EFFICIENCY ASSESSMENT ON CODIFIED KNOWLEDGE PRODUCTS: AN SFA APPROACH

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ABSTRACT

Knowledge applied to innovation is increasingly recognized as an explanatory factor of economic growth. Innovation derives from applying knowledge to generate new products or processes. National Innovation Systems (NIS) performs as the formal or informal network of people within institutions interacting to produce and apply knowledge to innovation. NIS can be understood as two subsystems: one based on scientific and technological work, producing codified products (publications and patents), and the other centered on practical actions to diffuse, apply, and use knowledge. Our objective is to assess cost efficiency in the production of codified knowledge outputs (CKO), being our unit of analysis NIS (countries). To attain our goal, we apply a Stochastic Frontier Analysis (SFA) to estimate a cost frontier of CKO. The panel sample includes 1189 observations for 23 years (1996-2019) and 82 countries. Our main results identify determinants and patterns of efficiency and productivity, tendencies, and specifics of countries and groups of them.

KEYWORDS

Efficiency frontiers, cost frontier, codified scientific knowledge, National Innovation Systems

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Highlights

- *Given human and non-human resources, some National Innovation Systems perform better than others in producing codified knowledge outputs.*
- *Efficiency assessment concentrates on the best administration of resource scarcity and is useful for ex-ante planning and ex-post evaluation.*
- *Our empirical assessment identifies the best performers within 82 countries in producing scientific publications and patents.*

INTRODUCTION

Knowledge production is a key explanatory factor of economic growth. Early economic growth models treated technical change as exogenous, while more recent ones incorporated its endogenous role (Barro and Sala-i-Martin, 2003). The latter is the recognition that an important part of generated knowledge is not fortunate random discoveries; instead, it is derived from the deliberate effort in human and non-human investments, which depends on cost-benefit analysis, the resource allocation of its production process, and the efficiency in the use of those resources. Understanding the drivers of knowledge can provide useful policy implications for economic development.

Evaluating the outcomes of knowledge production is challenging. You can look at output indicators or an inventory of inputs to produce knowledge, or you can focus on the relationship between outputs and inputs and calculate partial productivity indexes. However, both analyses are insufficient. Partial productivity measures often omit the effect of interactions between relevant inputs. For instance, a ratio between production and labor units would leave out the complementarities between labor and capital in the production process. When it comes to productivity, it is relevant to consider the input and output vector altogether because it will be a more complete representation of a production or cost function for efficiency estimation.

The National Innovation System (NIS) is the formal or informal network of people within institutions, interacting to apply knowledge to innovation (that is, to generate new or improved products or processes). NIS can be divided into two subsystems: one based on scientific and technological work, producing codified knowledge outputs (CKO) (e.g., scientific publications and patents of inventions), and the other centered on practical and non-codified actions to diffuse, apply, and use knowledge. CKO can be measured directly because they are countable, and thanks to the effort of scientists working on bibliometrics and of international organizations compiling statistics of costs, inputs, and outputs. Instead, because non-codified knowledge is embodied in people's minds or embedded in organizations, its measurement is quite elusive. Our objective is to assess cost efficiency in the production of CKO by country. CKO efficiency is related to the optimum usage of its output/input ratio, while CKO productivity considers the transformation of inputs into outputs (Nasierowski and Arcelus, 2003). Efficiency estimates can be made on pure technical conditions (output-to-input relationships) or in terms of allocative conditions (cost-to-output relationships). In the measurement of the efficiency of CKO activities, observation units (whether countries, regions, research institutes, or firms) are regarded as entities operating a production process where inputs - mainly capital and manpower - are transformed to produce CKO (Carrillo, 2019). Efficiency assessment is a tool to evaluate the administration of resource scarcity, and it is useful for ex-ante planning and ex-post evaluation. Knowing which efficient systems ex-ante could guide future investments, while ex-post evaluations teach about adjustments and possible improvements.

To estimate the technical efficiency of NIS, we apply a Stochastic Frontier Analysis (SFA) to estimate a cost frontier of CKO, considering relevant inputs and "environmental" (in the sense of contextual) conditions to address country-specific conditions. Our database is built on different sources for outputs (Scimago and WIPO), costs, inputs, and input prices (UNESCO), and macroeconomic and institutional issues to characterize the environment of CKO production (The World Bank and Heritage Foundation). The sample is a panel that includes 1189 observations for 23 years (1996-2019) and 82 countries, each one being a NIS.

Our work makes three main contributions. First, we developed an extensive literature review documenting the development of the concept of NIS. Second, we put together and performed an efficiency analysis on a database encompassing developed and developing countries, contrasting with most of the literature focusing on comparisons within OECD countries. Lastly, the method of analysis employed is econometric and concentrates on technical and allocative efficiency, which contrasts with the use of mathematical programming approaches for technical efficiency estimation only.

The article is organized as follows. Section 2 reviews the literature on NIS. Section 3 introduces the material and methods used to estimate the allocative efficiency of codified knowledge. Section 4 shows the main results, while Section 5 discusses the implications of our findings. Lastly, Section 6 summarizes the main conclusions.

LITERATURE REVIEW

On the NIS concept

A National Innovation System (NIS) can be defined as a network of private and public sector institutions whose formal or informal activities and interactions start, import, modify, and diffuse new technologies, characterizing collective innovation efforts (Manzini, 2012). It is *national* because of the central role of spatial proximity and concentration in this process (Acs et al., 2016). *Innovation* means technologies or practices that are new to a given society, made by entrepreneurs, and depend on a society's adoption (The World Bank, 2010). The *system* notion emphasizes cooperation and linkages in the innovation process (Manzini, 2012). As Lundvall (2005) points out, mechanistic versions of NIS denote something that can be constructed, governed, and manipulated by policymakers. When applied to developing countries, the emphasis is on system building and promotion (Lundvall, 2007b).

Modes of innovation

Within NIS, there are two modes of innovation: the STI mode - comprehending learning from *science, technology, and invention*, and the DUI mode - encompassing learning by *doing, using, and interacting*. The STI mode produces CKO (such as scientific papers, patents, books, presentations at conferences, etc.). On the other hand, the DUI mode produces innovations through non-codified knowledge (or know-how), which is tacit, embodied in people, or embedded in organizations (Lundvall, 2005, 2007a, 2007b; Manzini, 2012; Atkinson, 2020; Acs et al., 2016; Eggink, 2013; OECD, 1997). The output of each mode of innovation is diverse, and the sensibility to measure them is disparate. The DUI mode subsystem (experience-based) is elusive to measure (Cirillo et al., 2019). Indicators capturing institutions, linkages, policies, and social capabilities, or DUI modes of learning, are less susceptible to quantitative representation. Instead, CKO from the STI mode (science-based) is relatively easy to account for, and there was progress in bibliometrics to improve measurement, both in output quantity and quality (Lundvall, 2007a; Manzini, 2012; Atkinson, 2020; Acs et al., 2016, Eggink, 2013).

Codified products of knowledge

The CKO varies in its degree of public good: something whose consumption is non-rival as well as non-excludable. A patent is a private good (the owner can exclude third parties), and the content of a scientific paper is mostly a public good. Embodied personal knowledge is mostly private. Practices and norms are normally common knowledge within the interior of firms or other institutions. However, the benefits of research generated in one place can hardly be captured in other places. Secrecy would prevent innovation. A technological advantage can thus only be private and locally captured temporarily since people move and knowledge diffuses (Etzkowitz, 2011).

Conversely, as CKO has components of public goods, the incentives of market actors are not adequate to produce the socially desired level of scientific knowledge because of the challenges of appropriating or owning it. Economic theory provides a robust rationale for the public support of only a component of innovation (discovery or invention). In contrast, public financing for applied research and commercialization is debatable because of the private appropriation of benefits through trade secrecy, intellectual property, or maintaining a competitive lead (Schot and Steinmueller, 2018). The "market failure" argument, however, does not guide how much governments should spend on science. Besides the public good argument, uncertainty (another market failure) may also prevent firms from investing in innovation. Empirically, the most used appropriation methods are lead time and secrecy, the complexity of design, and trademarks (Faberger, 2017).

Latecomers, in comparison with first movers, are challenged with many disadvantages in developing their innovation capabilities, such as technological leadership of incumbents, preemption of assets, and buyer switching costs, but they benefit from free-rider effects, information spillovers and learning from the experiences of pioneers (Fan, 2014).

Institutions within NIS

The differences in NIS quality depend on the quality of "institutions" (Bartels et al., 2014). Institutions are intended as organizations, as well as '*habits, routines, rules, norms, and laws, which regulate the relations between people, and shape social interaction*'. Some of these interactions may be cooperative, while others may be competitive. The linkages between agents can be formal or informal, intentional or incidental, conscious or not conscious, and synergetic or not (Eggink, 2013).

The historical role of universities has been to establish what is considered 'reasonably reliable knowledge.' They had enjoyed relative autonomy from the state as well as from private interests. The primary function of universities remains to train people to solve complex problems (Heller and Eisenberger, 1998). In the late 19th century, research was added to teaching as a second university mission. In the USA, at the time, funds from philanthropists were given to fund new universities and expand old ones. There were concerns among academics that the gifts would try to influence professors' hiring and firing, as well as to decide research priorities. To preserve independence for science from economic interests, a doctrine of pure research was promoted. In 1942, Merton stated the normative structure of science with an emphasis on universalism and skepticism as a response to Nazi and Soviet political control of knowledge to also protect science from politics. The third element in establishing scientific autonomy was the Bush Report of 1945. The distribution of government funds to academic research was assigned to "peer reviewers", a criterion adapted from foundation practices in the 1920s and 1930s. Endowed with higher education and research goals, the increased role of knowledge and research in economic development opened the third mission for universities after WWII, which is the promotion of economic development, more pronounced since the end of the Cold War (Etzkowitz and Leydesdorff, 2000).

The so-called Triple Helix of university-industry-government relations states that the university can promote innovation in knowledge-based societies. Most countries and regions are presently trying to attain some form of Triple Helix, with university spin-off firms and strategic alliances among firms, government laboratories, and academic research groups (Etzkowitz and Leydesdorff, 2000). The model is analytically different from the NSI approach, in which entrepreneurs lead innovation, and from the "Triangle" model of Sábato (1975) and Sábato and Mackenzie (1982) in which the nation-state encompasses academia and industry and directs the relations between them. Its strongest version was the Soviet-type system. The weakest versions were present in Latin America. Both experiences are deemed as failed developmental models, with little "bottom-up" initiatives, and where innovation was discouraged rather than encouraged. Higher education and training systems that assist only public administration or produce large numbers of underemployed scholars do not promote innovation (Lundvall, 2007a). Another policy model consists of separate institutional spheres with strong borders dividing them and highly circumscribed relations among the spheres, exemplified in Sweden and the US (Etzkowitz and Leydesdorff, 2000).

Nevertheless, Lundvall (2007b) argues that American tendencies in pharmaceuticals and biotechnology face the risk of being generalized to the relationships between universities and industry in general, inspiring reforms that neglect other universities' functions. The great US entrepreneurial universities rest on a national policy of funding mission-oriented research areas mainly for defense and health (Etzkowitz, 2015), largely to federal labs, and support for basic, curiosity-directed research through university funding (Atkinson, 2020; Faberger, 2017). Lundvall (2007a) adds that the long-term implications and costs of making scholars and universities profit-oriented seem to be that scholars become less engaged in sharing their knowledge otherwise salable.

Teaching guarantees universities a comparative advantage as a source of innovations over other forms of knowledge producers, such as consultants, which is student turnover. In solving clients' problems, a consulting company reunites together dispersed personnel transiently for individual projects and then disperses them again after projects are completed. They lack a cumulative research program. The university combines organizational and research memory with flows of new persons and new ideas (Etzkowitz and Leydesdorff, 2000; Etzkowitz, 2011).

Two established models co-exist in STI innovation policy discussions. The first began with a post-WWII institutionalization of government support for CKO, seeking economic growth and addressing market failure in the private generation of new knowledge. The second emerged in the 1980s and focused on building links, clusters, and networks, stimulating learning between elements in the systems, and enabling entrepreneurship (Schot and Steinmueller, 2018).

Innovation: process or system?

There seem to be two ways to conceptualize the role of knowledge in innovation activities: a process or a system. Before the early 1970s, theorists studied innovation in terms of a process composed of "sequences" and "stages" or "chains" of activities (Godin, 2017). The linear model of innovation begins with basic research, followed by applied research, development, and commercialization. In this, innovation is seen as a process made up of sequential stages that are temporally and conceptually distinct and characterized by unidirectional causality (Guan and Chen, 2012). The conception of a linear innovation model was first proposed by White House science advisor Vannevar Bush in the post-war period, and it was based on the notion that funding basic research will lead almost automatically to innovation (Fan, 2014).

On the other hand, between 1930 and 1950, official statisticians started to define, classify, and register basic research, applied research, and development data. In 1951, the National Science Foundation (NSF) was mandated by law to measure scientific and technological activities in the USA. The organization developed surveys on R&D based on precise definitions and categories. Industrialized countries followed the NSF definitions when they adopted the OECD Frascati manual in 1963. The manual offers methodological conventions that allowed international comparisons (Godin, 2017).

Before the linear model, there were other process models. One is the invention-diffusion framework. It came from anthropologists in the 1920s and 1930s and served to analyze changes in culture among societies. Another early process model since the 1940s is the stage model from rural sociologists, who studied the diffusion of innovation as a sequential process. Criticism of the linear model gave rise to the demand-pull model (c. 1965), which places the origin of the process of innovation on social needs or market demand instead of a supply perspective. The idea became formalized into a demand-pull model in the 1970s and 1980s, which was of limited use in explaining technological innovation (Godin, 2009).

A new kind of explanation appeared in the post-WWII era: the system model. The system concept was popular in the 1950s and 1960s. The NIS approach suggests that the research system's goal is technological innovation and that it is part of a larger system composed of government, university, and industry. The approach also emphasizes the relationships between the components or sectors to explain the performance of innovation systems. The NIS approach is due to researchers such as Chris Freeman, Richard Nelson, Bengt-Ake Lundvall, and early OECD work from the 1960s. The NIS framework has been very influential as a rationale for the development of national policies to stimulate technological innovation (Godin, 2017).

The actors in the NIS innovation model have a division of labor and responsibility. Scientists are expected to pursue scientific advancement and publish their results, disclosing their methods and findings. The public sector is expected to fund scientific research. The private sector transforms scientific discoveries into innovations that support economic growth. The NIS approach is thus complementary to a competitiveness agenda (Schot and Steinmueller, 2018). Both tacit knowledge (or know-how) exchanged through informal channels and codified knowledge are inputs for innovation (OECD, 1997).

The most traditional type of knowledge flow in a NIS may be technology dissemination in the form of new equipment and machinery. However, the innovative performance of firms increasingly depends on adopting and using innovations and products developed elsewhere. The movement of people and the tacit knowledge they carry with them is key in NIS. Personal interactions are important channels of knowledge transfer (OECD, 1997).

MATERIAL AND METHODS

The following three subsections discuss the variables and data, the method we employ, and the models we estimate.

Data

Our data is a combination of country-level sources. Table 1 presents the variable definitions, classifying them according to their role in the estimates. One of the main concepts of the Frascati manual was GERD (gross expenditures on R&D), defined as the sum of the expenditures from the four main economic sectors of the economy: government, university, industry, and nonprofit (Godin, 2017). R&D expenditures are "*current and capital expenditures (both public and private) on creative work undertaken systematically to increase knowledge, including knowledge of humanity, culture, and society, and the use of knowledge for new applications*" (Godin, 2017). In a production frontier, GERD represents the non-human resources, and in a cost frontier (our concern), it is the cost of production of the R&D outputs, the dependent variable. GERD is expressed in the US dollar, at PPP constant values of 2010, attributes which allow comparisons between countries and years. On the other hand, according to the World Bank (2010), researchers in R&D are "*professionals engaged in the conception or the creation of new knowledge, products, processes, methods, or systems, and the management of the projects concerned*" (Godin, 2017). Researchers are the human resources in a production frontier, and for a cost frontier, it is an important variable to compute, along with GERD, the relative price of inputs.

Our analysis runs different specifications using alternative measures for the outputs. We report the production of published documents or of citable published documents, which are a subset of the former (correlation 0.99). In the same vein, we report patenting by patent publication or patent grants (correlation 0.90). We include an input relative price, a time trend, and some environmental variables. These include the per capita GDP. We also defined some partial productivity indicators that are useful to characterize and compare countries and to give consistency to efficiency analysis. Inputs are human and non-human, the latter measured in monetary units. All monetary issues were converted to constant 2020 dollars at PPP values since the cost of living, salaries, and cost of materials are different among countries. Concerning the environmental conditions, we try to address the differences in costs between arts and social sciences publications and natural sciences ones through a dummy, and to identify the "modernity" of the NIS, we developed a dummy to differentiate between patents that we characterize as belonging to IV Industrial Revolution.[1]

Table 2 shows the descriptive statistics of the variables included in the analysis. We use an unbalanced panel of 82 countries over 24 years, from 1996 to 2019[2].

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1 The characterization of the technologies in each industrial revolution (IR) is as follows:

1. The First IR used water and steam power for mechanization.
2. The Second IR applied electricity to create mass production.
3. The Third IR employed electronics and information technology for automation.
4. The Fourth IR combined physical, digital, and biological technologies in disruptive ways (Lacy et al., 2019).

2 To get the final number of observations, we first dropped countries with incomplete information, and we removed the countries that contributed less than 0.005% of total publications.

Name	Type	Definition
gerd	Cost	Dollar 000, PPP constant values of 2010, according to UNESCO.
docs	Output	Published documents, according to the SCIMAGO database
citabledocs	Output	Citable published documents, according to the SCIMAGO database
patpublications	Output	Patent publications, according to the WIPO database
patgrants	Output	Patent grants, according to the WIPO database
w	Relative Price of Human and non-Human Inputs	Dollar 000, PPP constant values of 2010, according to UNESCO on Number of researchers full-time equivalent, according to UNESCO
gdppc	Environmental	Per capita GDP (PPP values) in constant dollars of 2010, according to World Bank
heritageeconomicfreedom	Environmental	Global Heritage Economic Freedom Index, according to Heritage Foundation
gerdpc	Environmental	Gerd/Inhabitants
socialdocsshare	Environmental	Share of social sciences and art disciplines on total published documents
socialcitabledocsshare	Environmental	Share of social sciences and art disciplines on total citable published documents
ivirpatpublicationsshare	Environmental	Share of IV Industrial Revolution Technologies on Total Patents Publications
ivirpatgrantsshare	Environmental	Share of IV Industrial Revolution Technologies on Total Patent Grants
trend	Time trend	1 for 1996 to 23 for 2019
sqtrend	Time trend squared	Trend squared
	Partial productivity	
doc_on_res		Docs/researchers
citabledocs_on_res		Citabledocs/researchers
patpublications_on_res		Patpublications/researchers
grants_on_res		Patgrants/researchers
	Average costs	
GERD_on _docs		Gerd/docs
GERD_on_citabledocs		Gerd/citabledocs
GERD_on_patpublications		Gerd/ Patpublications
GERD_on_patgrants		Gerd /Patgrants

note: Researchers are counted as Full-Time Equivalents.

Sources: Table 1: Variable definitions (source: Authors' elaboration on Scimago Journal & Country Rank, https://www.scimagojr.com/countryrank.php, UNESCO Institute for Statistics (UIS), http://data.uis.unesco.org/, WIPO Information Resources on Patents, https://www.wipo.int/patents/en/, World Bank Open Data, https://data.worldbank.org/, Heritage Foundation Index of Economic Freedom, https://www.heritage.org/index/download)

	Observations	Mean	Sd	Min	Max
Gerd	1189	19728.50	57358.19	20.60	444589.66
docs	1189	66948.47	148742.54	142.00	1213339.00
patpublications	1189	55205.47	194938.96	2.00	2922482.00
citabledocs	1189	75329.43	175254.25	136.00	1337148.00
patgrants	1189	15339.31	47559.53	1.00	361771.00
W	1189	143.69	96.42	10.57	978.02
GDP per capita	1189	24876.13	21319.87	234.00	111968.00
Overall Score Heritage Economic Freedom	1189	66.41	9.35	41.80	90.20
GERD per capita	1189	358.33	387.26	1.00	1691.00
socialdocsshare	1189	0.09	0.05	0.01	0.31
ivirpatpublicationsshare	1189	0.40	0.14	0.00	0.83
ivirpatgrantsshare	1189	0.65	0.15	0.00	1.00
socialcitabledocsshare	1189	0.08	0.05	0.01	0.32
Researchers (FTE)	1189	110763.19	248438.50	142.00	1866109.00
docs_on_res	1189	0.90	0.72	0.03	5.75
citabledocs_on_res	1189	0.95	0.74	0.03	5.66
patpublications_on_res	1189	0.12	0.19	0.00	1.42
grants_on_res	1189	0.08	0.10	0.00	0.78
GERD_on _docs	1189	201.00	152.73	17.95	2152.50
GERD_on_citabledocs	1189	188.51	147.20	14.05	2218.73
GERD_on_patpublications	1189	21946.19	119677.48	110.18	2585170.00
GERD_on_patgrants	1189	22250.35	131032.18	146.67	3834244.00

Table 2: Descriptive statistics (sources: Authors' elaboration on Scimago Journal & Country Rank, https://www.scimagojr.com/countryrank.php, UNESCO Institute for Statistics (UIS), http://data.uis.unesco.org/, WIPO Information Resources on Patents, https://www.wipo.int/patents/en/, World Bank Open Data, https://data.worldbank.org/, Heritage Foundation Index of Economic Freedom, https://www.heritage.org/index/download)

Method

Efficiency in the production of codified outputs of knowledge in the STI mode of NIS is the focus of this assessment. The simplest possible approach consists of computing simple measures of partial productivity (i.e., output/input ratios) or average costs (i.e., costs/output ratios). These approaches neglect relations of complementarity and substitution between inputs and synergies of joint production in outputs. Most sophisticated techniques use frontier approaches, such as mathematical programming methods and econometric estimates. Inputs are usually represented by indicators such as the amount of R&D investment and the number of researchers in R&D, whereas output measures are reflected by indicators such as patents and scientific and technical journal paper publications. These data are territory-based.

The SFA approach decomposes the deviations of each observation from the frontier (residues) into two components: a stochastic error term and an inefficiency term. In a panel data context, where multiple decision-making units (DMU) and periods exist, SFA permits efficiency to vary within a DMU, over time, and among DMU. Accordingly, panel data SFA models can be classified into four groups:

1. Models with invariant inefficiency both in time and DMU (Pitt and Lee, 1981; Battese and Coelli, 1988).
2. Models with time-varying and DMU invariant inefficiency (Kumbhakar, 1990; Battese and Coelli, 1992).
3. Models with both time and DMU varying inefficiency (Battese and Coelli, 1995, Greene 2005a, and Greene 2005b).
4. 4) Models with persistent and residual inefficiency and with unobserved heterogeneity were considered across DMU (Kumbhakar and Heshmati, 1995; Kumbhakar et al., 2014).

The most used production (cost) function specifications are the Cobb-Douglas in logarithms and the Translogarithmic (Translog) defined, respectively as

$$\ln y = \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_n \qquad (1)$$

$$\ln y = \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_n + \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} \beta_{nm} \ln x_n \ln x_m \qquad (2)$$

In the former, y represents output(costs) and x inputs(outputs) in production(cost) frontiers, respectively.

The Translog is more flexible, not assuming constant elasticities over the full sample and considering quadratic effects and the possible interactions (complementarity, substitution, or no interaction) between the inputs (outputs in cost frontiers). The elasticities of the Translog frontier are:

$$\frac{\partial \ln y}{\partial \ln x_n} = \beta_n + \sum_{m=1}^{N} \beta_{nm} \ln x_m \qquad (3)$$

Battese and Coelli (1995) propose a model in which $_{it}$ can be influenced by DMU-specific effects, exogenous determinants, or covariates, z_{it}, uncorrelated with the regressors of the frontier. In these time-varying SFA models, the intercept α is the same across all DMU (Belotti et al., 2013), not addressing time-invariant unobservable factors, assumed to be random on DMUs over time. Thus, their performance is underestimated. We employ the Battese and Coelli (1995) model, where:

$$y_{it} = \alpha + x_{it}\beta + v_{it} - Su_{it} \qquad (4)$$

And

$$u_{it} = z_{it}\delta + W_{it} \qquad (5)$$

Where:

$S = 1$ *for production frontiers*, and $S = -1$ *for cost frontiers* where y_{it} represents the output(cost) for the i DMU in the t period; x_{it} denotes a vector of inputs(outputs) for the DMU (country in this case) i in the t period, β is a vector of parameters. The composed error term ε_{it} is the sum (or difference) of v_{it}, representing statistical noise, and a one-sided disturbance u_{it}, addressing for inefficiency. S assumes the value of 1 in production frontiers and -1 in cost frontiers.

The error term is expressed as the sum of two terms, u_{it} and v_{it}, which are assumed independent of each other, as well as independent and identically distributed.

$$e = v_{it} + u_{it} \qquad (6)$$

The first part of the error term is a random error with distribution independent and identically distributed to account for possible noise, data typing, or reporting errors.

$$v_{it} \sim N\left(0, \sigma_v^2\right) \qquad (7)$$

The second part of the error term is the inefficiency itself, and it accounts for unobserved factors that are in control of the decision unit.

$$u_i \sim N^+\left(\mu, \sigma_u^2\right) \qquad (8)$$

The SFA model is usually estimated through maximum likelihood (ML) methods in two steps: firstly, the estimation of the parameters of the model and secondly, the point estimates of inefficiency through the mean of the conditional distribution:

$$E(u_{it} | v_{it} + u_{it}) \qquad (9)$$

In Battese and Coelli (1995), parameters of the SFA and the model for the technical inefficiency effects are estimated simultaneously by maximum likelihood. The likelihood function is expressed in terms of the variance parameters for the compound error term σ^2, the sum of the variances $\sigma_v^2 + \sigma_u^2$ and the ratio between the variances $\gamma = \frac{\sigma^2_u}{\sigma^2}$, where $\gamma \in (0;1)$.

If $\gamma = 0$, volatility is fully explained by randomness, while if it is the unit, inefficiency explains the whole volatility.

Models

We estimate two Translog models. The dependent variable is the logarithm of GERD in constant 2010 PPP values, representing the cost of CKO of each country, regressed against the logs of its outputs (scientific publications -docs- or citable scientific publications -citabledocs-; patent publications -patpublications- or patent grants -patgrants-), its squared and interaction (cross-) effects, and the logarithm of the relative price of human and non-human inputs (w). We added some environmental variables to capture the level of economic development of the country (logarithm of per capita GDP), the level of institutional development of the country (logarithm of Economic Freedom Index of Heritage Foundation), the importance of the activity in the country (logarithm of the per capita GERD), the share of publications which demand lower non-human resources (arts and social sciences publications or citable publications), the share of IV Industrial Revolution patents on total (patent publications or patent grants).

Variables	Model A	Model B
Costs (dependent)	lgerd	lgerd
Outputs (linear, cross-, and squared effects)	ldocs	---
	---	lcitabledocs
	lpatpublications	---
	---	lpatgrants
	lsqdocs	---
	---	lsqcitabledocs
	lsqpatpublications	---
	---	lsqpatgrants
	ldocspatpublications	---
	---	lcitabledocspatgrants
Input relative prices	lw	lw
Environmental	lgdppc	lgdppc
	lheritageeconomicfreedom	lheritageeconomicfreedom
	lgerdpc	lgerdpc
	socialdocsshare	---
	---	socialcitabledocsshare
	lvirpatpublicationsshare	---
	---	ivirpatgrantsshare

Table 3: Estimated models (source: Authors' elaboration)

RESULTS

The model used for the estimations is Battese and Coelli's (1995) time-varying model of inefficiency.

In Table 4, we present both estimates for models a and B, which are introduced in Table 3. The differences between the two models are the outputs (and their crossed and squared effects). Not all publications are cited, nor are the cited publications the same as the former. There is a lag between the paper being sent to publishing and its finally being published, and there is also a lag between the publication and the new publications citing them. We do not apply lags to publications nor the citable publications. If, say, a couple of years is needed on average to publish, and another couple of years until the former publications start to impact, we could lose four years of observations. Instead, we assume that the current costs are spent to finance the current inputs, while most probably, they are being spent on outputs that will be published in a couple of years. A similar thing happens with patents: a patent granted in the current period had a process initiated in some period in the past. The same is true for patent publications, however, the set of patent grants is different from patent publications, and they are both different from patent presentations. In the case of patents, there is no consensus on the adequate lag to apply. We perform some sensitivity tests, with two years lag, to address these complex issues, and the results are not remarkably different from the main scenario presented here.

The coefficients of outputs are positive as expected in both models, even when the linear coefficients of patpublications and patgrants are not significantly different from zero. Quadratic values are positive for both inputs, and the cross effect is negative and significant, also as expected, because patents and publications compete for the resources they employ (human and non-human inputs, researchers, and money). The log of the relative price of inputs is also significant and positive, as expected.

Concerning the environmental variables, the logarithm of the GDP per capita is negative, indicating that the costs of producing COK decline with the level of development of the country, proxied by the cited variable. Also, production in model a declines with the Heritage Foundation Index of Economic Freedom, while it is not significantly different from zero in model B. The fourth industrial revolution type of patent publication reveals no significant difference from zero in model A, while the same consideration made for patent grants is significant and negatively affects costs. This can be explained by the synergy of different types of technologies in the Fourth Industrial Revolution's type of inventions, as stated by Lacy et al. (2019). Social sciences published documents and citable documents reveal both as significant and negatively correlated with costs. This is reasonable since the production costs of the remaining papers in natural sciences, medicine, or engineering are more expensive to produce in terms of laboratories, materials, experimentation, etc. Finally, the sign of the time trend is negative, indicating in the case of model a that costs are decreasing at a rate of -1.38 percent per year on average, and for model B, at -1.62 percent yearly.

The value of lambda is high, indicating that the standard deviation of the inefficiency component is nearly nine times the standard deviation of the pure randomness component of the composite error term ($u_{it} + v_{it}$).

It is worth mentioning that $\lambda = \frac{\sigma_u}{\sigma}$, $(0 < \lambda < 1)$, where λ is the ratio between the standard deviation of u (σ_u and σ, which is the sum of the standard deviation of v and u (σ_v and σ_u). If $\lambda = 1$, the residual variability can be totally explained by the efficiency component u. Instead, if $\lambda = 0$, all the residual variability is randomness.

	Ln(gerd)		Ln(gerd)
Model A		Model B	
Ln(docs)	0.538***	Ln(citabledocs)	0.688***
	(0.0732)		(0.0786)
Ln(patpublications)	0.0393	Ln(patgrants)	-0.0226
	(0.0443)		(0.0470)
Ln(docs)*Ln(patpublications)	-0.0493***	Ln(citabledocs)*Ln(patgrants)	-0.0325**
	(0.0168)		(0.0146)
Ln(docs)^2	0.0276***	Ln(citabledocs)^2	0.0144**
	(0.00626)		(0.00591)
Ln(patpublications)^2	0.0191***	Ln(patgrants)^2	0.0212***
	(0.00345)		(0.00287)
lnw	0.508***	lnw	0.523***
	(0.0196)		(0.0203)
lngdppc	-0.505***	lngdppc	-0.537***
	(0.0247)		(0.0259)
lnheritageeconomicfreedom	-0.167*	lnheritageeconomicfreedom	-0.0629
	(0.101)		(0.105)
lngerdpc	0.369***	lngerdpc	0.390***
	(0.0232)		(0.0232)
ivirpatpublicationsshare	0.0974	ivirpatgrantsshare	-0.285***
	(0.0728)		(0.0789)
socialdocsshare	-2.271***	socialcitabledocsshare	-1.995***
	(0.273)		(0.308)
trend	-0.0138**	trend	-0.0162**
	(0.00612)		(0.00633)
sqtrend	-0.000314	sqtrend	-0.000115
	(0.000261)		(0.000271)
Constant	8.611***	Constant	8.066***
	(0.484)		(0.504)
Mu	-15.26	Mu	-15.37
	(33.89)		(23.33)
Usigma	1.515	Usigma	1.582
	(2.105)		(1.436)
Vsigma	-2.825***	Vsigma	-2.767***
	(0.111)		(0.103)
Log-likelihood	-465.78	Log-likelihood	-515.90
Prob>chi2	0.0000	Prob>chi2	0.0000
Wald Chi2(13)	45324.04	Wald Chi2(13)	42663.74
SigmaU	2.13	SigmaU	2.20
SigmaV	0.24	SigmaV	0.25
Lambda	8.76	Lambda	8.80
Observations	1189	Observations	1189
Number of countries	82	Number of countries	82

*Note: ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.*

Table 4: Cost SFA Estimates

In Table 5, we present the efficiency estimates and descriptive statistics of Models A and B. On average, technical efficiency is 0.7770 for Model a and 0.7660 for Model B, respectively. Even though the variables included are different and represent different timing in the publication process, we see that standard deviations and ranges in both cases are similar.

Variable	Obs	Mean	Std. Dev.	Min	Max
TE Model A	1,189	0.7760	0.1360	0.0947	0.9615
TE Model B	1,189	0.7660	0.1422	0.0842	0.9600

Table 5: Technical efficiency for Models a & B

Tables 6 and 7 show Tests for differences in characteristics by TE quantiles. Column 1 shows the average and standard deviation for each quartile of the TE distribution, going from the least to the most efficient countries. The number of countries will not be equally distributed by quartile because we use the average TE by country to split an unbalanced panel. The following columns have the t-tests for the differences by quantile, and lastly, we present a joint orthogonality test for all the distributions. Countries have significant differences in terms of inputs and partial productivity measures when looking at the joint orthogonality test for all the variables by quartiles. When looking at individual differences, the test over the 3^{rd} and 4^{th} quantiles shows the differences between the two most efficient groups of countries. We have positive differences in gerd, docs, citable docs, and patgrants, which means that the most efficient group has less of each of these concepts than the second efficient group. We have a negative difference in docs/res and citable docs/res, which are both partial productivity measures, meaning that the most efficient countries produce more articles and citable articles. However, they also have a higher average cost of production gerd on docs and gerd on citable docs.

Variable	Mean/SE				T-test Difference						F-test
	1st quartile	2nd quartile	3rd quartile	4th quartile	(1)-(2)	(1)-(3)	(1)-(4)	(2)-(3)	(2)-(4)	(3)-(4)	orthogonality
gerd_000	14110.849	25342.021	35838.691	3845.920	-11231.172***	-21727.842***	10264.929***	-1.05e+04*	21496.101***	31992.771***	0.000***
	[1844.626]	[3415.377]	[5258.848]	[337.119]							
docs_000	36.230	90.035	113.677	29.598	-53.806***	-77.448***	6.632*	-23.642	60.438***	84.080***	0.000***
	[3.215]	[9.549]	[13.394]	[2.330]							
patpublications_000	62.426	78.865	70.184	9.189	-16.439	-7.758	53.236***	8.681	69.676***	60.994***	0.000***
	[11.833]	[16.501]	[9.746]	[1.067]							
citabledocs_000	38.253	102.577	130.309	32.296	-64.324***	-92.056***	5.958	-27.732	70.281***	98.013***	0.000***
	[3.359]	[11.386]	[15.833]	[2.546]							
patgrants_000	19.516	18.537	20.420	2.602	0.979	-0.904	16.914***	-1.883	15.935***	17.818***	0.000***
	[3.634]	[2.733]	[2.865]	[0.289]							
W	133.437	148.458	165.559	127.706	-15.021***	-32.122***	5.730	-17.101*	20.751***	37.852***	0.000***
	[4.197]	[3.337]	[8.017]	[5.387]							
docs_on_res	0.561	0.737	1.047	1.255	-0.176***	-0.486***	-0.694***	-0.310***	-0.518***	-0.207***	0.000***
	[0.019]	[0.016]	[0.051]	[0.053]							
citabledocs_on_res	0.584	0.784	1.097	1.356	-0.200***	-0.513***	-0.772***	-0.313***	-0.572***	-0.259***	0.000***
	[0.019]	[0.016]	[0.050]	[0.056]							
patpublications_on_res	0.105	0.124	0.123	0.122	-0.019	-0.018	-0.017	0.001	0.002	0.001	0.536
	[0.013]	[0.009]	[0.009]	[0.011]							
grants_on_res	0.065	0.088	0.086	0.075	-0.023**	-0.022**	-0.010	0.002	0.013*	0.011	0.017**
	[0.008]	[0.005]	[0.005]	[0.005]							
gerd_on_docs	287.597	227.378	176.203	108.251	60.220***	111.394***	179.347***	51.175***	119.127***	67.953***	0.000***
	[11.916]	[6.871]	[6.850]	[2.837]							
gerd_on_citabledocs	276.795	209.280	163.494	99.669	67.515***	113.301***	177.126***	45.786***	109.611***	63.825***	0.000***
	[11.822]	[6.303]	[6.122]	[2.580]							
gerd_on patpublications	37965.295	16245.952	13248.288	19298.674	21719.343*	24717.008**	18666.621	2997.664	-3052.722	-6050.387	0.047**
	[10261.227]	[4456.902]	[3818.279]	[6642.684]							
gerd_on_patgrants	52631.290	9134.886	5655.729	19579.226	43496.404***	46975.562***	33052.064**	3479.157	-1.04e+04**	-1.39e+04***	0.000***
	[13577.388]	[1815.420]	[1119.183]	[4469.435]							
TE by quartile (upper bound)	0.7360	0.8160	0.8605	0.9161							
Num. of countries (Obs)	26 (312)	18 (286)	17 (298)	21 (293)							

*Note: the values displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.*

Table 6: T-test difference by quartile of the technical efficiency distribution Model A

Variable	Mean/SE				T-test Difference						F-test
	1st quartile	2nd quartile	3rd quartile	4th quartile	(1)-(2)	(1)-(3)	(1)-(4)	(2)-(3)	(2)-(4)	(3)-(4)	orthogonality
gerd_000	15014.967	18212.647	40779.308	3980.447	-3197.680	-25764.341***	11034.520***	-22566.661***	14232.200***	36798.861***	0.000***
	[1899.510]	[3206.774]	[5171.379]	[346.349]							
docs_000	39.727	69.136	126.092	30.646	-29.409***	-86.366***	9.081**	-56.956***	38.490***	95.447***	0.000***
	[3.299]	[9.106]	[13.126]	[2.389]							
patpublications_000	65.482	52.403	90.744	9.487	13.079	-25.262	55.994***	-38.341**	42.916***	81.257***	0.000***
	[12.233]	[15.405]	[9.798]	[1.101]							
citabledocs_000	41.830	78.929	144.572	33.447	-37.099***	-102.742***	8.383*	-65.643***	45.482***	111.125***	0.000***
	[3.448]	[10.836]	[15.528]	[2.610]							
patgrants_000	20.400	9.353	28.227	2.680	11.047**	-7.828	17.720***	-18.874***	6.673***	25.547***	0.000***
	[3.757]	[2.295]	[2.988]	[0.298]							
W	145.677	128.047	167.556	132.991	17.630***	-21.879**	12.686*	-39.510***	-4.944	34.565***	0.000***
	[3.995]	[3.630]	[7.914]	[5.545]							
docs_on_res	0.603	0.747	0.959	1.302	-0.144***	-0.356***	-0.699***	-0.211***	-0.554***	-0.343***	0.000***
	[0.019]	[0.018]	[0.052]	[0.053]							
citabledocs_on_res	0.621	0.791	1.012	1.408	-0.170***	-0.391***	-0.787***	-0.221***	-0.617***	-0.396***	0.000***
	[0.020]	[0.017]	[0.051]	[0.056]							
patpublications_on_res	0.121	0.095	0.135	0.122	0.026	-0.015	-0.001	-0.041***	-0.027*	0.013	0.061*
	[0.014]	[0.008]	[0.010]	[0.012]							
grants_on_res	0.073	0.059	0.108	0.072	0.014*	-0.035***	0.001	-0.049***	-0.013**	0.036***	0.000***
	[0.008]	[0.003]	[0.006]	[0.006]							
gerd_on_docs	295.367	185.402	209.955	107.853	109.965***	85.412***	187.514***	-24.552**	77.549***	102.102***	0.000***
	[11.932]	[5.186]	[8.462]	[2.916]							
gerd_on_citabledocs	285.400	171.089	193.345	99.029	114.312***	92.055***	186.371***	-22.257**	72.060***	94.316***	0.000***
	[11.826]	[4.537]	[7.775]	[2.663]							
gerd_on patpublications	33549.939	23294.112	10897.203	19908.183	10255.827	22652.736**	13641.756	12396.909**	3385.929	-9010.980	0.138
	[10473.714]	[5162.270]	[2985.262]	[6874.144]							
gerd_on_patgrants	28679.260	35387.223	3916.853	20800.404	-6707.963	24762.407***	7878.856	31470.369**	14586.819	-16883.551***	0.021**
	[2681.278]	[13907.884]	[666.318]	[4648.083]							
TE by quartile (upper bound)	0.7340	0.8060	0.8500	0.9100							
Num. of countries (Obs)	24 (301)	19 (304)	18(301)	21 (283)							

*Note: the values displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.*

Table 7: T-test difference by quartile of the technical efficiency distribution Model B

Table 8 shows the ranking of countries by GERD participation. We add the other input (researchers), the relative price, and outputs to characterize countries. We include the cumulative summation of countries by quartile. It is worth noticing that the 20 biggest countries of the sample explain more than 92 percent of GERD, 88 percent of the researchers, 82 percent of documents and published documents, and nearly 95 percent of patent publications and grants. The big three, the USA, China, and Japan, explain the 58 percent of the GERD of the sample. Almost 20 percent of the researchers of the sample are in China, and another 20 percent are in the USA. In documents, both published and citable, the United States produces more than China, but in patent publications, China is ahead, while in grants, the USA continues to be the first. The averages mask the growth of China, a country which, at the beginning of the sample, was well behind the USA and had converged steadily. There are differences in productivity and CKO patterns among countries with similar efficiency levels. Take, for instance, South Korea and France, each one spending the same and with a similar number of researchers. France produces more publications, while South Korea produces more patents. The UK and India devote the same non-human resources. Still, the UK, on average, has four times the number of researchers than India, produces many more publications, and has overwhelmingly high patent publications or grants. A similar situation is true for Canada and Brazil. Most of the countries in the twenty biggest are developed. However, there are some big emerging, such as Brazil, India, Russia, and Turkey.

Rank	country	Gerd (%/World's)	Researchers (%/World's)	Docs (%/World's)	Patpublications (%/World's)	Citabledocs (%/World's)	Patgrants (%/World's)
1	United States	31.91000	19.13017	21.47678	18.55775	22.96982	21.56487
2	China	14.97007	20.11941	12.48207	22.32981	13.57460	12.47574
3	Japan	11.53345	11.46194	5.19384	24.94443	4.87247	27.97039
4	Germany	6.61783	5.38924	5.60740	8.25879	5.60793	7.86141
5	South Korea	3.92512	3.95123	2.29399	6.60833	2.13783	9.21395
6	France	3.82045	3.86941	3.95252	3.18725	4.10803	3.79616
7	United Kingdom	2.90494	4.05727	5.99758	2.02159	5.69084	1.96624
8	India	2.83957	1.02663	3.43079	0.23879	3.25227	0.17025
9	Canada	2.10245	2.27026	3.16762	1.03348	2.95609	0.99014
10	Brazil	1.99352	1.26631	1.72083	0.27435	1.63787	0.08036
11	Italy	1.78724	1.64756	3.21153	1.15420	3.23678	1.30946
12	Russia	1.76558	8.14913	2.16681	1.48867	2.14734	2.57173
13	Spain	1.21502	1.84335	2.57986	0.37163	2.50836	0.45294
14	Netherlands	1.05193	0.99109	1.77825	1.63181	1.65450	1.57009
15	Sweden	0.83225	0.78582	1.21145	1.03762	1.12164	1.19054
16	Austria	0.71645	0.46324	0.71074	0.46995	0.68070	0.54683
17	Belgium	0.68323	0.67439	0.99090	0.45206	0.93020	0.47227
18	Australia	0.66740	0.47310	2.47654	0.47137	2.26989	0.44821
19	Turkey	0.55956	0.87786	1.01813	0.12104	0.97128	0.04381
20	Singapore	0.51758	0.42415	0.59071	0.19378	0.54620	0.16075
	Cumulative	**92.41364**	**88.87156**	**82.05835**	**94.84671**	**82.87465**	**94.85613**
21	Mexico	0.49519	0.51102	0.61755	0.06617	0.58141	0.03081
22	Finland	0.48052	0.44653	0.63107	0.57466	0.59988	0.64885
23	Denmark	0.42993	0.51991	0.72054	0.43841	0.66115	0.41084
24	Poland	0.42435	1.18415	1.27633	0.20929	1.26919	0.22844
25	Norway	0.31024	0.36848	0.56190	0.22955	0.52023	0.24420
26	Czech Republic	0.30391	0.44213	0.62149	0.07187	0.60601	0.08136
27	Malaysia	0.28814	0.37981	0.61192	0.03722	0.57152	0.03882
28	South Africa	0.28037	0.25725	0.50467	0.10780	0.45858	0.12443
29	Argentina	0.27301	0.65299	0.38839	0.02896	0.36012	0.01094
30	Switzerland	0.26094	0.16996	1.29668	1.61823	1.20719	1.67879
31	Iran	0.25798	0.37896	1.06568	0.00429	1.09743	0.00278
32	Egypt	0.23755	0.46615	0.41427	0.00694	0.40101	0.00723

Rank	country	Gerd (%/World's)	Researchers (%/World's)	Docs (%/World's)	Patpublications (%/World's)	Citabledocs (%/World's)	Patgrants (%/World's)
33	Portugal	0.22716	0.51574	0.60382	0.03895	0.57865	0.02845
34	Ukraine	0.22542	0.53639	0.39617	0.12105	0.39374	0.22276
35	Thailand	0.20581	0.38863	0.35245	0.01382	0.31911	0.00822
36	Ireland	0.18826	0.25902	0.37480	0.18225	0.33891	0.16065
37	Hong Kong	0.17402	0.29497	0.60928	0.10559	0.57863	0.10367
38	Hungary	0.16179	0.33316	0.35325	0.07702	0.34373	0.06563
39	Greece	0.13445	0.27313	0.57695	0.04346	0.55513	0.04992
40	United Arab Emirates	0.11147	0.04815	0.11196	0.00976	0.10041	0.00638
41	Indonesia	0.09482	0.20499	0.30345	0.00376	0.27759	0.00204
	Cumulative	**97.97897**	**97.50309**	**94.45097**	**98.83578**	**94.69425**	**99.01133**
42	Romania	0.09371	0.35805	0.40516	0.05261	0.39520	0.06908
43	Pakistan	0.08221	0.19578	0.30083	0.00103	0.30542	0.00081
44	Slovenia	0.07805	0.11241	0.17983	0.03846	0.17774	0.05149
45	Colombia	0.07701	0.01312	0.20197	0.01554	0.18635	0.00336
46	Slovakia	0.06457	0.21268	0.21652	0.01942	0.20707	0.01591
47	New Zealand	0.05558	0.12773	0.42443	0.10066	0.38326	0.06501
48	Croatia	0.04457	0.10587	0.18950	0.02129	0.18051	0.01923
49	Bulgaria	0.04419	0.20686	0.14865	0.02090	0.14381	0.02043
50	Chile	0.04286	0.05639	0.28202	0.02625	0.26977	0.00890
51	Tunisia	0.03901	0.14404	0.18574	0.00491	0.17422	0.00093
52	Lithuania	0.03591	0.14125	0.10054	0.00846	0.09984	0.01284
53	Luxembourg	0.03540	0.03094	0.03961	0.11683	0.03654	0.11071
54	Vietnam	0.02872	0.15213	0.11743	0.00174	0.11863	0.00100
55	Algeria	0.02480	0.02993	0.14183	0.00082	0.13646	0.00028
56	Kuwait	0.02396	0.01204	0.04736	0.00258	0.04249	0.00369
57	Estonia	0.02352	0.06035	0.07811	0.01386	0.07788	0.01610
58	Morocco	0.01961	0.16107	0.12576	0.00934	0.12005	0.01005
59	Philippines	0.01793	0.05219	0.06724	0.00689	0.05944	0.00372
60	Costa Rica	0.01722	0.01700	0.02280	0.00247	0.02009	0.00115
61	Ecuador	0.01599	0.02337	0.04395	0.00540	0.04001	0.00052
62	Latvia	0.01444	0.06068	0.05277	0.01269	0.04940	0.01940
	Cumulative	**98.85823**	**99.77698**	**97.82301**	**99.31794**	**97.91841**	**99.44593**
63	Uruguay	0.01286	0.01984	0.03647	0.00407	0.03316	0.00151
64	Oman	0.00993	0.00513	0.03691	0.00040	0.03231	0.00021
65	Sri Lanka	0.00759	0.01943	0.03963	0.00133	0.03627	0.00052
66	Panama	0.00733	0.00431	0.01354	0.00603	0.01175	0.00549
67	Cyprus	0.00705	0.01132	0.05192	0.01694	0.05187	0.01503
68	Ethiopia	0.00592	0.01577	0.04448	0.00003	0.03947	0.00002
69	Moldova	0.00466	0.03237	0.01692	0.01594	0.01541	0.02888
70	Malta	0.00427	0.00816	0.01349	0.01298	0.01197	0.01082
71	Jordan	0.00351	0.01736	0.08142	0.00180	0.07892	0.00144
72	Georgia	0.00344	0.02126	0.03072	0.00591	0.03501	0.01034
73	Kenya	0.00338	0.00864	0.06303	0.00122	0.05485	0.00062
74	Bolivia	0.00290	0.00526	0.01384	0.00016	0.01220	0.00010
75	Paraguay	0.00276	0.00691	0.00561	0.00022	0.00411	0.00004

Rank	country	Gerd (%/World's)	Researchers (%/World's)	Docs (%/World's)	Patpublications (%/World's)	Citabledocs (%/World's)	Patgrants (%/World's)
76	Trinidad and Tobago	0.00223	0.00114	0.01257	0.00051	0.01085	0.00049
77	Madagascar	0.00221	0.00987	0.00775	0.00009	0.00678	0.00006
78	Guatemala	0.00212	0.00394	0.00567	0.00146	0.00493	0.00022
79	Senegal	0.00174	0.01797	0.01833	0.00179	0.01595	0.00327
80	Botswana	0.00132	0.00056	0.01371	0.00016	0.01203	0.00014
81	Ghana	0.00094	0.00289	0.03864	0.00023	0.03413	0.00027
82	Bahrain	0.00025	0.00037	0.01314	0.00070	0.01127	0.00048
	Total	**98.94463**	**99.98950**	**98.38079**	**99.38993**	**98.43167**	**99.52589**

Table 8: Ranking by country (sorted by average participation in World's GERD)

Table 9 shows efficiency estimates from our two estimated models ranked by GERD. Of the top 10 countries, Germany is the most efficient country (0.8429-0.8497), and Brazil is the least efficient (0.5856-0.5003). The rest of the top 10 countries have an efficiency that ranges from 0.7240 to 0.8418. There are some small countries (small should be understood as relative to the size of the country in terms of the world's figure in GERD, researchers, and their products) with good efficiency scores (they can attain relatively high-efficiency levels with low absolute levels of inputs and outputs). Nevertheless, their devoted resources and output yields are very modest in importance. Recall the averages are 0.7670 for Model a and 0.7660 for Model B, respectively.

Rank	Country	Gerd (%/World's)	TE Model A	TE model B
1	United States	31.91000	0.8174	0.8405
2	China	14.97007	0.8008	0.7791
3	Japan	11.53345	0.7240	0.7240
4	Germany	6.61783	0.8429	0.8497
5	South Korea	3.92512	0.8163	0.8177
6	France	3.82045	0.8083	0.8257
7	United Kingdom	2.90494	0.8418	0.8198
8	India	2.83957	0.8373	0.7714
9	Canada	2.10245	0.8004	0.7658
10	Brazil	1.99352	0.5856	0.5003
11	Italy	1.78724	0.8659	0.8678
12	Russia	1.76558	0.5828	0.6114
13	Spain	1.21502	0.8021	0.7920
14	Netherlands	1.05193	0.8701	0.8526
15	Sweden	0.83225	0.8461	0.8368
16	Austria	0.71645	0.7904	0.8061
17	Belgium	0.68323	0.8281	0.8023
18	Australia	0.66740	0.7575	0.7347
19	Turkey	0.55956	0.7279	0.7081
20	Singapore	0.51758	0.7894	0.7470
21	Mexico	0.49519	0.5440	0.4885
22	Finland	0.48052	0.7974	0.7920
23	Denmark	0.42993	0.8123	0.7765
24	Poland	0.42435	0.8717	0.8638
25	Norway	0.31024	0.6457	0.6322
26	Czech Republic	0.30391	0.8631	0.8623
27	Malaysia	0.28814	0.7181	0.7026

Rank	Country	Gerd (%/World's)	TE Model A	TE model B
28	South Africa	0.28037	0.7367	0.7290
29	Argentina	0.27301	0.5558	0.4975
30	Switzerland	0.26094	0.9045	0.8935
31	Iran	0.25798	0.8713	0.8720
32	Egypt	0.23755	0.7686	0.7478
33	Portugal	0.22716	0.7736	0.7618
34	Ukraine	0.22542	0.8031	0.8208
35	Thailand	0.20581	0.5352	0.5272
36	Ireland	0.18826	0.7606	0.7064
37	Hong Kong	0.17402	0.8668	0.8653
38	Hungary	0.16179	0.8479	0.8294
39	Greece	0.13445	0.8458	0.8352
40	United Arab Emirates	0.11147	0.2676	0.2586
41	Indonesia	0.09482	0.3439	0.3336
42	Romania	0.09371	0.8279	0.8267
43	Pakistan	0.08221	0.7279	0.7772
44	Slovenia	0.07805	0.8880	0.8961
45	Colombia	0.07701	0.9031	0.8910
46	Slovakia	0.06457	0.8271	0.8171
47	New Zealand	0.05558	0.8348	0.8068
48	Croatia	0.04457	0.8799	0.8755
49	Bulgaria	0.04419	0.8717	0.8643
50	Chile	0.04286	0.8731	0.8604
51	Tunisia	0.03901	0.9064	0.9087
52	Lithuania	0.03591	0.7256	0.7523
53	Luxembourg	0.03540	0.5772	0.5387
54	Vietnam	0.02872	0.3754	0.4077
55	Algeria	0.02480	0.6724	0.7217
56	Kuwait	0.02396	0.8196	0.8067
57	Estonia	0.02352	0.8680	0.8758
58	Morocco	0.01961	0.4590	0.4589
59	Philippines	0.01793	0.3121	0.2934
60	Costa Rica	0.01722	0.6473	0.6379
61	Ecuador	0.01599	0.4667	0.4419
62	Latvia	0.01444	0.8195	0.7956
63	Uruguay	0.01286	0.8010	0.7873
64	Oman	0.00993	0.8763	0.8848
65	Sri Lanka	0.00759	0.7084	0.7580
66	Panama	0.00733	0.8606	0.8298
67	Cyprus	0.00705	0.8985	0.9034
68	Ethiopia	0.00592	0.8904	0.8662
69	Moldova	0.00466	0.8723	0.8463
70	Malta	0.00427	0.8180	0.7801
71	Jordan	0.00351	0.8737	0.8893
72	Georgia	0.00344	0.8205	0.8607

Rank	Country	Gerd (%/World's)	TE Model A	TE model B
73	Kenya	0.00338	0.7795	0.8130
74	Bolivia	0.00290	0.5117	0.6190
75	Paraguay	0.00276	0.3658	0.3963
76	Trinidad and Tobago	0.00223	0.7912	0.8175
77	Madagascar	0.00221	0.8720	0.8389
78	Guatemala	0.00212	0.6129	0.5975
79	Senegal	0.00174	0.6312	0.7585
80	Botswana	0.00132	0.8192	0.8832
81	Ghana	0.00094	0.9161	0.8988
82	Bahrain	0.00025	0.7606	0.8019

Table 9: Model a and B (Efficiency sorted by average participation in the world's GERD)

DISCUSSION

Efficiency scores are similar between models, even though they represent different knowledge cost functions. Countries have significant differences in terms of inputs and partial productivity measures. The most efficient group has more of gerd, docs, citable docs and patgrants compared to lower quantiles of the TE distribution. In contrast, costs in developed countries are higher than in developing countries. We also show that the costs of producing COK decline with the level of development of the country, the costs of producing knowledge decrease with output volume, and the production costs of papers in natural sciences, medicine, or engineering are more expensive to produce than social sciences. Also, our results show that there is competition between resources for patents and publications and that the lag between the production of an article and its first citation may affect the estimations.

A concern in the literature is the separated presentation of resource and output statistics; some studies engaged with the former, some do in the latter, and hardly both are considered together. We address this issue by generating a database composed of outputs, inputs, costs, and relative prices of the inputs. Aksnes et al. (2017) raise this issue; they investigate methodological problems in measuring research productivity on the national level by comparing official R&D statistics from the OECD with data on publications from the Web of Science for 18 countries. They propose improvements to enhance the comparability of data sources. They point out that resource and output statistics are customarily presented as separated instead of combining them into productivity measurements.

In our study, the unit of analysis is more aggregated than those commonly found in the literature, and we focus on SFA. Nor is SFA superior to DEA; conversely, both methods have relative advantages and disadvantages. A comprehensive review of the application of parametric and non-parametric frontier techniques to analyze Research and Development (R&D) systems efficiency can be found in Bonaccorsi and Daraio (2004). Also, Bonaccorsi and Daraio (2003), as an example of more aggregated studies than ours, analyze data on scientific productivity at institutes of the French INSERM and biomedical research institutes of the Italian CNR for the year 1997. Available data on human capital input and geographical agglomeration allows the estimation and comparison of efficiency measures for the two institutions.

Quality of contributions is an important discussion in science and technology efficiency and productivity measurement. In our database, and because of its aggregation level, we cannot address more precisely quality aspects. Nevertheless, the generation of environmental variables points to solving this issue. We are aware that qualitative aspects have a subtle but important difference from environmental ones: quality addition implies volition and deliberate efforts, while environmental conditions can be passive from the point of view of the NIS (for example, NIS cannot influence the global quality of national institutions). For instance, using the Science and Engineering Indicators report of the US National Science Foundation, Bornmann et al. (2018) investigated 21 countries' literature cited in top-quality journals from 2004 to 2013, assuming citation as a qualitative distinction for publications. China has emerged as a major player in science. However, in the Bornmann et al. (2018) sample, China remains a low contributor in the citations of the top 1 percent of articles. That can be attributed to the recent growth of this country to the pool of contributions; on the other hand, citations are a proxy of the quality of the contribution.

Publication in scientific journals is a product of inventive effort; however, it is more an indicator of scientific exploration than of commercialization. Thus, scientific innovation can be perceived as the non-commercial final output. For us, it is a challenge to measure the DUI outputs and inputs to perform a sequel of this paper's analysis, the part we do not cover in this article on NIS efficiency. In the literature, we find that Guan and Chen (2012) propose a relational network data envelopment analysis (DEA) model for measuring the innovation efficiency of the 22 OECD countries' NIS by decomposing the innovation process into a two-stage production framework: an upstream STI knowledge production process, and a downstream DUI knowledge commercialization process. They identify in most countries a significant rank difference between STI and DUI subsystems, indicating a non-coordinated relationship between both stages. The empirical study benchmarked the relative efficiency of the two internal NIS sub-processes of 22 OECD nations. It also explored the determinants of variations in efficiency across those nations in the two individual sub-processes.

Universities and similar institutions are evaluated either by peer review or by bibliometrics, which is cheaper and more objective than peer review, although biased to scholars and disciplines with relatively intensive publication activity. Results change according to each scientific field and technique applied. In our case, we address the differences in costs between publications in social versus natural sciences and corroborate that the latter are more expensive. Preceding us, Coccia (2008) addresses how is it possible to separate high performing from low-performing research units within each research field, recognizing the differences.

We find that the most important contributors to global R&D expenditure are not necessarily ranked as world-top performers. Several recent studies address efficiency and productivity measurement in science and technique on a national basis. Carrillo (2019) assesses the R&D efficiency of countries using DEA. Afterward, the overall performance score is obtained with the cross-efficiency method, and countries are listed according to their R&D performance. Switzerland, the United Kingdom, and the Netherlands are the three leading countries. The sample of Carrillo (2019) comprises 33 countries with significant involvement in R&D activities (above 1 percent of the World's activity), to which efficiency scores were obtained with an output-oriented VRS DEA model. Also, Ferro and Romero (2021), using a Data Envelopment Analysis (DEA) efficiency frontier approach, study which countries are more efficient at producing scientific articles and patents. They find efficient countries that are both small and not traditional knowledge producers. When scale and regional effects are controlled, the results favor developed countries and Eastern and Central Asian ones.

There are some small countries with good efficiency scores. Nevertheless, their devoted resources and output yields are very modest in importance. The small country issue is puzzling and already discussed in the literature. Kotsemir (2013) reviews the application of the DEA method for measuring the efficiency of national innovation systems (NIS), providing a comprehensive review of 11 empirical studies on a cross-country analysis. When "small" (in terms of national innovation system scope and the level of development) countries are included in the country sample, those become the efficient ones. In general, the studies use samples from less than 30 countries in the studies. The most efficient national innovation systems are OECD countries, normally overrepresented in the samples because of data availability.

Since the main drawback of the SFA approach is that it cannot include multiple outputs in its production analysis, there are two possibilities to overcome the problem: one is the cost function analysis we apply in this study, and the other is the distance function approach that is an appropriate method for the multiple input-output frameworks of SFA. Hu et al. (2014) apply the distance function approach for stochastic frontier analysis (SFA) to compare R&D efficiency across 24 nations during 1998-2005. R&D expenditure stock and R&D manpower are treated as inputs, while patents, scientific journal articles, royalties, and licensing fees are the outputs. Intellectual property rights protection, technological cooperation among business sectors, knowledge transfer between business sectors and higher education institutions, agglomeration of R&D facilities, and involvement of the government sector in R&D activities are environmental conditions that significantly improve national R&D efficiency.

The discussion on the scale is also present in the R&D efficiency debate. Some of the big ones in the top ten are developing countries, which are consistent with the trend of decreasing costs. Most of the countries in the twenty biggest are developed. However, there are some big emerging, such as Brazil, India, Russia, and Turkey. Nasierowski (2010) aims to clarify whether the so-called innovation leaders are efficient in transforming innovation inputs into outputs. Based on the European Innovation Scoreboard (EIS), the efficiency of investment in innovation is examined with the use of the DEA model. It is observed a similar phenomenon as we observed in our sample: the so-called laggards in innovation are often efficient in their use of resources, whereas leaders of innovation fall short in returns to scale and congestion.

Previous empirical results indicate that the overall technical inefficiencies of the NIS activities in European and Asian countries are primarily due to pure technical inefficiencies rather than scale inefficiencies. This is also visible in our cost-efficiency study. Pan et al. (2010) apply the traditional DEA models, bilateral models, and critical performance measures, respectively, combining multiple outputs and inputs to measure the magnitude of performance difference between NIS in 33 Asian and European countries. The bilateral comparison analysis indicates that the Asian group is a better performer than the European group in production activities.

As already mentioned, innovation leaders do not always have the most efficient innovation systems, and modest innovators are not necessarily inefficient in transforming innovation inputs into outputs of innovation. Matei and Aldea (2012) measure and compare the performance of some NIS using the IUS 2011 database to estimate efficiency.

The big three, the USA, China, and Japan, compete and alternate in productivity and efficiency rankings. The relative price between non-human and human inputs reflects the relative intensity of non-human resources technology of production in the USA compared to other countries. Nasierowski and Arcelus (2003) present a non-parametric approach to identify the extent to which a decrease in the productivity growth of many countries can be explained by differences in efficiency and differences in scale and congestion. The model recognizes two types of outputs as the result of the R&D process: patents and their spillover effect onto the economic base of the country. The database consists of the countries included in the World Competitiveness Report.

Environmental conditions are important to explain differences in the performance of NIS since "institutions" vary between national realities. Carvalho et al. (2015) examine the socio-economic factors that contribute to the EU's innovative performance, using two linear regressions, considering as dependent variables, respectively, the patents required and the percentage of innovative sales. This study concludes that the most important explanatory variables for patents are private

R&D expenditure, percentage of innovative firms, and public R&D. Similarly, addressing environmental or contextual issues, Coccia and Rolfo (2007) investigate the relationships between organizational changes and productivity in public research institutions within the Italian national system of innovation, during the period 1999-2003, which is characterized by mergers and consolidation among research units. Their sample is analyzed through DEA and applied to researchers, technicians, administrative staff, cost of personnel as inputs, and the number of domestic and international publications as outputs. They find that new policy is generating lower research productivity and scale diseconomies in larger laboratories due to the bureaucratization of these larger new bodies.

Our national focus has obvious limitations. Knowledge production is an increasingly global endeavor. Despite robust increases in scientific production by traditional leaders, their relative share has decreased in recent decades because the pace of growth in science by other nations has been even more rapid. The share of international collaborations has also increased, as has the share of citations to papers with foreign authors. However, location retains considerable importance in science (Packalen, 2019) because borders continue to influence scientist interactions and because many important science policy decisions are set at the national level.

CONCLUSIONS

Endogenous growth models emphasize the importance of knowledge to generate sustained economic growth. There are several explanations of how knowledge is produced and is conducive to innovation. An encompassing concept in this discussion is NIS, which highlights the interlinks between different kinds of actors to produce knowledge aimed at innovation. The NIS can be split into two subsets: one based on scientific and technological work, producing codified products (scientific publications and patents of inventions), and the other centered on practical and non-codified actions to diffuse, apply, and use knowledge. Our objective is to measure the cost efficiency of the codified knowledge outputs, which are produced with human and non-human resources. In the literature there are inventories of resources and outputs, often studied separately, there are also partial productivity indexes tempting to compare performance, and frontier studies are trying to capture the efficiency of the whole process. The frontier studies are developed as empirical assessments that resort to mathematical programming or econometric techniques.

We examine efficiency using an SFA model; adding to the two versions of explanatory cost frontiers, we estimate some environmental conditions to address differences between development levels of the countries and types of patented technologies to differentiate social from natural sciences in the production of publications, etc. Our database uses information from different sources on scientific publications and patents for 82 countries for 23 years, totaling 1189 observations. Patents and publications are produced by human resources (researchers) together with non-human inputs (funds).

In the sample, 20 out of 82 countries explain more than 92 percent of the financial resources devoted to research and development, 88 percent of the researchers, 82 percent of documents and published documents, and nearly 95 percent of patent publications and grants. The average efficiency of the estimates is in the order of 0.77, indicating 23 percent of cost redundancy. Of the biggest countries in the sample, the United States, spending 32 percent of the sample costs, has efficiency scores of 0.82 to 0.84, depending on the model. China, which is the second country in importance, has an efficiency score of 0.80 to 0.78, depending on the specification.

The growth of China in the last two decades is impressive. Among developed countries, the most efficient are Switzerland and the Netherlands. In Latin America, the best performers are Colombia and Chile by far, while Brazil, Argentina, and Mexico have poor efficiency scores, on the verge of 0.50. There are small countries by their participation in the sample and by all criteria (population, GDP, territory, scientific tradition) that perform well, even though the absolute levels of output and inputs are modest.

The next is to examine efficiency in the DUI subsystem of NIS and the interactions between DUI and STI subsystems, which is challenging because of the difficulty of measuring DUI outputs.

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