European Commission

JRC SCIENTIFIC AND POLICY REPORTS

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October 2013

Report EUR 26411 EN

Joint Research Centre

European Commission
Joint Research Centre
Institute for the Protection and Security of the Citizen

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http://www.jrc.ec.europa.eu/

JRC87027

EUR 26411 EN

ISBN 978-92-79-35011-5

ISSN 1831-9424

doi:10.2788/52038

Luxembourg: Publications Office of the European Union, 2013

Printed in Italy

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Executive summary

The main contribution of this project lies in the assessment of the efficiency of national research systems in achieving excellent research performances. The efficiency assessment is not only restricted to the production of research excellence in general, but is disentangled by type of research field, distinguishing between science and technology. This distinction provides a helpful tool for policy makers in assessing the discrepancy of efficiency in both science and technology excellence within and across countries. For this purpose, we develop a conceptual and empirical framework. The conceptual framework mainly builds on a previous project of (Hardeman et al., 2013) aiming at constructing a composite indicator measuring scientific and technological research excellence. Based on this work, we define the basic notions and concepts needed to understand the results of this study. We explain what is meant by research; we define the notion of national research systems and describe the different building blocks that constitute them. Finally, we introduce the notion of efficiency in achieving excellent research performances at the national level. A national research system's efficiency can be defined as the extent to which a country is able to transform research assets into excellent research.

After having outlined the target of this study and the main concepts related to it, we addressed empirical issues concerning data requirements and mathematical methods used for efficiency analyses. Overall, we conducted efficiency analyses on three main model specifications in which we relate the amount of resource assets to the performance on excellent research. In a first type of model we relate public R&D capital investments to measures of excellent scientific output. Estimating this efficiency relationship is of particular interest for policymakers as the allocation of public investments in R&D can directly be influenced by them. Public R&D investments are measured by the R&D investments in the government sector and the higher education sector, while the excellence of scientific output is captured by the number of highly cited publications.

In a second model specification private R&D investments (i.e. business enterprise expenditure on R&D) are related to an output measure capturing the technological research excellence. In this model specification, the number of PCT patents is used as proxy for the technological research excellence.

Finally, a third type of model relates the total R&D investments to output measures capturing both scientific and technological research excellence. We use the gross R&D expenditures as measure for the total R&D investments and we proxy the scientific and technological research excellence by the number of highly cited publications and the number of PCT patents. Efficiency analyses are conducted for the period 2004-2008 and are including 37 countries, capturing the EU28, the candidate countries, most EFTA countries and some international benchmark countries (China, US, South-Korea and Japan).

We use various methods to address efficiency empirically. After having reviewed the various methodologies used in the literature, we choose to primarily report on two methodologies here: output/input ratios and robust production frontiers. While the former present partial measures of efficiency, the latter present complete and robust measures. Two robust production frontier methods have been developed by (Daraio and Simar, 2007a): order-m and order-alpha method. First, we observe a positive relation between input measures of research and their respective output

measures, indicating that countries employing more research resources in science (or technology) are in general recording higher levels of excellent scientific (or technological) research.

Second, we observe that most of the top ranking countries in terms of research inputs also classify highly on excellent research output. Countries with extensive research resources in terms of financial R&D expenditures do probably perform better on the underlying factors that influence research excellence (e.g. attracting and employing top scientists and having better (pre)conditions to encourage innovative entrepreneurship).

Third, most of the countries improved in their efficiency over time in the period of analysis (2004-2008). The best performing countries in terms of efficient use of public research assets to achieve excellent scientific research are Belgium, Switzerland, Greece, Ireland and United Kingdom. The Republic of Korea, Japan and the Russian Federation are among the least performing ones. Efficiency scores and rankings for technological research show a different pattern. Top performing countries in this category are the Netherlands, Switzerland, Denmark, Sweden and Germany. Romania, Luxembourg and the Russian Federation are among the lowest in ranking. Exploring the top level countries on efficiency in achieving research excellence in general, we note a mixture of previous categories, including the Netherlands, Denmark, Switzerland, Norway and United Kingdom. The least performing countries are similar to those mentioned for the technological efficiency.

Finally, we find that efficiency performances in science and technology do not coincide as there is no clear-cut relationship among them. In addition here, we observe that top (or least) performing countries on research excellence do record the best (or lowest) positions on the efficiency rankings. However, efficiency performances vary significantly for countries not belonging to the extreme tails of the distribution on research excellence. Hence, we do not find a clear-cut relationship between research excellence and efficiency.

From the analysis and results presented in this report we draw several main conclusions and derive various recommendations from them. A first conclusion holds that some of the results of the analysis seem to be counter-intuitive at first sight. For example, while Greece ranks as highly efficient when it comes to public inputs and excellent scientific outputs, the US ranks low in efficiency when it comes to public inputs and excellent scientific outputs. Note however, that efficiency is not the same as excellence as such. In other words, countries that are generally considered as excellent scientific research performers might by virtue of investing a lot of public money turn out less efficient in the end.

Second, countries that are efficient in the production of excellent scientific research need not necessarily also be efficient in the production of excellent research in technology or even in producing excellent research in general (i.e. including both excellent science and excellent technology outputs). As such, there seems to be room for most countries to either improve in efficiency in the production of scientific research excellence or to improve their efficiency in the production of technological research excellence. It remains for further research to address the underlying mechanisms that drive differences in efficiency scores across countries.

Third, most European countries have improved over time in their use of research assets to produce excellent research in general. Disentangling efficiency in science from efficiency in technology, we notice that - except for Switzerland scoring well on both dimensions - the ranking and scores are

quiet heterogeneous. These results suggest that efficiency in science does not necessarily imply efficiency in technology. Moreover, empirical evidence shows that countries performing well on research excellence record relatively high efficiency scores, while this relationship is more scattered for countries with medium to poor research excellence performances.

To conclude here, we note that for many countries then efficiency in the production of research excellence is less an issue than the production of research excellence itself. For sure, there are some countries that perform low in both excellence and efficiency. However, there are many more countries that despite their performance in efficiency perform relatively weak on excellence itself. This would seem to suggest that for most (or at least, these) countries (that are efficient already) emphasis should be placed more on excellence itself rather than efficiency.

Contents

1 Introduction

1.1 Background of the project

With the introduction of the Europe 2020 strategy and its Innovation Union flagship initiative, the European Commission has made a shift in orientation from fostering 'research in Europe' towards fostering 'European research' (Nedeva and Stampfer, 2012). Recognizing that coordinating national research efforts on a case-by-case basis is practically unfeasible, attention has shifted towards the construction of a pan-European research system called the European Research Area (ERA). Accompanying this, it is widely acknowledged that many European countries are outperformed by countries like the United States when it comes to both technological and scientific research (Pavitt, 2000, Dosi et al., 2006). To remedy this situation, the European Commission aims at stimulating research excellence by increasing competition among researchers at a European level; for example, by establishing a central research funding agency, the European Research Council (ERC). Meanwhile, the current economic crisis has increased budgetary pressures across the board. Hence, allocating scarce resources to research has become an issue to be dealt with in the context of growth promoting policies. Overall then, it is unlikely that the economic crisis has no impact on research at all (Filippetti and Archibugi, 2011).

While some take investments in research as a necessary condition to foster welfare growth (Gruss, 2012), others discuss the kind of institutional and organizational arrangements that are needed to make research most productive (Marty, 2012). This project follows the latter strand of thought and investigates these issues for research at the country level. The results reported follow from a project initiated by the Directorate-General for Research and Innovation of the European Commission (DG RTD) within the context of developing indicators for the Innovation Union. The *main objective* of the overall project is to develop indicators that are capable of measuring and monitoring patterns and trends in research across countries. As such, the focus is on measuring three dimensions to research. One is about the interactions that take place between research actors within and across Europe. The main aim here is to track patterns of mobile researchers, R&D investment flows, and collaborative research endeavors across and beyond EU member states. Another dimension is about research interactions that take place between different kind of actors, such as universities, industry and government actors. Again the main aim is to track patterns of mobile researchers, R&D investment flows, and collaborative research endeavors along these institutional lines. Finally, a third dimension is about the impact that research activities have in terms of the outcomes produced and the ease with which inputs to research are transformed into research outputs. While follow-up reports address the first two dimensions, this report addresses the latter dimension.

Most in particular, this report assesses the efficiency of national research systems in transforming research inputs into excellent research outputs. As such, this report is a follow up of and builds on a previous study in which we developed a composite indicator measuring research excellence (Hardeman et al., 2013). That is, the conceptual framework and the variables used for the empirical analysis – though more limited in number – are the same as in the previous study. Whereas the previous study provided a characterization of countries' performance in terms of producing research excellence, this study moves on to characterize a country's ability to transform research inputs into research outputs; that is, what we are interested in here is an assessment of the efficiency with which national research systems produce research excellence as outputs from their research assets as inputs.

1.2 Contributions of the project

The main contribution of this report lies in a proposal for measuring and monitoring national research systems' efficiency in the production of research excellence using a robust production frontier approach. The added value of measuring efficiency in the production of research excellence at the country level using a robust production frontier approach is threefold. One is that at the country level such an analysis is generally lacking in the literature so far. Though partial measures of efficiency have been produced before (Adams, 1998, May, 1998, Dosi et al., 2006), we know of no study that provides a complete measure of efficiency at the country level; that is, combining multiple output indicators in an assessment of efficiency in the production of research excellence simultaneously. Second, the efficiency analysis presented throughout this report is not only restricted to the production of research excellence in general but also distinguishes between efficiency in the production of scientific research excellence and efficiency in the production of technological research excellence. This distinction provides a helpful tool for policy makers in assessing the discrepancy of efficiency in both science and technology within and across countries. Finally, the empirical analyses are conducted with robust production frontier methods (Daraio and Simar, 2007b). The main advantage of employing these models lies in the obtainment of results that are not affected by the presence of outliers or extreme values in the data. In addition, these methods provide relative measures of efficiency scores allowing for cross-country comparisons. Overall, and to our best knowledge, this is the first study that provides empirical evidence on efficiency in the production of research excellence at the EU country level using a robust production frontier approach.

1.3 Outline of the report

The report proceeds as follows. Section 2 provides the conceptual framework of this study. In order to empirically assess the efficiency of national research systems in achieving research excellence, we first provide a concise and clear overview of the main concepts needed to understand the results of this study. For this purpose, we explain what is meant by research in general and which dimensions are characterizing research in particular. We define the notion of national research systems and discuss the various building blocks that constitute them. Furthermore, we describe the role of research excellence as the main goal orientation of national research systems. Finally, we introduce the notion of efficiency in the production of research excellence at the country level.

Section 3 addresses the data and methodology used to empirically assess efficiency in the production of research excellence at the country level. First, we discuss the variables included in the analysis. This discussion strongly relies on the previous study in which we developed a composite indicator measuring scientific and technological research excellence (Hardeman et al., 2013). Second, we provide an overview of the existing methods to measure efficiency and explain the rationale for using robust production frontier methods. Finally, we outline the various model specifications that have adopted measure the efficiency of national research systems.

In section 4 we turn to the main findings of the report. The scores and ranking of countries' performances in terms of their efficiency in achieving excellent research are discussed. What is more, efficiency scores are related to countries' levels of research excellence. Finally, section 5

concludes. Here, the main findings are summarized, discussed and recommendations are made as regards policy implications and directions for further research.

2 Theoretical framework

2.1 Background: research in an age of austerity

Since 2006 gross expenditures in research of E.U. member states amount to over 200,000 billion Euros annually (based on statistics of Eurostat). However, in the current age of austerity, research is just as subject to budget concerns as any other economic activity. As such, the economic crisis has increased budgetary pressures and therewith accentuated the issue of allocating resources for research prudently.

In line with the tenets of the austerity mantra, research has been characterized by a period of professionalization and accountability (Elzinga, 2012). According to Nowotny (2006, pp. 1-2) "*from the 70s onwards … the budget cuts from the government initially triggered by a situation of economic stringency, were never to return to normal, but became a new normality themselves. … It became deeply enmeshed in a culture of searching utilitarian objectives, driven by norms of efficiency and accountability.*" An interest in efficiency in research then follows from a concern with trying to get the best out of the research system at the least cost. In other words, research should not only produce excellent outcomes, it should also do so in the upmost efficient way.

Assessing the optimal amount of resources to be allocated to research is not straightforward, as we have to take into account the uses of all other activities to which resources could be allocated. Overall then, ascertaining 'what research is really worth' is a difficult if not impossible task to fulfill (Nelson, 1959, Macilwain, 2010). Some studies attempt to determine the average rate of return on investments in research (for recent reviews see e.g. Salter and Martin, 2001, Hall et al., 2010). The main finding of these studies holds that there are considerable returns to be expected from investments in research. Notwithstanding this important finding, estimating the average returns from research says little about the performance of individual countries in transforming research resources into excellent research performance (Bonaccorsi and Daraio, 2005). Although answering the question "how much does an extra unit of resource devoted to research render us in terms of extra units of research output?" might give valuable information about the relation between research resources and research performance in general, it says little to nothing about this relation for any country in particular. Yet, it is the latter issue that is of particular interest to policy makers trying to steer the efficiency of countries in doing research.

2.2 A definition and stylized description of research

Following the OECD (2002, p. 30) research (including experimental development) can be defined as "*creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications.*". Traditionally, a distinction is made among basic (scientific) research, applied research (sometimes called invention), and the development of research towards commercial ends (often called innovation). As such, in a linear model of research and innovation, the transformation of research into welfare follows three steps. In the first step, basic research takes place within the public realm of science. Given the public nature of scientific research, the outcomes of this research are 'freely' available to society at large (Arrow, 1962, Foray, 2004). In a second step then, economic agents use the publicly available outcomes from science to develop new technologies. Finally, in a third step these technologies diffuse on the market to become widely used in society. A main

drawback of the linear model of research and innovation is that it obscures the processes that underlie the transformation of research into welfare growth in a 'black box' (Rosenberg, 1982).

Alternative approaches have been proposed to address research and innovation, such as the national and regional innovation systems approach (Lundvall, 1988, Nelson, 1993, Cooke et al., 1997, Edquist, 1997), post-academic science (Ziman, 1994), mode 2 knowledge production (Gibbons et al., 1994), Pasteur's quadrant (Stokes, 1997), post normal science (Funtowicz and Ravetz, 1993), and the triple helix of university-industry-government interactions (Leydesdorff and Etzkowitz, 1996, Etzkowitz and Leydesdorff, 2000). Whatever the differences among these approaches (for an overview of this literature see (Hessels and van Lente, 2008)), most of them treat research as taking place within a dynamic complex system and as such take issue with at least five features of the linear model of research and innovation.

First, instead of conceiving of research as a sequential process, treating research as a dynamic complex system means that research involves many feedbacks between basic and applied research, science and technology, invention and innovation. Although in the very long run one might be able to identify distinct scientific discoveries that form the basis of subsequent technological break troughs (Balconi et al., 2010), in the short to medium run the relation between science and technology is much more obscure.

Second, the relation between research inputs (such as investments made in R&D) and research outputs cannot be taken for granted a priori. Rather, research involves considerable and fundamental uncertainties (Knight, 1921); ex ante it is hard – if not impossible – to determine whether and if so what exactly comes out of research. Instead of following a mechanistic, deterministic process, the research process can best be characterized as indeterminate and uncertain (Kline and Rosenberg, 1986).

Third, it follows that research actors can hardly be conceived of as optimizing their behavior. Given that research actors face fundamental uncertainty with respect to the outcomes of their efforts, their rationality is bounded instead of perfect (Simon, 1996). Hence, research actors are satisificers trying to meet an acceptable level of outcome they believe is feasible rather than some hypothetical optimum they do not and cannot even know of.

Fourth, from the idea that research actors are satisficers instead of optimizers it follows that any two research actors are never exactly alike. For one thing, research actors differ with respect to their rate of success (Alchian, 1950). On another level, research actors differ in terms of their roles in the research process. As such, there are many different types of actors involved in research. These types range from venture capitalists and public funding agencies to public research organizations (such as universities) and private firms (such as pharmaceutical companies). Hence, treating research as a dynamic complex system means recognizing that research actors are heterogeneous instead of homogenous (Nelson, 1991).

Fifth, within the notion of research as a dynamic complex system, research is taken as a collective, interactive activity (Lundvall, 1988). The various actors involved in research compete but also collaborate with each other in the production of research outcomes. Note that the possibility of interaction among research actors does not exist within the linear model of research and innovation. Yet, while in the linear model of research and innovation research actors are treated as atomistic

entities (i.e. forming a collection of parts only), research as involving a dynamic complex system implies having a holistic perspective on research actors and their interactions (i.e. collections being more than the sum of its parts).

Table 2.1: Two stylized accounts of research

The linear model of research and innovation	Research as a dynamic complex system
1. Research as a sequential process	1. Research as a non-linear process
2. Research as a mechanistic (deterministic) process	2. Research as an indeterminate (fundamentally uncertain) process
3. Research actors as optimizers (perfect rationality)	3. Research actors as satisficers (bounded rationality)
4. Research actors as homogenous	4. Research actors as heterogeneous
5. Research as an individual activity (atomism)	5. Research as a collective activity (holism)

The main characteristics of these two approaches describing research are presented in Table 2.1. While the linear model takes research as a sequential, mechanistic, and pre-determined process; the complex system approach to research emphasizes non-linearities, fundamental uncertainties and indeterminacy therein. Likewise, while the linear model takes research actors as optimizers, perfectly rational, homogenous in kind, and atomistic entities; the complex system approach to research takes actors as satisficers, subject to bounded rationality, heterogeneous in kind, and operating in continuous interaction with others.

2.3 National research systems and efficiency

Akin to the idea of national innovation systems (Freeman, 1987, Lundvall, 1988, Lundvall, 2010, Nelson, 1993, Edquist, 1997), a national research system is made up of the actors within a country that jointly (i.e. in interaction with each other) produce research outcomes. As other systems, national research systems contain three core elements (Carlsson et al., 2002, Edquist, 2005): components, relationships, and attributes. First, components are about "*the operating parts of a system*" (Carlsson et al., 2002, p. 234). In other words, the people doing research, the organizations providing the environments for doing research, the instruments that are needed to perform research, and the institutions (i.e. norms, rules, and policies) operating in a country that facilitate doing research. In what follows we refer to the components in terms of research assets when concerned with the people and organizations of national research systems and with structural capabilities when concerned with the institutional and sectorial make up of national research systems (Van Looy et al., 2006, Cimoli et al., 2009).

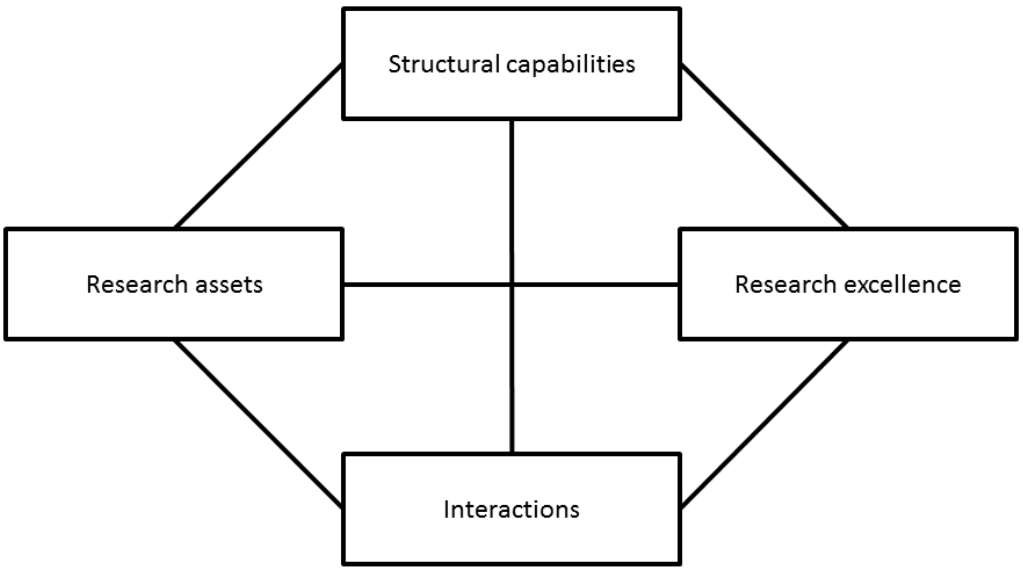
Second, relationships concern the connections among the components. Relationships among researchers, the organizations they work in, and the institutions that shape their behavior, bind the research capabilities of a country to make it an actual system. In other words, relationships are about the interactions among the components of system. Hence, following (Lundvall, 1988) in his description of innovation as an interactive process, we refer to the relationships among the components of national research systems as research interactions.

Both the components and relationships that constitute a system have certain attributes or properties. In the context of national research systems, these attributes characterize the nature of the assets and capabilities. Likewise, research interactions have different properties. While some interactions concern competitive pressures among researchers, others are about collaborative efforts (Carlsson et al., 2002). At a different level still, interactions in research can be about the transfer of knowledge or the sharing of research facilities. Taken together, research assets, structural capabilities and research interactions have various – what we call – dimensions to them.

Apart from the components, relationships, and dimensions; national research systems are characterized by their particular goal or orientation (Carlsson et al., 2002). From the definition of research provided above, it follows that national research systems are oriented at the provision of new knowledge. Notwithstanding the difficulties in defining what is new (Witt, 2009), here we take new knowledge to refer to the outcomes of national research systems as excellent. That is, new knowledge is not about the obvious, the straightforward or the usual. Rather, new knowledge is about the remarkable, the original, the striking. In other words, the prime objective of national research systems is to produce what we call research excellence (Hardeman et al., 2013).

Figure 2.1 pictures our conceptual framework (see also Hardeman et al., 2013). Apart from singling out the different components of national research systems, these are in turn interlinked with each other. These inter-linkages, however, should not be understood in causal terms going in one direction. The fact that there is a relation between the components of national research systems need not imply causality between them. Going from the literature on national innovation systems as complex evolving systems, these linkages are to be interpreted in terms of the influence different components of national research systems have on one another. As such, research excellence feeds back into structural capabilities, research assets, and research interactions just as the latter three building blocks of national research systems shape research excellence.

Figure 2.1: Conceptual building blocks of national research systems



In the remainder of this report we are primarily interested in exploring the relationship between research assets and research excellence. The aim of this report is to analyze to what extent the former dimension is used in an efficient way to reach excellent research performances at the national level. Hence, what we are interested in when assessing the efficiency of national research systems, is a characterization of the line connecting research assets with research excellence. Although, structural capabilities and interactions are likely to influence the efficiency of national research systems, we do not include them in the analysis and do not aim to disentangle their effects on the efficiency performance. What holds for our understanding of efficiency of national research systems then is that it involves a characterization of the link between research assets as inputs to the research process as research excellence as outputs of the research process.

3 Data and methodology

3.1 Measuring research assets and research excellence of countries

Taking the measure of national research systems is not straightforward (Carlsson et al., 2002, Katz, 2006). For one thing, given that research is a dynamic complex system, distinguishing research assets as inputs to research from research excellence as outputs from research is sometimes difficult if not impossible. In the case of science, some research outputs such as publications might subsequently help researchers to attain funds (Latour and Woolgar, 1979). Hence, research performance might influence the availability of research assets. Likewise, for technological research, some technological inventions might enter as assets to the production of other technologies.

At the macro level however, that is at the level of our concern (i.e. countries), we believe that a distinction can be made between resources that go into research as inputs or research assets; organizational mechanisms that potentially affect the nature of research outcomes such as research interactions (e.g. collaborations between scholars) and structural research capabilities (e.g. the institutional make-up of a country); and the main outputs of research being excellent. A national research system's efficiency is then defined as the extent to which a country is able to transform research assets into excellent research; that is, research inputs into research outputs.

In order to assess the efficiency of national research systems, we use two sets of variables to quantify research assets and research excellence at the country level. Table 3.1 lists all the variables measuring research assets and research excellence that we use in the efficiency analyses. All variables are briefly summarized according to their advantages and limitations in their use for empirical analyses in general and an analysis of efficiency in the production of excellent research in particular.

Table 3.1: Main variables for assessing efficiency of national research systems[1]

Measures of research excellence				
Variable name	**Measuring**	**Description**	**Advantages**	**Limitations**
Number of highly cited publications	Performance in excellent scientific research	Field normalized number of highly cited publications on which a country is listed in the affiliation information of authors (Source: Science Metrix based on Scopus Elsevier)	- Indicator of research quality rather than quantity - Highly correlated with other indicators of research excellence - Systematically collected across years and countries	- Publication based indicators capture only a fraction of research outputs - Biased towards Anglo-American science
Number of PCT patents	Performance in excellent technological research	Patent applications filed under PCT by inventors' country of residence (fractional counting) in all IPC classes (Source: OECD)	- PCT patent applications do not suffer from home country bias -PCT patent indicators are relatively timeliness	- PCT patent applications do not result in the grant of a patent, but rather in the option of patent filing in different national patent authorities - PCT applications may be biased towards large international organizations

Measures of research assets				
Variable name	**Measuring**	**Description**	**Advantages**	**Limitations**
Gross expenditures in R&D (GERD)	Total research assets	Gross expenditures in R&D expressed in Euro	- All national surveys that collect R&D expenditure data are aligned, following the definitions outlined in the Frascati manual. - National R&D survey are in a constant improvement process, resulting in more accurate and reliable R&D data over time	- R&D statistics may not be completely comparable across countries and over time given that national systems slightly differ in survey methods
Government and higher education sector expenditures in R&D (GOVERD+HERD)	Assets for scientific research	Government and higher education sector expenditures in R&D expressed in Euro		
Business expenditures in R&D (BERD)	Assets for technological research	Business expenditures in R&D in Euro		

[1] Further technical details about the data are listed in annex 1.

3.1.1 Measuring research excellence in science and technology

Measuring research excellence and disentangling excellent research in science from excellent research in technology is not straightforward (Hardeman et al., 2013). Research outputs are multi-faceted and according to some researchers "*benchmarking scientific and technological productivity needs to navigate through a difficult terrain between two equally unacceptable extremes: accepting that comparisons are impossible or coming up with nonsensical oversimplifications*" (Barré, 2001, p. 259). Taking this cautionary remark into account we admit that certain aspects of excellent scientific and technological research may be disregarded due to the particular choice of variables used to measure these phenomena. However, more important than being aware of the inability to capture all dimensions of research excellence (Barré, 2005, Godin and Doré, 2004, Edquist and Zabala, 2009, Bornmann, 2012), is to clearly specify which dimensions are captured by our measurements and which are not.

In the context of assessing national research systems' efficiency in producing excellent research, we base the choice of variables to measure research excellence in science and technology on a previous study (see Hardeman et al., 2013). The target of this study was to create a composite indicator measuring scientific and technological research excellence at the country level. The selection of the variables used to construct the composite indicators is based on a quality assessment of various measurements related to research excellence. Here, we briefly summarize which variables we select for countries' efficiency analyses. Concerning research excellence, we primarily emphasize the discussion on the different dimensions we are measuring with these variables, rather than focusing on the quality profile of the measurements, since this latter specification was already covered extensively in the aforementioned study.

Measuring scientific research excellence. We measure scientific research excellence with a field-normalized count of the 10% most cited publications. The number of highly cited publications does not just capture the overall amount of research produced (as with measuring the number of publications in general) nor the average quality of that research (as with the average citation rate of publications); rather, it measures the amount of top-research produced by a country. The fact that these data are systematically collected makes them reliable (Hardeman et al., 2013). While other indicators on scientific rewards (such as for example honorific awards) differ in interpretation from one country and year to another, the interpretation of highly cited publications is relatively straightforward and remains constant over time and place.

Nevertheless it should be noted that most bibliometric databases (including Scopus Elsevier) are biased in their representation of Anglo-American countries. As such, these data reflect on scientific research excellence of which the standard is set predominantly by this part of the world. Also, it should be noted that the number of highly cited publications captures a particular part of excellent research performance only; that is, only those excellent research outputs that actually end up in scientific publications. In addition, the extent to which received science citations is a valid indicator of research quality is not uncontested (Bornmann and Daniel, 2008, MacRoberts and MacRoberts, 1996): while some research that is considered of low quality gest cited extensively, other research that is considered high quality does not. Notwithstanding these cautionary remarks, the number of highly cited publications produced in a country present a valid indicator of research excellence at the macro level. Given that on an

aggregate (country) level science citation indicators correlate highly with other indicators of scientific reward makes these data at least to be considered valid proxies of the quality or impact of scientific research outputs (Tijssen et al., 2002, van Raan, 2006). In the presentation of the empirical results, we refer to this variable with the term "science output".

Measuring technological research excellence. To measure excellence in technological research, we employ the number of patent applications filed under PCT by inventors' country of residence. The use of patent data to measure research excellence is contingent upon an understanding of patent value. According to the OECD Patent Statistics Manual (Zuniga et al., 2009), patent value can refer both to the economic and social value of a patent. The first concept refers to the revenue flows to its holder; the second to a patent's contribution to the stock of technology. Consequently, in line with the understanding of excellence as top of a quality distribution, the most outstanding patents are distinguished by the very high revenue they generate or their outstanding technological content. These two features need not necessarily coincide, as the revenue generating potential of a patent depends not only on the technological content of the invention but also on whether the patent can be circumvented. Yet, despite this bias, it would be problematic to dismiss the economic value from an understanding of patenting as indicating research excellence, as the revenue generating potential is an important driver for research actors to patent new inventions.

A common way to distinguish higher value patents is to count those with a broader geographical scope, or patents that were filed in multiple patent offices (Putnam, 1996). If an applicant is ready to pay the additional costs of protecting the invention in many countries, it implies that the applicant expects that the patent will generate sufficiently high revenues. The two main patent count indicators for multiple patent filings are (i) patents filed under the Patent Cooperation Treaty (PCT) and (ii) Triadic Patent Families. For our efficiency analysis, PCT patent applications data allows the best time series cross-country comparison as it is consistently available for all the years and countries in our dataset (see also Hardeman et al., 2013). A cautionary remark on using PCT data holds that these are biased towards measuring research excellence of large –often multinational – organizations. In addition, rather than measuring actual market value, PCT data might only capture the expected market value foreseen by the applicant instead. Nevertheless, lacking viable alternatives that captures technological research excellence on a systematic basis across both time and countries, PCT data can be used as an additional indicator measuring research excellence on top of the number of highly cited publications. In the remainder of this study we refer to this variable using the term "technology output".

Overall, while the number of highly cited publications of a country captures its performance in terms of producing excellent scientific research, the number of patent applications filed under PCT captures a country's performance in terms of producing excellent technological research. Combining the research excellence in both fields allow us to obtain a measure for the overall performance in terms of research excellence. In the empirical analysis we refer to this variable as "total output". Note that, instead of the four variables measuring research excellence used previously (i.e. highly cited publications, PCT applications, ERC grants received, and the number of world class universities and research institutes; see Hardeman et al., 2013), we only use two of them here. We choose not to include ERC grants and the number of world class universities here because (i) ERC grants received are not available for non-ERA

countries and represent both on research inputs (i.e. research assets) as on research excellence "in the making" and (ii) the number of world class universities and research institutes both represents research excellence as well as research assets and structural research capabilities. In fact, these considerations were the prime reasons to consider these ERC grants received and the number of world class universities and research institutes "weak" indicators and highly cited publications and PCT applications "strong" indicators (Hardeman et al., 2013). Hence, here we choose to include strong indicators of research excellence only.

3.1.2 Measuring public and private research assets

Previously we defined research assets as *"the set of research agents available in a country. Research assets can be further divided into physical (machines, instruments, and laboratories), human (skilled labor) and intellectual assets (knowledge and ideas)"* (Hardeman et al., 2013, pp. 22-23). In the same line as for measuring research excellence, it is almost impossible to find variables covering all the dimensions of research assets. Based on the assumption that research assets are highly correlated with the financial resources devoted to research, we measure this building block of national research systems with expenditures in research and development (R&D). A main advantage of using R&D expenditures as a measure of research assets is that they are annually collected with national R&D surveys following the definitions of R&D data outlined in the Frascati manual (OECD, 2002).

The R&D expenditures data employed in our efficiency analyses are selected to measure research assets in general and research assets devoted to scientific and technological research in particular.[2] First, we measure a country's total research assets by gross expenditures made on intra-mural R&D in a country (GERD). In the remainder of this report we refer to this variable with the term "total input" (in R&D). Second, research assets available in a country's public domain are measured by that country's government and higher education sector expenditures in R&D (GOVERD+HERD); further denoted as "public input" in R&D. Finally, research assets available in a country's private domain are measured by business expenditures in R&D (BERD). In what follows we refer to this variable as "private input" in R&D as it captures the R&D investments made by the private sector. In the analysis that follows, both measures of research assets and research excellence are normalized by countries' gross domestic product (GDP) as to correct for differences in the size of countries' national research systems.

[2] Apart from investments in R&D we considered two other variables as inputs to research. One is the number of people involved in research. However, given that a significant part of investments in R&D go to labor costs and to avoid double counting we decided not to include the number of researchers (in terms of either fulltime equivalent or head count) as an input variable. Another variable we considered is the available stock of knowledge in a country. However, lacking an accepted methodology to define its depreciation rate, we decided not to include this as an additional research input variable.

3.2 Modeling efficiency in the production of research excellence

3.2.1 From the production function approach to a robust production frontier approach

Different approaches have been proposed in the literature to address efficiency empirically, ranging from production function approaches on the one end of the spectrum to production frontier analysis on the other (Bonaccorsi and Daraio, 2005). From taking into account the nature of the research process itself and balancing the advantages and disadvantages of the different methodologies that have been proposed throughout the literature, we use robust production frontier techniques to address the efficiency in the operation of European research systems towards producing excellent research.

Table 3.2 summarizes our main rationale for using the robust production frontier approach in four steps. From our prime concern with identifying the countries' individual performance in terms of their efficiency it follows that we are not interested in specifying how on average research inputs transform into excellent research outputs as is mostly done when applying a production function approach. In addition, while production function approaches require that the nature of the relation between research inputs and research outputs is well specified, preferably one would like to leave this relation at the macro level in the midst as it is extremely complex and hence everything but well specified in reality. Hence, from a systems perspective on research, one would like to address efficiency without specifying the exact nature of the production process a priori; i.e. without making too many restrictive assumptions about how research inputs are transformed into research outputs. From a somewhat different angle, a systems approach to addressing efficiency in research should allow for heterogeneity among its main constituents (here: countries). However, assessing average efficiency as in the production function approach, assumes that researchers optimize their excellent research outputs without wasting inputs. In reality, researchers can hardly be conceived of as optimizers; that is, not all researchers succeed under all circumstances. Again, although the production function approach might give valuable information about the relation between research inputs and research outputs in general, it says little to nothing about this relation for any country in particular.

Table 3.2: Overview of advantages and disadvantages of different methodologies used for efficiency analysis

Why use the robust production frontier approach to address efficiency of national research systems?
1. Our prime interest resides in addressing how *particular* countries perform in transforming research inputs into excellent research outputs, not in addressing how *on average* research inputs are transformed into excellent research outputs. o Here, using a *production function approach* is disadvantageous in that allows one to estimate *the average rate of return* of research inputs in terms of excellent research outputs but not *the performance of individual countries* therein. 2. The *complex nature of the research process* implies that the exact relation between research inputs and excellent research outputs cannot be specified a priori. The preferred methodology, therefore, should impose *as little as restrictions possible* on specifying the nature of the relation between research inputs and excellent research outputs. o Here again, using a *production function approach* is disadvantageous in that it requires one to specify the nature of the relation between research inputs and excellent research outputs a priori. o Also, underlying a production function approach is the assumptions that research is made up of homogenous, optimizing research actors, while a dynamic complex systems approach to research takes research actors as heterogeneous and boundedly rational. 3. Given that the research process is characterized by *multiple research inputs* and *multiple excellent research outputs* , the preferred methodology should allow for the inclusion of multiple inputs and outputs *simultaneously* . o Output/input ratios provide *partial measures of efficiency* as they relate one output to one input only. 4. Given that we use the country as our basic unit of analysis, the preferred methodology should be capable of *generating reliable estimates from relatively few observations* . o While data envelopment analysis and free disposal hull analysis are sensitive to extreme *outliers* and suffer from the *curse of dimensionality* , the robust production frontier approach does allow for *an estimation of efficiency based on a restricted number of observations* .

A first step to address efficiency of national research systems without specifying the exact nature of the relation between inputs and outputs is based on a comparison of output/input ratios (Bonaccorsi and Daraio, 2005).[3] Output/input ratios have the advantage of offering simple numbers that relate one type of research output (e.g. highly cited scientific publications) with one kind of research input (e.g. public investments made in R&D). A main disadvantage of simple output/input ratios is that each ratio can only include one input and one output. Hence, output/input ratios reflect partial measures of productivity only. In order to avoid that gains in one output are wrongly attributed to gains in another output, one would preferably like to obtain a complete measure of productivity that is based on all combinations of inputs and outputs simultaneously.

In order to assess the efficiency of national research systems by taking into account multiple inputs and outputs simultaneously several non-parametric methods have been developed. The first method that has been developed is data envelopment analysis (DEA) (Farrell, 1957). Overall, the calculation of efficiency measures in this method starts from the definition of a production possibility set. This

[3] A more detailed and technical description of the methodologies considered for this report can be found in annex 2.

production possibility set denotes which set of output can be produced by which set of inputs. The production possibility set is delimited by the technology frontier, which is determined by the countries with the highest output performance. Its frontier is defined in such a way that it envelopes all the observed data points (i.e. all observed data points are situated on or below the production frontier). The frontier denotes actually the best possible outcome that can be reached, hence countries lying on this frontier can be seen as the best performers and are said to be "efficient". Likewise, countries that are situated below the technology frontier are denoted as "inefficient". The DEA method constraints the technology frontier to be convex, which means that all the linear input-output combinations between efficient countries are also included in the production possibility set.

The procedure to calculate the efficiency scores of the DEA method follows a relatively simple linear programming algorithm. The efficiency scores are obtained by comparing the input or output performance of countries relative to the best practice within the group of countries. Hence, the method does not provide absolute efficiency scores per country but rather relative efficiency score among countries included in the data set. To obtain the efficiency scores of inefficient countries, their combination of inputs and outputs are projected on the technology frontier. A focal country is identified as inefficient if a composite of countries (i.e. a linear combination of countries in the dataset) can be found that obtains more (or at least the same) output level than the focal country while utilizing the same amount (or less) input levels. As such, the efficiency score of an inefficient country measures the amount by which all outputs could be proportionally expanded without altering the inputs used in order to reach the efficiency frontier.

An alternative method to calculate relative efficiency scores, called Free Disposal Hull (FDH), has been developed (Deprins et al., 1984). This method was developed in response to one of the main disadvantages of the DEA method: the convexity of its technology frontier. This particular drawback implies that the DEA frontier consists of linear combinations of efficient countries. As such, the efficiency scores of inefficient countries are compared with countries having input and output combinations that actually do not exist. To overcome this disadvantage, the FDH method relaxes the assumption of convexity. As such, in this method inefficient countries are necessarily compared with existing input-output combinations. By relaxing the unrealistic assumption underlying DEA, the less restrictive FDH method is preferred.

Notwithstanding the advantage of DEA and FDH compared to output/input ratios in using multiple inputs and outputs within the efficiency analyses, there are also some severe disadvantages to these methodologies (Bonaccorsi and Daraio, 2005). Among the most important disadvantages, both DEA and FDH are extremely sensitive to outliers in the data and suffer from the curse of dimensionality. The problem emerges from the fact that the technology frontier in both methods is defined by all the data points observed in the dataset. Hence, the efficiency estimations can easily be influenced by extreme values, potentially rendering a group of countries inefficient solely due to the fact that they are compared with countries recording extreme or outlier values in terms of inputs or outputs. The latter problem means that with relatively few observations, DEA and FDH are prone to provide an imprecise estimate of the true efficiency frontier and accordingly provide inaccurate estimates of each observation's distance to the efficiency frontier. To overcome these issues, robust production frontier

analyses have been proposed as a viable alternative to DEA and FDH (Daraio and Simar, 2007a). By only enveloping a peer group of observations rather than all observations to estimate the technology frontier, robust production frontier analyses are better able to deal with a small set of observations and potential outlier observations than both DEA and FDH.

There are two forms of robust production frontier analyses: (i) the robust order-m analysis and (ii) the robust order-α analysis. With robust order-m analysis the efficiency of each observation is benchmarked against the average maximal output by m-number of peers that are randomly drawn from the population of countries using fewer or an equal amount of inputs than a focal country. Defining the number of m peer countries allows for a benchmark comparison between the focal data point and a pre-specified number of peers. Hence, the application of the order-m method can be seen as the evaluation of a potential competitor scenario. However, as our efficiency analysis is conducted on country-level in which competitiveness in research systems is less applicable than for organizations, we favor an alternative robust frontier method; that is, order-α analysis. The rationale behind the order- α efficiency models is quite similar to that of order-m efficiency models. Like order-m models, the aim of order-α models is to estimate an efficiency frontier that is less sensitive to extreme values. In this type of models a percentile (i.e. α) is fixed beforehand as to select a subset of peer countries from the distribution of all countries that will be taken into account to estimate the efficiency frontier. As such, the output level of a focal country is benchmarked against the output level not exceeded by 100(1- α) of units in the population of countries using fewer or an equal amount of inputs. Using a percentile to determine the degree of robustness rather than an a priori defined number of countries as in the order-m models is more intuitive in country-level efficiency models.

Note that robust production frontiers estimated by both order-m and order-α analyses will always be downward estimations of the DEA and FDH frontiers as the former frontiers are only enveloping a subset of all data points, leaving out the outliers and extreme values that are included in DEA and FDH. Hence, the estimations of order-m and order-α are less prone to be biased towards outliers and are by consequence more likely to approximate the true efficiency frontier. Of course, robust frontier analyses cannot completely overcome issues revolving outliers, especially when these might be due to the quality of the data.

3.2.2 Model specifications of the robust production frontier approach

In view of previous considerations we run three different models to estimate efficiency scores (see Table 3.3). First, we will assess the relation between total inputs and total outputs. That is, efficiency will be addressed in terms of the relation between GERD per GDP as an input variable and highly cited publications per GDP and PCT applications per GDP as output variables. Here, we adopt two modeling strategies. One modeling strategy includes the full sample of countries between 2004-2008; in other words, 37 countries across 5 years rendering a total number of 185 observations. For the other modeling strategy, we exclude countries that are considered outlier in either their input or output levels. Countries are flagged as outliers when the input or output measures normalized by GDP show a growth rate from one year to another that exceeds two standard deviations from the average of that

year across all countries. In the restricted sample then, 26 countries are included across 5 years (2004-2008) rendering a total number of 130 observations.

Table 3.3: Model and sample specifications

Model specifications					
Model	**Input**	**Output**	**Period**	**Sample**	**Observations**
Public Input - Science Output	(GOVERD + HERD)/GDP measured as three-year averages for time t, t-1 and t-2	Number of highly cited publications/GDP in time t	2004-2008	Full sample: 37 countries	185
				Restricted sample: 29 countries	145
Private Input - Technology Output	BERD/GDP measured as three-year averages for time t, t-1 and t-2	Number of PCT patents/GDP in time t	2004-2008	Full sample: 37 countries	185
				Restricted sample: 28 countries	140
Total Input - Science & Technology Output	GERD/GDP measured as three-year averages for time t, t-1 and t-2	Number of highly cited publications/GDP in time t and Number of PCT patents/GDP in time t	2004-2008	Full sample: 37 countries	185
				Restricted sample: 26 countries	130
Sample specifications					
Full sample models include countries: AT, BE, BG, CH, CY, CZ, DE, DK, EE, ES, FI, FR, GR, HR, HU, IE, IL, IS, IT, JP, KR, LT, LU, LV, MT, NL, NO, PL, PT, RO, RU, Restricted sample of Public Input - Scientific Output excludes : CY, LV, LT, LU, MT, PT, RO, SI Restricted sample of Private Input - Technology Output excludes : BG, CY, EE, LV, LT, MT, PT, SI, TR Restricted sample of Total Input - Scientific & Technology Output excludes : BG, CY, EE, HR, LV, LT, LU, MT, PT, RO, SI					

Second, we will assess the relation between public input and science output as a means to address efficiency in the production of scientific research excellence. That is, efficiency will be addressed in terms of the relation between GOVERD+HERD per GDP as an input variable and highly cited publications per GDP as an output variable. Estimating this efficiency relationship is of particular interest for policymakers as the allocation of public investments in R&D can most directly be influenced by them. Admittedly, such an efficiency assessment follows from maintaining the relatively strong assumption that scientific research excellence is related predominantly to public research assets. However, we know from the literature on the knowledge economy (Gibbons et al., 1994, Powell and Snellman, 2004, David and Foray, 2002, Hardeman et al., 2013) that this relation need not be clear cut. That is, public research assets might well turn into technological research excellence and scientific research excellence might well stem from private research assets. Hence, we stress to interpret the relation between public input and science output in terms of efficiency with great caution. As with the assessment of the relation between total inputs and total outputs, we adopt two modeling strategies. One modeling strategy includes the full sample of countries between 2004-2008; in other words, 37 countries across 5 years rendering a total number of 185 observations. For the other modeling strategy, we again exclude countries that are considered outliers in either their input or output levels. In the restricted sample then, 29 countries are included across 5 years (2004-2008) rendering a total number of 145 observations.

Finally, we will assess the relation between private input and technology output as a means to address efficiency in the production of technological research excellence. That is, efficiency will be addressed in terms of the relation between BERD per GDP as an input variable and PCT applications per GDP as an

output variable. As with assessing efficiency in the production of scientific research excellence, assessing efficiency in the production of technological research excellence is conditional upon the assumption that PCT patents primarily stem from efforts made by commercial firms. Again however, it should be noted that while on the one hand private organizations produce scientific outputs, public organizations on the other hand also produce technological research outcomes. Hence, also here, any relation of efficiency between public (private) investments in R&D and scientific (technological) research excellence has to be interpreted with great caution. As with the assessment of the relation between total inputs and total outputs and public input and science output, we adopt two modeling strategies. One modeling strategy includes the full sample of countries between 2004-2008; in other words, 37 countries across 5 years rendering a total number of 185 observations. For the other modeling strategy, we again exclude countries that are considered outliers in either their input or output levels. In the restricted sample then, 28 countries are included across 5 years (2004-2008) rendering a total number of 140 observations.

Lacking data that better captures the link between scientific research assets and scientific research excellence on the one hand and technological research assets and technological research excellence on the other, we choose to include these sets of variables for our preliminary analysis of efficiency in the production of scientific and technological research excellence here. For all model specifications it holds that, as R&D efforts may not directly lead to research excellence in the same year, we measure all input indicators in time t as three-year averages of time t, t-1 and t-2. As such, we introduce a time lag between input and output measures.

Table 3.4 to Table 3.7 present descriptive statistics for all five variables going from the full sample of countries and years. Note that all input variables correlate highly with the output variables. This is important for any kind of efficiency analysis given that a relation – in whatever form or direction - between inputs and outputs is assumed. Were inputs not to correlate with outputs, efficiency analysis would not make sense in the first place.

Table 3.4: Descriptive statistics for the full sample (185 observations)

Variable	Obs	Mean	Std. Dev.	Min	Max	(1)	(2)	(3)	'(4)	(5)
(1) GERD/GDP	185	1.642	1.063	0.340	4.623	1 ***				
(2) GOVERDHERD/GDP	185	0.568	0.238	0.160	1.287	0.795 ***	1 ***			
(3) BERD/GDP	185	1.051	0.865	0.073	3.737	0.986 ***	0.697 ***	1 ***		
(4) Number of highly cited publications/GDP	185	5.140	3.550	0.488	17.300	0.681 ***	0.707 ***	0.631 ***	1 ***	
(5) Number of PCT patents/GDP	185	2.850	2.910	0.132	11.300	0.936 ***	0.750 ***	0.761 ***	0.761 ***	1 ***

Note: The input indictators (1), (2) and (3) are calculated as three year averages in period t, t-1 and t-2. The output indicators (4) and (5) are measured for time t and are presented in this table per billion GDP. The database covers 37 countries for the period 2004-2008 (185 observations). Significance levels of the correlations: * = 0.05, ** = 0.01, *** = 0.005.

Table 3.5: Descriptive statistics for the Public Input-Science Output model without outlier countries (145 observations)

Variable	Obs	Mean	Std. Dev.	Min	Max	(1)	(2)
(1) GOVERDHERD/GDP	145	0.629	0.221	0.240	1.287	1 ***	
(2) Number of highly cited publications/GDP	145	5.810	3.620	0.667	17.300	0.660 ***	1 ***

Note: The input indictator (1) is calculated as three year averages in period t, t-1 and t-2. The output indicator (2) is measured for time t and are presented in this table per billion GDP. This restricted database covers 29 countries for the period 2004-2008 (145 observations). Significance levels of the correlations: * = 0.05, ** = 0.01, *** = 0.005.

Table 3.6: Descriptive statistics for the Private Input-Technology Output model without outlier countries (140 observations)

Variable	Obs	Mean	Std. Dev.	Min	Max	(1)	(2)
(1) BERD/GDP	140	1.289	0.859	0.140	3.737	1 ***	
(2) Number of PCT patents/GDP	140	3.550	3.020	0.132	11.300	0.912 ***	1 ***

Note: The input indictator (1) is calculated as three year averages in period t, t-1 and t-2. The output indicator (2) is measured for time t and are presented in this table per billion GDP. This restricted database covers 28 countries for the period 2004-2008 (140 observations). Significance levels of the correlations: * = 0.05, ** = 0.01, *** = 0.005.

Table 3.7: Descriptive statistics for the Public Input-Science & technology Output model without outlier countries (130 observations)

Variable	Obs	Mean	Std. Dev.	Min	Max	(1)	(2)	(3)
(1) GERD/GDP	130	1.993	1.059	0.473	4.623	1 ***		
(2) Number of highly cited publications/GDP	130	6.110	3.680	0.667	17.300	0.622 ***	1 ***	
(3) Number of PCT patents/GDP	130	3.750	3.040	0.164	11.300	0.930 ***	0.723 ***	1 ***

Note: The input indictator (1) is calculated as three year averages in period t, t-1 and t-2. The output indicators (2) and (3) are measured for time t and are presented in this table per billion GDP. This restricted database covers 26 countries for the period 2004-2008 (130 observations). Significance levels of the correlations: * = 0.05, ** = 0.01, *** = 0.005.

4 Results

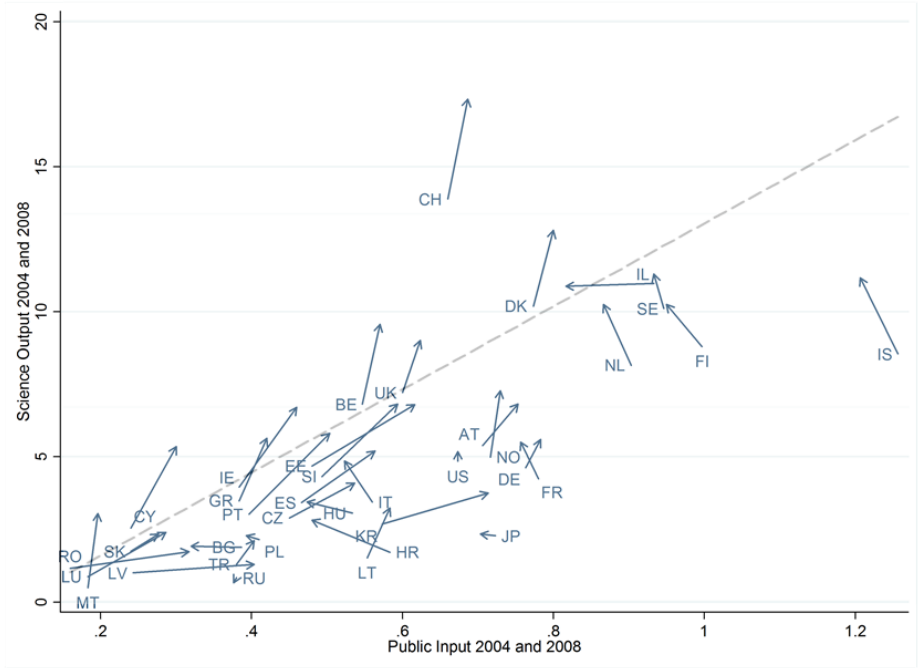
4.1 Output/input ratios

Figure 4.1 and Figure 4.2 plot inputs and outputs for respectively the public input/science output model and the private input/technology model for the full sample of countries for two years (2004 and 2008). For each country we present changes in the relationship between research input and output between 2004-2008 by connecting the data points for these two years with an arrow (the arrow denoting the change between 2004 and 2008). The dotted line in the figures is a linear fit through all the data points and represents the average efficiency line across all observations. Countries situated above this line are more efficient than countries below the line. First, in line with the correlations shown before, Figure 4.1 on efficiency in the production of scientific research excellence shows that higher public input levels generally go hand in hand with higher science output levels.

Second, nevertheless, there is considerable variation among countries' combination of public input and science output. For example, for about the same level of public input Switzerland has considerable higher levels of science output than Japan and the US. Alternatively, for about the same level of science output the Netherlands uses considerably higher levels of public input than the UK and Belgium. Note that this variation in combinations of public input and science output seems to be an important driver of the average efficiency line. That is, a few countries (most notably Switzerland, Denmark, Belgium, and the UK) seem to tilt the efficiency line towards the upper left part of the figure.

Third, some countries have improved their efficiency in the production of scientific research excellence. That is to say, for the Netherlands, Iceland, Finland, France, Poland, Hungary, Italy, and Croatia the arrow connecting 2004 with 2008 points at the upper left direction of the figure indicating that science output has gone up whilst public input has gone down. For most other countries, the direction of change in their efficiency is much more ambiguous as most of them show increases in both science output and public input.

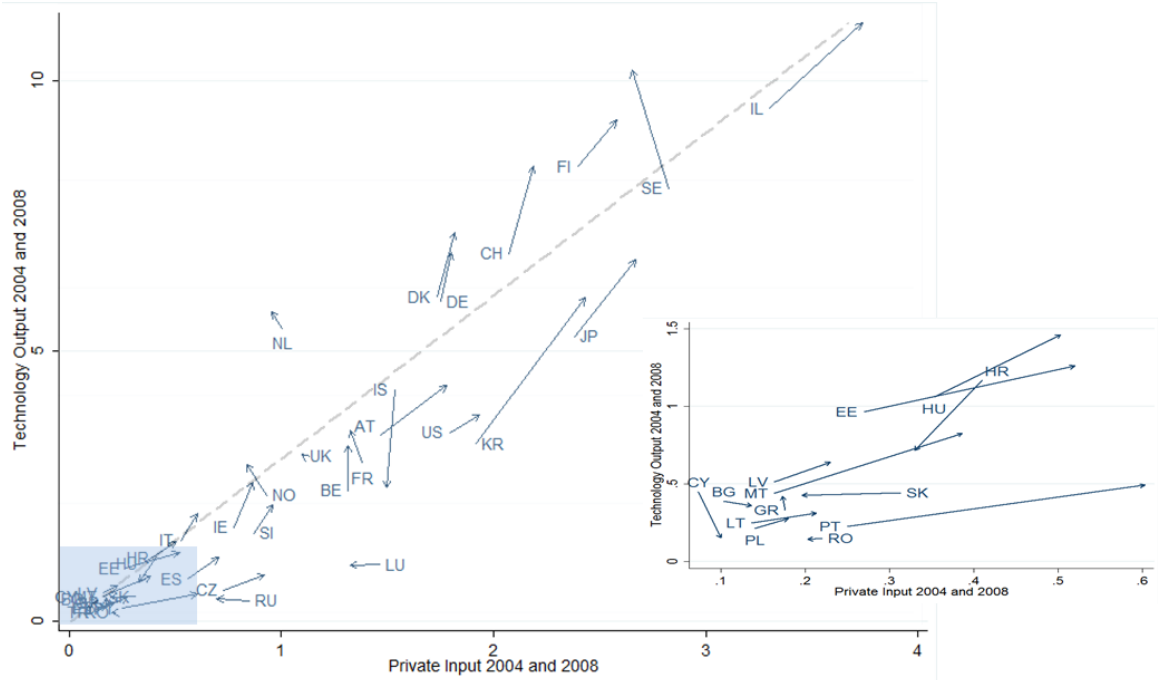
Figure 4.1: Public inputs versus scientific research excellence outputs



Note: The input and output measures are normalized by GDP (see Table 3.3). The output levels are displayed per billion GDP. The arrows represent the change output/input combinations from 2004 to 2008.

Similar patterns hold for the relation between private inputs and technological research excellence outputs (Figure 4.2). First, higher levels of private input are associated with higher levels of technology output. Second, though perhaps less than is the case for public input/science output, countries show considerable variation in combining private input with technology output. For example, while South Korea and Switzerland have about the same level of private input, Switzerland has a considerable higher level of technology output. Alternatively, while Japan and the Netherlands have about the same level of technology output, Japan uses a much higher level of private input. Again, there are some countries that seem to tilt the average efficiency line towards the upper left corner of the figure (most notably the Netherlands, Germany, Switzerland, Finland, and Denmark). Third, again only few counties have improved their efficiency in producing technological research excellence unambiguously. These countries are the Netherlands, Sweden, Russia, Norway, and Greece. In other words, these countries have improved on technology output while reducing their private input.

Figure 4.2: Input and output parameters for technology excellence



Note: The input and output measures are normalized by GDP (see Table 3.3). The output levels are displayed per billion GDP. The arrows represent the change in input/output combinations from 2004 to 2008.

In order to better assess the relationship between inputs and outputs of research systems, we rank the five best and least performing countries in terms of their input, output and output/input ratios for the year 2008. Table 4.1 presents the ranking of countries based on their public input, science output, and science output/public input ratio in 2008. First, again it is clear that high levels of science input go hand in hand with high levels of science output. Iceland, Sweden, and Israel appear among the top-5 countries with both highest levels of public input and highest levels of science output. Second, the statistics in Table 4.1 allows disentangling to what extent an outstanding performance in output/input ratio stems from the input or output dimension. Countries ranking high both in terms of inputs and outputs do generally not record the best output/input ratios compared to other countries. An exception is Denmark that ranks 4th on science output/public input whilst ranking 6th and 2nd on respectively public input and science output. Most countries ranking high on science output/public input ratios score rank either low on public input whilst being ranked moderately on science output (e.g. Cyprus) or high on science output whilst being ranked moderately on public input (e.g. Switzerland and Belgium).

Table 4.1: Ranking of countries based on their public input, science output, and science output/public input ratio in 2008

Statistics for Public Input - Science Output												
Country	Code	Rank	Input	Country	Rank	Code	Output	Country	Code	Input Rank	Output Rank	Output/Input
Iceland	IS	1	1.21	Switzerland	1	CH	17.33	Switzerland	CH	13	1	25.23
Finland	FI	2	0.95	Denmark	2	DK	12.80	Cyprus	CY	34	19	17.83
Sweden	SE	3	0.93	Sweden	3	SE	11.30	Belgium	BE	19	8	16.78
Netherlands	NL	4	0.87	Iceland	4	IS	11.18	Denmark	DK	6	2	16.00
Israel	IL	5	0.82	Israel	5	IL	10.88	Malta	MT	37	27	15.44
Romania	RO	32	0.32	Turkey	32	TR	2.11	South Korea	KR	11	24	5.25
Cyprus	CY	33	0.30	Bulgaria	33	BG	1.91	Turkey	TR	28	33	5.24
Luxembourg	LU	34	0.29	Romania	34	RO	1.73	Japan	JP	12	31	3.31
Slovakia	SK	36	0.28	Latvia	36	LV	1.28	Latvia	LV	28	36	3.18
Malta	MT	37	0.20	Russia	37	RU	0.67	Russia	RU	31	37	1.77

Note: Output measures are presented per billion GDP.

Table 4.2 presents the ranking of countries based on their private input, technology output, and technology output/private input ratio in 2008. Again, high levels of (private) input go hand in hand with high levels of (technology) output. Israel, Sweden, and Finland are ranked in the top-5 countries for both private input levels and technology output levels. Alternatively, Cyprus and Bulgaria are ranked in the bottom-5 countries for both private input and technology output. Of all countries in both the top-5 private input and technology output rankings, only Sweden appears in the top-5 of countries with the highest technology output/private input ratio. Again it seems that having a high ratio here is either caused by low levels of private input given levels of technology output or high levels of technology output given levels of private input. That is, few countries manage to combine high levels of technology output with low levels of private input (with the exception of Sweden mentioned before and to a lesser extent also Germany).

Table 4.2: Ranking of countries based on their private input, technology output, and technology output/private input ratio in 2008

Statistics for Private Input - Technology Output												
Country	Code	Rank	Input	Country	Code	Rank	Output	Country	Code	Input Rank	Output Rank	Output/Input
Israel	IL	1	3.74	Israel	IL	1.00	11.07	Netherlands	NL	17	9	5.99
Japan	JP	2	2.67	Sweden	SE	2.00	10.18	Denmark	DK	8	5	3.95
Sweden	SE	3	2.65	Finland	FI	3.00	9.26	Switzerland	CH	6	4	3.84
Finland	FI	4	2.58	Switzerland	CH	4.00	8.41	Sweden	SE	3	2	3.84
South Korea	KR	5	2.43	Denmark	DK	5.00	7.18	Germany	DE	9	6	3.77
Slovakia	SK	32	0.20	Bulgaria	BG	32.00	0.36	Czech Republic	CZ	18	24	0.92
Poland	PL	33	0.18	Lithuania	LT	33.00	0.31	Portugal	PT	23	28	0.82
Greece	GR	34	0.17	Poland	PL	34.00	0.28	Luxembourg	LU	12	23	0.77
Bulgaria	BG	36	0.14	Cyprus	CY	36.00	0.15	Romania	RO	32	37	0.71
Cyprus	CY	37	0.10	Romania	RO	37.00	0.14	Russia	RU	22	32	0.57

Note: Output measures are presented per billion GDP.

4.2 Robust efficiency measures

In this section we present the results of the robust production frontier analysis for the three different model specifications discussed before (total input/total output, public input/science output, and private

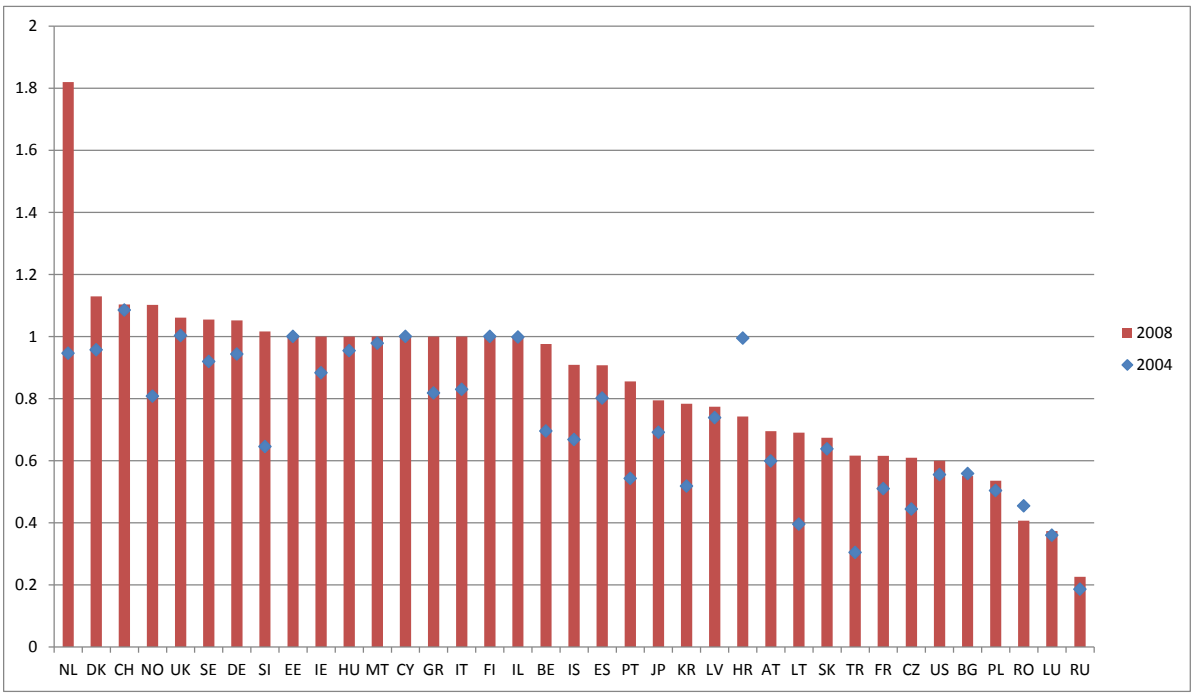
input/technology output). For each model specification we estimated order-α and order-m efficiency models. The order-α models are reported in the main text while the order-m models are presented in annex 4. The values of α and m vary across the models since their values were chosen to approximate as close as possible a threshold value of five percent super-efficient countries (i.e. countries reporting Shepard efficiency scores above one). All the models are estimated for the period 2004-2008, resulting in yearly efficiency scores for all the countries in the analysis. However, for ease of presentation and to obtain a clear-cut overview of efficiency dynamics over time, we only present the efficiency scores for the first and last year of the time period.

4.2.1 Efficiency scores and rankings for total input-science & technology output models

The efficiency scores and rankings across countries in the years 2004 and 2008 for the order-α model on the full sample of countries are presented in Figure 4.3. In this model, eight countries are reported as super-efficient. Among them the Netherlands is again a top performer, followed by Scandinavian countries (Denmark, Norway, Sweden), Switzerland, United Kingdom, Sweden, Germany and Slovenia. Besides the super-efficient performers, a large group of countries is situated on the efficiency frontier. This group is quite heterogeneous ranging from Scandinavian countries (Finland), West European countries (Ireland), to Mediterranean and East-European countries (e.g. Italy, Greece, Hungary and Estonia).

Among the efficient and super-efficient countries, some results should be taken with caution as they may be caused by large fluctuations in input and output indicators (especially for countries as Slovenia, Estonia, Malta and Cyprus). Few countries seem to be located below the efficiency frontier, as indicated by the efficiency scores below one. Among the countries that are close to the efficiency frontier are Israel, Belgium, Iceland and Spain. From then on the efficiency scores ranges from 0.8 to 0.2, including West-European countries (e.g. Austria, France), international benchmark countries (US, Japan, South Korea) and some East-European countries (e.g. Hungary, Latvia). Romania, Luxembourg and Russia belong to the group of countries with the lowest efficiency scores. Most countries increase in efficiency scores over time, while a few decline in efficiency (e.g. Latvia and Romania) and some stay constant (e.g. Italy and Finland).

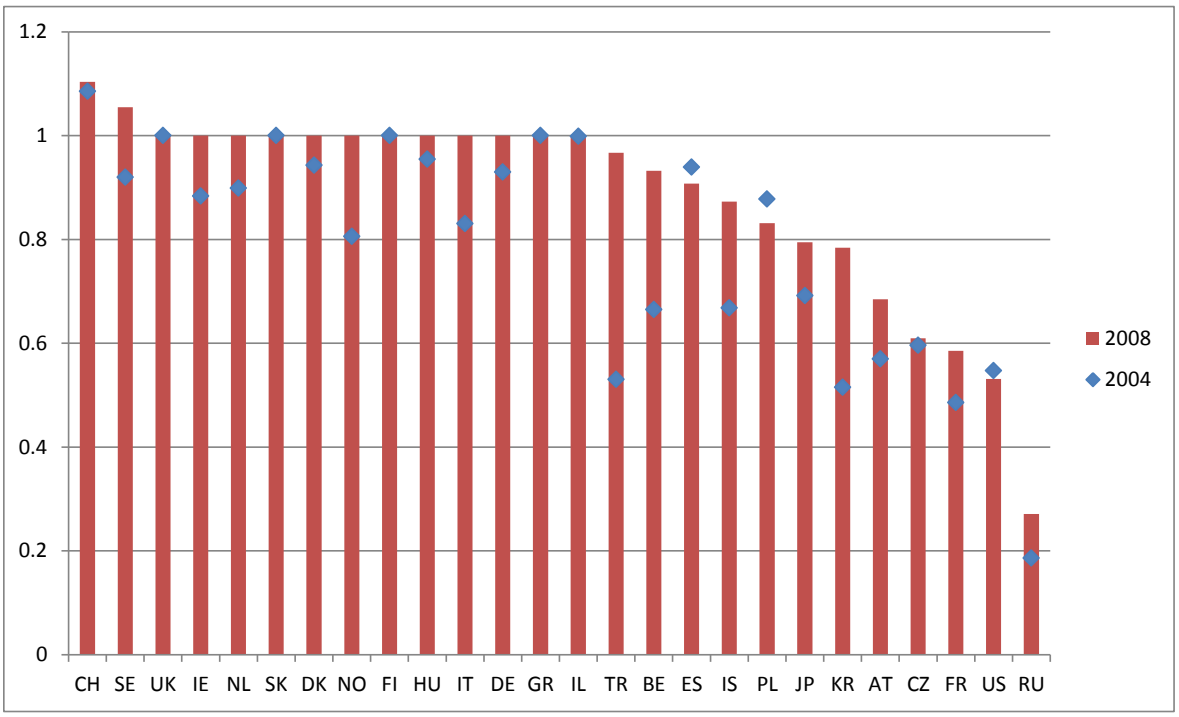
Figure 4.3: Ranked efficiency scores total input-science & technology output model (order alpha; 2004 and 2008; full sample)



Note: Efficiency scores are measured in Shepard values and alpha = 0.99.

Figure 4.4 reports on the efficiency scores and rankings across countries in the years 2004 and 2008 for the order-α model on the restricted sample of countries. Comparing the order-alpha models on the full and restricted sample, we notice some differences in the scores and rankings in 2008. Partly, the difference in scores is due to the fact that the order-α model on the restricted sample contains less super-efficient countries (two compared to eight in the full sample model). As previously mentioned, the α value is set such that the model generates a number of super-efficient countries compared to the total number of countries that is as close as possible to five percent of the total number of countries. By consequence, in the restricted model, Switzerland and Sweden are still super-efficient countries, while other countries that belonged to this group in the full sample model are related to the group of efficient countries. The remainder of the ranking in 2008 remains similar to the full sample model.

Figure 4.4: Ranked efficiency scores total input-science & technology output model (order alpha; 2004 and 2008; restricted sample)

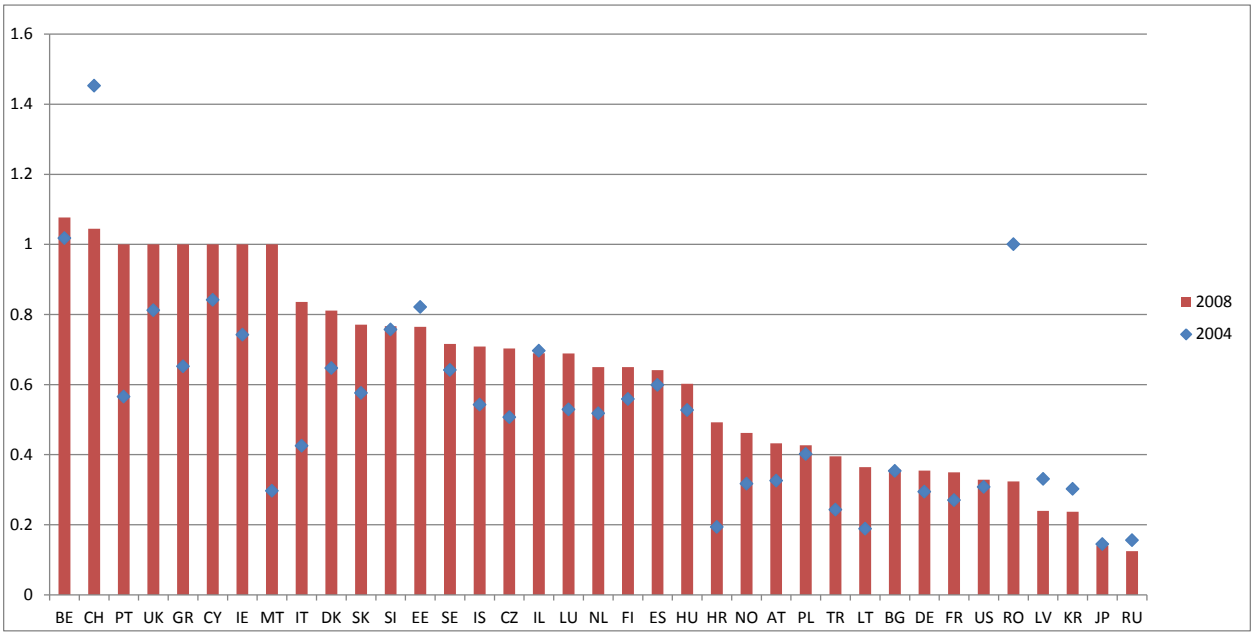


Note: Efficiency scores are measured in Shepard values and alpha = 0.99.

4.2.2 Efficiency scores and rankings for public input-science output models

The efficiency scores and rankings across countries in the years 2004 and 2008 for the public input – science output order alpha model are presented in Figure 4.5. Two countries, Belgium and Switzerland, seem to outperform all other countries in 2008 in their efficient use of public inputs in the creation of excellent scientific research. These countries are denoted as super-efficient as they are situated beyond the efficiency frontier (i.e. having Shepard efficiency scores above one). In 2008, six countries are reported to be on the efficiency frontier: United Kingdom, Ireland, Greece, Cyprus, Portugal and Malta. The results for the latter three countries should be taken with caution as the scores could be biased through large fluctuations in their input and output indicators over time. Besides these efficient and super-efficient countries, most countries are reported to be below the efficiency frontier, with efficiency scores below one and approximately ranging from 0.8 to 0.1. Two groups of inefficient countries can be distinct. A first group contains most of the Scandinavian countries, some West-European countries (Luxembourg, Netherlands), Mediterranean countries and some East-European countries (e.g. Hungary, Slovakia, Estonia). These countries report scores from 0.8 to 0.6. Finally, the second group fluctuates between 0.5 and 0.1 in efficiency, and regroups East-European countries (e.g. Latvia, Lithuania), some West-European countries (e.g. Austria, Norway, Germany, France) and most international benchmark countries (US, Japan, South-Korea). Turning to the efficiency scores in 2004, we notice that most of the countries have increased in efficiency over time between 2004 and 2008, with some remarkable exceptions of Switzerland and Romania, reporting decreases over time.

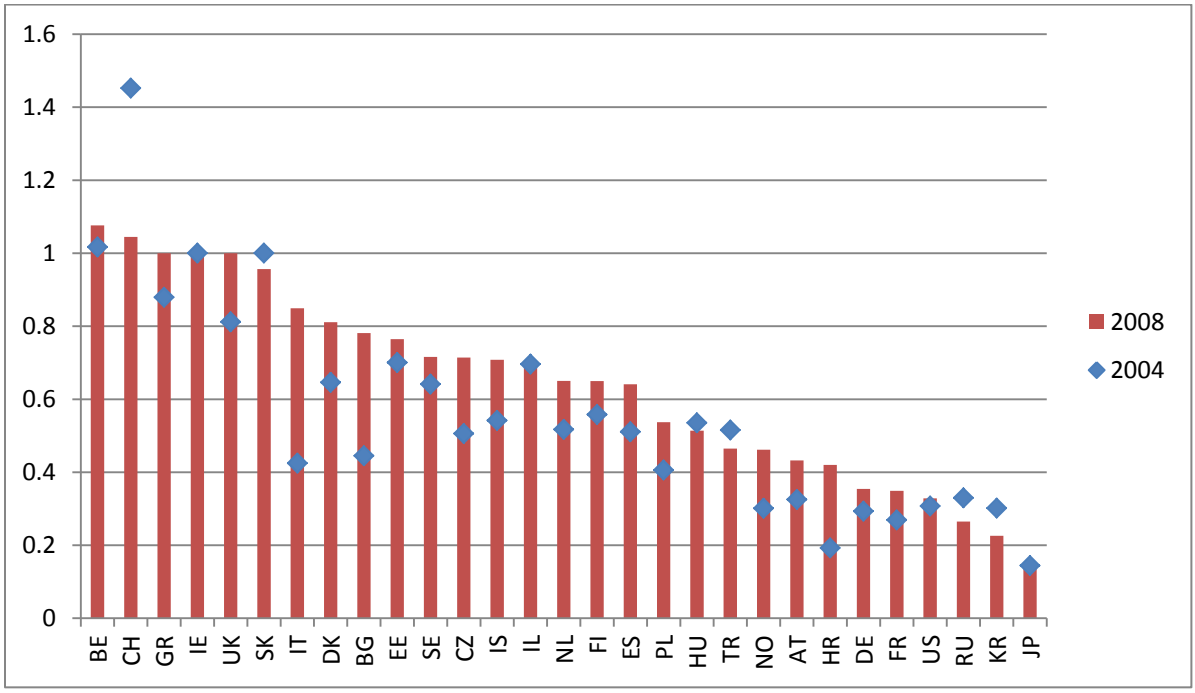
Figure 4.5: Ranked efficiency scores public input-science output model (order alpha; 2004 and 2008; full sample)



Note: Efficiency scores are measured in Shepard values and alpha = 0.985.

To avoid that the efficiency scores may be biased due to countries with large fluctuations in their input or output indicators, we run the models on a restricted sample of countries (see paragraph in which we present the model specifications). The efficiency scores and rankings in 2004 and 2008 for the public input – science output models on the restricted samples are presented in Figure 4.6 (order-alpha model).

Figure 4.6: Ranked efficiency scores public input-science output model (order-alpha; 2004 and 2008; restricted sample)



Note: Efficiency scores are measured in Shepard values and alpha = 0.98.

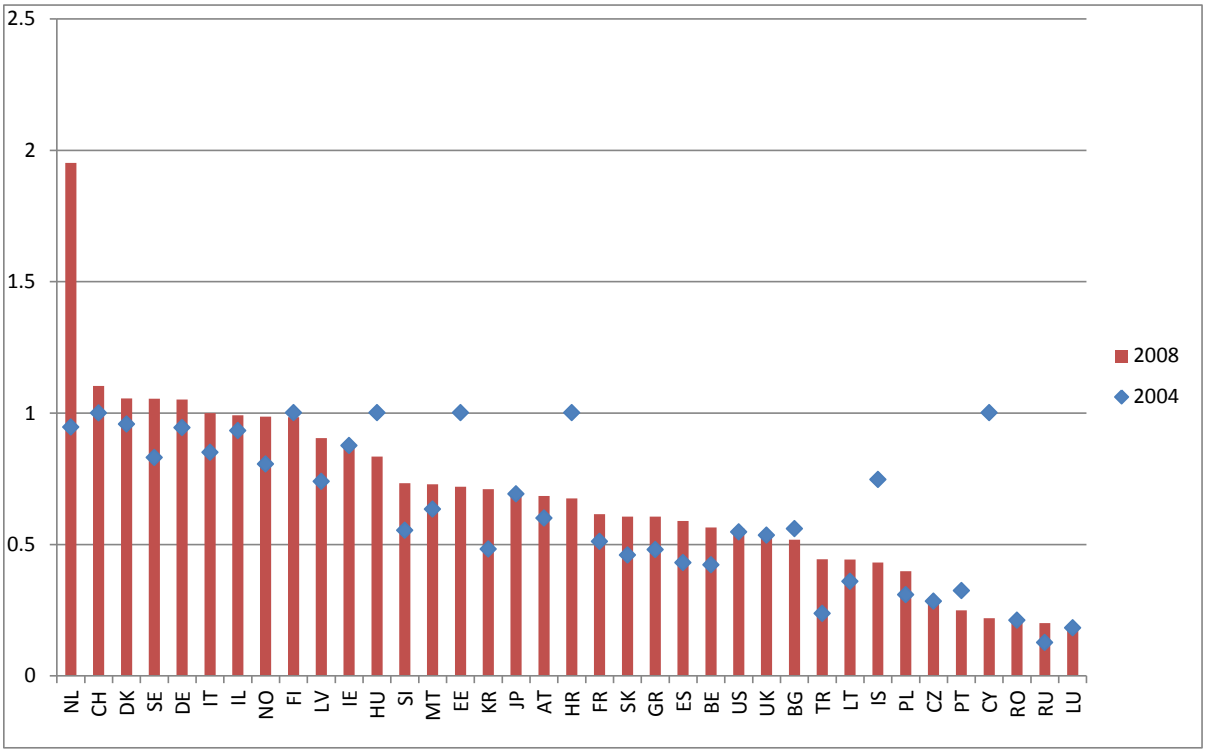
Comparing the order-alpha models on the full and restricted sample, we can draw several conclusions. The best performing countries in terms of public input – science output are still Switzerland and Belgium, followed by Ireland, Greece and the United Kingdom. No tremendous change is reported in the group of less efficient countries, with the notable exception of Bulgaria. While in the full sample Bulgaria was part of the second group of most inefficient countries, in turns out to be much more efficient when observing the results of the restricted sample. This remarkable difference in efficiency score for Bulgaria between the two samples is caused by the fact that some of the outlier countries that were left out in the restricted sample are peer countries (i.e. countries that have a lower or equal level of public inputs). As a consequence, when leaving out these outlier countries, it seems that Bulgaria may be more efficient in producing excellent scientific research given its small public resources.

4.2.3 Efficiency scores and rankings for private input-technology output models

While in the public input – science output models, only two countries are reported as being super-efficient, this efficiency analysis (Figure 4.7) reports a group of five countries in this category. Among them the Netherlands is a top performer in the efficient use of private R&D inputs in creating excellent research in technology. With an efficiency score of 1.9 it leads the efficiency ranking in 2008 and outperforms other super-efficient countries from which the efficiency score ranges from 1.05 to 1.1. This latter group contains Scandinavian countries (Denmark, Sweden), Switzerland and Germany.

Although not being super-efficient, a large group of countries seems to have (closely) reached the efficiency frontier, reporting efficiency scores (almost) equal to one. This group includes Scandinavian countries (Norway, Finland), Mediterranean countries (Italy) and Israel. A large amount of countries have still opportunities for improvements in their efficient use of resources, as indicated by the efficiency scores below one. Among them, Latvia, Ireland and Hungary are closest to the frontier. However, the efficiency for Latvia should be treated with caution as this score may be influenced by high fluctuations in input and output indicators. The worst performing countries in terms of efficient use of private R&D investments to reach technological research excellence are Romania, Russia and Luxembourg. While most of the countries report an increase in efficiency between 2004 and 2008, some others (drastically) decline in their efficiency (e.g. Estonia, Croatia, Cyprus, Hungary, Iceland and Cyprus). However, note that most of these latter countries have been flagged as outliers.

Figure 4.7: Ranked efficiency scores private input-technology output model (order alpha; 2004 and 2008; full sample)



Note: Efficiency scores are measured in Shepard values and alpha = 0.99.

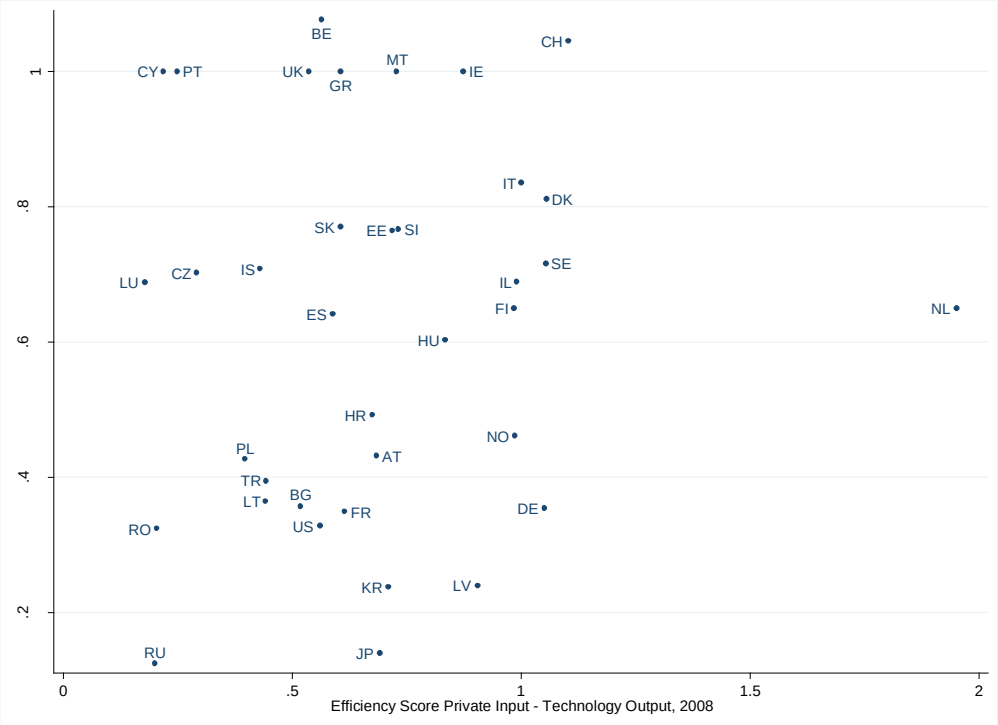
To evaluate whether the efficiency scores are affected by countries with growth patterns in their input or output indicators that exceed two standard deviations from the average, we run previous models on restricted samples, leaving out outlier countries. The efficiency scores and rankings in 2004 and 2008 for the private input – technology output models on the restricted samples are presented in Figure 4.7

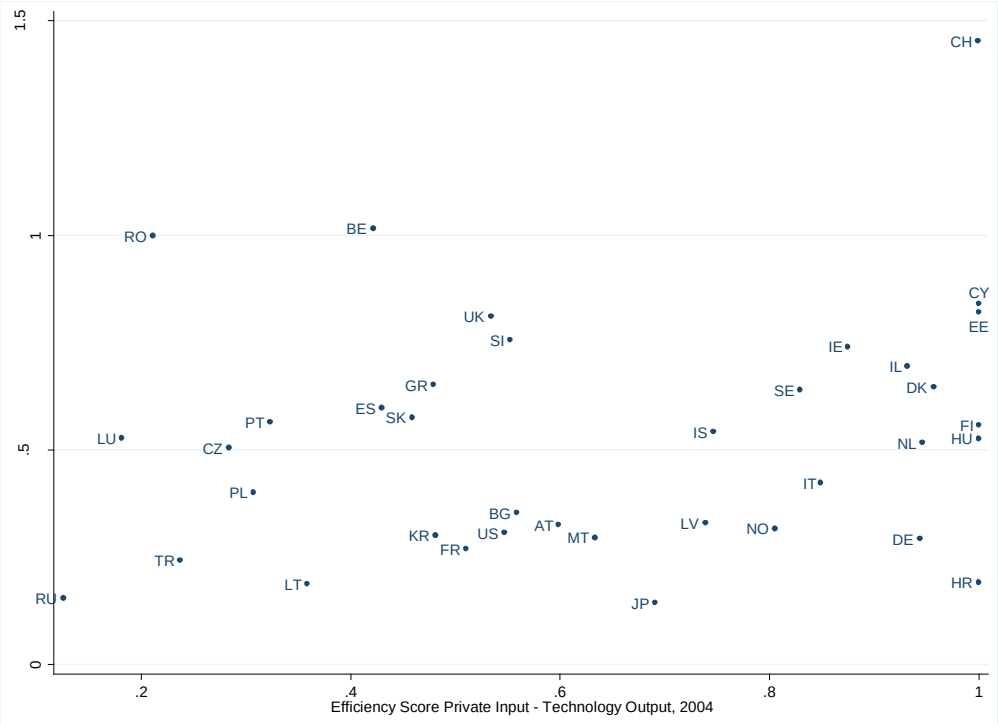
(order-alpha model). Comparing the order-alpha models on the full and restricted sample, we notice some differences in the scores and rankings in 2008. A first difference concerns the lower amount of super-efficient countries, as in this model the Netherlands is reported to be on the efficiency frontier. Second, and more remarkable, is the increase in efficiency of Greece. Similar to the Bulgarian case in the public input – science output models, this country loses its benchmark countries when performing the analyses on a restricted sample. Third, fewer countries seem to suffer from a decrease in efficiency over time.

4.3 The relation between efficiency in the production of scientific research excellence and technological research excellence

In order to analyze the relationship between the efficiency in scientific research and technological research we plot countries along these two dimensions for the respective periods of 2004 and 2008 in Figure 4.8. These plots indicate that both dimensions of efficiency do not necessarily go hand in hand, as can be observed by the overall scattered representation of countries within the figure. Countries performing well in terms of the efficient use of input resource related to their production of excellent science, do not necessarily score well on their efficiency in technology excellence. Although countries may be positioned on the efficiency frontier of science excellence (e.g. Belgium in 2004, United Kingdom in 2008) or even beyond it (e.g. super-efficient Switzerland in 2004 and 2008), they may drastically differ in their efficiency in technology (e.g. Switzerland being still super-efficient in technology efficiency while Belgium and UK report only mediocre technology efficiency scores in respectively 2004 and 2008). Other countries may perform rather well on efficiency in technology excellence but relatively low in terms of science efficiency (e.g. Croatia, Germany and Italy in 2004 or Germany and Latvia in 2008). For some countries the relationship between efficiency scores points in the same direction, i.e. low scores on both dimensions (e.g. Russia and Turkey in 2004 or Romania and Russia in 2008) or relatively high scores (e.g. Cyprus and Estonia in 2004 or Switzerland and Ireland in 2008). Overall, we can conclude that efficiency scores in science and technology do not coincide as there is no clear-cut relationship among them.

Figure 4.8: Relationship between efficiency in science and technology excellence for 2004 and 2008





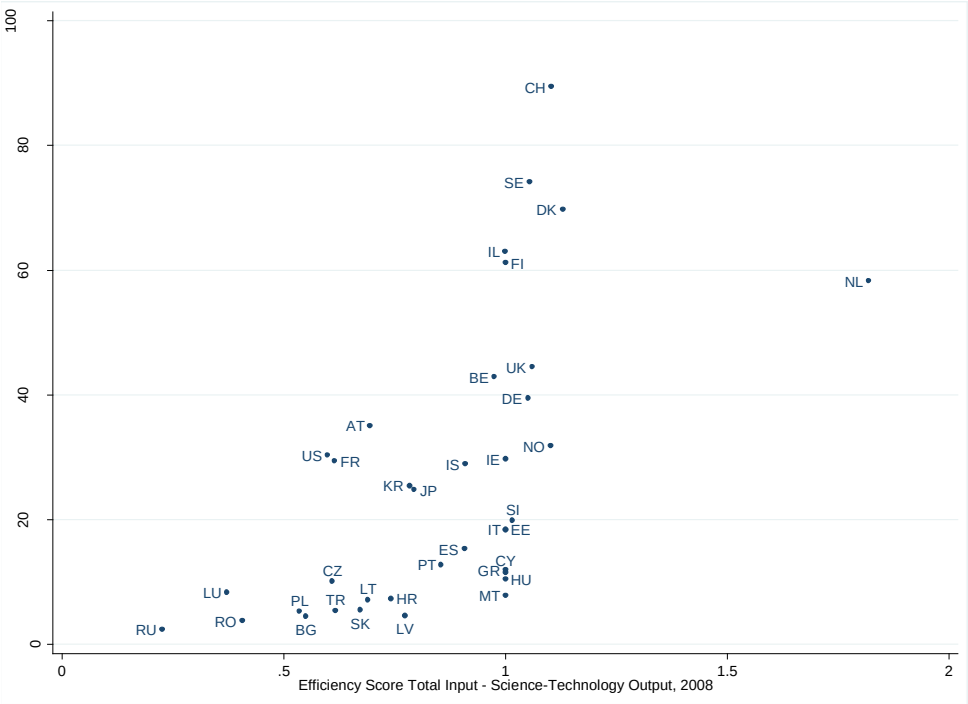
Note: The overall pairwise correlation between the efficiency score in science excellence and technology excellence is respectively 0.29 and 0.21. The respective spearman rank correlations are 0.18 and 0.14.

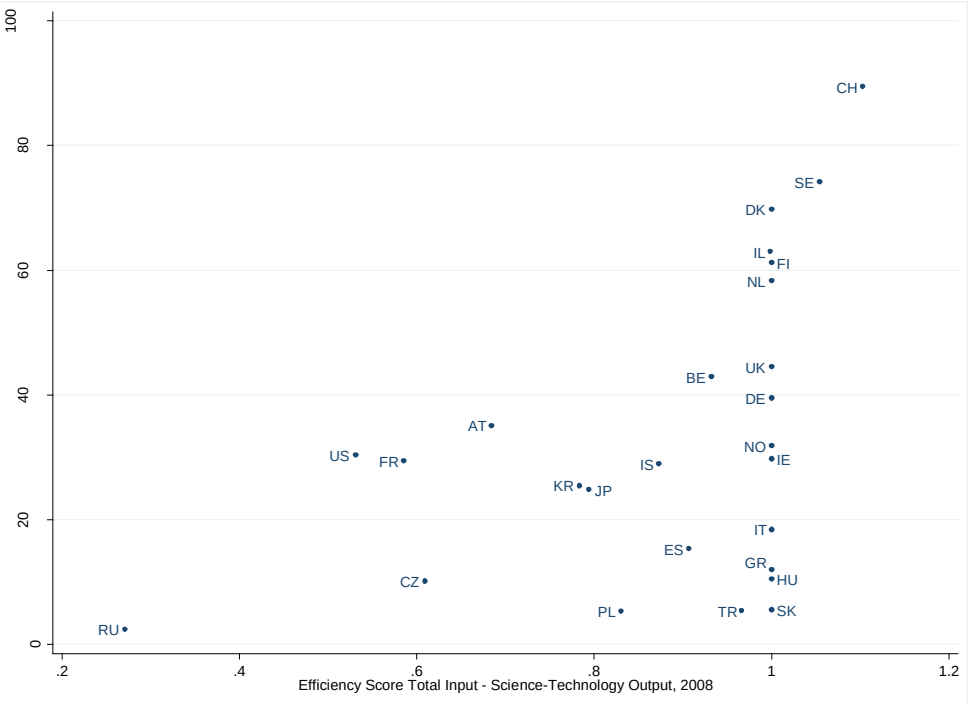
4.4 The relation between efficiency and excellence

From a policy perspective it is primordial to explore the relationship between the production of excellent research on the one hand and the efficiency in research excellence on the other. We recall that the former issue is primarily related to the quantity of excellent research produced in a country, while the latter explores to what extent input measures dedicated to research excellence actually leads to its production. Relating these two dynamics is important to understand the interplay and relationship between efficiency and research excellence as countries with a high performance in research excellence do not necessarily score well on their efficient use of research inputs. For this purpose, we relate the composite indicator of research excellence of 2008 (Hardeman et al., 2013) to the efficiency scores of total input – science and technology of 2008 in Figure 4.9. The figure depicts the relationships both for the full (top) and restricted (bottom) sample of countries.

From the relative position of countries within the two figures and the respective rank correlations between the efficiency scores and the research excellence (respectively 0.44 and 0.48 for the full and restricted sample) we can conclude that there is positive but weak relationship between the two dimensions. These correlations are positively influenced by countries reporting scores for the two dimensions that point in the same direction (e.g. high scores on efficiency and excellence: Switzerland, Denmark, Sweden, Israel; low scores on efficiency and excellence: Russia, Romania, and Luxembourg). In sharp contrast to these observations, a large part of countries performing well in terms of efficiency do however report mediocre to low scores on research excellence (e.g. Cyprus, Greece, Hungary and Malta). The position of this latter group of countries is not surprising. As indicated by the research excellence index, these countries perform low in terms of qualitative research output. However, given the proportionally low input resources they use for their research production, they are able to obtain relatively high efficiency scores.

Figure 4.9: Efficiency scores versus composite indicator of research excellence in 2008





Note: The first and second figure reflect on the relationship between efficiency and research excellence indicator for respectively the full and restricted sample of countries in 2008. For the full sample graph, the pairwise correlation between the two indicators is 0.60 while the spearman rank correlation is 0.70. For the restricted sample the correlations respectively elevate at 0.44 and 0.48.

5 Conclusions

5.1 Summary

The main contribution of this project lies in the assessment of the efficiency of national research systems in achieving excellent research performances. The efficiency assessment is not only restricted to the production of research excellence in general, but is disentangled by type of research field, distinguishing between science and technology. This distinction provides a helpful tool for policy makers in assessing the discrepancy of efficiency in both science and technology excellence within and across countries. For this purpose, we develop a conceptual and empirical framework. The conceptual framework mainly builds on a previous project of (Hardeman et al., 2013) aiming at constructing a composite indicator measuring scientific and technological research excellence. Based on this work, we define the basic notions and concepts needed to understand the results of this study. We explain what is meant by research; we define the notion of national research systems and describe the different building blocks that constitute them. Finally, we introduce the notion of efficiency in achieving excellent research performances at the national level. A national research system's efficiency can be defined as the extent to which a country is able to transform research assets into excellent research.

After having outlined the target of this study and the main concepts related to it, we addressed empirical issues concerning data requirements and mathematical methods used for efficiency analyses. Overall, we conducted efficiency analyses on three main model specifications in which we relate the amount of resource assets to the performance on excellent research. In a first type of model we relate public R&D capital investments to measures of excellent scientific output. Estimating this efficiency relationship is of particular interest for policymakers as the allocation of public investments in R&D can directly be influenced by them. Public R&D investments are measured by the R&D investments in the government sector and the higher education sector, while the excellence of scientific output is captured by the number of highly cited publications. This latter indicator is defined as the field-normalized count of the 10% most highly cited publications. In a second model specification private R&D investments (i.e. business enterprise expenditure on R&D) are related to an output measure capturing the technological research excellence. In this model specification, the number of PCT patents is used as proxy for the technological research excellence. Finally, a third type of model relates the total R&D investments to output measures capturing both scientific and technological research excellence. We use the gross R&D expenditures as measure for the total R&D investments and we proxy the scientific and technological research excellence by the number of highly cited publications and the number of PCT patents. All country-specific measures are normalized by their respective GDP. Efficiency analyses are conducted for the period 2004-2008 and are including 37 countries, capturing the EU28, the candidate countries, most EFTA countries and some international benchmark countries (China, US, South-Korea and Japan).

Various methodologies have been developed to address efficiency empirically. After having reviewed the various methodologies we choose to primarily report on two methodologies here: output/input ratios and robust production frontiers. While the former present partial measures of efficiency, the latter present complete and robust measures. Two robust production frontier methods have been developed by (Daraio and Simar, 2007a): order-m and order-alpha method. With robust order-m analysis the efficiency of each observation is benchmarked against the average maximal output by m-

number of peers that are randomly drawn from the population of countries using fewer or an equal amount of inputs than the focal observation. The rationale behind the order-alpha efficiency models is quite similar to that of order-m efficiency models, but may be more intuitive for the reader. In this type of models a percentile alpha is fixed beforehand as to select a subset of peer countries from the distribution of all countries that will be taken into account to estimate the efficiency frontier. As such, the output level of a focal country is benchmarked against the output level not exceeded by 100(1-alpha) of units in the population of countries using fewer or an equal amount of inputs. Important to note is that although both methods use a different approach to approximate the production frontier, they generate similar results.

In section 4 we turned to the main findings of the report. In a first attempt to gain insights in the data, we relate input measures of research to their respective output measures. A positive trend between research inputs and outputs is revealed, indicating that countries employing more research resources in science (or technology) are in general recording higher levels of excellent scientific (or technological) research. Second, we rank the five best and least performing countries in terms of their research input, excellent research output and their respective output/input ratios. We observe that most of the top ranking countries in terms of research inputs also classify highly on excellent research output. Countries with extensive research resources in terms of financial R&D expenditures do probably perform better on the underlying factors that influence research excellence (e.g. attracting and employing top scientists and having better (pre)conditions to encourage innovative entrepreneurship). In addition, most of the countries rank well on the output/input ratio due to a high value on the numerator, while just a few outperform in efficiency due to an extremely low level of their denominator.

After a first exploration of the input and output measures, we turn to the findings on efficiency scores and country rankings obtained with robust production frontier methods. A number of patterns stand out from the analyses. Overall, most of the countries improved in their efficiency over time in the period of analysis (2004-2008). The best performing countries in terms of efficient use of public research assets to achieve excellent scientific research are Belgium, Switzerland, Greece, Ireland and United Kingdom. The Republic of Korea, Japan and the Russian Federation are among the least performing ones. Efficiency scores and rankings for technological research show a different dynamic. Top performing countries in this category are the Netherlands, Switzerland, Denmark, Sweden and Germany. Romania, Luxembourg and the Russian Federation are among the lowest in ranking. Exploring the top level countries on efficiency in achieving research excellence in general, we note a mixture of previous categories, including the Netherlands, Denmark, Switzerland, Norway and United Kingdom. The least performing countries are similar to those mentioned for the technological efficiency.

Finally, we explore to what extent efficiency in science is related to efficiency in technology by plotting countries along these two dimensions. We find that efficiency performances in science and technology do not coincide as there is no clear-cut relationship among them. In addition, we explore the relationship between the production of excellent research excellence and efficiency in achieving research excellence. We observe that top (or least) performing countries on research excellence do record the best (or lowest) positions on the efficiency rankings. However, efficiency performances vary

significantly for countries not belonging to the extreme tails of the distribution on research excellence. Hence, we do not find a clear-cut relationship between research excellence and efficiency.

5.2 Discussions and recommendations

From the analysis and results presented in this report we draw several main conclusions and derive various recommendations from them. A first conclusion holds that some of the results of the analysis seem to be counter-intuitive at first sight. For example, while Greece ranks as highly efficient when it comes to public inputs and excellent scientific outputs, the US ranks low in efficiency when it comes to public inputs and excellent scientific outputs. Note however, that efficiency is not the same as excellence as such. In other words, countries that are generally considered as excellent scientific research performers might by virtue of investing a lot of public money turn out less efficient in the end.

Second, countries that are efficient in the production of excellent scientific research need not necessarily also be efficient in the production of excellent research in technology or even in producing excellent research in general (i.e. including both excellent science and excellent technology outputs). As such, there seems to be room for most countries to either improve in efficiency in the production of scientific research excellence or to improve their efficiency in the production of technological research excellence. It remains for further research to address the underlying mechanisms that drive differences in efficiency scores across countries.

Third, most European countries have improved over time in their use of research assets to produce excellent research in general. Disentangling efficiency in science from efficiency in technology, we notice that - except for Switzerland scoring well on both dimensions - the ranking and scores are quiet heterogeneous. These results suggest that efficiency in science does not necessarily imply efficiency in technology. Moreover, empirical evidence shows that countries performing well on research excellence record relatively high efficiency scores, while this relationship is more scattered for countries with medium to poor research excellence performances. To conclude here, we note that for many countries then efficiency in the production of research excellence is less an issue than the production of research excellence itself. For sure, there are some countries that perform low in both excellence and efficiency. However, there are many more countries that despite their performance in efficiency perform relatively weak on excellence itself. This would seem to suggest that for most (or at least, these) countries (that are efficient already) emphasis should be placed more on excellence itself rather than efficiency.

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7 Annexes

7.1 Annex 1: Data

This section liberally quotes sections of a previous study of Hardeman et al. (2013).

Number of highly cited publications. The indicator was computed based on an initial data processing carried out by Science Metrix in the following way, as described in the Analysis and Regular Update of Bibliometric Indicators: Suite of Methods. All publications in Scopus (17.5 million publications considered over the time period 2000-2011) were attributed to a document type, a subfield (or scientific specialties, such as anatomy, evolutionary biology, and analytical chemistry) and field (such as chemistry, physics, and biology) by Science Metrix in a mutually exclusive journal-based definition. To account for different citation patterns across fields and subfields of science (e.g., there are more citations in biomedical research than in mathematics), each paper's citation count is divided by the average citation count of all publications of the corresponding document type (i.e., a review would be compared to other reviews, whereas an article would be compared to other articles) that were published the same year in the same subfield to obtain a Relative Citation count (RC).

Given that publication and citation practices differ across disciplines, differences in the extent to which highly cited publications are attributed to countries might arise just by virtue of different countries being specialized in different disciplines. This raises the question of how to delineate disciplines. While some simply use standard classifications to delineate disciplines, others very much question these standard classifications. Our position holds that there is no and in fact cannot be one single best classification of disciplines and industries. Preferably then, preferably we would pay attention to whether different disciplinary and industrial classification systems render different outcomes to our analysis (e.g. in terms of rankings and explanations). As of now however, we only have access to data on highly cited publications that are normalized using the disciplinary classification of ScienceMetrix. For the attribution of 15.000 journal sources, see the Ontology Report of Science Metrix: [URL: www.science-metrix.com/SM_Ontology_103.xls; Retrieved: November 2012].

Note that the threshold of highly citedness is arbitrarily set. While some consider only the top 1% highly cited publications as representing excellent scientific research outputs, others take a broader view focusing on the top 10%. Both measurements seem to correlate well with other (more ad hoc) measures of scientific excellence (Tijssen et al., 2002). Although we would have preferred to experiment with different threshold levels, the data that is available to us only involves a 10% threshold.

The number of publications by an entity (e.g., the world, a country, a NUTS2 region, an institution) in the 10% most cited publications in the database is determined using the relative citation (RC) scores of publications computed using a 3-year citation window following the year of publication. Because some publications are tied based on their RC score, including all publications in the database that have a RC score equal or greater than the 10% threshold often leads to the inclusion of slightly more than 10% of the database. To ensure that the proportion of publications in the 10% most cited publications in the database is exactly equal to 10% of the database, publications tied at the threshold RC score are each given a fraction of the number of remaining places within the top 10%. For example, if a database

contains 100 publications (i.e., the top 10% should contain 10 publications) and that the 9th, 10th, 11th and 12th publications all have the same RC score, they are each given a quarter of the remaining two places in the top 10% (0.5 publications of the top 10% each). An institution whose publications rank 2nd and 9th would therefore have 1.5 publications in the top 10% using whole counting (at the level of addresses). Both full and fractional (here there can be fractions of fractions if, for example, the publication in 9th place in the top 10% has been co-authored) counting of publications are used. The total number of citations for an aggregate (e.g., the world or a country) is obtained by totaling the number of citations of the papers that were assigned to this aggregate. The indicator 'highly cited publication' (HICIT) is then computed by taking the share of highly cited publications to total publications (full counting method) of a given country. In this way, both publications with co-authors in different locations, as well as with authors with multiple country affiliation are attributed to all countries listed in the affiliations.

7.2 Annex 2: Methodology

In this annex we briefly present the mathematical calculations behind various non-parametric efficiency models: data envelopment analysis (DEA), full disposal hull (FDH) and the robust efficiency models: order-m and order-alpha. This section has by no means the intention to fully unravel the mathematical formulas in a detailed way, but it is rather meant to explain the intuitive logics of the different models. As such, we only present the most important mathematical steps. For all the models we present the efficiency scores in Farrell-Debreu measures from an output-oriented approach. The output-oriented approach refers to the fact that we are primarily interested in assessing to what extent a country could lower its amount of inputs given its current level of outputs in order to be fully efficient. Note that the efficiency scores and rankings that we present in the main text of this document are defined in Shepard values, i.e. measured as 1/Farrell-Debreu efficiency scores.

Data Envelopment Analysis (DEA)

Data envelopment analysis is the first non-parametric approach to measure the relative efficiency scores for a set of decision making units (in our case: countries). Assume that we have a number of J countries (j=1,…,J). All these countries use a common set of input parameters (say, M, with m=1,…,M) to produce a common set of output parameters (say, N, with n=1,…,N).

In order to be able to construct an efficiency score, one should define the potential production set in which countries can operate. In DEA, the possible production set S_{DEA} is defined as:

S_{DEA} ={(x,y) : y can be produced by x}=

$$\{(x, y) : \sum_{n=1}^{N} \lambda_n Y_{nj} \geq y; x \geq \sum_{m=1}^{M} \mu_m X_{mj}\} \; for \; \{\lambda_1, \ldots, \lambda_n\} \text{ and } \{\mu_1, \ldots, \mu_m\}$$

Such that $\sum_{n=1}^{N} \lambda_n = 1, \lambda_n \geq 0, \forall n; \sum_{m=1}^{M} \mu_m = 1, \mu_m \geq 0, \forall m$

Where:

λ_n: non-negative weights given to output parameter *n*
μ_m: non-negative weights given to input parameter *m*
Y_{nj}: amount of output *n* produced by country *j*
X_{nj}: amount of output *m* produced by country *j*

This production possibility set as defined by the DEA method envelopes all data points within the smallest convex hull. The way the production set is defined above, it allows for variable returns to scale. The definition of the weights for input and output can easily be adopted to allow for other types of returns to scale (e.g. constant, non-increasing or non-decreasing).

The output-oriented relative performance (efficiency) of a country c, is then defined as the maximized value of the ratio of the aggregated input measures and aggregated output levels over all possible aggregated multipliers such that no country in the group will perform better than unity. Mathematically it can be expressed as:

$$F_c\text{: Max } \frac{\sum_{n=1}^{N} \lambda_n Y_{nc}}{\sum_{m=1}^{M} \mu_m X_{mc}}$$

$$\text{Such that: } \frac{\sum_{n=1}^{N} \lambda_n Y_{nj}}{\sum_{m=1}^{M} \mu_m X_{mj}} \leq 1,\ j = 1, \ldots, J \quad with\ \lambda_n, \mu_m \geq 0, \forall n, m$$

This model yields the maximum efficiency score for a country c, denoted by F_c, as the maximum ratio of the output/input, given that other countries also use the same aggregated weights for their input and output parameters. As such, the maximum relative efficiency score operating at aggregated input level and aggregated output level can be obtained by solving following linear programming problem:

$$Eff_{DEA,\,c} = \max \theta_c\ such\ that \sum_{j=1}^{J} \lambda_n Y_{nj} - \theta_c Y_{nc} \geq 0, \forall m$$

$$X_{nc} - \sum_{j=1}^{J} \mu_m X_{mj} \geq 0, \forall n$$

$$\sum_{n=1}^{N} \lambda_n = 1, \lambda_n \geq 0, \forall n; \sum_{m=1}^{M} \mu_m = 1, \mu_m \geq 0, \forall m$$

Each type of output is scaled up with the same factor θ_c until the technology frontier is reached. The countries with positive weight λ_n are denoted as "peers". As such the θ_c denotes the proportional increase in outputs that a country *c* could reach holding its input quantities constant.

Free Disposal Hull Methodology (FDH)

Similar to previous method, the Free Disposal Hull method measures the relative efficiency score of a group of decision making units. However, this approach imposes fewer restrictions to the possible production set by relaxing the convexity assumption. Accordingly, the production set for the FDH method can be described as:

S_{FDH} ={(x,y) : y can be produced by x}=

{(x, y) : $\sum_{n=1}^{N} \lambda_n Y_{nj} \geq y; x \geq \sum_{m=1}^{M} \mu_m X_{mj}, \sum_{n=1}^{N} \lambda_n = 1, \lambda_n \in \{0,1\}, \forall n; \sum_{m=1}^{M} \mu_m = 1, \mu_m \in \{0,1\}, \forall m$ } for {λ_1,..., λ_n} and {μ_1,..., μ_m}

The efficiency score of a country c can be denoted by the following function:

$$Eff_{FDH,c} = \max \theta_c \, such\, that \sum_{j=1}^{J} \lambda_n Y_{nj} - \theta_c Y_{nc} \geq 0, \forall m$$

$$X_{nc} - \sum_{j=1}^{J} \mu_m X_{mj} \geq 0, \forall n$$

$$\sum_{n=1}^{N} \lambda_n = 1, \lambda_n \in \{0,1\}, \forall n; \sum_{m=1}^{M} \mu_m = 1, \mu_m \in \{0,1\}, \forall m$$

Robust frontier efficiency models[4]

In contrast to the non-parametric frontier models of DEA and FDH in which all data points are used to define the technology frontier, robust frontier efficiency models resolve the problem of biased efficiency estimations that may emerge from the presence of extreme values or outliers. As all efficiency models, they look at the support of function $S_{Y|X}(\cdot|x)$ defining the attainable set of output values Y for a country with an input level of *x*. However, instead of looking at the maximum boundary of this support as in DEA and FDH models to define the technology frontier, robust efficiency models use benchmark values that allow for more robust estimations of efficiency scores. In following paragraphs we explain the methodology of order-m and order-alpha models in mathematical terms.

1) Order-m robust frontier methodology

To obtain a more robust efficiency score, order-m models are using benchmark values measuring the average of the maximal value of output for *m* countries randomly drawn from $S_{Y|X}(\cdot|x)$, i.e. countries employing at most *x* inputs. The number of *m* countries that serves as benchmark is defined a priori. Given this a priori integer, the order-m maximum boundary of Y is defined as the expected value of the maximum of *m* random output variables Y_1,...,Y_m drawn from the distribution of Y given that X ≤ *x*. So, for every level of input *x* in the overall set of X inputs, we consider the *m* random variables drawn from the distribution function $S_{Y|X}(y|x)$ and define the set as:

[4] The mathematical explanation of the robust efficiency frontiers is extensively based on Simar and Daraio (2007). As previously mentioned, the efficiency scores that are mathematically presented in this section are Farrell-Debreu measures. The efficiency rankings that we present in the rest of this document are efficiency scores in Shepard values, i.e. measured as 1/Farrell-Debreu efficiency scores.

$$S_m(x) = \{(\mathrm{x}, \mathrm{y}) \in \text{production set} \,|\, x \le X, Y_i \le y, i = 1, ..., m\}$$

For every *y*, we define a weight $\tilde{\lambda}_m(x, y)$ as such that the combination of input and weighted output belongs to the potential production set $S_m(x)$. This is done by taking the supremum of the ratio of the randomly drawn output variables for the multivariate set of outputs (Y_i^j) with the corresponding outputs in the focal country (y^j):

$$\begin{aligned}\tilde{\lambda}_m(x, y) &= \sup\{\lambda \,|\, (x, \lambda y) \in S_m(x)\} \\ &= \max_{i=1,...,m} \left\{ \min_{j=1,...,\mathrm{q}} \left(\frac{Y_i^j}{y^j} \right) \right\}\end{aligned}$$

The order-m efficiency score from an output oriented approach for any *y* belonging to the set of output vectors and a given vector of inputs x belonging to the input set X, is then defined as the expected value of $\tilde{\lambda}_m(x, y)$:

$$\lambda_m(x, y) = E(\tilde{\lambda}_m(x, y) \,|\, X \le x)$$

Mathematically, the non-parametric estimation of $\lambda_m(x, y)$ for a country *n*, defined as $\hat{\lambda}_{m,n}(x, y)$, is obtained by the following integral function that contains the empirical form of the distribution function $S_{Y|X}(\mu \mathrm{y} \,|\, x)$, denoted by $\hat{S}_{Y|X}(\mu y \,|\, x)$:

$$\hat{\lambda}_{m,n}(x, y) = \int_0^\infty \left[1 - (1 - \hat{S}_{Y|X}(\mu y \,|\, x))^m \right] d\mu$$

For a more detailed explanation of the order-m method in mathematical terms we refer to Simar and Daraio (2007).

2) Order-alpha robust frontier methodology

The order-alpha model follows the same logic as the order-m efficiency score in leaving out the most extreme observations to define the production frontier. However, instead of defining a certain number of *m* countries that will serve as benchmark and will eventually define the percentage of observations that are situated above the technology frontier, the order-alpha model actually starts from an opposite approach. This latter model allows for an a priori fixation of the probability (1-α) of observations that will be above the technology frontier. As such, the benchmark value in this method is defined as the output level not exceeded by (1-α)x100 percent of countries among the population of countries using at most a level *x* inputs. Using the same mathematical terminology as for the order-m model , the output-oriented order-alpha efficiency score for a vector level of input *x* and output *y*, can be denoted as:

$$\lambda_\alpha(x, y) = \sup\{\lambda \,|\, S_{Y|X}(\lambda y \,|\, x) > 1 - \alpha\}$$

The $\lambda_\alpha(x,y)$ expresses the Farrell-Debreu output efficiency score and can be interpreted as follows: it gives the proportionate reduction (when lower than unity) or increase (if bigger than unity) in outputs to move the specific unit (x,y) to the order-alpha frontier. In the document we present the efficiency scores of order-alpha in Shepard values, denoted as $1/\lambda_\alpha(x,y)$. An estimation of $\lambda_\alpha(x,y)$ is actually obtained by plugging in the empirical version of $S_{Y|X}(\lambda y|x)$ in the expression above, yielding:

$$\widehat{\lambda}_\alpha(x,y) = \sup\{\lambda \,|\, \widehat{S}_{Y|X}(\lambda y|x) > 1-\alpha\}$$

7.3 Annex 3: Input and output statistics

Table 7.1: Summary statistics for Public Input – Science Output and Private Input – Technology Output

Statistics for Public Input - Science Output								
Country	Code	Input	Country	Code	Output	Country	Code	Output/Input
Iceland	IS	1.21	Switzerland	CH	17.33	Switzerland	CH	25.23
Finland	FI	0.95	Denmark	DK	12.80	Cyprus	CY	17.83
Sweden	SE	0.93	Sweden	SE	11.30	Belgium	BE	16.78
Netherlands	NL	0.87	Iceland	IS	11.18	Denmark	DK	16.00
Israel	IL	0.82	Israel	IL	10.88	Malta	MT	15.44
Denmark	DK	0.80	Netherlands	NL	10.26	Ireland	IE	14.57
Germany	DE	0.78	Finland	FI	10.25	UK	UK	14.46
France	FR	0.76	Belgium	BE	9.57	Greece	GR	13.40
Austria	AT	0.75	UK	UK	9.02	Israel	IL	13.32
Norway	NO	0.73	Norway	NO	7.29	Sweden	SE	12.11
South Korea	KR	0.71	Austria	AT	6.82	Netherlands	NL	11.84
Japan	JP	0.70	Slovenia	SI	6.81	Portugal	PT	11.55
Switzerland	CH	0.69	Estonia	EE	6.79	Slovenia	SI	11.48
United States	US	0.67	Ireland	IE	6.70	Estonia	EE	11.02
UK	UK	0.62	Portugal	PT	5.81	Finland	FI	10.79
Estonia	EE	0.62	Greece	GR	5.63	Norway	NO	9.98
Slovenia	SI	0.59	Germany	DE	5.59	Italy	IT	9.28
Lithuania	LT	0.58	France	FR	5.51	Iceland	IS	9.26
Belgium	BE	0.57	Cyprus	CY	5.35	Spain	ES	9.22
Spain	ES	0.56	Spain	ES	5.19	Austria	AT	9.05
Czech Republic	CZ	0.54	United States	US	5.19	Slovakia	SK	8.46
Italy	IT	0.52	Italy	IT	4.86	Luxembourg	LU	8.35
Portugal	PT	0.50	Czech Republic	CZ	4.09	United States	US	7.70
Croatia	HR	0.48	South Korea	KR	3.74	Czech Republic	CZ	7.61
Hungary	HU	0.47	Hungary	HU	3.45	France	FR	7.28
Ireland	IE	0.46	Lithuania	LT	3.24	Hungary	HU	7.28
Greece	GR	0.42	Malta	MT	3.04	Germany	DE	7.14
Turkey	TR	0.40	Croatia	HR	2.82	Bulgaria	BG	5.98
Latvia	LV	0.40	Luxembourg	LU	2.39	Croatia	HR	5.87
Poland	PL	0.39	Slovakia	SK	2.34	Poland	PL	5.80
Russia	RU	0.38	Japan	JP	2.33	Lithuania	LT	5.55
Bulgaria	BG	0.32	Poland	PL	2.28	Romania	RO	5.47
Romania	RO	0.32	Turkey	TR	2.11	South Korea	KR	5.25
Cyprus	CY	0.30	Bulgaria	BG	1.91	Turkey	TR	5.24
Luxembourg	LU	0.29	Romania	RO	1.73	Japan	JP	3.31
Slovakia	SK	0.28	Latvia	LV	1.28	Latvia	LV	3.18
Malta	MT	0.20	Russia	RU	0.67	Russia	RU	1.77

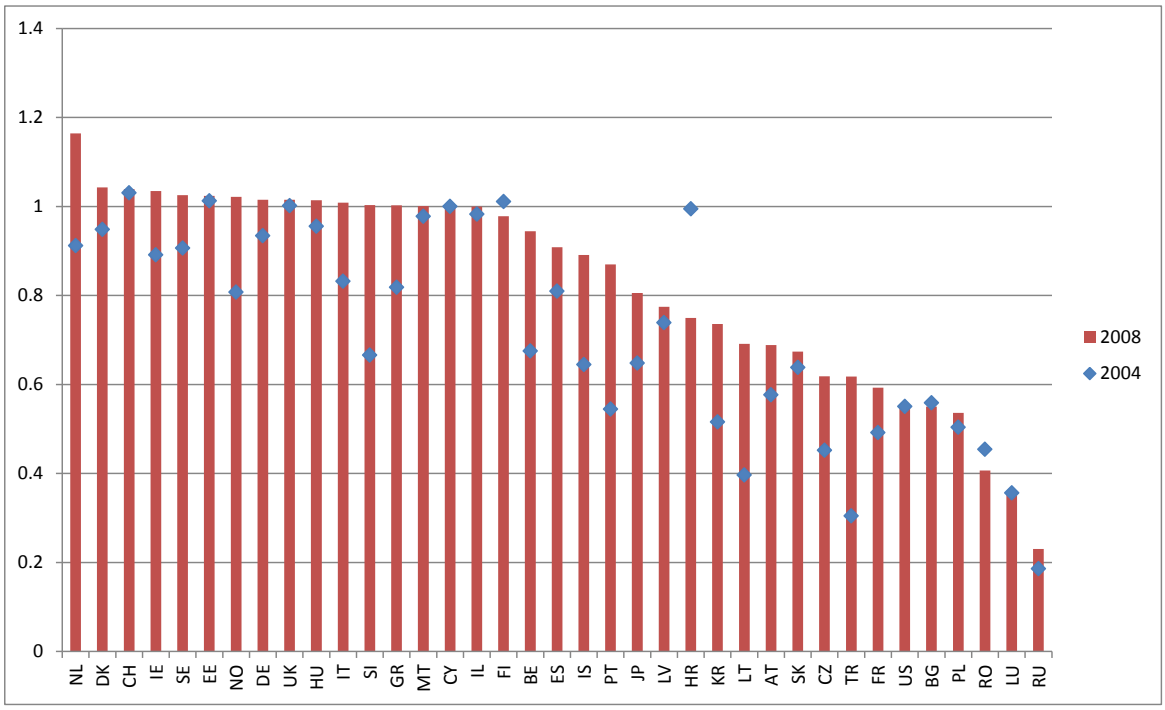
Statistics for Private Input - Technology Output								
Country	Code	Input	Country	Code	Output	Country	Code	Output/Input
Israel	IL	3.74	Israel	IL	11.07	Netherlands	NL	5.99
Japan	JP	2.67	Sweden	SE	10.18	Denmark	DK	3.95
Sweden	SE	2.65	Finland	FI	9.26	Switzerland	CH	3.84
Finland	FI	2.58	Switzerland	CH	8.41	Sweden	SE	3.84
South Korea	KR	2.43	Denmark	DK	7.18	Germany	DE	3.77
Switzerland	CH	2.19	Germany	DE	6.80	Finland	FI	3.59
United States	US	1.94	Japan	JP	6.68	Norway	NO	3.45
Denmark	DK	1.82	South Korea	KR	5.97	Italy	IT	3.27
Germany	DE	1.80	Netherlands	NL	5.71	Israel	IL	2.96
Austria	AT	1.78	Austria	AT	4.35	Ireland	IE	2.95
Iceland	IS	1.50	United States	US	3.81	Hungary	HU	2.90
Luxembourg	LU	1.32	France	FR	3.52	UK	UK	2.80
France	FR	1.32	Belgium	BE	3.23	Latvia	LV	2.78
Belgium	BE	1.32	UK	UK	3.08	France	FR	2.66
UK	UK	1.10	Norway	NO	2.89	Bulgaria	BG	2.63
Slovenia	SI	0.96	Ireland	IE	2.56	Japan	JP	2.50
Netherlands	NL	0.95	Iceland	IS	2.47	Belgium	BE	2.46
Czech Republic	CZ	0.92	Slovenia	SI	2.15	South Korea	KR	2.45
Ireland	IE	0.87	Italy	IT	1.98	Austria	AT	2.45
Norway	NO	0.84	Hungary	HU	1.46	Greece	GR	2.43
Spain	ES	0.71	Estonia	EE	1.26	Estonia	EE	2.42
Russia	RU	0.70	Spain	ES	1.16	Slovenia	SI	2.23
Italy	IT	0.60	Luxembourg	LU	1.02	Slovakia	SK	2.18
Portugal	PT	0.60	Czech Republic	CZ	0.84	Croatia	HR	2.17
Estonia	EE	0.52	Malta	MT	0.83	Malta	MT	2.14
Hungary	HU	0.50	Croatia	HR	0.72	United States	US	1.97
Malta	MT	0.39	Latvia	LV	0.64	Iceland	IS	1.65
Croatia	HR	0.33	Portugal	PT	0.49	Spain	ES	1.65
Turkey	TR	0.27	Turkey	TR	0.43	Turkey	TR	1.57
Latvia	LV	0.23	Slovakia	SK	0.43	Poland	PL	1.54
Lithuania	LT	0.21	Greece	GR	0.42	Cyprus	CY	1.52
Romania	RO	0.20	Russia	RU	0.40	Lithuania	LT	1.47
Slovakia	SK	0.20	Bulgaria	BG	0.36	Czech Republic	CZ	0.92
Poland	PL	0.18	Lithuania	LT	0.31	Portugal	PT	0.82
Greece	GR	0.17	Poland	PL	0.28	Luxembourg	LU	0.77
Bulgaria	BG	0.14	Cyprus	CY	0.15	Romania	RO	0.71
Cyprus	CY	0.10	Romania	RO	0.14	Russia	RU	0.57

Note: We refer to Table 3.3 for an overview of the indicators used for the respective input and output measures mentioned in the table above. In this table the output measures are presented per billion GDP. Output/input refers to the ratio of outputs and inputs as defined in the table.

7.4 Annex 4: Results

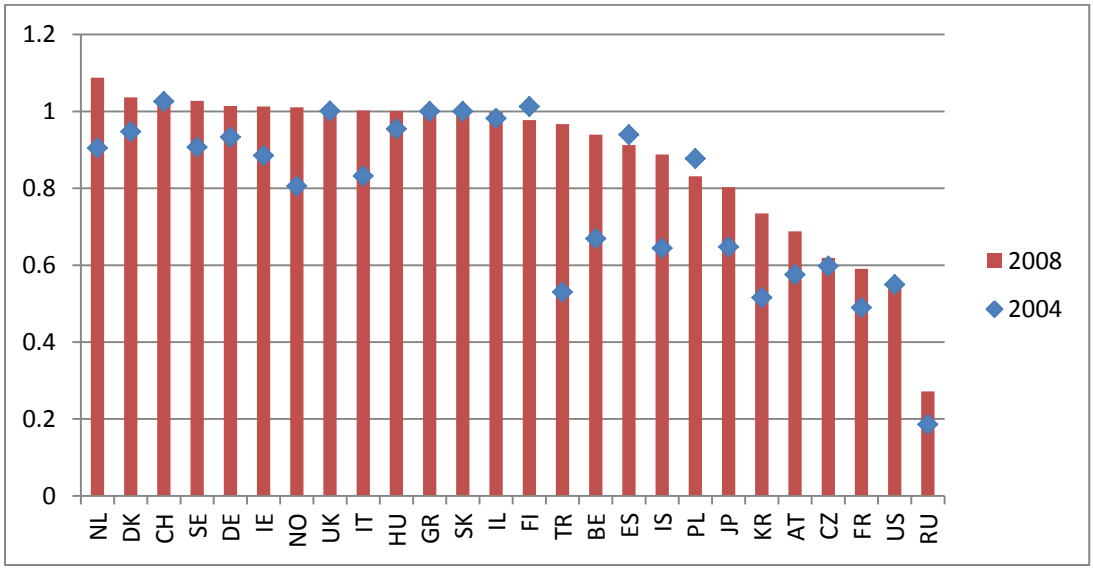
Order-m efficiency results for "total input – science & technology output" model

Figure 7.1: Ranked efficiency scores total input-science & technology output model (order m; 2004 and 2008; full sample)



Note: Efficiency scores are measured in Shepard values and m = 185.

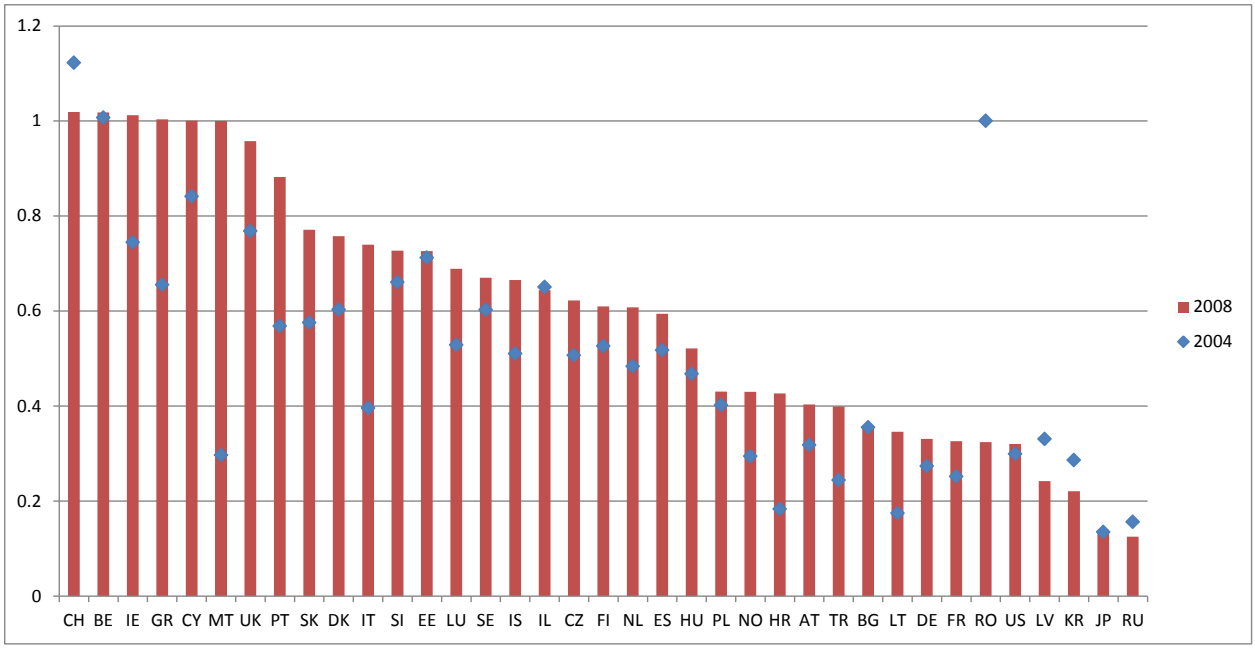
Figure 7.2: Ranked efficiency scores total input-science & technology output model (order m; 2004 and 2008; restricted sample)



Note: Efficiency scores are measured in Shepard values and m = 130.

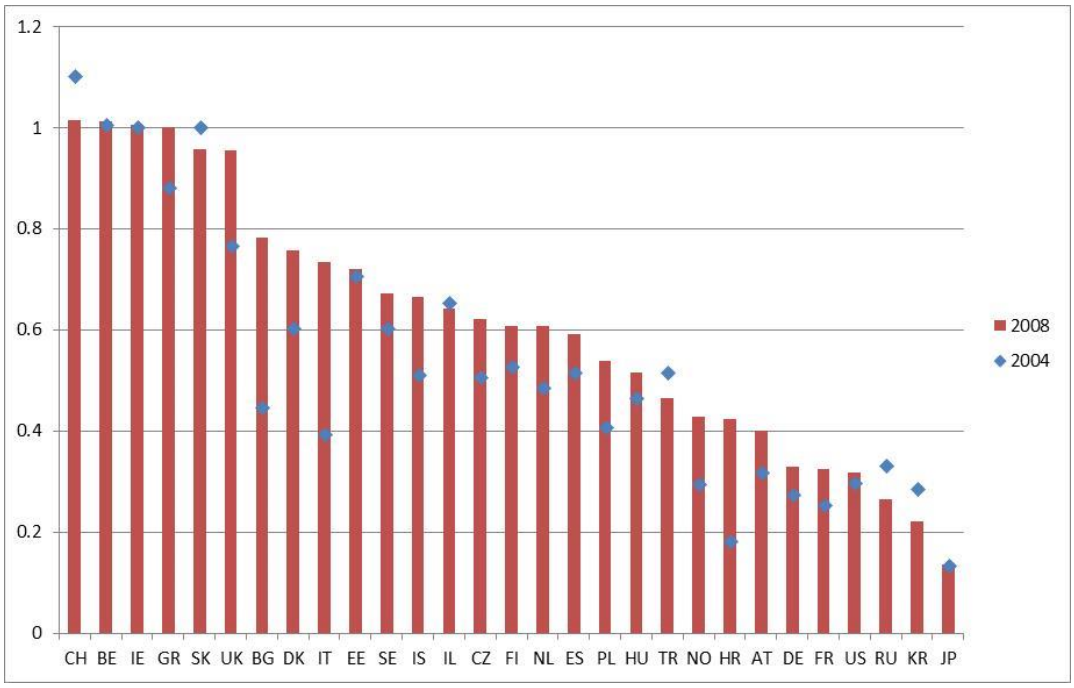
Order-m efficiency results for "Public Input – Science Output" Model

Figure 7.3: Ranked efficiency scores public input-science output model (order-m; 2004 and 2008; full sample)



Note: Efficiency scores are measured in Shepard values and m = 170.

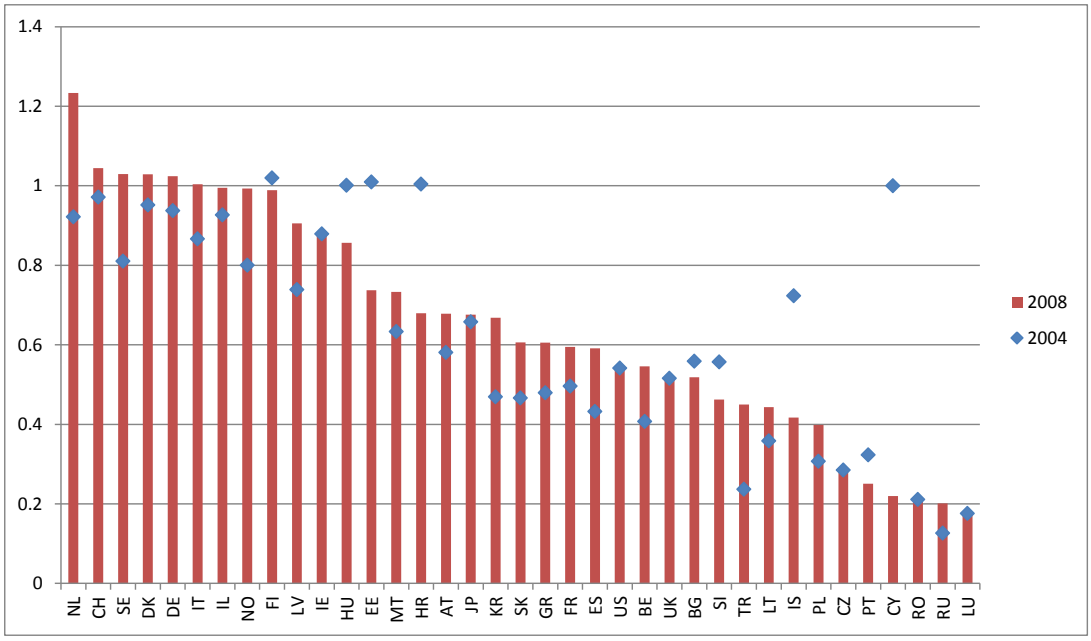
Figure 7.4: Ranked efficiency scores public input-science output model (order-m model; 2004 and 2008; restricted sample)



Note: Efficiency scores are measured in Shepard values and m = 130.

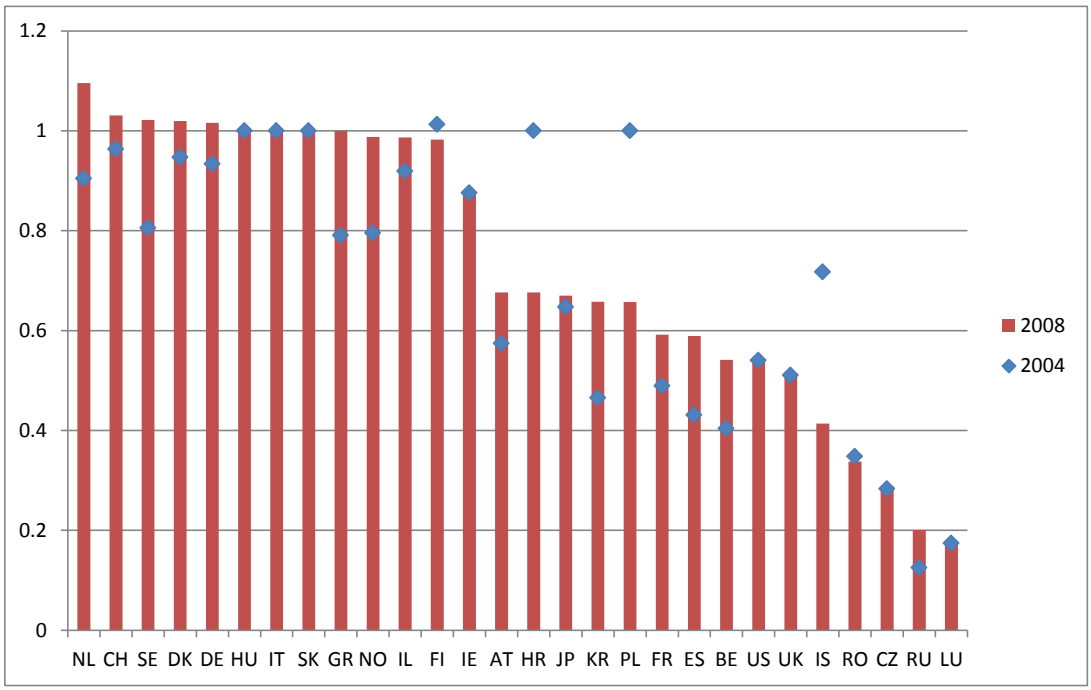
Order-m efficiency results for "Private Input – Technology Output" Model

Figure 7.5: Ranked efficiency scores private input-technology output model (order m; 2004 and 2008; full sample)



Note: Efficiency scores are measured in Shepard values and m = 150.

Figure 7.6: Ranked efficiency scores private input-technology output model (order m; 2004 and 2008; restricted sample)



Note: Efficiency scores are measured in Shepard values and m = 140.

Acknowledgements

The authors express their gratitude for valuable comments made by Cinzia Daraio (Sapienza - Università di Roma), Johan Stierna (DG RTD), Raquel Saiz Tome (DG RTD), Daniel Vertesy (JRC), Michaela Saisana (JRC), Andrea Saltelli (JRC) and Stefano Tarantola (JRC) throughout the whole project. Comments made by the participants of the workshop on "Indicators for the Innovation Union" (Ispra, Italy; October 25-26, 2012) are highly appreciated. As always, all remaining errors are those of the authors.

European Commission
EUR 26411 EN – Joint Research Centre – Institute for the Protection and Security of the Citizen

Title: An analysis of national research systems (II): Efficiency in the production of research excellence
Authors: Sjoerd Hardeman and Vincent van Roy

Luxembourg: Publications Office of the European Union

2013 – 61 pp. – 21.0 x 29.7 cm

EUR – Scientific and Technical Research series – ISSN 1831-9424

ISBN 978-92-79-35011-5

doi: 10.2788/52038

Abstract
The main contribution of this project lies in the assessment of the efficiency of national research systems in achieving excellent research performances. The efficiency assessment is not only restricted to the production of research excellence in general, but is disentangled by type of research field, distinguishing between science and technology. This distinction provides a helpful tool for policy makers in assessing the discrepancy of efficiency in both science and technology excellence within and across countries. In our conceptual framework, a national research system's efficiency can be defined as the extent to which a country is able to transform research assets into excellent research.
We conducted efficiency analyses on three main model specifications in which we relate the amount of resource assets (public, private, total R&D expenditure) to the performance on excellent research. In our empirical analysis of efficiency, we report on two methodologies: output/input ratios (partial measures of efficiency) and robust production frontiers (complete and robust measures, order-m and order-alpha method, as developed by Daraio and Simar (2007a). Various conclusions are drawn based on these analyses.

LB-NA-26411-EN-N

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Publications Office

ISBN 978-92-79-35011-5

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