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 the application of knowledge to generate new products or new 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 scientifical 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 countries. To attain our goal, we apply a Stochastic Frontier Analysis (SFA) to estimate a cost frontier of CKO. The sample is a panel that 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, Knowledge, Codified scientific knowledge

JEL Codes

1. Introduction

Knowledge applied to innovation is increasingly recognized as an explanatory factor of economic growth. Early economic growth models treated technical change as exogenous, while more recent ones recognize its endogenous role (Barro and Sala-i-Martin, 2003). Thus, if knowledge production is assumed as endogenous, derived from the deliberate effort in human and non-human investments in that endeavor, its production process can be analyzed, its cost function can be estimated, efficiency in the use of the resources can be explored, and some policy conclusions can be drawn.

Nevertheless, evaluating the outcomes of knowledge production is challenging. While some authors look at indicators of output or an inventory of inputs to produce knowledge, others look at the relationship between outputs and inputs and calculate partial productivity indexes. However, it is relevant to consider the relevant input and output vector altogether in a production or cost function estimation, and if the discussion is on efficiency, in production or cost frontiers estimates. Knowledge generation is not synonymous with innovation. The latter derives from the application of knowledge to generate new products or new processes.

After a conceptual evolution of the knowledge production and innovation processes explanations, made in the literature section, there is some consensus about the role of National Innovation Systems (NIS) performs as the formal or informal network of people within institutions, interacting to produce and apply knowledge to innovation. These NIS can be understood, in turn, as two subsystems: one based on scientifical 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.

Codified knowledge products 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

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costs, inputs, and outputs, while non-codified knowledge is embodied in people's minds or embedded in organizations, and its measurement is quite elusive.

Our objective is to assess cost efficiency in the production of codified knowledge outputs (CKO), being our unit of analysis countries. 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). 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 at the root of economic analysis: it concentrates on the best administration of resource scarcity, and it is useful for ex-ante planning and ex-post evaluation. Efficiency estimates can be made on pure technical conditions (output to input relationships) or in terms of allocative conditions (cost to output relationships), which is our approach. In the same vein, frontier methods permit estimating efficiency from databases using mathematical programming or through econometric methods, which is our choosing. A methodological discussion is made in the respective section.

To attain our goal, we apply a Stochastic Frontier Analysis (SFA) to estimate a cost frontier of CKO, considering relevant inputs and "environmental" conditions to address country-specific conditions.

Our database is built on different sources for outputs (Scimago for publications and citations and WIPO for patents), costs, inputs, and input prices (UNESCO), and macroeconomic and institutional issues (The World Bank and Heritage Foundation) to characterize the environment of CKO production. The sample is a panel that 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. There are several efficiency frontiers analyses on the issue we discuss. We develop a literature review to discuss the antecedents and we find that our contribution differs from precedent in 1) the extensive database, built from different sources and encompassing developed and developing countries; most of the literature uses smaller databases, focused on OECD countries; 2) the method and the approach since in the literature predominates mathematical programming studies concentrated on technical efficiency, while our approach is econometric and concentrates on allocative efficiency since we estimate a cost frontier.

After this introduction, section 2 makes a literature review, section 3 presents the sample, the method, and the models, section 4 shows the estimates and discusses the results, and section 5 concludes.

2. Literature Review

A national innovation system (NIS) can be defined as a network of institutions in the public and private sectors whose formal or informal activities and interactions initiate, import, modify and diffuse new technologies. The concept is used to characterize 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, often finding new solutions to existing problems, and it does not need previous research. Innovations are made by entrepreneurs and depend on a society's adoption (The World Bank, 2010). The system notion emphasizes cooperation and linkages in the process of innovation (Manzini, 2012).

As Lundvall (2005) points out, mechanistic versions of NIS indicate something that can be constructed, governed, and manipulated by policymakers. Nevertheless, the NIS approach has not been applied to system building. When applied to developing countries, the emphasis is on system construction and promotion (Lundvall, 2007 b). The experience of the former Soviet Union as well as from middle-income developing countries is that the separation and lack of interaction between the CKO infrastructure and the firms prevent innovation. Higher education and training systems that assist only public administration or produce large numbers of underemployed scholars do not promote innovation (Lundvall, 2007 a).

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, et cetera). 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, 2007 a, 2007 b, Manzini, 2012, Atkinson, 2020, Acs et al., 2016, Eggink, 2013, OECD, 1997).

The CKO varies in its degree of public good: the definition of the latter concept designs 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. The benefits of research generated in one place can hardly be captured locally. Secrecy would prevent innovation. A technological advantage can thus only be private and locally captured temporarily (Etzkowitz, 2011).

Thus, 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) while 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 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 (Faberger, 2017). 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 are benefited from free-rider effects, information spillovers, and learning from the experiences of pioneers (Fan, 2014).

The differences in NIS quality depend on “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 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, 2007 a, Manzini, 2012, Atkinson, 2020, Acs et al., 2016, 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 for solving complex problems (Heller and Eisenberger, 1998). In the late 19th century research was added 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 the ideology of pure science 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. 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).

Lundvall (2007 b) 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 for the creation of new technology platforms in areas relating to defense and health (Etzkowitz, 2015). The US system for supporting scientific research is based on support for mission-oriented research (e.g., defense and health) largely to federal labs, and support for basic, curiosity-directed research through university funding (Atkinson, 2020, Faberger, 2017). Lundvall (2007 a) 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 with others. Therefore, private companies might expect barriers to access to accumulated knowledge since universities would come more reluctant to share knowledge otherwise salable.

Teaching guarantees to universities a comparative advantage as a source of innovations over other forms of knowledge producers, 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, through student generations (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 with an emphasis on national competitiveness. STI policy focused on building links, clusters, and networks, stimulating learning between elements in the systems, and enabling entrepreneurship (Schot and Steinmueller, 2018).

There seem to be two ways to conceptualize knowledge utilization in innovation activities: a process or a system. Before the late 1960s and early 1970s, theorists studied innovation in terms of a process composed of “sequences” and “stages”. The process is meant a sequence of acts. The idea of a sequential process emphasizes a series or “chain” of activities, where research is conceived as a modern method of accelerating industrial evolution. (Godin, 2017). The linear model of innovation postulates that technological 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 the linear model of research 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).

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 1920 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 1970 and 1980s, which was of limited use to explain technological innovation (Godin, 2017).

A new kind of explanation appeared in the Post WWII: the system model. The system concept was popular in the 1950 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, and Bengt-Ake Lundvall to early OECD works from the 1960s. Such a national framework has been very influential as a rationale for the development of national policies to stimulate technological innovation (Godin, 2017).

Table 1: A Synthesis of innovation models

Type of model	Contextual factors involved	Actors
Invention-diffusion	Civilizing and modernizing social practices and societies	Anthropologists (studying culture as a biological organism)
Stage chain process (from invention to adoption)		Sociologists (studying mechanisms of social change)
Linear innovation (basic research leads to applied research, development, and commercialization)	Funding research	Industrialists and economists (studying ways to promote economic development)
Demand-led innovation (social needs or market demand leads to basic research, applied research, development, and commercialization)		
National Innovation System (by STI and DUI modes and through interactions, leads to innovation within national contexts and institutions)	Supporting firms' innovative activities	Managers and policymakers

Source: Authors' elaboration on 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 in publications, patents, and other sources, are inputs for innovation (OECD, 1997).

The most traditional type of knowledge flow in the innovation system may be the dissemination of technology as 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. The concept of NIS points to solving systemic failures which may impede innovation, such as lack of interaction between actors, mismatches between basic and applied research, malfunctioning of the technology transfer institutions, and information and absorptive deficiencies in enterprises (OECD, 1997).

The measurement and the evaluation of scientific research are important and useful activities to allocate resources. However, most research has elements of public goods not easy to quantify, and the goals of scientific institutions are more complex than those of private businesses. Universities or public research units seek to maximize prestige, which in turn is a function of other variables that are not easily measured. Measurement of efficiency and productivity of science and technology involves also difficult choices between different techniques, each one containing relative advantages concerning alternatives. We discuss this issue in the next section.

Aksnes et al. (2017) 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.

A comprehensive review of the application of parametric and non-parametric frontier techniques to in analysis the efficiency of Research and Development (R&D) systems can be found in Bonaccorsi and Daraio (2004). Bonaccorsi and Daraio (2003) 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. The methods applied are nonparametric envelopment techniques and robust nonparametric techniques.

Quality of contributions is an important discussion in science and technology efficiency and productivity. Using the Science and Engineering Indicators report of the US National Science Foundation Bornmann et al. (2018), investigate 21 countries' literature cited in top-quality journals, from 2004 to 2013. China has emerged as a major player in science. However, in his sample, China remains a low contributor in the citations of the top 1 percent of articles.

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. 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

Coccia (2008) addresses how is it possible to separate high performing from low-performing research units within each research field. Universities and similar institutions are evaluated either by peer review, which has some drawbacks due to its subjectivity and high cost, or by bibliometrics, which is cheaper and more objective than peer review, although biased to scholars who publish and disciplines with relatively intensive results publication. A model is presented to measure and evaluate the scientific research performance of Italian public research institutes. Results change according to each scientific field and technique applied. DEA method shows that research units with a higher percentage of efficiency are in the Technological, Engineering, Information Sciences, and Basic Sciences, whereas a lower percentage of efficiency is found in Social and Human Sciences. Conversely, other methods show that high performers are present in Basic and Social–Human Sciences, which are less intensive in non-human resources than their counterparts in the natural sciences.

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, obtains the overall performance score 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, while other countries that make important investment efforts in terms of their GDP, such as Japan or Israel, do not seem to obtain comparable results. 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. The most important contributors to global R&D expenditure are not necessarily ranked as world-top performers, with some lower R&D-intensive economies ranking higher than some of the largest world investors such as the United States, China, or the Republic of Korea.

Ferro and Romero (2021) explore how the best-performer countries produce more outputs (scientific articles and patents) with the same inputs or produce the same with fewer inputs. Using a Data Envelopment Analysis (DEA) efficiency frontier approach, they study which countries are more efficient at producing codified knowledge. They distinguish efficiency by country, geographical region, and income area. Under constant returns to scale, the most traditional producers of knowledge are not fully efficient. Instead, a handful of small countries with limited resources appear to be efficient. When environmental conditions are added, both sets of countries are efficient producers of knowledge outputs. High-income regions, on the one hand, and East Asia, North America, Europe, and Central Asia, on the other, are the most efficient regions at producing knowledge.

The small country issue is puzzling. 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. Different indicators of R&D personnel were used as "human capital" input variables in many reviewed papers. The main "investment" input variables were different indicators of R&D expenditures. These indicators were used in all reviewed studies. Different indicators of patent activity were taken as output variables in all reviewed papers. Publication activity indicators were included in the list of output variables in six cases. Indicators of high-tech export variables were taken as output variables in five cases, while authors take different meanings of high-tech export in their studies. In general, the small size of country samples is the main limitation of all reviewed studies. The review detects general trends and differences in the sets of variables and the content of country samples and highlights the problem of "small countries bias" in the reviewed studies. 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 all reviewed studies countries from Western Europe and North America were dominant. In general, the studies use samples of less than 30 countries in the studies. The most efficient national innovation systems (countries) are OECD countries, usually 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 analysis, the distance function approach 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. 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 that 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. For small countries, there may be a lack of economies of scale and associated synergies. In other cases, problems with congestion may result from a lack of clearly identified patterns of specialization, poor coordination between government-supported research institutions and businesses, inefficient commercialization of inventions, and inadequate transfer of knowledge between various agents involved in innovative activities.

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. Empirical results indicate that the overall technical inefficiencies of the NIS activities in these countries are primarily due to pure technical inefficiencies rather than scale inefficiencies. The bilateral comparison analysis indicates that the Asian group is a better performer than the European group in production activities.

Matei and Aldea (2012) measure and compare the performance of some NIS using the IUS 2011 database to estimate efficiency. Their analysis tries to capture the interactions among the actors involved in the process, and how their inputs are translated into outputs. The inputs selected to describe NIS capture the availability of an educated workforce, the quality of the research system, collaboration efforts among firms and the public sector, and intellectual assets. On the other hand, the outputs describe the economic effects of the innovation measured by labor market quality and the value of exports. Matei and Aldea (2012) conclude that innovation leaders do not always have the most efficient innovation systems as well as modest innovators, are not necessarily inefficient in transforming innovation inputs into outputs of innovation.

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 by 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. The NIS inputs reflect each country's ability to improve technology, either by production or through acquisition from abroad. They also involve its ability to include the private sector in such an endeavor and to educate and attract the labor force needed within a NIS.

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. The private R&D investment explained 86.6 percent of the variation in the number of patents.

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 laboratories, due to the bureaucratization of these larger new bodies. The results also show that institutes of small size are more productive than large-sized labs.

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. While this perspective suggests a diminishing influence of location in scientific work, location may have considerable importance in science. Location may thus influence the tendency to pursue work that is close to the edge of the scientific frontier in the sense that it builds on recent ideas. Packalen (2019), calculates each nation’s position concerning the scientific frontier by measuring its propensity to build on relatively new ideas in biomedical research and selects countries as the unit of analysis because borders continue to influence scientist interactions and because many important science policy decisions are set at the national level. Daily interactions with colleagues, the training environment, and ready access to potential collaborators thus become especially important in work that is close to the edge of the scientific frontier in the sense that the work builds on recent advances.

3. Data, Method, and Models

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

3.1 Data

Table 2 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”. 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. On the other hand, according to the World Bank, 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”. Researchers are the human resources in a production frontier and an important variable to compute, along with GERD, the relative price of inputs, needed in the cost frontier estimates. GERD is expressed in the US dollar, at PPP constant values of 2010, attributes which allow comparisons between countries and years.

In our models (see subsection 3.3) we run 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. Table 2 displays the variable definitions. We also defined some partial productivity indicators which 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[3].

Table 2. Variable definitions

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	Input Relative Price	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	

[3] 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).

GERD_on _docs	Gerd/docs
GERD_on_citabledocs	Gerd/citabledocs
GERD_on_patpublications	Gerd/ Patpublications
GERD_on_patgrants	Gerd /Patgrants

Researchers are counted as Full-Time Equivalent.
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.

Table 3 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[4].

Table 3. Descriptive statistics

	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

Source: See Table 2.

3.2 Method and Models

[4] To get the final number of observations, first, we drop countries with incomplete information: Serbia, Sudan, Iraq, Montenegro, North Macedonia, Macau, Seychelles, Brunei Darussalam, Mauritius, Kazakhstan, Bermuda, Kyrgyzstan, Saint Vincent and the Grenadines, the Democratic Republic of the Congo, Angola, Saint Lucia, Togo, Monaco, Papua New Guinea, Burundi, Central African Republic, Iceland, Tajikistan, Namibia, Bosnia and Herzegovina, Cambodia, Chad, Rwanda, Gambia, Uzbekistan, American Samoa, Libya, Nauru, Qatar, Syria, Venezuela, Myanmar, Albania, Mali, Nigeria, Tanzania, Uganda, Zambia. Moreover, we remove the countries that contributes with less than 0.005% of total publications (Cabo Verde, El Salvador , Eswatini, Gabon, Guinea, Honduras, Laos, Lesotho, Mauritania, Nicaragua, Niger). To avoid removing Canada in 1996, we approximate the missing GDP per capita by subtracting the population growth rate (0.998%) to the real GDP growth (in 2012 prices) between 1996 and 1997 (4.56%). Hence, the GDP per capita is approximately 3.56% less than the GDP per capita in 1997.

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 in 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 frontiers 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 publication. 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 there are multiple decision-making units (DMU) and periods, 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 2005 a, and Greene2005 b).
4) Models with persistent and residual inefficiency, and with unobserved heterogeneity 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 Trans logarithmic (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 Trans log 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 trans log 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 u_{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 Battesse and Coelli (1995) model, where:

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

and

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

Where

$$S = 1\ for\ production\ frontiers, \text{ and } and\ S = -1\ for\ cost\ frontiers$$

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 terms u_{it} and v_{it} are assumed independent of each other, as well as independent and identically distributed as:

$$v_{it} \sim N(0, \sigma_v^2)$$

$$u_{it} \sim N^+(z_{it}, \sigma^2)$$

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:

$$E(u_{it}|v_{it} + u_{it}) \text{ (6)}$$

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, which is 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 totally explained by randomness, while if it is the unit, inefficiency explains the whole volatility.

The general form of our cost frontier is:

$$C_{it} = C(y_{it}, w_{it}, z_{it}; \beta) + v_{it} + u_{it} \qquad (7)$$

Where C_{it} is the observed cost for each DMU *i*, in period *t*; y_{it} is the output vector; w_{it} is the input price vector; z_{it} is the environmental variable vector; β is the unknown parameter vector to estimate.

3.2 Models

We estimate two trans-log 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).

Table 4. Estimated models

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
	Ivirpatpublicationsshare	---
	---	ivirpatgrantsshare

Source: Authors' elaboration

4. Estimates

The model used for the estimations is Battese & Coelli's (1995) time-varyingng model of inefficiency. Using the sfpanel command, the model is available as bc95. From the help in Stata: "the Battese and Coelli (1995) model, in which the u_{it} is obtained by truncation at zero of the normal distribution with mean (Z_{it}*), where Z_{it} is a set of covariates explaining the mean of inefficiency".

In Table 5, we present both estimates for models A and B, respectively. The differences between the two models are the outputs (and their crossed and squared effects). Not all publications are cited, nor the citable publications are the same as the former. There is a lag between the paper being sent to publishing and it being finally 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 started 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 here presented (See Annex).

Continuing with the discussion of the results, 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 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.

Fourth industrial revolution type of patent publications reveals non significantly different from zero in model A, while the same consideration made for patent grants is significant and negatively affecting costs. This can be explained by the synergy of different types of technologies in the Fourth industrial revolution 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, et cetera.

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, in -1.62 percent yearly.

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

Table 5. Cost SFA Estimates

Model A	Ln(gerd)	Model B	Ln(gerd)
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.

In Table 6, we present the efficiency estimates and descriptive statistics Models A and B. On average, technical efficiency is 77.7% for Model A and 76.6% for Model B, respectively. Even that 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.

Table 6. Technical efficiency for Models A & B

Variable	Obs	Mean	Std. Dev.	Min	Max
TE Model A	1,189	77.66%	13.60%	9.47%	96.15%
TE Model B	1,189	76.60%	14.22%	8.42%	96.00%

Tables 7 and 8 show Tests for differences in characteristics by TE quantiles. Columns 1 show 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 distribution. 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 3rd and 4th quantile is showing the differences between the two most efficient group 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 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 on res and citable docs on 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.

Table 7. T-test difference by quartile of the technical efficiency distribution Model A

	Mean/SE				T-test Difference						F-test
Variable	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)	73.6%	81.6%	86.05%	91.61%							
Num. of countries (Obs)	26 (312)	18 (286)	17 (298)	21 (293)							

Note: The value 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 8. T-test difference by quartile of the technical efficiency distribution Model B

Variable	Mean/SE 1st quartile	1st quartile	1st quartile	1st quartile	T-test Difference (1)-(2)	(1)-(3)	(1)-(4)	(2)-(3)	(2)-(4)	(3)-(4)	F-test 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)	73.4%	80.6%	85.0%	91.0%							
Num. of countries (Obs)	24 (301)	19 (304)	18(301)	21 (283)							

Note: The value 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 9 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 near to 95 percent of patent publications and grants. The big three, 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, country which at the beginning of the sample was well behind the USA and had converged steadily. The relative price between non-human and human inputs reflects the relatively intensive in non-human resources technology of production in the USA concerning other countries. Differences in productivity and patterns of CKO. Take for instance South Korea and France, each one spending the same and with similar number of researchers. France produces more publications, while South Korea produces more patents. The UK and India devote the same non-human resources, but the UK, on average, has four times the number of researchers than India, produces much more publications, and has overwhelmingly high patent publications or grants. A similar situation is true for Canada and Brazil. Most of the countries into the twenty biggest are developed, however, there are some big emerging, such as Brazil, India, Russia, and Turkey.

Table 9. Ranking by country. Sorted by average participation in total GERD

Ranking	country	gerd	researchers	w	docs	patpublications	citabledocs	patgrants
1	United States	31.91	19.13	3.74	21.48	18.56	22.97	21.56
2	China	14.97	20.12	1.57	12.48	22.33	13.57	12.48
3	Japan	11.53	11.46	2.50	5.19	24.94	4.87	27.97
4	Germany	6.62	5.39	3.06	5.61	8.26	5.61	7.86
5	South Korea	3.93	3.95	2.41	2.29	6.61	2.14	9.21
6	France	3.82	3.87	2.52	3.95	3.19	4.11	3.8
7	United Kingdom	2.90	4.06	1.82	6.00	2.02	5.69	1.97
8	India	2.84	1.03	0.61	3.43	0.24	3.25	0.17
9	Canada	2.10	2.27	2.01	3.17	1.03	2.96	0.99
10	Brazil	1.99	1.27	2.00	1.72	0.27	1.64	0.08
11	Italy	1.79	1.65	2.80	3.21	1.15	3.24	1.31
12	Russia	1.77	8.15	0.55	2.17	1.49	2.15	2.57
13	Spain	1.22	1.84	1.65	2.58	0.37	2.51	0.45
14	Netherlands	1.05	0.99	2.75	1.78	1.63	1.65	1.57
15	Sweden	0.83	0.79	2.22	1.21	1.04	1.12	1.19
16	Austria	0.72	0.46	2.23	0.71	0.47	0.68	0.55
17	Belgium	0.68	0.67	2.53	0.99	0.45	0.93	0.47
18	Australia	0.67	0.47	0.70	2.48	0.47	2.27	0.45
19	Turkey	0.56	0.88	1.55	1.02	0.12	0.97	0.04
20	Singapore	0.52	0.42	2.93	0.59	0.19	0.55	0.16
	Cumulative	**92.42**	**88.87**	**--**	**82.06**	**94.83**	**82.88**	**94.85**
21	Mexico	0.5	0.51	2.02	0.62	0.07	0.58	0.03
22	Finland	0.48	0.45	1.25	0.63	0.57	0.6	0.65
23	Denmark	0.43	0.52	1.88	0.72	0.44	0.66	0.41
24	Poland	0.42	1.18	0.85	1.28	0.21	1.27	0.23

25	Norway	0.31	0.37	1.66	0.56	0.23	0.52	0.24
26	Czech Republic	0.30	0.44	1.73	0.62	0.07	0.61	0.08
27	Malaysia	0.29	0.38	1.71	0.61	0.04	0.57	0.04
28	South Africa	0.28	0.26	2.05	0.50	0.11	0.46	0.12
29	Argentina	0.27	0.65	0.96	0.39	0.03	0.36	0.01
30	Switzerland	0.26	0.17	1.17	1.30	1.62	1.21	1.68
31	Iran	0.26	0.38	0.37	1.07	0.00	1.10	0.00
32	Egypt	0.24	0.47	0.56	0.41	0.01	0.40	0.01
33	Portugal	0.23	0.52	1.12	0.60	0.04	0.58	0.03
34	Ukraine	0.23	0.54	0.33	0.40	0.12	0.39	0.22
35	Thailand	0.21	0.39	0.70	0.35	0.01	0.32	0.01
36	Ireland	0.19	0.26	1.99	0.37	0.18	0.34	0.16
37	Hong Kong	0.17	0.29	1.36	0.61	0.11	0.58	0.10
38	Hungary	0.16	0.33	1.19	0.35	0.08	0.34	0.07
39	Greece	0.13	0.27	0.66	0.58	0.04	0.56	0.05
40	United Arab Emirates	0.11	0.05	0.56	0.11	0.01	0.10	0.01
41	Indonesia	0.09	0.2.	0.26	0.30	0.00	0.28	0.00
	Cumulative	**97.98**	**97.50**	--	**94.44**	**98.82**	**94.71**	**99.00**
42	Romania	0.09	0.36	0.68	0.41	0.05	0.40	0.07
43	Pakistan	0.08	0.20	0.40	0.30	0.00	0.31	0.00
44	Slovenia	0.08	0.11	1.71	0.18	0.04	0.18	0.05
45	Colombia	0.08	0.01	1.30	0.20	0.02	0.19	0.00
46	Slovakia	0.06	0.21	0.74	0.22	0.02	0.21	0.02
47	New Zealand	0.06	0.13	0.54	0.42	0.10	0.38	0.07
48	Croatia	0.04	0.11	0.95	0.19	0.02	0.18	0.02
49	Bulgaria	0.04	0.21	0.52	0.15	0.02	0.14	0.02
50	Chile	0.04	0.06	0.92	0.28	0.03	0.27	0.01
51	Tunisia	0.04	0.14	0.25	0.19	0.00	0.17	0.00
52	Lithuania	0.04	0.14	0.63	0.10	0.01	0.10	0.01
53	Luxembourg	0.04	0.03	2.14	0.04	0.12	0.04	0.11
54	Vietnam	0.03	0.15	0.08	0.12	0.00	0.12	0.00
55	Algeria	0.02	0.03	0.07	0.14	0.00	0.14	0.00
56	Kuwait	0.02	0.01	5.90	0.05	0.00	0.04	0.00
57	Estonia	0.02	0.06	0.84	0.08	0.01	0.08	0.02
58	Morocco	0.02	0.16	0.06	0.13	0.01	0.12	0.01
59	Philippines	0.02	0.05	0.32	0.07	0.01	0.06	0.00
60	Costa Rica	0.02	0.02	1.31	0.02	0.00	0.02	0.00
61	Ecuador	0.02	0.02	1.09	0.04	0.01	0.04	0.00
62	Latvia	0.01	0.06	0.58	0.05	0.01	0.05	0.02
	Cumulative	**98.85**	**99.77**	--	**97.82**	**99.30**	**97.95**	**99.43**
63	Uruguay	0.01	0.02	0.79	0.04	0.00	0.03	0.00
64	Oman	0.01	0.01	1.76	0.04	0.00	0.03	0.00
65	Sri Lanka	0.01	0.02	0.48	0.04	0.00	0.04	0.00
66	Panama	0.01	0.00	2.46	0.01	0.01	0.01	0.01
67	Cyprus	0.01	0.01	1.42	0.05	0.02	0.05	0.02
68	Ethiopia	0.01	0.02	0.21	0.04	0.00	0.04	0.00
69	Moldova	0.00	0.03	0.21	0.02	0.02	0.02	0.03

70	Malta	0.00	0.01	0.95	0.01	0.01	0.01	0.01
71	Jordan	0.00	0.02	0.05	0.08	0.00	0.08	0.00
72	Georgia	0.00	0.02	0.06	0.03	0.01	0.04	0.01
73	Kenya	0.00	0.01	0.10	0.06	0.00	0.05	0.00
74	Bolivia	0.00	0.01	0.40	0.01	0.00	0.01	0.00
75	Paraguay	0.00	0.01	0.51	0.01	0.00	0.00	0.00
76	Trinidad and Tobago	0.00	0.00	0.05	0.01	0.00	0.01	0.00
77	Madagascar	0.00	0.01	0.45	0.01	0.00	0.01	0.00
78	Guatemala	0.00	0.00	0.85	0.01	0.00	0.00	0.00
79	Senegal	0.00	0.02	0.04	0.02	0.00	0.02	0.00
80	Botswana	0.00	0.00	0.35	0.01	0.00	0.01	0.00
81	Ghana	0.00	0.00	0.21	0.04	0.00	0.03	0.00
82	Bahrain	0.00	0.00	0.07	0.01	0.00	0.01	0.00
	Total	**98.92**	**100.05**	**--**	**98.42**	**99.38**	**98.50**	**99.53**

Table 10 shows efficiency estimates from our two estimated models ranked by GERD. Of the top 10 countries, we have Germany as the most efficient country (84.2-84.9 percent) and Brazil as the least efficient (50-58 percent). The rest of the top 10 countries have an efficiency that ranges from 72 percent to 84 percent. There are some small countries with good efficiency scores. Nevertheless, their devoted resources and output yields are very modest in importance. Recall the averages are 77.7% for Model A and 76.6% for Model B, respectively.

Table 10. Model A and B Efficiency ranked by GERD

Ranking	Country	gerd	TE Model A	TE model B
1	United States	31.91	81.74%	84.05%
2	China	14.97	80.08%	77.91%
3	Japan	11.53	72.40%	72.40%
4	Germany	6.62	84.29%	84.97%
5	South Korea	3.93	81.63%	81.77%
6	France	3.82	80.83%	82.57%
7	United Kingdom	2.90	84.18%	81.98%
8	India	2.84	83.73%	77.14%
9	Canada	2.10	80.04%	76.58%
10	Brazil	1.99	58.56%	50.03%
11	Italy	1.79	86.59%	86.78%
12	Russia	1.77	58.28%	61.14%
13	Spain	1.22	80.21%	79.20%
14	Netherlands	1.05	87.01%	85.26%
15	Sweden	0.83	84.61%	83.68%
16	Austria	0.72	79.04%	80.61%
17	Belgium	0.68	82.81%	80.23%
18	Australia	0.67	75.75%	73.47%
19	Turkey	0.56	72.79%	70.81%
20	Singapore	0.52	78.94%	74.70%
21	Mexico	0.50	54.40%	48.85%
22	Finland	0.48	79.74%	79.20%
23	Denmark	0.43	81.23%	77.65%

24	Poland	0.42	87.17%	86.38%
25	Norway	0.31	64.57%	63.22%
26	Czech Republic	0.30	86.31%	86.23%
27	Malaysia	0.29	71.81%	70.26%
28	South Africa	0.28	73.67%	72.90%
29	Argentina	0.27	55.58%	49.75%
30	Switzerland	0.26	90.45%	89.35%
31	Iran	0.26	87.13%	87.20%
32	Egypt	0.24	76.86%	74.78%
33	Portugal	0.23	77.36%	76.18%
34	Ukraine	0.23	80.31%	82.08%
35	Thailand	0.21	53.52%	52.72%
36	Ireland	0.19	76.06%	70.64%
37	Hong Kong	0.17	86.68%	86.53%
38	Hungary	0.16	84.79%	82.94%
39	Greece	0.13	84.58%	83.52%
40	United Arab Emirates	0.11	26.76%	25.86%
41	Indonesia	0.09	34.39%	33.36%
42	Romania	0.09	82.79%	82.67%
43	Pakistan	0.08	72.79%	77.72%
44	Slovenia	0.08	88.80%	89.61%
45	Colombia	0.08	90.31%	89.10%
46	Slovakia	0.06	82.71%	81.71%
47	New Zealand	0.06	83.48%	80.68%
48	Croatia	0.04	87.99%	87.55%
49	Bulgaria	0.04	87.17%	86.43%
50	Chile	0.04	87.31%	86.04%
51	Tunisia	0.04	90.64%	90.87%
52	Lithuania	0.04	72.56%	75.23%
53	Luxembourg	0.04	57.72%	53.87%
54	Vietnam	0.03	37.54%	40.77%
55	Algeria	0.02	67.24%	72.17%
56	Kuwait	0.02	81.96%	80.67%
57	Estonia	0.02	86.80%	87.58%
58	Morocco	0.02	45.90%	45.89%
59	Philippines	0.02	31.21%	29.34%
60	Costa Rica	0.02	64.73%	63.79%
61	Ecuador	0.02	46.67%	44.19%
62	Latvia	0.01	81.95%	79.56%
63	Uruguay	0.01	80.10%	78.73%
64	Oman	0.01	87.63%	88.48%
65	Sri Lanka	0.01	70.84%	75.80%
66	Panama	0.01	86.06%	82.98%
67	Cyprus	0.01	89.85%	90.34%
68	Ethiopia	0.01	89.04%	86.62%
69	Moldova	0.00	87.23%	84.63%
70	Malta	0.00	81.80%	78.01%

71	Jordan	0.00	87.37%	88.93%
72	Georgia	0.00	82.05%	86.07%
73	Kenya	0.00	77.95%	81.30%
74	Bolivia	0.00	51.17%	61.90%
75	Paraguay	0.00	36.58%	39.63%
76	Trinidad and Tobago	0.00	79.12%	81.75%
77	Madagascar	0.00	87.20%	83.89%
78	Guatemala	0.00	61.29%	59.75%
79	Senegal	0.00	63.12%	75.85%
80	Botswana	0.00	81.92%	88.32%
81	Ghana	0.00	91.61%	89.88%
82	Bahrain	0.00	76.06%	80.19%

5. 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 National Innovation Systems which highlight the interlinks between different kinds of actors to produce knowledge aimed to innovate. The NIS can be split into two subsets: one based on scientifical 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 which resort to mathematical programming or econometric techniques.
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). 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, types of patented technologies, to differentiate social from natural sciences in the production of publications, et cetera. 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 near to 95 percent of patent publication and grants.
The average efficiency of the estimates is in the order of 77 percent, 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 82 to 84 percent, depending on the model. China, which is the second country in importance has efficiency score of 80 to 78 percent, depending also on the specification.
The growth of China is impressive in the last two decades. 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 50 percent. There are small countries by their participation in the sample and by all criteria (population, GDP, territory, scientific tradition) which perform well, even though the absolute levels of output and inputs are modest.

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Appendix. Correlations between variable used in the SFA (n=1189)

	gerd	docs	patpub..	citabble	patgrants	w	gdppc	heritage	gerdpc	socialdocs	ivirpatp	ivirpatg.	socialcit	trend	sqtrend
gerd	1														
docs	0.9659	1													
patpublications	0.8150	0.7591	1												
citabledocs	0.9687	0.9963	0.7468	1											
patgrants	0.8344	0.7508	0.9012	0.7316	1										
w	0.2662	0.2487	0.2056	0.2465	0.2320	1									
gdppc	0.1610	0.1831	0.1309	0.1694	0.1885	0.4260	1								
heritage	0.0989	0.1054	0.0578	0.0948	0.1072	0.3190	0.5723	1							
gerdpc	0.3729	0.3672	0.3211	0.3500	0.4271	0.3990	0.8032	0.5629	1						
socialdocsshare	-0.0631	-0.0128	-0.1502	-0.0198	-0.1514	0.0512	0.2418	0.3824	0.0983	1					
ivirpatpublications	0.1686	0.1791	0.0548	0.1757	0.1500	0.0678	0.2230	0.1795	0.3171	0.0571	1				
ivirpatgrant	0.1628	0.1683	0.1274	0.1670	0.1397	-0.0225	0.1000	0.1205	0.2127	0.0025	0.3100	1			
socialcitabledocsshare	-0.1039	-0.0560	-0.1695	-0.0651	-0.1726	0.0531	0.2242	0.3611	0.0779	0.9877	0.0495	-0.0177	1		
trend	0.0454	0.1012	0.0634	0.0798	0.0722	-0.0520	0.0762	0.0750	0.1248	0.4487	0.0985	0.1836	0.4567	1	
sqtrend	0.0465	0.1033	0.0680	0.0792	0.0776	-0.0559	0.0671	0.0663	0.1172	0.4457	0.0817	0.1727	0.4590	0.9672	1