance in recent years (Kacprzyk and Świeczewska, 2019; Karadayi and Ekinci, 2019; Paramati et al., 2021). In addition, Mergoni and De Witte (2021) affirm that competitiveness and the development of innovation are relevant concepts in public investment, one of the main sustainable development objectives of the EU.

Mahroum and Al-Saleh (2013) affirm that the efficiency of R&D&I is mainly focused on the cross-sectional static efficiency in a specified period. However, the evaluation of the general efficiency of national investment in R&D&I should be carried out in several long-term periods to determine the performance of governments in the allocation of resources, and in the management of R&D activities, thus establishing the temporal and spatial dimensions within the economy as a whole. These need to quantify efficiency from a dynamic perspective, explained in the Theory of Dynamic

Efficiency (Kirzner, 1997, 1998) which considers dynamic efficiency as the capacity of an economic system to promote creativity, innovation, and business coordination (North, 1990; Moreno-Casas and Bagus, 2022; Fils et al., 2023).

Nevertheless, there is still a significant research gap in the body of literature on how to measure the dynamic efficiency of R&D&I, and on the relationships between the resources used and the results obtained (Chen and Guan, 2012; Mahroum and Al-Saleh, 2013; Gong et al., 2014; Liu et al., 2014; Chen et al., 2018; Xiao et al., 2021; Liu et al., 2022), in line with UN SDG 9. Specifically, one of the issues that requires more research is related to the interdependence of national R&D&I activities since, to date, studies consider it independently between different periods (Chen and Guan, 2012; Guan and Chen, 2012; Carayannis et al., 2015; Lee et al., 2020). This leads us to affirm that the R&D&I of one period is not independent of the next period, in practice. Further, there are relationships between investments and their results that normally make innovation systems advance or regress in achieving their objectives.

In this context, the first objective of this work consists of developing a framework for the analysis of R&D&I efficiency, based on a dynamic network optimization model, where the analyzed periods present interdependence based on the relationships between the inputs and outputs of the R&D&I of SDG 9. To meet this objective, the output-oriented Dynamic DEA with Network structure based on SBM framework (DNSBM) is used under constant returns in order to first, verify how European countries are positioned in their contribution to realizing SDG 9; and, second, define the long-term relationships between them by applying the Cumulative Divisional Malmquist Index (CDMI) model. Therefore, an analysis of the efficiency of R&D&I, based on a dynamic network optimization model, was carried out, whereby the periods analyzed show interdependence based on the relationships between the inputs and outputs of R&D&I. The model that we propose in this paper aims to solve the problem that characterizes the measurement of the global dynamic efficiency of R&D&I over multiple periods (Chen et al., 2018), and in our case the study period is 2005-2019.

To confirm the robustness of our results, we have completed the Global Efficiency analysis with an analysis of the Malmquist Index, taking into account that it is a dynamic model (Zhu et al., 2020). Therefore, these results make it possible to determine which European countries have grown or not in terms of their R&D&I policies during the period under study. This objective allows progress in the intelligent systems that are implemented in companies, not only for models that are aimed measuring efficiency in R&D&I, but also for models from other fields that require concepts whose analysis is based on dynamic and interdependent data (Zhang et al., 2023).

In addition, as a second objective of the present work, a new conceptual model was developed, in order to measure efficiency in the management of R&D&I. There are studies on R&D&I in countries, cities, or regions (Rousseau and Rousseau, 1997; Nasierowski and Arcelus, 2003; Hollanders and Esser, 2007; Zabala-Iturriagagoitia et al., 2007; Cullmann et al. 2012; Matei and Aldea, 2012; Lee et al., 2020; Brody et al., 2023), where those authors did not distinguish between quantity and scientific quality; that is, measuring efficiency by differentiating between scientific and research production, or knowledge generation and scientific quality, or its transfer phase. The model shown in the present study allows solving one of the main limitations identified by Carayannis et al. (2016) in the measurement models of efficiency in R&D&I, with the result that producing a greater number of scientific articles is not necessarily related to a higher level of quality in scientific production. Therefore, the usefulness of the proposed model lies precisely in dividing the levels of efficiency into two divisions; on the one hand, the levels of efficiency for scientific production (i.e., the number of documents published in journals) and on the other hand, the quality and scientific impact of those publications (i.e., h-index, number of citations or patents).

The data used in our study were extracted from the system of outputs and inputs of R&D&I in Europe during the period 2005-2019 (published by Eurostat), and specifically the data related to UN SDG 9, in relation to publications, citations, and h-index of European researchers, classified by country, in data published by Scival (Elsevier). The structure of the rest of this work is as follows. In section 2 a review of the literature of the common measures on R&D&I and on SDG 9 at the European level is carried out, collecting the existing studies in the body of literature on the measurement of R&D&I efficiency when applying the DEA methodology, which is the methodology used in the present study. Next, in section 3, the longitudinal and cross-sectional R&D&I dynamic study framework is explained, proposing a dynamic network DEA model for multiple periods and presenting the empirical study of 32 European countries for the period of 2005 to 2019. Finally, the results, the discussion, and the conclusions are presented in the remaining sections.

2. Literature review.

2.1. The importance of measuring R&D&I efficiency in European countries.

Currently, countries move in a dynamic environment that they must face if they want to continue growing and developing as a nation. Therefore, they must monitor, and respond flexibly to, the steps and strategies that are detected in that environment. Innovation has become one of the main objectives to achieve compliance with the SDGs (Bastien and Holmarsdottir, 2017; Chataway et al., 2017; Dahl-Andersen and Johnson, 2015; Schot et al., 2018). Innovation and technological progress are key to discovering durable solutions to economic and environmental challenges, such as increasing energy and resource efficiency (United Nations Economic and Social Council, 2019). Orhan and Guajardo (2021) explain the importance of United Nations Sustainable Development Goals (UNSDGs) in developing countries, including the innovation goal.

The United Nations SDG 9 states that policies have been carried out to promote innovation in the EU. According to a worldwide report published by the United Nations Economic and Social Council (2019), investment in R&D&I as share of Gross Domestic Product (GDP) increased from 1.5% in 2000 to 1.7% in 2015, and remained almost unchanged in 2017. To promote innovation and to achieve SDG 9, European institutions have reached a political agreement on Horizon Europe and the EU Research and Innovation Framework Program for the period of 2021-2027 (European Union, 2019).

In addition, as an economic activity, innovation is a dynamic concept that requires a methodology which allows its performance to be measured over time (Tone and Tsutsui, 2014), and in the present study is supported by the Theory of Dynamic Efficiency (Kirzner, 1997, 1998). This theory explains that dynamic efficiency can be considered as the capacity of an economic system to promote creativity, innovation, and business coordination (North, 1990). For this reason, the Theory of Dynamic Efficiency demonstrates that in the analysis of economic efficiency of activities that evolve rapidly (such as innovation), the dynamic dimension should not be forgotten, since it is a basic element to be considered in all studies of economic efficiency, which not only opens a valuable field for future researchers in this discipline, but also results in the development of economic science in the service of humanity, which is much more high-yielding and dynamically efficient (Leibestein, 1966; Robbins 1972; Lipsey 1973; North, 1999).

2.2. Measurement of R&D&I efficiency: the DEA methodology used by countries.

The measurement of innovation becomes a complex process since it affects different parts of the organization (Tidd and Bessant, 2020). In this sense, the methods that present a higher degree of precision in the measurement of efficiency are non-parametric (the most prominent being Data Envelopment Analysis, DEA), allowing to quantify the multiple innovation factors and obtain robust results on its impact on public and private organizations (Nasierowski and Arcelus, 2003).

The DEA methodology has been used to measure the efficiency of some innovation factors in certain countries (Sharma and Thomas, 2008; Matei and Aldea, 2012). Because innovation is a relatively complex process that affects various activities of the organization, Network DEA has been applied in some studies to solve this problem (Chen and Guan, 2012; Guan and Chen, 2012; Carayannis et al., 2015), but it is mostly static in its approach.

To study the effect of innovation in certain regions and countries (Zabala-Iturriagagoitia et al., 2007; Chen and Guan, 2012; Chen et al., 2018), two innovation processes (production and commercialization of knowledge) are used that affect various stages of their respective value chains (Carayannis et al., 2015). The Network DEA model is, therefore, an appropriate method with which to measure the impact of innovation in different geographical locations.

Kotsemir (2013) performed a bibliographic analysis on the most suitable variables that can be used to measure innovation using DEA models. Among them, inputs such as spending on innovation or R&D personnel over total GDP are noteworthy. As outputs, there are patents, high technology exports, or the number of publications. Broekel et al. (2018) use a DEA model with shared inputs and outputs to explain the innovation efficiency of different regions of Germany using R&D employees as inputs and patents as outputs.

Furthermore, it is necessary to explain why efficiency models are linked to innovation processes. Guan and Chen (2012) undertook a study in which they identified Greece and Ireland as efficient countries in all the models they applied. Those authors concluded that being an innovative country resulted in a higher level of efficiency of that country in the use of physical, human, and financial resources that are directly related to innovation (Matei and Aldea, 2012; Nasierowski and Arcelus, 2012).

However, Zabala-Iturriagagoitia et al. (2007) note that in their study, having fewer resources did not mean countries would consequently achieve lower levels of efficiency in innovation because, with the few financial, physical, and human resources of certain regions, they were able to obtain more efficient results in innovation than regions with more resources whose results were less efficient (since they needed to use more resources to achieve results in innovation). Therefore, in some cases, countries with more stable innovation policies were unable to achieve better innovation efficiency results than countries with fewer resources.

Carayannis et al. (2016) note that in many cases a DEA model with several stages is used to measure innovation, because innovation efficiency requires a common set of inputs and outputs, which in many cases are considered intermediate inputs and outputs (Lewis and Sexton, 2004; Färe et al., 2007).

Network DEA defines multiple stages or levels in the innovation model, allowing and helping to measure the efficiency of innovation management in certain countries, and the models in some studies are noteworthy (Wu et al., 2010; Lv, 2011; Cullmann et al., 2012; Choi et al., 2013; Chun et al., 2015; Kou et al., 2016).

Table 1 shows the most relevant studies that measure the levels of efficiency in innovation at the international, national, regional, and local levels.

Table 1 Studies on the measurement of R&D&I Efficiency.

AUTHORS	DEA MODEL	LEVEL	INPUTS	OUTPUTS
(Sharma and Thomas, 2008)	VRS (variable returns to scale) and CRS (constant returns to scale), input-oriented DEA model	International	-Gross Domestic Expenditure on R&D -Researchers per Million population. -Gross Domestic Product (GDP) as input Population.	-External patents by residents. -Patents by a country’s residents. -National productivity.

AUTHORS	DEA MODEL	LEVEL	INPUTS	OUTPUTS
(Pan et al., 2010)	VRS (variable returns to scale), input-oriented DEA model; Super-efficiency in DEA model; Bilateral comparisons in DEA model	International	-Total public expenditure on education. -Imports of goods and commercial services -Total expenditure on R&D. -Direct investment stocks abroad. -Total R&D personnel nationwide.	-Number of patents granted to residents. -Number of patents secured abroad by national residents. - Published scientific articles by origin of author.
(Abbasi et al., 2011)	DEA-based innovation index using VRS (variable returns to scale) output-oriented DEA model	International	-Number of scientists in R&D -Expenditure on education and R&D expenditures.	-Patent counts, royalty incomes and license fees, -High-technology export and manufacturing exports.
(Chen et al., 2011)	CRS (constant returns to scale) output-oriented DEA model	International	-R&D expenditure stocks (million US dollars in year 2000). -Total R&D manpower (full-time equivalent units).	-Patents applied for in the EPO and USPTO. -Scientific journal articles. -Royalty and licensing fees. (million US dollars in year 2000).
(Guan and Chen, 2012)	CRS and VRS, Network (2-stage) output-oriented Super-efficiency model	National	-Number of full-time equivalent scientists and engineers, Incremental R&D. -Expenditure funding innovation activities, Prior accumulated knowledge stock breeding upstream knowledge production -Consumed full-time equivalent labour for non-R&D activities. -Number of patents granted (intermediate)	-Number of patents granted (intermediate). -International scientific papers, Added value of industries. -Export of new products in high-tech industries.

AUTHORS	DEA MODEL	LEVEL	INPUTS	OUTPUTS
(Carayannis et al., 2015)	VRS multistage, multilevel (2 stages x 2 levels) model	National and Regional	-Science graduates in tertiary education. -Participation in lifelong learning. -Total R&D expenditures, R&D capital stock. -Citable documents (intermediate). -Patent applications (intermediate). -Employment in knowledge-intensive services/manufacturing intermediate). -SMEs collaborating with others (intermediate). -Venture capital investment (intermediate).	-High Tech Exports. -Sales of new to market and new to firm innovation. -License and patent revenues from abroad. -Number of trademark applications in national offices.
(Carayannis, et al., 2016)	Network DEA model	International	-Science graduates in tertiary education (thousands). -Eurostat Participation in lifelong learning (%). -Eurostat Total R&D expenditure (billion euros). -IUS, own calculations R&D capital stock. Intermediate variables: -Citable documents (thousands). -SCImago Patent applications (thousands). Employment in knowledge-intensive services/manu-facturing (% of employment). -SMEs collaborating with others (% of SMEs).	-High Tech Exports (billions USD). -World Bank Sales of new to market and new to firm innovation (% turnover). -License and patent revenues from abroad (billions of euros). -Number of trademark applications in national offices (thousands).

AUTHORS	DEA MODEL	LEVEL	INPUTS	OUTPUTS
			-Venture capital investment (billions of euros).	
(Kou et al., 2016)	Multi-period, multi-division DEA model	International	-R&D personnel. -R&D capital Stock. -Technology import; patents.	-S&T_papers Export of high-tech products GDPP of employment.
(Zuo and Guan, 2017)	Parallel DEA game model	Regional	Full-time equivalent Researchers, Expenditure on R&D.	-Number of granted patents.
(Broekel et al., 2018)	Shared-input DEA model	Regional	R&D employment	-Patent.
(Zemtsov and Kotsemir, 2019)	Long-period DEA model	Regional	-Technological development (R&D expenditures per GDP, R&D expenditures per GDP). -Industrial specialization (share of the processing industry in GDP).	-Embeddedness -Knowledge spillovers ln -RIS inner interactions ln
(Lee et al., 2020)	SBM-DEA	Local	-R&D cost (US$ Billion) and Researchers (person).	-Papers and Patents.

Sharma and Thomas (2008) use the number of researchers and R&D funding as a function of GDP (%) as input variables and publications and patents as output variables. Guan and Chen (2012) use a Network DEA model with intermediate outputs such as the number of patents. One of the most recent works on innovation management in certain regions of Russia is by Zemtsov and Kotsemir (2019) where they use a dynamic DEA with variables such as R&D expenses or the potential of knowledge of the region as a function of total GDP (%). Some authors (Sharma and Thomas, 2008; Pan et al., 2010; Lee et al., 2020) use the number of publications as final output variable.

Based on the studies undertaken in recent years that were analyzed, we can affirm that innovation is a multidimensional concept and, in order to measure efficient management in innovation policies, the need to use models integrating factors that affect international innovation systems should be taken into account at the national, regional, and local levels (Carayannis et al., 2016).

However, although the DEA methodology is widely used to measure R&D&I efficiency, there are other methodologies that also allow it to be measured. Prokop et al. (2019) have used a logistic regression analysis to measure innovation collaboration networks in small countries, Meissner (2019) has measured innovation cooperation through a qualitative methodology, Weerakoon et al. (2019) have studied the creation of knowledge in innovation in companies using structural equations, and Prokop et al. (2021) have evaluated the efficiency in national ecosystems through a two-step DEA model, using fsQCA (Fuzzy-set Qualitative Comparative Analysis).

3. Empirical study.

3.1. Objectives

The objective of this study is to develop (i) a framework for the analysis of R&D&I efficiency based on a dynamic network optimization model, where the analyzed periods present interdependence based on the relationships between the inputs and outputs of the R&D&I of SDG 9, and (ii) a new conceptual model to measure efficiency in the management of R&D&I in countries by establishing two divisions: (1) the quantity of publications generated is indicated, or knowledge generation phase (Division 1 and Division 2 in period t in the model), and (2) the quality of these publications is measured (publication impact index), or knowledge transfer phase (Division 1 and Division 2 in the period t+1 in the model). To meet these objectives, the output-oriented Dynamic DEA with Network structure based on SBM framework (DNSBM) is used under constant returns in order to first, verify how European countries are positioned in their contribution to realizing SDG 9, considering the dynamic relationships between the resources allocated to R&D&I and their results; and, second, define the long-term relationships between them by applying the Cumulative Divisional Malmquist Index (CDMI) model.

European countries are administratively and economically independent geographical regions, and both the mobilization of the workforce and the operation of the entire innovation process occur at the national level. We have studied the R&D system in Europe in the dataset published by the European Commission and for this, panel and year data are used during the period of 2005-2019 to monitor the SDGs. In order to promote the strategy to achieve the SDGs at the European level and build a more innovative Europe, the European Commission began to record the performance of the UN SDG 9 in 2005 through indicators linked to development.

3.2. Indicators and measurements

The analysis is based on Eurostat data for the period of 2005 to 2019 for 32 European countries. SDG 9 recognizes the importance of technological progress and innovation in finding durable solutions to social, economic, and environmental challenges. Monitoring SDG 9 in the EU context focuses on the progress made in strengthening R&D&I and promoting sustainable transport. Based on these objectives, the variables used in the model are shown in Table 2.

Table 2 Study variables.

Efficiency model	Variables	Data description	Unit of measure	Sources	References

Inputs	X1: Gross domestic expenditure on R&D by sector (Input)	The indicator measures gross domestic expenditure on R&D (GERD) as a percentage of the gross domestic product (GDP). "Research and experimental development (R&D) comprise creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society and the use of this stock of knowledge to devise new applications"	% of GDP	Eurostat	Sharma and Thomas (2008); Kou et al. (2016); Zemtsov and Kotsemir (2019).
	X2: Human resources in science and technology (Input)	The indicator measures human resources in science and technology (HRST) as a share of the active population in the age group 25-64 years. HRST encompasses people who have successfully completed tertiary education or who are employed in science and technology occupations where this education level is required.	% of active population aged 25 to 64 years.	Eurostat	Sharma and Thomas (2008); Pan et al (2010); Abbasi et al. (2011);Chen et al. (2011); Guan and Chen (2012); Carayannis et al. (2015); Carayannis et al. (2016); Kou et al. (2016); Zuo and Guan (2017); Broekel et al. (2018); Lee et al (2020).
	X3: R&D personnel by sector (Input)	The indicator measures the share of R&D personnel broken down into the following institutional sectors: business enterprise (BES), government (GOV), higher education (HES), private non-profit (PNP).	% of active population.	Eurostat	Sharma and Thomas (2008); Pan et al (2010); Abbasi et al. (2011);Chen et al. (2011); Guan and Chen (2012); Carayannis et al. (2015); Carayannis et al. (2016); Kou et al. (2016); Zuo and Guan (2017); Broekel et al. (2018); Lee et al (2020).

	Y1: Patent applications to the European Patent Office (Output)	The indicator measures the number of applications for patent protection of an invention filed with the European Patent Office (EPO) regardless of whether or not they are granted.	Number of Patents per year.	Patent applications to the European Patent Office	Sharma and Thomas (2008); Pan et al (2010); Abbasi et al. (2011);Chen et al. (2011); Guan and Chen (2012); Carayannis et al. (2015); Carayannis et al. (2016); Kou et al. (2016); Zuo and Guan (2017); Broekel et al. (2018); Lee et al (2020).
	Y2: Documents (Output)[1]	Published scientific publications for country.	Number of publications per year.	Scimago Journal & Country Rank	Pan et al (2010); Chen et al. (2011); Guan and Chen (2012).
	Y3: Citation (Output)[2]	Whole period citations for documents published during the year.	Number of citations for documents published.	Scimago Journal & Country Rank	Pan et al (2010); Chen et al. (2011); Guan and Chen (2012); Carayannis et al. (2015); Carayannis et al. (2016).
Outputs	Y4: h-index (Output)[3]	The h-index is a system proposed by Jorge Hirsch, from the University of California, in 2005 to measure the professional quality of physicists and other scientists, based on the number of citations their scientific articles have received.	It is calculated by ordering the scientific articles according to the number of citations received, the H-Index being the number for which the order number coincides with	Scimago Journal & Country Rank	Guan and Gao (2009); Montazerian et al. (2019).

[1] This variable (Y2) refers to the number of papers published (quantity) by European researchers.
[2] This variable (Y3) is a proxy variable for quality such as the number of total citations in absolute values that these published research papers have received.
[3] Scopus® also displays citations from Web and patent sources that are cited in Scopus® records in the Abstract + Citation database. Patent Citations are from key patent offices, and Web Citations are from carefully selected Web resources such as Courseware sites, theses and dissertation databases, institutional repositories, as well as other carefully selected Web resources. See page 8 of the document on SCOPUS® that has been prepared by Elsevier: {HYPERLINK https://www.elsevier.com/?a=69451} and Scimago: [HYPERLINK https://www.scimagolab.com/productos/informe-cienciometrico}.

			the number of citations.		

3.3. DEA methodology: Dynamic DEA with Network structure based on SBM framework (DNSBM).

The DNSBM is the composite of network SBM (NSBM) and dynamic SBM (DSBM) (Tone and Tsutsui, 2014). Mariz et al. (2018) note that there is an increase in the number of publications with Dynamic Data Envelopment Analysis (DDEA) models in recent years. We suggest using the efficiency evaluation, taking into account the vertical relationships, which consist of different efficiency models with different inputs and outputs connected through Links. We have called each of the groupings of indicators Divisions, as define by those authors. The horizontal relationships are made by combining the previous network structure with the carry-over between periods, or carry-over variables.

In this case, we measure the efficiency of the European countries, taking into account: (a) The global efficiency in the entire period under observation, (b) the dynamic change that occurs in the efficiency of the period, and (c) the dynamic change within each Division.

This model can be oriented to (i) both inputs and outputs, or (ii) both constant returns to scale (CRS) or variables (VRS).

One of the possibilities of dynamic analysis is the application of a new Malmquist Divisional index. In Fig. 1 we have collected the Dynamic DEA with Network structure (Tone and Tsutsui, 2014).

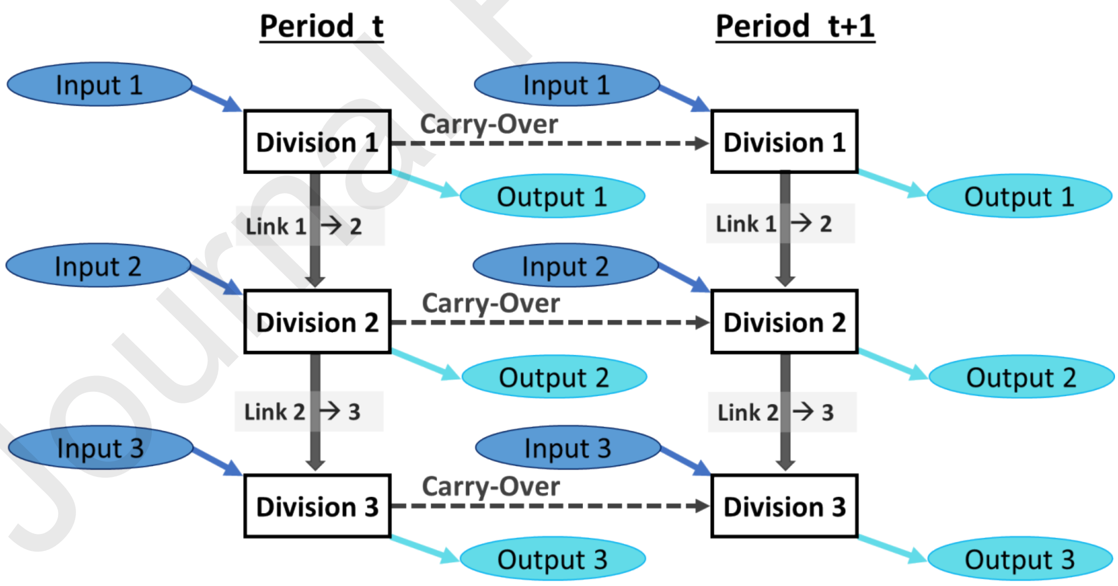


Fig. 1. Dynamic DEA with Network Structure Model. Adapted from Tone and Tsutsui (2014).

The DMUs “n” (j = 1, ..., n) of each Division “K” (k = 1, ..., K) are in each period of time T (t = 1, ..., T). For each link that leads from Division “k” to Division “h” by (k, h) and the set of links by “L”, the inputs and outputs and link variables are the following:

i) Inputs and outputs:

$\{X^t_{ijk} \in R_+\}$ $(i = 1, \text{K}, m_k; j = 1, \text{K}, n; k = 1, \text{K}, K; t = 1, \text{K}, T)$ (input resource "i" to DMU$_j$ for Division "k" in period "t") (1)

$\{Y^t_{ijk} \in R_+\}$ $(i = 1, K, r_k; j = 1, K, n; k = 1, K, K; t = 1, K, T)$ (output product "i" from DMU$_j$, Division "k", in period "t"). (2)

ii) Links:

$\{Z^t_{j(kh)_l} \in R_+\}$ $(j = 1, \text{K}, n; l = 1, \text{K}, L_{kh}; t = 1, \text{K}, K; t = 1, \text{K}, T)$ (3)

This links the intermediate products between the DMUs from the Division "k" to Division "h" in period "t", where L_{kh} is the number of variables from "k" to "h".

iii) Carry-overs:

$\{Z^{(t,t+1)}_{jk_l} \in R_+\}$ $(j = 1, \text{K}, n; l = 1, \text{K}, L_k; k = 1, \text{K}, K; t = 1, \text{K}, T - 1)$ (4)

From DMU$_j$ of Division "k", from period "t" to period t+1, where L_K is the number of indicators in the carry-over from Division "k").

Related activities are treated as output from the preceding Division to the next.

$$\boldsymbol{z}^t_{o(kh)out} = \boldsymbol{Z}^t_{(kh)out}\boldsymbol{\lambda}^t_k - \boldsymbol{s}^t_{o(kh)out} \quad ((kh)out = 1,...linkout_k) \qquad (5)$$

where $\boldsymbol{s}^t_{o(kh)out} \in R^{L_{(kh)out}}$ is slacks-based and non-negative and $linkout_k$ is the number of "as output" links from Division "k".

The overall efficiency would be equal to:

$$\theta^*_o = min\frac{\sum_{t=1}^{T} W^t\left[\sum_{k=1}^{K} w^k\left[1 - \frac{1}{m_k + linkin_k + nbad_k}\left(\sum_{i=1}^{m_k}\frac{\boldsymbol{s}^{t-}_{iok}}{\boldsymbol{x}^t_{iok}} + \sum_{(k,h)_l=1}^{linkin_k}\frac{\boldsymbol{s}^t_{o(k,h)_l in}}{\boldsymbol{z}^t_{o(k,h)_l in}} + \sum_{k_l=1}^{nbad_k}\frac{\boldsymbol{s}^{(t,t+1)}_{ok_l bad}}{\boldsymbol{z}^{(t,t+1)}_{ok_l bad}}\right)\right]\right]}{\sum_{t=1}^{T} W^t\left[\sum_{k=1}^{K} w^k\left[1 - \frac{1}{r_k + linkout_k + ngood_k}\left(\sum_{i=1}^{r_k}\frac{\boldsymbol{s}^{t+}_{iok}}{\boldsymbol{y}^t_{iok}} + \sum_{(k,h)_l=1}^{linkout_k}\frac{\boldsymbol{s}^t_{o(k,h)_l out}}{\boldsymbol{z}^t_{o(k,h)_l out}} + \sum_{k_l=1}^{ngood_k}\frac{\boldsymbol{s}^{(t,t+1)}_{ok_l good}}{\boldsymbol{z}^{(t,t+1)}_{ok_l good}}\right)\right]\right]}$$

(6)

with $\sum_{t=1}^{T} W^t = 1, \sum_{k=1}^{K} w^k = 1, W^t \geq 0(\forall t), w^k \geq 0(\forall k)$, where $W^t(t = 1, \text{K}, T)$ is the weight of period t" y $w^k(k = 1, \text{K}, K)$ is the weight of Division "k".

The efficiency of each period is defined as follows:

$$\mathrm{T}^{t^*}_o = \frac{\sum_{k=1}^{K} w^k\left[1 - \frac{1}{m_k + linkin_k + nbad_k}\left(\sum_{i=1}^{m_k}\frac{\boldsymbol{s}^{t-}_{iok}}{\boldsymbol{x}^t_{iok}} + \sum_{(k,h)_l=1}^{linkin_k}\frac{\boldsymbol{s}^t_{o(k,h)_l in}}{\boldsymbol{z}^t_{o(k,h)_l in}} + \sum_{k_l=1}^{nbad_k}\frac{\boldsymbol{s}^{(t,t+1)}_{ok_l bad}}{\boldsymbol{z}^{(t,t+1)}_{ok_l bad}}\right)\right]}{\sum_{k=1}^{K} w^k\left[1 - \frac{1}{r_k + linkout_k + ngood_k}\left(\sum_{i=1}^{r_k}\frac{\boldsymbol{s}^{t+}_{iok}}{\boldsymbol{y}^t_{iok}} + \sum_{(k,h)_l=1}^{linkout_k}\frac{\boldsymbol{s}^t_{o(k,h)_l out}}{\boldsymbol{z}^t_{o(k,h)_l out}} + \sum_{k_l=1}^{ngood_k}\frac{\boldsymbol{s}^{(t,t+1)}_{ok_l good}}{\boldsymbol{z}^{(t,t+1)}_{ok_l good}}\right)\right]} \quad (t) = 1,\text{K},T)$$

(7)

On the other hand, p, the efficiency of each Division is defined as:

$$\rho_{ok}^{t^*} = \frac{1 - \frac{1}{m_k + linkin_k + nbad_k}\left(\sum_{i=1}^{m_k} \frac{s_{iok}^{t-}}{x_{iok}^{t}} + \sum_{(k,h)_l=1}^{linkin_k} \frac{s_{o(k,h)_l in}^{t}}{z_{o(k,h)_l in}^{t}} + \sum_{k_l=1}^{nbad_k} \frac{s_{ok_l bad}^{(t,t+1)}}{z_{ok_l bad}^{(t,t+1)}}\right)}{1 - \frac{1}{r_k + linkout_k + ngood_k}\left(\sum_{i=1}^{r_k} \frac{s_{iok}^{t+}}{y_{iok}^{t}} + \sum_{(k,h)_l=1}^{linkout_k} \frac{s_{o(k,h)_l out}^{t}}{z_{o(k,h)_l out}^{t}} + \sum_{k_l=1}^{ngood_k} \frac{s_{ok_l good}^{(t,t+1)}}{z_{ok_l good}^{(t,t+1)}}\right)} \quad (k = 1,\mathrm{K},K; t = 1,\mathrm{K},T) \tag{8}$$

The efficiency will be different for each Division in each period. In our case, having used an output-oriented model in this study, the global efficiency will be the geometric mean of the efficiencies of all the Divisions.

3.4. New Malmquist Index based on the period-divisional efficiency score.

In this paper, we define a Malmquist index based on the period-divisional efficiency score (Keikha-Javan and Rostamy-Malkhalifeh, 2014), as follows.

i) Divisional catch-up index (DCU).

We calculate the relationship between division-period efficiencies "t" and "t+1" using the catch-up index as follows:

$$DCU = \gamma_{ok}^{t \to t+1} = \frac{\rho_{ok}^{t+1^*}}{\rho_{ok}^{t^*}} \quad (t = 1,\mathrm{K},T - 1; k = 1,\mathrm{K},K; o = 1,\mathrm{K},n). \tag{9}$$

DCU >1, DCU = 1, DCU and DCU <1 indicate progress, status quo and regression in catch-up effect, respectively.

ii) Divisional frontier-shift effect (*DFS*).

We will study the effect on each border of each Division through the indicator: the divisional frontier-shift effect of $\sigma_{ok}^{t \to t+1}$.

iii) Divisional Malmquist index (*DMI*), Overall Malmquist index (*OMI*) and Cumulative Malmquist index (*CDMI*).

Taking into consideration the previous indicators, we will define the Divisional Malmquist index (DMI) by their product:

$$DMI = DCU \times DFS = \mu_{ok}^{t \to t+1} = \gamma_{ok}^{t \to t+1} \sigma_{ok}^{t \to t+1} \quad (t = 1,\mathrm{K},T - 1; k = 1,\mathrm{K},K; o = 1,\mathrm{K},n) \tag{10}$$

The overall Malmquist index (*OMI*) is obtained through the geometric mean of the Divisional Malmquist index (*DMI*)

$$OMI = \mu_o = \Pi_{k=1}^{K} (\mu_{ok})^{w_k} \qquad (o = 1,\mathrm{K},n) \tag{11}$$

Where μ_{ok} is the weighted geometric mean of $\mu_{ok}^{t \to t+1}$ $(t = 1,\mathrm{K},T - 1)$ and $w_k \geq 0$ is the weight of division "k" with $\sum_{k=1}^{K} w_k = 1$.

The Cumulative Divisional Malmquist Index (*CDMI*) would be:

(12)

$$CDMI = \xi_{ok}^{1 \to T} = \Pi_{t=1}^{T-1} \mu_{ok}^{t \to t+1} \qquad (o = 1, \mathrm{K}, n : k = 1, \mathrm{K}, K)$$

and the Cumulative Overall Malmquist Index (*COMI*) would be:

$$COMI = \xi_{o}^{1 \to T} = \Pi_{k=1}^{K} \left(\xi_{ok}^{1 \to T}\right)^{w_k} \qquad (o = 1, \mathrm{K}, n) \qquad (13)$$

CDMI turns out to be:

$$CDMI = \mu_{ok}^{1 \to T} \times \Pi_{t=2}^{T-1} \varphi_{ok}^{t} \qquad (14)$$

The intertemporal efficiency change between Period 1 and Period T will be modified at each moment of the different periods.

4. Estimation of R&D&I Efficiency in Europe. Proposal for Dynamic DEA with Network structure based on SBM framework (DNSBM) and Divisional Malmquist Index (DMI).

In this section we apply the DNSBM model, obtaining both the Global Efficiency Indices (*GEI*) by countries, as well as the Divisional Malmquist Index (*DMI*) and the Cumulative Divisional Malmquist Index (*CDMI*). With this model we aim to measure and study R&D&I dynamically in the network over a period of 15 years (2005-2019).

Although most approaches consider the innovation system as a single system, using a deeper approach an innovation system can be considered as being composed of two sub-processes. According to Chen et al. (2018) a knowledge production process (KPP) is responsible for the transformation of inputs related to research into knowledge results. This multi-stage approach is consistent with several innovation efficiency studies (see, for example, Guan and Chen, 2012; Liu et al., 2014). In a second stage, Chen et al. (2018) recognize a knowledge commercialization process (KCP) that is transformed into knowledge results and commercial/monetary results. This process also takes place on multiple levels.

It is important to consider the intertemporal dependence that influences the production ratio of the multi-period R&D&I system. When dealing with multiple interrelated periods, overall efficiency must be measured dynamically, in consecutive periods, otherwise the resulting efficiency measures will be misleading. In terms of the multi-stage production process over multiple periods, we have used the dynamic DEA model in order to model the national R&D efficiency of multiple periods. The model used is oriented to output under constant returns.

In this study, we use simultaneous measures of general efficiency and all period-specific efficiencies; specifically, the Tone and Tsutsui model (Tone and Tsutsui, 2014) based on the traditional SBM model in which we are dealing with multiple countries connected by network structure links within each period and, horizontally, we combine the network structure by means of transfer activities between two successive periods. As Chen et al. (2018) point out, this model can evaluate (1) the general efficiency during the whole observed period, (2) the dynamic change of the efficiency of the period, and (3) the dynamic change of the efficiency by countries.

Specifically, Fig. 2 shows the dynamic network DEA model proposed in this work.

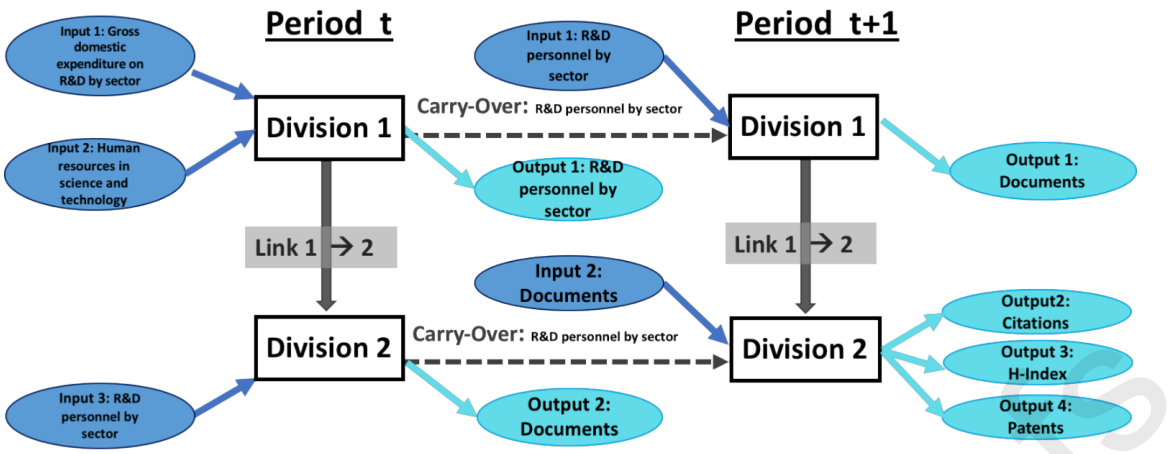


Fig. 2. Proposed model of dynamic efficiency of innovation. Own elaboration.

In the proposed model, and illustrated in Fig. 2, we represent how the efficiency of R&D&I is measured in several interconnected periods, both vertically and horizontally, where the DMUs are the 32 European countries analyzed. The horizontal network (or transfer) is composed of the input variables in period *t* that will be treated as outputs in period *t* + 1.

A knowledge production process (KPP) is responsible for the transformation of inputs related to research into knowledge results in period t. This multi-stage approach is consistent with several innovation efficiency studies (Guan and Chen, 2012; Liu et al., 2014; Carayannis et al., 2016). In a second stage, Chen et al. (2018) recognize a knowledge commercialization process (KCP) that is transformed into knowledge results and Knowledge transference in the period t+1. This process also takes place on multiple levels.

The vertical network in Period t connects the efficiency of the DMUs analyzed. In our model, Division 1 in period t is made up of the input variables: Gross domestic expenditure on R&D by sector and Human resources in science and technology, with the Output variable being the number of R&D personnel by sector. In Division 2 in period t, the input is: number of R&D personnel by sector and the output is: number of Documents.

The efficiency carry-over variable from one period to another (carry-over variable) is the “number of R&D personnel” by sector from one period to the next. Numerous studies consider R&D&I personnel to be the real driving force behind the efficiency of these activities, and there is currently great concern in the scientific field over increasing the recruitment of researchers in Europe (Çağlar and Gürel, 2019; Revuelta-Bordoy et al., 2021).

In Period t+1 we will consider this variable to be the scientific production of the country analyzed in the global R&D&I system and, therefore, the variable that carries efficiency from one period to another. In the first Division in period t+1, the quantity of published research papers is indicated, while in the second Division in period t+1, the quality of these publications is measured: Patents, Citations, and the h-index of researchers at the national level.

The divisions correspond to the R&D&I production system of each country and in each period, from *t* and *t* + 1… *t* + n. The production system corresponds, therefore, to each relationship between the set of inputs in period *t* and the production outputs in period *t* + 1 (in our study the link between the inputs and outputs will again be the number of R&D personnel by sector).

5. Results.

The results are presented, taking into account that the Malmquist productivity index is an index representing Total Factor Productivity (TFP) of growth of each country, reflecting: a) The progression or regression in efficiency along with b) The progression or regression of the frontier technology.

Table 3 shows the Overall Malmquist Index (*OMI*), equation (13) and, the Cumulative Divisional Malmquist Index (*CDMI*) (equation 14) in the complete period of fifteen years and for Divisions 1 and 2. The ranking by countries for each indicator is also reflected. The Overall Scores (*OS*) are also collected (equation 6).

Table 3. OS: Overall Scores (Divisions 1 and 2); OMI: Overall Malmquist Divisional Score (Divisions 1 and 2); CDMI: Cumulative Divisional Malmquist Index (Divisions 1 and 2)

DMU	OS DIV1 $\rho_{ok}^{t^*}$	RANK	OS DIV2 $\rho_{ok}^{t^*}$	RANK	OS $\rho_{ok}^{t^*}$	RANK	OMI DIV1 $\mu_o = \Pi_{k=}^{K}$	OMI DIV2 $\mu_o = \Pi_{k=}^{K}$	OMI $\mu_o = \Pi_{k=}^{K}$	RANK	CDMI DIV1 $\xi_o^{1\to T} = \Pi_k^K$	CDMI DIV2 $\xi_o^{1\to T} = \Pi_k^K$	CDMI $\xi_o^{1\to T} = \Pi_k^K$	RANK
AUSTRIA	0.6583	6	0.0438	13	0.0376	11	1.007	0.9836	0.9913	18	1.1028	0.7934	0.8854	18
BELGIUM	0.5817	15	0.0623	12	0.0507	9	1.0126	0.9666	0.9817	26	1.1918	0.6219	0.7725	26
BULGARIA	0.552	21	0.0055	27	0.0024	25	1.0091	1.0045	1.006	11	1.1355	1.0651	1.0881	11
CROATIA	0.4694	26	0.0039	29	0.0021	27	1.0048	0.9126	0.9424	30	1.0693	0.2778	0.4354	30
CYPRUS	0.3336	32	0.015	21	0.0071	21	0.9864	1.0028	0.9973	15	0.8253	1.0403	0.963	15
CZECHIA	0.6437	11	0.0204	17	0.0095	18	1.0267	1.0129	1.0175	8	1.4458	1.196	1.2741	8
DENMARK	0.8392	2	0.0365	14	0.0333	12	1.003	0.9857	0.9914	17	1.0432	0.8174	0.8866	17
ESTONIA	0.4324	28	0.0056	26	0.001	32	1.0037	1.1403	1.0928	1	1.0522	6.2834	3.4633	1
FINLAND	0.7978	3	0.0298	15	0.0274	14	0.9467	1.0008	0.9824	25	0.4644	1.0119	0.7805	25
FRANCE	0.6122	12	0.1893	5	0.1558	4	0.9996	0.9808	0.987	21	0.9947	0.7621	0.8329	21
GERMANY	0.5744	18	0.3508	2	0.2556	1	1.0161	0.9748	0.9884	20	1.2499	0.7001	0.8493	20
GREECE	0.7257	5	0.0092	23	0.0089	20	1.0058	0.9751	0.9852	23	1.0847	0.703	0.8123	23

HUNGARY	0.5162	24	0.0157	20	0.0098	17	1.0334	0.9421	0.9716	28	1.5834	0.434	0.6681	28
ICELAND	0.7674	4	0.0019	32	0.0015	30	0.9556	1.0068	0.9894	19	0.5296	1.1	0.8621	19
IRELAND	0.5944	14	0.0279	16	0.0238	15	1.0429	0.9794	1.0001	13	1.8011	0.7473	1.0019	13
ITALY	0.6444	10	0.2014	4	0.1555	5	1.04	0.8308	0.8954	32	1.7303	0.0747	0.2129	32
LATVIA	0.5091	25	0.0048	28	0.0016	29	1.0039	1.0063	1.0055	12	1.0562	1.0923	1.0801	12
LITHUANIA	0.5343	22	0.0064	25	0.0015	30	0.9947	0.8993	0.93	31	0.9284	0.2264	0.3624	31
LUXEMBOURG	0.9821	1	0.0039	29	0.0022	26	0.9992	1.109	1.0711	2	0.9886	4.2579	2.617	2
MALTA	0.5732	19	0.0031	31	0.0017	28	0.9995	1.0928	1.0608	4	0.9932	3.4629	2.2837	4
NETHER	0.5761	17	0.1322	6	0.1079	6	1.0198	0.9673	0.9845	24	1.3153	0.6283	0.8037	24
NORWAY	0.6468	8	0.0905	8	0.0157	16	1.0014	1.1034	1.0683	3	1.0194	3.9959	2.5343	3
POLAND	0.4386	27	0.063	11	0.0293	13	1.0125	1.0137	1.0133	10	1.1901	1.2095	1.203	10
PORTUGAL	0.652	7	0.0182	19	0.0093	19	0.999	1.0212	1.0137	9	0.9859	1.3415	1.2106	9
ROMANIA	0.4185	29	0.019	18	0.0047	23	0.9873	1.0983	1.06	5	0.8357	3.7159	2.2597	5
SLOVAKIA	0.5995	13	0.0094	22	0.0035	24	1.0048	1.0257	1.0187	7	1.0699	1.4264	1.296	7
SLOVENIA	0.646	9	0.0087	24	0.0056	22	1.0148	0.9526	0.9729	27	1.2276	0.5067	0.6805	27

SPAIN	0.5337	23	0.1318	7	0.0863	7	1.0008	0.9957	0.9974	14	1.0107	0.9418	0.9642	14
SWEDEN	0.5814	16	0.068	10	0.0555	8	0.9903	0.9958	0.994	16	0.873	0.9426	0.9188	16
SWITZERLAND	0.3896	30	0.8398	1	0.2198	2	0.9777	0.991	0.9865	22	0.7287	0.8807	0.8268	22
TURKEY	0.3624	31	0.0871	9	0.0458	10	1.0199	1.0455	1.0369	6	1.3169	1.8634	1.6598	6
UNITED KINGDOM	0.5603	20	0.313	3	0.198	3	0.9997	0.9539	0.9689	29	0.9954	0.5157	0.6421	29

In Table 3, we observe that the countries obtaining the highest efficiency scores are Germany, Switzerland, and the United Kingdom, and in the OS ranking they are placed in first, second, and third place, respectively. In Division 1 (related to the amount of scientific production), the countries obtaining the most efficiency were Luxembourg, Denmark, and Finland. In Division 2 (related to the quality of scientific production), the most efficient countries were Switzerland, Germany, and the United Kingdom.

The countries with the highest Overall Malmquist Index (*OMI*) were: Estonia, Luxembourg, and Norway. It is observed that these countries have experienced an increase in efficiency over the years, and on a continuous basis. The Cumulative Divisional Malmquist Index (*CDMI*) also indicates that these countries have had the most growth in the last 15 years, which is an expected result given the nature of the index and its method of calculation.

Table 4. DCU: Divisional catch-up index (Division 1 and Division 2); DFS: Divisional frontier-shift effect (Divisions 1 and 2).

DMU	*DCU DIV1* $\gamma_{ok}^{t\to t+1} = \frac{\rho_o^t}{\rho}$	Rank	*DCU DIV2* $\gamma_{ok}^{t\to t+1} = \frac{\rho_o^t}{\rho}$	Rank DCU	*DFS DIV1* $\sigma_{ok}^{t\to t+1}$.	Rank DFC	*DFS DIV2* $\sigma_{ok}^{t\to t+1}$.	Rank
Austria	1.0322	11	0.9836	20	0.9756	28	1	4
Belgium	1.0304	12	0.9666	25	0.9827	23	1	4
Bulgaria	1.0154	19	1.0041	12	0.9938	7	1	4
Croatia	1.0184	15	0.9114	31	0.9866	14	1	4

Cyprus	0.9902	32	1.0032	13	0.9961	5	1	4
Czechia	1.0385	5	1.0133	10	0.9886	13	1	4
Denmark	1.0448	4	0.9857	19	0.96	30	1	4
Estonia	1.0128	20	1.1491	1	0.9909	11	1	4
Finland	1.0043	23	1.0007	14	0.9426	32	1	4
France	1.0192	14	0.976	22	0.9808	24	1.0048	3
Germany	1.036	8	0.9663	26	0.9808	24	1.0089	2
Greece	1.0083	22	0.9748	23	0.9975	4	1	4
Hungary	1.0495	3	0.942	30	0.9847	17	1	4
Iceland	0.9973	29	1	15	0.9582	31	1	4
Ireland	1.0541	2	0.9797	21	0.9894	12	1	4
Italy	1.0543	1	0.9459	29	0.9864	15	0.8784	32
Latvia	1.0014	27	1.0076	11	1.0025	1	1	4
Lithuania	1.0028	26	0.8993	32	0.9919	9	1	4
Luxembourg	1	28	1.1041	3	0.9992	3	1	4
Malta	1.0035	24	1.092	5	0.996	6	1	4
Netherlands	1.0342	10	0.9564	27	0.986	16	1.0115	1
Norway	1.0175	16	1.1124	2	0.9841	20	0.9909	29
Poland	1.0208	13	1.0137	9	0.9919	9	1	4
Portugal	1.036	8	1.0217	8	0.9643	29	1	4

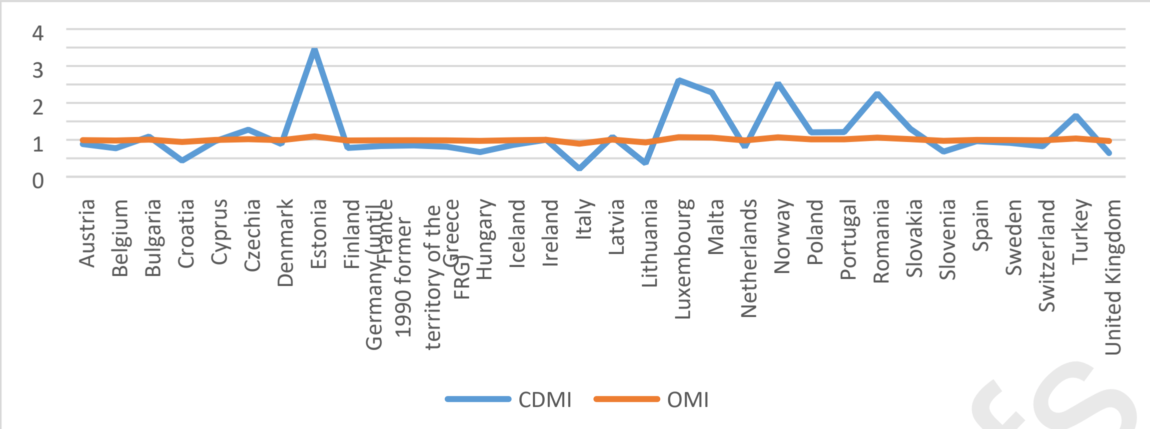
Romania	0.9949	30	1.0993	4	0.9923	8	1	4
Slovakia	1.0033	25	1.0258	7	1.0016	2	1	4
Slovenia	1.038	6	0.953	28	0.9776	27	1	4
Spain	1.0163	18	0.9958	17	0.9847	17	1	4
Sweden	1.0125	21	0.9957	18	0.9781	26	1	4
Switzerland	0.9928	31	1	15	0.9847	17	0.9909	29
Turkey	1.037	7	1.0453	6	0.9835	21	1	4
United Kingdom	1.017	17	0.9697	24	0.983	22	0.9835	31

Table 4 shows the results of the dynamic efficiency, the efficiency scores, the indices related to technological changes (*DCU*), equation (10) and the changes in the frontier (*DFS*), and equation (11) during the years analyzed.

With regards to the increase in efficiency due to technological change in the Division 1 model, the countries with geometric means above 1 (DCU> 1), have all been affected except for Cyprus, Iceland, and Switzerland. In this case, the countries that have grown the most have been Italy, Ireland, Hungary, and Denmark. In the Division 2 model, there is a total of 13 countries with geometric means greater than 1 (DCU> 1).

The DFS (Divisional frontier-shift effect) indicator has performed worse than the change in efficiency. In the Division 1 model, all countries, with the exception of Latvia and Slovakia, decreased the efficiency of R&D during the 15 years analyzed, leaving Luxembourg very close to 1 (the country with the highest growth in the Division). In the Division 2 model, the countries that have increased efficiency the most have been the Netherlands, Germany, and France, followed by Latvia, Slovakia, and Luxembourg.

Graph 1, shown below, shows the geometric mean of the dynamic productivity indicators OMI and CDMI for all years. The countries with the best results, and therefore those with the highest growth, have been Estonia, Luxembourg, and Norway, and the countries with the lowest growth have been Croatia, Italy, and Slovenia.



Graph 1. Dynamic evolution of the IMO and CDMI indices by country.

Subsequently, the descriptive data of the previous indices are shown in Tables A1, A2, A3, and A4 in Appendix A.

Table 5. Descriptive Statistics of the Cumulative Divisional Malmquist Index (*CDMI*) (2005-2019).

	Overall Score		Div1(0.333)	Div2(0.667)	Overall
Average	0.05	Average	1.004	0.9991	1.0001
Max	0.26	Max	1.043	1.1403	1.0928
Min	0	Min	0.947	0.8308	0.8954
St Dev	0.07	St Dev	0.02	0.063	0.0408
		Spearman's Rank correlation between Overall and Malmquist Overall =			
					-0.3393

As can be seen in Table 5, Spearman's correlation index between global efficiency and the OMI has been -0.3393. This corroborates the results explained above: those countries that have experienced the highest growth over the 15 years have not necessarily been the most efficient in the period analyzed.

Once the growth levels have been analyzed in terms of productivity, the dynamic efficiency will be analyzed. The dynamic efficiencies in the network of European countries give rise to results of optimization of R&D and the Human Resources linked to it.

To determine the distance to the dynamic efficiency frontier, in Table 6 we have collected the % deviation with respect to the data observed in all the input and output indicators of Division 1 and Division 2, for each country. The geometric mean of the % deviation is calculated for the 15 years. In order to better observe the behaviour of the inputs and outputs of each Division by country, in Fig. 6 we have represented the geometric mean of the dynamic deviation.

Table 6. Deviation in % with regards to the Network dynamic efficiency frontier by country.

DMU	**Input Differences Div1**	**Rank**	**Output Differences Div1**	**Rank**	**Input Differences Div2**	**Rank**	**Output Differences Div2**	**Rank**	**Geometric mean Inputs**	**Rank**	**Geometric mean Outputs**	**Rank**
Germany	-203.908	22	2865.978	2	-18.182	2	1041.186	1	-15990.48	13	1.953.582	1
Italy	-183.444	11	4393.48	5	-37.61	5	1837.888	3	-15915.888	12	3.115.684	2

United Kingdom	-186.5	13	4095.532	4	-26.194	4	3456.694	7	-15313.968	7	3.776.113	3
Spain	-197.422	19	10855.824	7	-38.084	7	2780.824	4	-16956.432	16	6.818.324	4
Switzerland	-189.108	16	42.426	1	-13.694	1	16594.76	16	-14601.744	6	8.318.593	5
Belgium	-206.286	24	15478.648	9	-41.486	9	4563.312	9	-17839.584	23	10.020.98	6
Netherlands	-204.198	23	4033.488	3	-25.248	3	23062.626	19	-16520.112	15	13.548.057	7
Austria	-177.088	9	23024.562	11	-45.81	11	9439.326	13	-16048.656	14	16.231.944	8
Denmark	-110.766	4	28777.954	12	-45.854	12	5341.174	10	-11276.64	3	17.059.564	9
Finland	-94.04	2	36781.368	15	-48.47	15	3079.8	6	-10260.72	2	19.930.584	10
France	-180.998	10	4858.484	6	-37.97	6	51482.55	25	-15765.696	10	28.170.517	11
Poland	-230.274	28	32816.896	14	-47.702	14	33608.77	20	-20014.272	28	33.212.833	12
Ireland	-221.432	25	32314.1	13	-45.916	13	38541.812	22	-19249.056	25	35.427.956	13
Norway	-166.986	7	52830.618	16	-48.552	16	35079.104	21	-15518.736	9	43.954.861	14
Hungary	-224.508	27	90749.45	17	-49.214	17	2914.624	5	-19707.984	26	46.832.037	15
Czechia	-191.538	18	110741.002	18	-49.344	18	1341.692	2	-17343.504	19	56.041.347	16
Turkey	-266.846	32	19274.406	10	-44.106	10	109095.282	29	-22388.544	32	64.184.844	17
Portugal	-169.482	8	119956.98	20	-49.624	20	20544.146	18	-15775.632	11	70.250.563	18
Cyprus	-251.936	31	126083.25	21	-49.66	21	56895.862	26	-21714.912	30	91.489.556	19
Slovenia	-186.742	14	162205.4	22	-49.838	22	45708.81	23	-17033.76	17	103.957.105	20
Romania	-233.498	29	215542.326	24	-53.3	24	47190.544	24	-20649.456	29	131.366.435	21

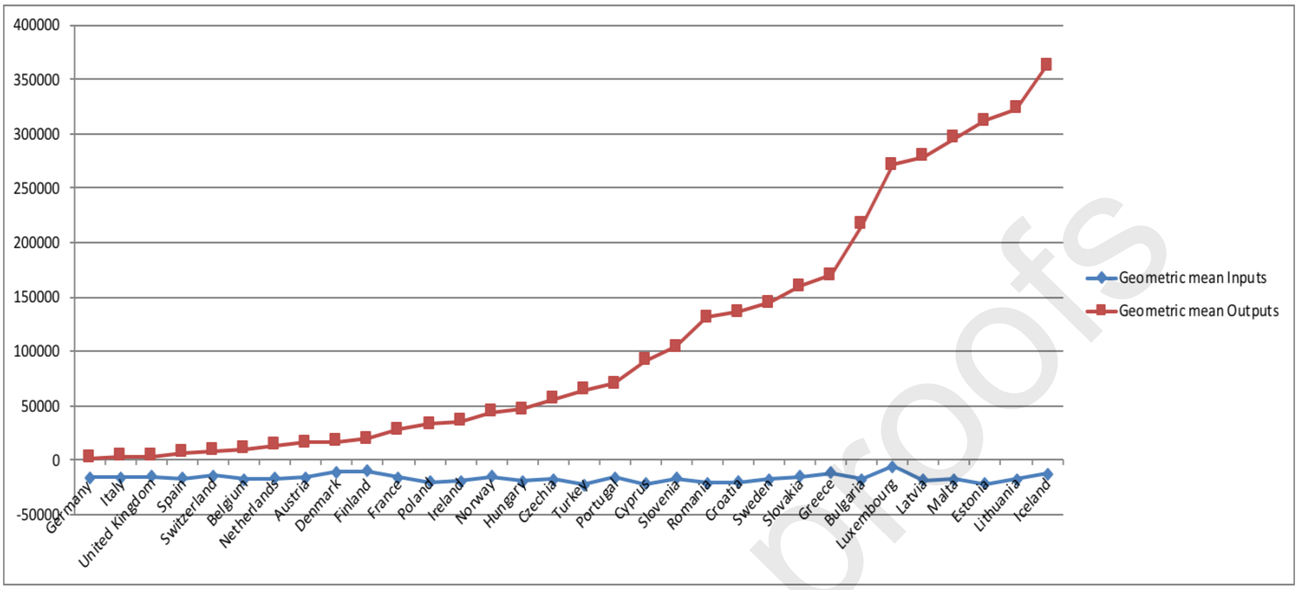
Croatia	-222.426	26	183734.328	23	-52.272	23	88555.22	28	-19778.256	27	136.144.774	22
Sweden	-200.592	20	15164.678	8	-39.29	8	273441.142	32	-17271.504	18	144.302.91	23
Slovakia	-159.47	6	304696.192	25	-54.066	25	14335.37	15	-15374.592	8	159.515.781	24
Greece	-111.576	5	115693.026	19	-49.546	19	224084.954	30	-11600.784	4	169.888.99	25
Bulgaria	-186.13	12	415225.504	27	-54.96	27	17445.524	17	-17358.48	20	216.335.514	26
Luxembourg	-29.128	1	535211.984	28	-55.036	28	8113.134	11	-6059.808	1	271.662.559	27
Latvia	-203.906	21	309537.146	26	-54.942	26	249064.95	31	-18637.056	24	279.301.048	28
Malta	-187.45	15	580120.486	30	-55.774	30	11192.764	14	-17512.128	21	295.656.625	29
Estonia	-248.736	30	619047.932	31	-59.076	31	4262.618	8	-22162.464	31	311.655.275	30
Lithuania	-191.126	17	566578.242	29	-55.52	29	79490.22	27	-17758.512	22	323.034.231	31
Iceland	-107.09	3	715757.17	32	-62.678	32	9009.874	12	-12223.296	5	362.383.522	32

As can be seen in Table 6, on the Input side the best performing countries in the first model (Division 1) have been Luxembourg and Finland, and on the Output side, Switzerland and Germany. This indicates that these countries have been more efficient, considering both economic and human resources in R&D at the national level, in relation to scientific production during the period analyzed.

In the case of the model (Division 2), the countries that have best managed their R&D resources have been Switzerland and Germany, the latter being the country obtaining the best results in scientific production, patents, number of citations and h-index of researchers (highest level of scientific quality), followed by the Czech Republic and Italy.

The geometric mean of the inputs, or use of economic and human resources in R&D, indicates that the most efficient countries in the 15 years analyzed have been: Luxembourg, Finland and Denmark. However, these countries still need to improve their scientific production in the number of publications, patents, and citations received by researchers, as well as an increase in the country's global h-index (the quality levels of its scientific production).

Regarding the countries that have been efficient from the perspective of scientific production, patents, citations and h-index they have been: Germany, Italy, and the United Kingdom. However, they could increase efficiency in relation to the volume of resources used in R&D compared to Luxembourg, Finland, or Denmark. Graph 2, displayed below, represents these data by country.



Graph 2. Global Deviation in % with respect to the Dynamic Network Efficiency frontier for the indicators *inputs and outputs per country.*

These data provide a window on the countries obtaining the lowest deviation, in terms of percentage in R&D expenditures and R&D personnel, with respect to the rest of the countries. They have not been the countries with the most growth in their contribution to the SDG 9, as reflected in the Malmquist productivity indexes in the 15 years analyzed. This explains why countries such as Luxembourg are growing in terms of innovation policies, but are still far from the Innovation Efficiency frontier unlike Germany or Italy, for example.

6. Discussion.

The discussion of the results will be carried out based on two aspects: (1) the contribution of the DNSBM and the OMI indices: Overall Malmquist Divisional Score and the Cumulative Divisional Malmquist Index (CDMI), and (2) the discussion of the dynamic results obtained in relation to SDG 9 of the European countries, focusing on R&D&I.

6.1. The contribution of the DNSBM and the OMI indices.

The gap between efficiency and innovation has been widely discussed in the body of literature on innovation. Its existence is justified due to the complexity of the innovation process, which makes its precision and modelling difficult. Mahroum and Al-Saleh (2013) note that it is quite difficult to measure the learning, adoption, and adaptation of knowledge taking place within the innovation process (Carayannis and Alexander, 2002).

The DNSBM model aims to solve the problem that characterizes the measurement of the dynamic global efficiency of R&D&I over multiple periods (2005-2019) (Chen et al., 2018). In our study, a set of weightings is obtained after the decomposition of the efficiencies of the periods, which are specific to each of the countries analyzed. This differs from the work of Tone and Tsutsui (2014), where a set of preset weights is supplied exogenously and is common for all DMUs. In R&D&I

models it is often difficult to pre-specify the weights, since the importance of each period can be difficult to understand or measure.

To confirm the robustness of our results, we have completed the Global Efficiency analysis with an analysis of the Malmquist Index, both global and by Divisions, taking into account that it is a dynamic model (Zhu et al., 2020). These results do not allow knowing the productivity growth of each country, but determine the progress or decline of efficiency along the technological frontier, using a sample with panel data (2005-2019) for R&D&I in Europe. Therefore, it allows us to explain which countries have grown considerably in terms of their R&D&I policies during the period under study.

One of the objectives of this work is to formulate a new model (DNSBM) that allows to measure global efficiency using the number of R&D personnel by sector and by countries as the "carry-out" variable. The model used has been the one oriented to output, since the variable "number of documents" is considered to be an output in all innovation studies (Pan et al., 2010; Chen et al, 2011; Emrouznejad and Yang, 2018). To the best of our knowledge, all this has allowed us to carry out a unique study to date in the body of literature, divided into two blocks: in the first block is the Division, and the scientific production of each country is measured quantitatively (Audretsch and Keilbach, 2004; Zemtsov and Kotsemir, 2019), and in the second block is the scientific quality in order to discriminate between published documents that have had a significant impact among the scientific community, or from which patents have been derived (Carayannis et al., 2015; Jurickova et al., 2019; Min et al., 2020).

6.2. Dynamic results obtained in relation to SDG 9 of the European countries focusing on R&D&I.

On the other hand, we discuss the results obtained from R&D&I efficiency by country, observing that the efficiency in terms of scientific and research production correspond to the countries that have achieved the best results; and these countries are: Luxembourg, Denmark, and Finland. This coincides with the results published by Zabala-Iturriagagoitia et al. (2007). However, those authors did not distinguish between quantity and scientific quality. In turn, Germany and Switzerland have a relatively high overall efficiency in terms of scientific quality (Rousseau and Rousseau, 1997; Nasierowski and Arcelus, 2003; Hollanders and Esser, 2007; Cullmann et al., 2012; Matei and Aldea, 2012).

Carayannis et al. (2016) confirm this result, which explains our model and makes it useful; it is not by producing a greater quantity of scientific articles that one can obtain greater efficiency related to quality. In this case, the usefulness of the proposed model lies precisely in dividing into divisions efficiency derived from the amount of scientific production for R&D&I expenses, and the number of scientists employed, with respect to quality and impact. The efficiency results in the proposed model indicate that Germany, Italy, the United Kingdom, Spain, and Switzerland are the most efficient countries. This indicates that the DEA (DNSBM) model assigns a higher weight to those countries having a higher scientific quality.

On the other hand, we have also analyzed the Malmquist Index, in order to know which European countries have grown in relation to the investment policies of the EU R&D&I. In this sense, the results show that the countries which have grown the most have been: Estonia, Luxembourg, and Norway. However, these countries remain considerably poorly positioned relative to frontier levels of production. By way of example, according to the EU (European Union, 2021), Luxembourg is the country that has grown the most in recent years in eco-innovation policies, which corroborates the results of our study in relation to productivity growth in the European countries.

7. Conclusions.

Currently, R&D plays an important role in the competitiveness of European countries, due to the added value it entails for the economy: obtaining sustainable growth, increasing productivity, and efficient use of all resources (Ferreira et al., 2021). For this reason, the European Union has incorporated into its statistical data (Eurostat), indicators related to R&D&I and, explicitly, data on the UN SDG 9. This SDG is related to R&D&I carried out by EU countries, as it is considered very useful for political decision-makers when making decisions on their future policies.

In the present study, a Dynamic DEA with Network structure based on SBM framework (DNSBM) is proposed and applied to R&D&I in Europe. The advantages of this model in the application of R&D&I efficiency are found in the dynamic relationships that DNSBM enables between the resources allocated to these activities and their results over time, since it allows measuring their efficiency by tracing a network of relationships between its inputs and outputs, and optimizing the efficiency of its processes.

This work shows the networks of relationships between the two processes of generation of scientific knowledge: the production of science and its commercialization in the form of quality of scientific results and its impact on efficiency.

The results of the proposed model show that there is a clear difference between the quantity and quality of scientific production. The countries with the highest scientific production are: Luxembourg, Denmark, and Finland, while those with the highest scientific quality are: Germany and Switzerland. In addition, it is observed that Germany, Italy, the United Kingdom, Spain, and Switzerland are the most efficient countries in terms of innovation policies (since they are the countries closer to the efficiency frontier) while Estonia, Luxembourg, and Norway are the countries with the highest growth during the period under study (2005-2019).

7.1. Implications for practice.

This work can guide R&D&I investment policies in Europe, favouring those countries that are continuously making the greatest efforts in the development of these activities over time, and not only for those countries that, although they achieved best results in efficiency, that have the least growth in R&D&I. In order to contribute to SDG 9, regarding innovation according to the results obtained, the implications for increasing the efficiency of R&D&I in the countries that have grown the least in the period analyzed would be, on the one hand, greater investment in economic and human resources at the national level, which would give rise to greater scientific production, and on the other hand, the improvement of the management of resources in R&D&I, as is observed in the present study, and which would lead to better results in scientific production, a greater number of patents, and a greater impact of publications by country.

Finally, from the perspective of the contribution to the studies carried out to date on Dynamic Network models, the present work can help other researchers to use the Malmquist Divisional models because, to our knowledge, very few models are used in the literature on efficiency measurement, in general, and on the measurement of R&D&I efficiency, in particular. Therefore, through this model we can disseminate knowledge to other researchers, thus advancing a method of quantifying dynamic efficiency, and more specifically regarding R&D&I.

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APPENDIX A. DESCRIPTIVE DATA OF CATCH-UP INDEX AND FRONTIER-SHIFT EFFECT.

Table A1. Divisional Descriptive Statistics catch-up index (*DCU*) (Division 1) (2005-2019).

Overall Score		2005-> 2006	2006-> 2007	2007-> 2008	2008-> 2009	2009-> 2010	2010-> 2011	2011-> 2012	2012-> 2013	2013-> 2014	2014->2015	2015->2016	2016->2017	2017->2018	2018->2019	Geometric mean
0.0491	Average	1.0698	1	0.9521	1.0099	1.5623	0.5588	1.8411	1.1327	0.9837	1.0044	1.0194	1.0149	1.026	1.0543	1.0198
0.2556	Max	1.5031	1	1.0408	1.2388	12.9331	1.0202	6.9041	1.9425	1.1848	1.0836	1.9431	1.2425	1.7281	1.3383	1.0543
0.001	Min	0.8363	1	0.6854	0.0866	1	0.1196	0.7367	0.9691	0.5181	0.9396	0.8647	0.5374	0.9091	0.5537	0.9902
0.0711	St Dev	0.0962	0	0.0715	0.1803	2.0785	0.1905	1.0133	0.181	0.1065	0.0391	0.178	0.1196	0.1421	0.1201	0.0185

Table A2. Divisional Descriptive Statistics catch-up index (*DCU*) (Division 2) (2005-2019).

Overall Score		2005->2006	2006->2007	2007->2008	2008->2009	2009->2010	2010->2011	2011->2012	2012->2013	2013->2014	2014->2015	2015->2016	2016->2017	2017->2018	2018->2019	Geometric mean
0.0491	**Average**	1.5147	1	1.0097	1.043	1.1107	0.8881	1.05	7.144	0.2888	1.0137	8.7702	0.2544	8.4357	1.7076	1.0029
0.2556	**Max**	13.4416	1	1.5841	1.5678	3.5666	1.1338	1.6772	20.4625	3.7373	1.3253	29.9376	3.3128	82.5444	36.661	1.1491
0.001	**Min**	0.8801	1	0.0765	0.556	0.4326	0.5691	0.8386	0.2676	0.0408	0.1776	0.3019	0.0455	0.0273	0.012	0.8993
0.0711	**St Dev**	2.1979	0	0.2448	0.2177	0.4841	0.1525	0.1993	4.1044	0.6355	0.1894	5.9346	0.5714	14.8126	6.41	0.0571

Table A3. Divisional Descriptive Statistics frontier-shift effect (*DFS)* (Division 1) (2005-2019).

Overall		2005->	2006-	2007->	2008->	2009-	2010-	2011-	2012-	2013-	2014-	2015->	2016->	2017->	2018-	Geometric

Score		2006	> 2007	2008	2009	>2010	>2011	>2012	>2013	>2014	>2015	2016	2017	2018	>2019	mean
0.0491	Average	1.0076	1	1.0055	1.0033	1.0014	1.0094	0.9979	0.872	1.7357	0.9998	0.8675	1.694	0.942	1.3558	0.9959
0.2556	Max	1.0538	1	1.0386	1.0231	1.0171	1.0882	1	1	7.3956	1.0291	1	8.6549	1.0429	7.3245	1.0115
0.001	Min	1	1	1	1	0.9925	0.9916	0.9781	0.134	1	0.9823	0.1159	1	0.1079	0.8437	0.8784
0.0711	St Dev	0.0166	0	0.0119	0.0072	0.0046	0.0242	0.0055	0.3024	1.7815	0.0068	0.313	1.9303	0.2168	1.429	0.0219

Table A4. Divisional Descriptive Statistics frontier-shift effect (*DFS)* (Division 2) (2005-2019).

Overall Score		2005-> 2006	2006-> 2007	2007-> 2008	2008-> 2009	2009->2010	2010->2011	2011->2012	2012->2013	2013->2014	2014->2015	2015-> 2016	2016-> 2017	2017-> 2018	2018->2019	Geometric mean
0.0491	Average	0.9484	1	1.0597	0.9683	0.8263	1.9668	0.6152	0.8943	0.9966	0.9936	1.002	1.0091	1.0236	0.9722	0.9843
0.2556	Max	0.9672	1	1.2765	0.9761	0.8834	3.3992	1	0.9529	1.0002	1.0327	1.0481	1.0187	1.0414	1.0451	1.0025
0.001	Min	0.8113	1	1.0353	0.9625	0.6538	0.9738	0.3188	0.7501	0.992	0.9553	0.9678	1.0062	0.9764	0.9409	0.9426
0.0711	St Dev	0.0266	0	0.0515	0.0037	0.0579	0.6043	0.1483	0.045	0.0019	0.0129	0.0181	0.0024	0.0097	0.0204	0.013

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