R&D efficiency in the OECD

A two stage semi-parametric approach

by

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Abstract

This paper analyzes the efficiency of public and private R&D expenditures in promoting innovation and evaluates the influence of R&D tax credits on the innovation process. We conduct our analysis in two steps. Firstly, we measure R&D efficiency applying a nonparametric DEA. We estimate an intertemporal knowledge production frontier where each observation is accounted for as a single unit. This procedure allows us to track the development of country research efficiencies over time. In a second step we identify the differences in the R&D efficiencies on the country level assessing the influence of the R&D tax system on technical efficiency using the recently developed bootstrap procedure proposed by Simar and Wilson (2007). Our results suggest that Germany, Sweden and the United States belong to the best performing countries, located on or close to the world technology frontier. The red lantern in research efficiency goes to Mexico, China and Turkey which are characterized by a very low capacity of ideas production suggesting that they are still in the phase of imitating and replicating existing technologies. Preliminary results on the truncated, bootstrapped regression in the second stage suggest a weak influence of tax incentives on research efficiency.

Keywords: R&D efficiency, Data envelopment analysis, Truncated regression

JEL Classification: O31, C14, C24, O57

1 Introduction

The notion of an ideas production function is central to many models of endogenous economic growth where ideas productivity growth plays a crucial role in sustaining long-term growth (Porter and Stern 2000). True innovation, in contrast to imitation, becomes even more important for productivity growth when a country approaches the world technology frontier because less room is left for copying. The empirical literature affirms the importance of level and dynamics of R&D expenditures for economic growth (e.g. Guellec and Van Pottelsberghe, 2004). Therefore, the efficient usage of the scarce resources a country invests in R&D becomes increasingly important especially with respect to globalization. Countries are exposed to high levels of competition in domestic and foreign markets for innovative products and future technologies. This process forces nations to continuously update their technological capabilities. Countries utilizing their R&D resources inefficiently will be penalized with a growth discount.

Since the resources allocated to the generation of ideas are limited, they should be used as efficiently as possible given the local institutional, organizational and legal constraints. Hereby government policies aimed to encourage R&D play a major role in ensuring an sufficient level of R&D spending in the research process. A specific character of the knowledge creation process is the emergence of spillovers. Technological spillovers occur when the research activity of one firm induces higher productivity in other firms. The presence of positive spillovers means that without further policy invention the private sector would tend to under-invest in R&D. This underinvestment can lead to a suboptimal allocation of resources in the ideas production function. Government's can address this problem in several ways. One is to undertake R&D on its own or fund others to do so. Another way is to encourage more R&D investment through the tax system via allowing tax credits aimed at lowering the cost of undertaking R&D. Although there are many perverse incentives induced by the design of different research taxation systems which could cause distortions in the efficient use of input factors of the R&D process. R&D tax credits aimed on specific aspects of the research process might lead to a misallocation of resources and thereby lowering the efficiency of countries.

Based on the concept of an ideas production function framework, we build on the existing literature applying a production function framework and evaluate the efficiency of the ideas generation process across countries and years.

We hereby proceed in two steps. Firstly, to measure R&D efficiency we follow the nonparametric DEA approach. The assumption underlying the analysis is a constant intertemporal frontier, thus we consider the relative changes of the countries toward the one estimated DEA technology frontier. This procedure allows us to track the development of country research efficiencies over time. Analyzing selected countries in depth provides us with a clear picture about the catching up processes of countries lagging behind.

In a second step we identify the differences in the R&D efficiencies on the country level assessing the R&D tax system on the technical efficiency. We find that R&D tax incentives have a negative influence on innovative output when applying the recently developed single bootstrap procedures proposed by Simar and Wilson (2007). Due to unknown serial correlation among the estimated efficiencies, conventional approaches for drawing inferences are invalid.

We contribute to the existing literature ion the following three aspects. Firstly, we add a dynamic perspective by conducting an intertemporal analysis covering a time frame of ten years. Secondly, we test the impact of R&D taxation incentives on research efficiency by applying a consistent two stage truncated regression approach. Thirdly, we account for the possibility of multiple inventors when determining research output.

The paper is organized as follows: Section 2 introduces the theoretical framework and briefly summarizes the relevant literature in this field. In section 3, the methodology of the two stage efficiency analysis is explained while section 4 summarizes previous DEA studies. Section 5 describes the data source. The empirical results for the two stage efficiency analysis are presented in section 6. Section 7 recapitulates the findings and concludes.

2 Ideas Production Function

In his seminal model of endogenous technological change Romer was one of the first to incorporate an ideas production sector into a growth model (Romer, 1990). His work was followed by Grossman and Helpman (1991a, 1991b), and Aghion and Howitt (1992) using a similar framework. The aim of all these models is to explain the role of technological progress in the growth process. R&D-based models take technology as the primary determinant of growth and model it as an endogenous variable. At the heart of R&D based growth models is a knowledge/ideas production function that describes the creation of new knowledge within an economy. According to this specification, the rate of new ideas produced ($\dot{A}$) in an economy is a simple function of the number of ideas worker (H_A) and the accumulated ideas/ knowledge available to these researcher (A_t) $\dot{A} = \delta H_A A$ where δ is a parameter for the productivity in the research process.

Building on this theoretical framework we consider the knowledge creation activity in each country a as a country specific production process. Similar to Pakes and Griliches (1984) and Griliches (1990) we see the production process as a continuum leading from R&D investment and researchers as input factors in the knowledge creation process to some observable measure of innovative activity. Since the output of knowledge creation is hard to capture, patent applications serve as a valuable resource for approximating innovative output. Despite several drawbacks patent applications are extensively used in the literature (e.g. Hausman, Hall, and Griliches (1984), and Kortum (1997)).

Using the production function framework empirical literature affirms the importance of level and dynamics of research personnel and R&D expenditure as a measure for the knowledge creation process but little attention has been paid so far on the importance of research efficiency – the parameter δ - in this context. Since the resources allocated to the generation of ideas are limited, they should be used as efficiently as possible accounting for the local institutional, organizational and legal constraints. The efficient and productive use of the input factors assets and human capital is a key factors in determining the rate of new ideas produced and thereby the growth of an economy. Thus the focus of our paper lies on measuring the efficiency of the ideas production process. This is a prerequisite for designing policies to improve resource allocations.

3 Efficiency Analysis

A natural measure of evaluating the performance at the level of firms is the productivity ratio, a relative concept which compares the transformation process of converting input into output. To measure the R&D efficiency we apply this concept that has proven to be useful in other sectors and applications (for a survey on the theoretical literature see Cooper et al., 2004). Each production process involves a production frontier: the current state of technology, representing the maximum output attainable from each input level which is called the efficiency frontier (see Coelli et al., 2005). According to the literature (see Section 2 and Section and 4) we assume an ideas production function to describe the underlying (R&D) production process on the country level. A country operating on the R&D efficiency frontier is technically efficient, with respect to physical quantities without considering the allocative efficient allocation.

We apply the deterministic nonparametric Data Envelopment Analysis (DEA) approach to measure and compare the relative efficiency levels providing a ranking of countries with regard to their achieved performance level. The identified efficient countries could serve as peers to help improve performance of less efficient ones. We further assess changes in R&D efficiency on the country level over time.[1] In a subsequent step we analyze whether the indicator of R&D taxation causes differences in R&D efficiency. The second step is based on the semi-parametric model derived by Simar and Wilson (2007) who provide a consistent two-stage procedure to account for exogenous factors that might affect country performance.

3.1 Data envelopment analysis

DEA relies on a production frontier defined as the geometrical locus of optimal production plans (see Simar and Wilson, 1998, 2007).[2] It involves the use of linear programming methods to construct a piecewise linear surface or frontier enveloping the data and measuring the efficiency for a given unit relative to the boundary of the convex hull of the input-output vectors. The individual efficiencies of the countries relative to the R&D production frontier are then calculated by means of distance functions. They can be interpreted as the proportional reduction of inputs/or proportional increase of outputs to become technically efficient by a projection onto the efficient boundary, the R&D production frontier. Calculations can be made using either an input-orientation where the output vector is hold fixed and inputs are minimized to be efficient. Contrary in case of output-orientation the input vector is fixed and outputs are maximized to be efficient. We apply output orientation since it is reasonable to assume that countries aim to optimize and maximize the research output with a given level of R&D expenditures and the number researchers. The determination of the efficiency score of the i-th firm in a sample of N firms in the constant returns to scale (CRS) model is equivalent to the following optimization (see Coelli et al., 2005):

[1] Applied work distinguishes between nonparametric and parametric efficiency measurement and considers the tradeoffs. Fully parametric estimation concepts involve strong assumptions about the functional forms describing the production process as well as the probability model, or the distribution functions of the stochastic part in the model (see Simar and Wilson, 2007). Fully nonparametric approaches assume no parametric restrictions for any features of the probability model and the frontier is not described by a specific analytical function. Thus, specification errors that can result from making parametric assumptions about technology are avoided.

[2] Farrell (1957) originally proposed estimating production efficiency scores in a non- parametric framework. He drew upon the work on activity analysis by Koopmans (1951) and Debreu (1951). Charnes et al. (1978) and Banker et al. (1984) extended Farrell’s ideas by imposing returns to scale properties.

$$\min_{\theta,\lambda} \theta$$
$$s.t$$
$$-y_i + Y\lambda \geq 0$$
$$\theta x_i - X\lambda \geq 0$$
$$\lambda \geq 0$$

where λ is a N×1 vector of constants, and X, Y represent input and output matrices, respectively. θ measures the radial distance between the observation x_i, y_i and the efficiency frontier. The efficiency score is the point on the frontier characterized by the level of inputs that should be reached to be efficient (Simar and Wilson, 1998). A value of $\theta = 1$ indicates that a country is fully efficient and thus is located on the efficiency frontier.[3]

Different assumptions regarding the frontier can be made: the underlying technology determined either by constant returns to scale (CRS), (see Charnes et al., 1978, who first derived the DEA under CRS); or by variable returns to scale (VRS) which assume that scale inefficiencies are present (see Banker et al., 1984, who first allow for VRS). To determine efficiency measures under the variable returns to scale (VRS) assumption, a further convexity constraint ∑λ=1 must be considered. Within this framework countries of similar sizes concerning the input requirements are compared. It is both, statistically and economically, important to determine whether the underlying technology exhibits increasing, constant, or decreasing returns to scale. If we assume `a priori a CRS technology without investigating the possibility that it is non-constant, we incur the risk that our efficiency estimates will be inconsistent. On the other hand, if we assume variable returns to scale when in reality the technology exhibits global constant returns to scale, there may be a loss of statistical efficiency (Simar and Wilson, 2002). According to Simar and Wilson (2002) we test by means of bootstrapping for the adequate returns to scale assumption of our technology.

[3] The DEA estimates may depend heavily on the assumption that the production frontier is convex. Another common nonparametric estimator is the FDH estimator which does not incorporate the convexity constraint into the production set. The FDH estimator is based on the idea of the smallest free disposal set covering the observation sample of firms. FDH is a consistent estimator, whatever the shape of the attainable production set (convex or nonconvex) given free disposability. DEA is only consistent if this set is convex (Simar and Wilson, 2007). The FDH estimator is particularly affected by dimensionality. Thus, a large number of observations will lie on the efficient boundary. In applied work with a finite sample this is often the case, and leads to misinterpretation of the results. We dispose of a sample containing less than 30 countries which represents for nonparametric estimation a small data set. This motivation us to apply DEA instead of FDH.

The DEA estimator belongs to the deterministic frontier models which imply that all observations are assumed to be technically attainable. They are highly sensitive to outliers and extreme values in the data (Simar and Wilson, 2000, 2007). It is therefore important to assess ex ante if outliers are present in the data which drive the location of the efficiency boundary and inappropriately influence the estimation of the performance of other countries in the sample. This paper uses the method of super-efficiency (see Banker and Chang 2006 and Anderson and Peterson, 1993) to identify and delete extreme values ex-ante. Within the super-efficiency approach, decision-making utilities within the efficiency frontier might obtain an efficiency score greater than one because the observation itself cannot be used as a peer (see Coelli et al., 2005) and therefore cannot form part of its reference frontier.[4]

3.2 Two stage semi-parametric approach

In addition to the relative R&D performance of OECD countries we assess the impact of R&D taxation on efficiency differences. This represents an important step when deriving policy implications with regard to a favourable tax treatment while assuring research efficiency. Thus, after the determination of the individual efficiencies in a first stage we regress in a second stage the efficiency scores on the country specific exogenous R&D tax indicators to assess their impact on the relative efficiency.

The econometric model is based on Simar and Wilson (2007) who propose and derive a bootstrap procedure which permits valid inference in the second-stage truncated regression. They show that conventional approaches for drawing inference in truncated Tobit regressions, which have been widely applied in the past, are invalid when regressing non-parametric DEA scores on environmental variables in a second stage. The inconsistency of simple second stage Tobit regressions is due to complicated, unknown serial correlation among the estimated efficiencies.[5] The semi-parametric two stage parametric model has been used already in other sectors and applications (see e.g. Barros and Dieke 2008 for an evaluation of airports and Barros and Peypoch 2007 for a measurement of technical efficiency of thermoelectric power plants).

[4] According to Banker and Chang (2006) countries obtaining in a specific point in time efficiency score larger than 1.2 are supposed to be an outlier and therefore deleted from the sample.

[5] They argue that the serial correlation arises due to the fact that perturbations of observations lying on the frontier will often cause changes in efficiencies estimated for other observations.

The econometric model is specified as follows:

$$\hat{TE}_i = Z_i \beta + \varepsilon_i \text{ with } i = 1,...,n$$

where $\hat{TE}_i$ represents the estimated technical average efficiencies on the country level; Z_i a vector of observation (country) specific variables which we expect to have an impact on the technical efficiencies; and β the coefficients to be estimated. Both sides are bounded by unity (see Simar and Wilson 2007 and Barros and Dieke 2008), thus ε_i is restricted by the condition $\varepsilon_i \geq 1 - Z_i \beta$. Therefore a truncated normal distribution for ε_i with a left truncation point at $1 - Z_i \beta$ is assumed. The truncated regression model is estimated by means of maximum likelihood. The bootstrap procedure is used to estimate standard errors and confidence intervals for the estimated coefficients (for a detailed description of the estimation algorithm see Simar and Wilson 2007.)

4 Previous DEA Studies

Rousseau and Rousseau (1997) were the first using a DEA approach to assess the relative efficiency of the R&D process. They apply an input oriented, constant return to scale model on 18 developed countries with two outputs, number of publications and number of granted patents at the European Patent Office (EPO) and use GDP as well as population and R&D investment as input factors. Based on their data and specification, they find Switzerland to be the most efficient country in Europe in the year 1993, closely followed by the Netherlands.

Using the same inputs and outputs Rousseau and Rousseau (1998) extended their work on R&D efficiency by including the non European countries USA, Canada, Australia and Japan.

Mentioning a possible bias caused by the use of EPO patent application for the non European countries, they come to the same conclusion as in their previous paper, with Switzerland, followed by the Netherlands as the countries exhibiting the highest research efficiency.

Wang and Huang (2006) propose a three stage approach to evaluate the relative technical efficiency of R&D across 30 OECD member and non-member countries, by controlling for cross country variation in external factors like the enrollment rate of tertiary education, the PC density and the English proficiency. In the first stage, an input- oriented DEA analysis is applied where patents and publications serve as outputs and R&D expenditure and researcher as inputs. These findings indicate that about half of the countries are efficient in their R&D activities. In a second stage input slacks generated by the first stage are taken as the dependent variable for a Tobit regression in order to purge external effects caused by environmental factors outside the efficiency evaluation. Using the results from the second stage, an additional DEA is conducted indicating a decrease in the number of efficient countries due to the external factors. Wang and Huang were the first taking external environmental factors into account while trying to measure the research efficiency of countries. Nevertheless, their proposed method is statistically invalid as shown by Simar and Wilson (2007)

In a recent study Sharma and Thomas (2008) measure the R&D efficiency of the R&D process across 18 countries using a DEA approach with constant as well as variable returns to scale. Their framework deviates from the Rousseau and Rousseau in two ways. Firstly they consider a time lag between R&D expenditure and the patents granted and secondly encompass developing countries in their analysis. Their main findings indicate Japan, the Republic of Korea and China lying on the efficiency frontier using constant returns to scale approach, whereas within the variable returns to scale framework Japan, the Republic of Korea, China, India, Slovenia and Hungary are found to be efficient.

5 Data

This study analyzes research efficiency based on a sample of 30 OECD member countries and and three non-member countries (Argentina, China, Israel). Data on input and output of the ideas production process are collected from two underlying datasets. In line with previous research, patents are used to approximate innovative output. The European Patent Office's Worldwide Patent Statistical Database (PATSTAT, accessed in 1/2008) serves as the base of information on patent applications. This database, maintained by the European Patent Office, contains all national and international patent applications with inventors, applicants and their location, priority date and technological classification. Central to our exercise is the construction of patent aggregates by country and year. We build this variable by using all patent applications filed with the European Patent Office according to their priority date between 1995 and 2004. The term priority date refers to the date where the given invention was covered by a patent for the first time. However, this first filing of a given invention mainly occurs at the national level and therefore the majority of patent applications at the EPO are second filings. Accordingly, in this study we date patent applications using the priority date instead of the usual application date because it is the relevant date being closest to the date of invention and the decision to apply for a patent on this invention (de Rassenfosse and van Pottelsberghe 2007). In order to build our patent aggregates, patent applications need to be assigned to the country of the inventor which is compared to the country of the applicant closer to the location of invention. Literature so far usually considers only the first inventor's country of residence (e.g. Wang 2007, WIPO 2008) and thereby ignores research cooperations across country borders. To overcome this problem, we construct patent aggregates based on all inventors' countries of residence and compare them with the conventional first inventor approach. The aggergation based on multiple inventors is conducted in two different ways:

- firstly, an unweighted sum over all inventors' countries of residence is generated which is by definition at least as large as first inventor aggegate since patents with more than one inventor also count more than once. Since such an aggregation procedure might induce a bias.
- Secondly, we use a weighted sum where all patent applications are assigned the reciprocal of the number of inventor countries in the original patent application as weights, meaning that an application with three inventor countries only contributes a third to each country aggregate. Empirical testing of the correlation between the three output measures lead to the conlcusion that all can be used as an approxiamtion of inventive output. However in case of small countries the usual first inventor approach could lead to an underestimation of patent aggrgates. Therefore, we argue in favor of weighted patent aggregates as the appropriate output for the DEA application.

Based on the notion of an ideas production function, human capital and R&D serve as inputs in the efficiency analysis. Data on variables approximating these inputs are taken from the Main Science Technology Indicators published by the OECD. Manpower invested into R&D equals the number of researchers[6] per country. The R&D ressources can be approximated by the level of R&D expenditures or an R&D stock[7], which is build according to the perpetual inventory method suggested by Guellec and van Pottelsberghe (2001). R&D expenditures can either be used on aggregate or separated according to the financier. Especially the distinction between private and public R&D is useful since the question whether public R&D are a complement or a substitute is not answered satisfactory in the literature so far (David et al 2000).

[6] Full time equivalents
[7] Depreciation rate: 15%

Consistent with recent literature on research efficiency (Sharma and Thomas 2008, Wang and Huang 2007), we impose a lag structure for inputs to account for the fact that R&D efforts do not immediately lead to innovative output (Hall et al 1986). Therefore, inputs are lagged by two years in the DEA application.

In the second step of our empirical analysis, we investigate the influence of R&D tax treatment on research efficciency. A “B-Index methodology” approach as suggested by Warda (2001) is used since it allows to compare the importance of R&D taxation incentives across different tax laws and jurisdictions. The B-Index is part of the Science, Technology and Industry Scoreboard, published by the OECD, and captures the generosity of the tax system with respect to R&D. Mathematically spoken is the B-Index given by the ratio between the after-tax cost of R&D expenditures of $1 and one minus the given corporate income tax rate. The B-Index can be written as

$$B - Index = \frac{1 - A}{1 - t}$$

where A is the present value of existing tax incentives like depreciation and special allowances or tax credits and t being the statutory corporate income tax rate. Without taxation $A = t = 0$ the B-Index is equal to one and no research project with a cost-benefit analysis smaller than one will be conducted. Hence, the B-index will be smaller or larger than one depending on the degreee of deductability of R&D expenditures, meaning than partial deductability implies B>1. Hence, larger tax incentives lead to a lower B- Index.

The OECD measures the amount of taxation incentives as one minus the B-Index and therefore the measure increases with rising tax incentives. The indicators is published separately for small and medium and large enterprises because it is widely assumed that tax incentives mainly influence investment decisions of large companies. Due to data availability problems, we only use the most year in year in our sample, 2004, for the second stage regressions so far. Furthermore, real GDP in PPPs is used to control for size effects across economies.

6 Empirical Results

The empirical analysis is divided into two main sections. Part one starts with the derivation of an adequate empirical model describing the R&D production process. Applying the super-efficiency approach (Banker and Chang 2006) we detect and delete extreme observations from the sample in order to obtain a consistent and robust technology frontier. We then estimate the relative efficiency using DEA for specific points in time to identify the OECD countries that perform efficiently with respect to R&D efforts. Based on a ranking we assess countries which could serve as peers to help improve performance of less efficient countries. Furthermore we analyze for specific countries how efficiency evolved over the observation period. In the first part we estimate an intertemporal frontier, more precisely a cross section pooled frontier, where each observation is accounted for as a single unit without considering any panel structure of the data. Country averages are then calculated over the observation period. In the second part we assess the impact of R&D tax incentives determining efficiency differences by means of a truncated regression (see Simar and Wilson 2007).

6.1 Intertemporal DEA technology frontier

The underlying model for nonparametric efficiency analysis has to fulfill the following criteria: it has to be robust against outliers and extreme values in the sample; it has to assume the adequate returns to scale property, and has to define a realistic production process of R&D expenditures into ideas production (patents). To ensure a consistent and robust technology frontier we conduct ex-ante outlier detection by means of super-efficiency analysis; test by means of bootstrapping for the returns to scale properties; and estimate by means of linear programming the relative technical efficiency of R&D expenditures for the OECD countries.

We start with the application of the extended DEA-approach: the calculation of technical efficiency scores under the assumption of super-efficiency. We apply the criterion outlined in Banker and Chang (2006) and define outliers by an efficiency score of larger than 1.2. Only two observations obtain an efficiency score larger than 1.2 and are exclude from further calculations. The small amount of observations revealing an efficiency score above 1.2 indicates that our frontier is not spanned by a number of unrealistic and extreme data points. Therefore we assume the frontier to be robust and consistent for the relative efficiency measurement of the remaining countries within the sample

According to Simar and Wilson (2002) we tested for the adequate assumption concerning the returns to scale property of the underlying technology (CRS versus VRS). The bootstrap algorithm in Simar and Wilson (2002) provides a statistical indication of which estimator leads to more reliable results about the nature of the production technology and the individual efficiency scores. We test H_0 of constant returns to scale and consider the entire pooled sample. We obtain a p-value of 0.10 for global constant returns to scale. Rejecting H_0 implies a type one error of 10 per cent. Taking into account that the VRS technology is consistent under both VRS and CRS we decide to apply the less restrictive VRS assumption for the following analysis. The VRS scores only represent the pure technical inefficiency. Therefore, we eliminate the scale effect and compare only countries within similar sizes of ideas production.

We argue that the appropriate empirical DEA model is specified as follows: four inputs (R&D expenditures, divided by the different sources, and number of researchers) and one output, namely patents weighted for multiple inventors. A number of applications of DEA on research efficiency in the past suggested the use of scientific publications as an additional output. Recent studies revealed a number of measurement problems inherent in the publication counts and therefore reject its usage (Sharma and Thomas 2008). Another issue of ongoing discussion in specifying ideas production is the distinction between R&D stocks and R&D expenditures (see e.g. Wang and Huang 2007 using R&D stocks as an input). From a theoretical point of view R&D stocks are preferable since they encompass the stock of knowledge available in an economy. In practice, assumptions need to be made for calculation due to missing data problems. We tested both approaches running separate DEA linear programming for each specification and found comparable results, which is not surprising because of high correlation between stocks and expenditures. Therefore we focus on R&D expenditures in what follows.

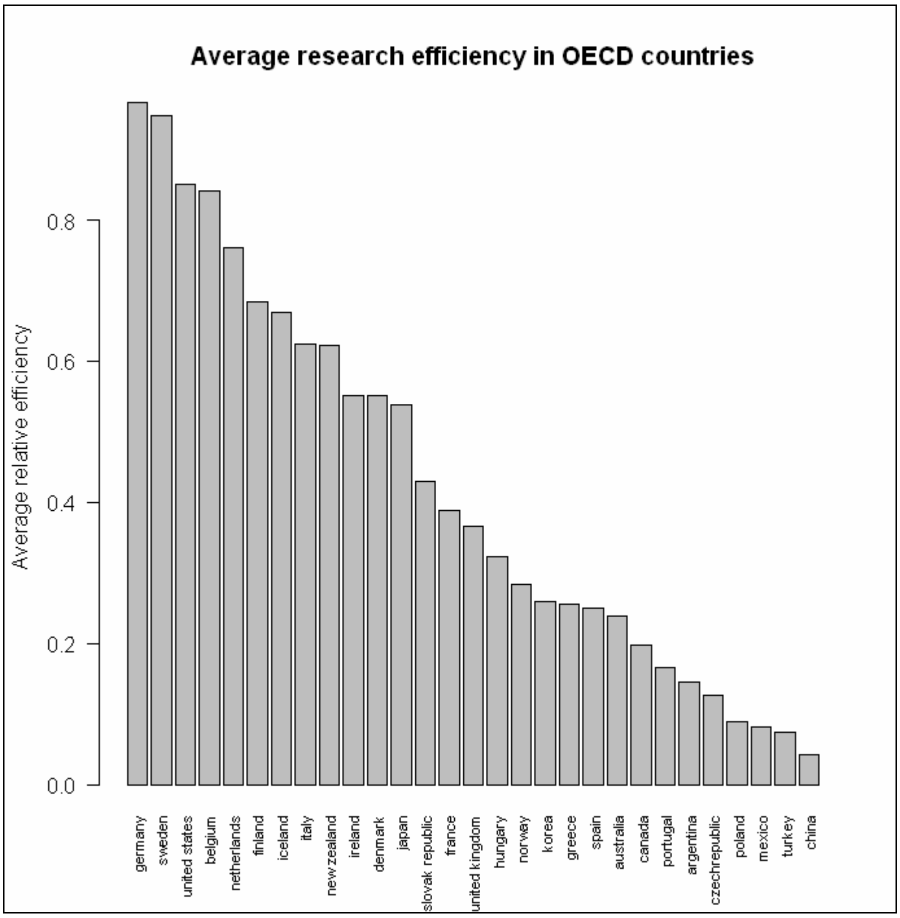
We estimate a cross section pooled frontier, where each observation is accounted for as a single country in time without considering any panel structure of the data. Our sample also includes East European countries like Poland and Czech Republic and Slovakia which underwent a transition period after 1989. In order to leave some room for transition time towards market oriented structures we define an observation period starting in 1994. To ensure comparability across countries and years we decided to skip countries for which less than four years are available.[8] In total we end up with a sample of 247 observations which is representative for nonparametric estimation of relative efficiency by means of DEA under the VRS assumption.

The intertemporal frontier estimation exhibits an average technical efficiency of 0.43 which is compared to other empirical work relatively low. This indicates that large inefficiencies are

[8] This is the case for Switzerland and Luxembourg which are observed only for one and two years respectively.

present within the ideas production process. The low mean efficiency might also be explained by the fact that the sample includes low innovation intensive countries like China or Korea from the early beginning of 1994; as shown below these countries started recently to adapt there R&D expenditure to increase the patent output. Furthermore the intertemporal frontier is defined by the most recent years in our sample, indicating that technological progress took place over time. Hence it is not surprising that covering a larger time span lowers mean efficiency.

We calculate the mean annual efficiency from 1994 to 2004 by averaging over the individual efficiency scores of the countries per year. We implicitly make the assumption of a constant intertemporal frontier, thus we consider the relative changes of the countries toward the estimated DEA technology frontier. This is motivated by two main aspects: First we face a small annual sample size (of less than 30 observations) which makes it difficult to obtain robust and meaningful results. Second, we do not dispose of a balanced panel data set, which prevents us from a comparison of different frontiers for different years, by means of e.g. Malmquist Indices (see Coelli, 2005).A ranking system of mean technical efficiencies over the observation period is shown in the following Graph 1.



Graph 1: Mean technical efficiency of OECD countries

Germany and Sweden are the most efficient OECD countries in providing R&D research output, followed by the United States and smaller countries like Belgium, the Netherlands and Finland. These countries could serve as peers to help improve performance of the least efficient countries. The leading position of Sweden and the US is confirmed by other empirical work. Especially in the case of the United States the high performance is remarkable since European Patent Data are used which usually lead to a home bias that would benefit European countries. Therefore we can conclude that the US is one of the leading countries in research and development worldwide which also exhibited a steadily improvement in their efficient R&D expenditures allocation (see Section 5.2). Compared to other European Regions the Scandinavian countries are all ranked among the top third of the performance ranking. An explanation could be their relatively higher quality of skilled labor that could make a difference in the human capital input factor of the efficiency analysis due to their excellent educational system as suggested by a number of comparative studies on schooling.

Historically Germany had its comparative advantages in traditional industries like machinery or metal fabrication and transport. These sectors still play a major role in research and development and thereby also in international patenting. Furthermore, Germany is leading country worldwide in renewably energy techniques, like solar and wind energy. However as already mentioned in the case of the United States, the use of EPO patents might lead to a slight overestimation of research efficiency in European countries. In light of this estimation bias the position of Japan is also worth mentioning since their performance is above average and they are as expected the leading Asian country. This is probably due to there leading role in communication and electronics as well as in the research intensive pharmaceutical industry.

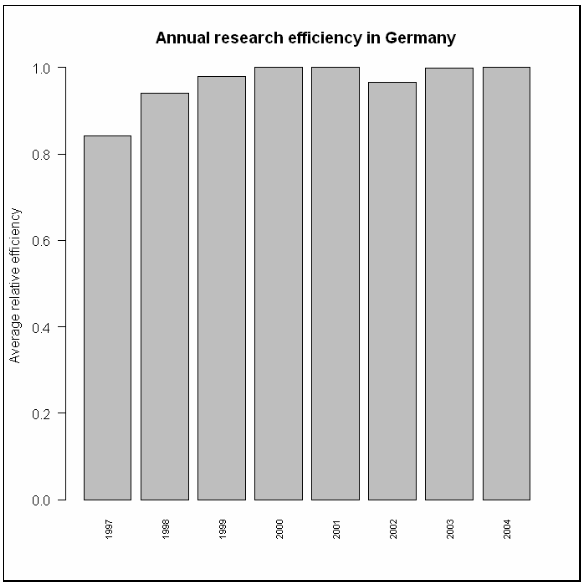
The innovative capacity of advanced industrial countries is their most important source of prosperity and growth. Overall, our results suggest that a matured economic system leads to higher research efficiency compared to countries still developing their industry and technology pattern. Therefore it is not surprising that the red lantern goes to Poland, Mexico, Turkey and China which are characterized by a very low capacity of ideas production suggesting that there are still in the phase of imitating and replicating existing technologies, while only little effort is made on innovating at the world technology frontier.

6.2 Towards more efficient R&D expenditures

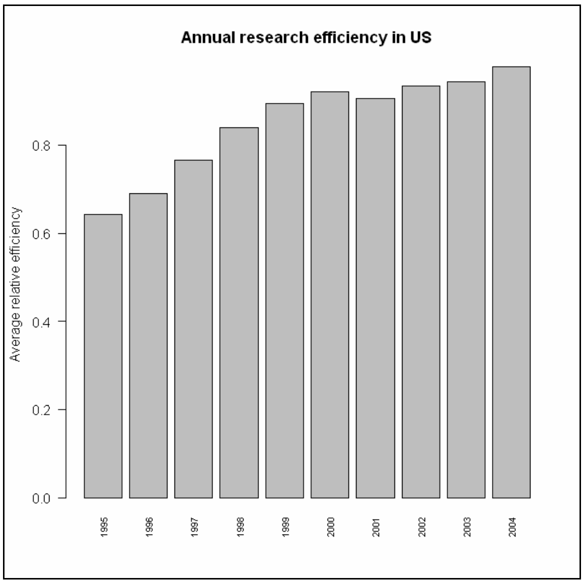
It is not only important to consider the level of performance of each country but in the same time how and to which extend efficiency evolved over the last years and which trends can be identified. Herby one has to distinguish again between countries lying on the world technology frontier and countries characterized by lower innovation capacities. As expected we assessed in Section 6.1 that more matured economies spanning the efficiency frontier, the world technology frontier, whereas developing countries are located in the lower range of research efficiency. However we observe that especially in Asian, but also other East European countries the catch-up process started in the last years.

6.2.1. The leading countries

Germany and the United States are two of the most efficient countries serving as peers to help improve performance of less efficient countries. Figure2 and 3 show that the efficiency increased in both countries in the 1990s but that no significant improvements are observed after 2000. This can be explained by the fact that for countries operating already on the world technology frontier it is more demanding and difficult to realize true process improvements towards a more efficient R&D production process. In contrast to the developing less mature economies they do not benefit from imitating innovative products in their home markets because less room is left for copying.



Graph 2: Efficiency development in Germany

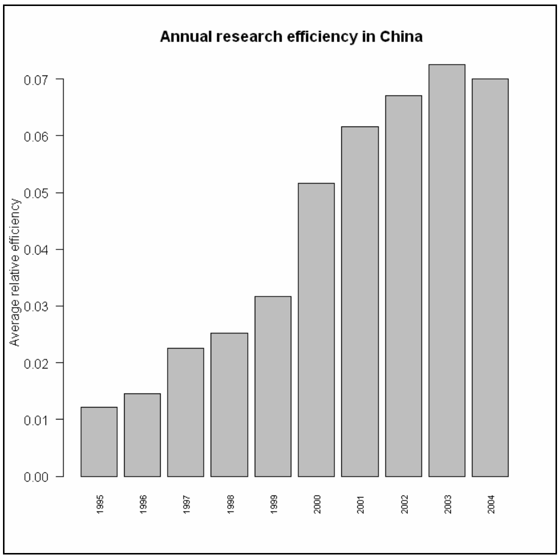


Graph 3: Efficiency development in the US

In contrast to Germany, the United States revealed a remarkable increase in efficiency between 1995 and 2000, which could also be linked to a rising tendency of American firms to seek patent protection in Europe

6.2.3. The Catch up in Asia and East European transition countries

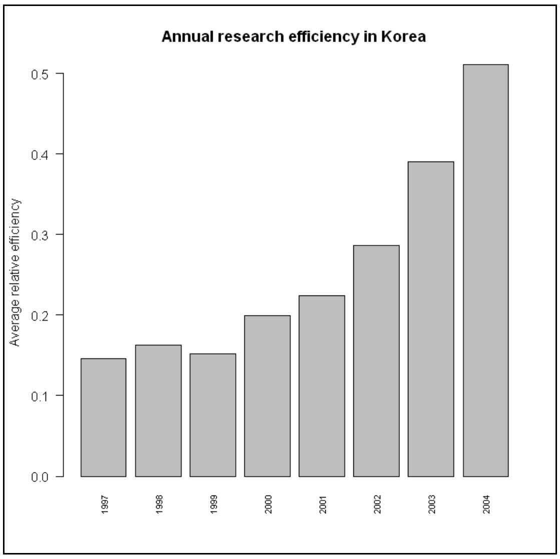
China and the East Asian Tiger Economies, particularly South Korea, have captured a growing share of international R&D. Nevertheless, their role remains relatively small compared to R&D efforts in Western Europe and the United States. Worldwide R&D is concentrated in Western Europe, the United States and Japan, where most patent applications originate. However, one observes an increasing number of patent filings in Asian countries, e.g. an average growth rate of 22% per year over the last ten years in China (OECD 2008). The low patenting intensity especially during the 90s is probably the main cause for the extremely low level of research efficiency in China. Furthermore, it is reported that Chinese inventors mainly seek for protection in China only which suggests that the home bias cause by the European patents applications plays an important role in determining research efficiency. Nevertheless, we find a clear trend towards a more efficient allocation of R&D expenditures since 2000.



Graph 4: Efficiency development in China

Several explanations could be brought in for justification: Firstly as our temporal results suggested a matured economic structure seems to be a prerequisite for an efficient usages of resources. This might imply that in future with growing R&D efforts, efficiency will improve as well. Secondly, there might be a change in Chinese inventor's behavior, meaning that they tend to file abroad more often with the aim to expand the markets for new Chinese products in Europe. This would lead to an increased patent intensity and thereby raise efficiency.

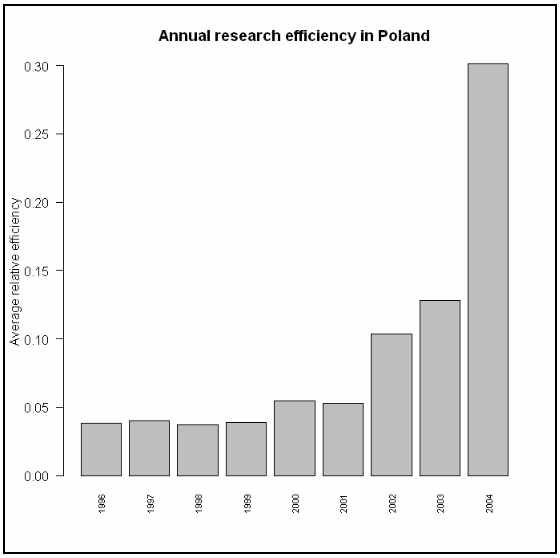
A similar pattern of efficiency improvement can be observed in South Korea, but at a higher performance level which already reaches 0.5 in 2004.



Graph 5: Efficiency development in South-Korea

This is in line with the results of the cross country analysis showing that South Korea already overtook European countries like Spain and Portugal. The evolvement in the past suggests a catching up in the performance level of South Korean research to the leading group of countries in the world in the near future.

The same pattern of recent efficiency increase is observed for Poland as an East European transition country. Following decades of socialist planning the East European transition countries finally underwent substantial market-oriented reforms during the past decade. This goes hand in hand with a change in inventor's behavior, showing an increase in patenting intensity.



Graph 6: Efficiency development in Poland

6.3 Quantify environmental exogenous factors

First results on the truncated, bootstrapped regression in the second stage suggest a weak influence of tax incentives on research efficiency when controlling for economic size. In case of R&D tax incentives for small and medium enterprises, we do not find a significant effect in terms of efficiency. This is not surprising since the majority of R&D projects and expenditures are conducted by large firms while small firms more often face liquidity constraints. In case of tax incentives for large companies we find a negative influence on research efficiency which might be counterintuitive at first sight. However, one explanation might be that taxation distorts the optimal choice of firms and thereby inducing inefficient behavior like overinvestment.

Further research in this study will be conducted: including an increase of the sample in the second stage and enlarging the set of environmental factors. Hence this is only a preliminary version of the paper, representing ongoing work in progress.

7 Conclusions

This paper assesses the relative efficiency of public and private R&D expenditures in the OECD using nonparametric efficiency analysis approaches, namely the data envelopment analysis (DEA). In times of globalization the efficient usage of the scarce resources a country invests in R&D becomes increasingly important. Therefore, this paper sheds light on the efficiency differences and changes among OECD countries over time and the evaluation of R&D tax incentives on efficiency. The assessment of R&D tax systems with respect to research efficiency is extremely given the ongoing discussion on reforms to promote innovation and growth in OECD countries. The empirical analysis is conducted in two steps: first an intertemporal knowledge production frontier is estimated. In a second stage we regress the efficiencies on a R&D tax system indicator using the recently developed single bootstrap procedures proposed by Simar and Wilson (2007).

Our results suggest that Germany, Sweden and the United States belong to the best performing countries, located on or close to the world technology frontier. These countries could serve as peers to improve efficiency for less efficient ones. We figured out that the innovative capacity of advanced industrial countries is their most important source of prosperity and growth. Thus, our results confirm the idea that a matured economic system leads to higher research efficiency compared to countries still developing their industry and technology pattern. The red lantern in research efficiency goes to Mexico, China and Turkey which are characterized by a very low capacity of ideas production suggesting that they are still in the phase of imitating and replicating existing technologies, while only little effort is made on innovating at the world technology frontier. However, we observe catch-up effects in Asian as well as transition countries after periods of socialist planning even though these countries started at very low levels. We conclude that these countries are on a promising way with regard to ideas production. However further efforts is needed to increase the overall relative performance. Preliminary results on the truncated, bootstrapped regression in the second stage suggest a weak influence of tax incentives on research efficiency. In case of R&D tax incentives for small and medium enterprises, we do not find a significant effect in terms of efficiency. For large companies we find a negative influence on research efficiency which might be explained by the fact that taxation distorts the optimal choice of firms and thereby inducing inefficient behavior like overinvestment.

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