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ABSTRACT

R&D Efficiency and Barriers to Entry: A Two Stage Semi-Parametric DEA Approach *

This paper assesses the relative efficiency of knowledge production in the OECD using a nonparametric DEA approach. In general, resources allocated to R&D are limited and therefore must be used efficiently, given the institutional and legal constraints. The efficiency scores presented are based on an intertemporal frontier estimation for the period 1995 to 2004. We analyze the impact of the regulatory environment using the single bootstrap procedure suggested by Simar and Wilson (2007a). The empirical evidence supports our hypothesis that barriers to entry aimed at reducing competition actually lower R&D efficiency by attenuating the incentives to innovate and to allocate resources efficiently.

JEL Classification: C14, C24, L50, O31, O57
Keywords: R&D efficiency, data envelopment analysis, truncated regulation

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1 Introduction

The notion of a knowledge production function is central to endogenous growth models in which innovation (ideas' productivity growth) is a main driver of sustainable, long-term growth (Porter and Stern, 2000). True innovation becomes even more important for productivity growth when a country approaches the world technology frontier, since there is less room for imitation and replication. The empirical literature affirms the importance of the level and dynamics of R&D expenditures for economic growth (e.g. Guellec and van Pottelsberghe, 2004). In today's globalized environment, it is both necessary and prudent for countries to efficiently utilize the scarce resources devoted to R&D. Countries are exposed to high levels of competition in domestic and foreign markets for innovative products and future technologies, a process which forces them to continuously update their technological capabilities. Those countries utilizing R&D resources inefficiently tend to be penalized with a growth discount.

Since the resources allocated to the generation of new knowledge are limited, they should be used as efficiently as possible given the local institutional, organizational and legal constraints. Government policies designed to encourage R&D play a major role in ensuring a sufficient level of R&D spending in the research process. Such policies, ensuring a high level of competition by reducing market entry barriers, are likely to influence innovation and R&D efficiency.

Market entry can affect R&D efficiency through different channels. First, it is often used as a vehicle for introducing product innovations (Geroski, 1995). New, innovative firms challenge incumbents, which in turn are forced to increase their R&D investment to acquire or maintain their competitive edge. Thus, more resources are allocated to R&D via growing incentives to innovate. Second, increasing competition from new entries forces firms to improve their R&D processes. In competitive markets, firms are punished severely for being inefficient (Boone, 2008). Competitive pressure induced by entrants increases the incentives to allocate the scarce resources optimally to ensure survival. High entry rates are associated with higher rates of innovation and increases in efficiency. The empirical literature widely confirms the innovation-enhancing effect of new firm formations. Among others, Acs and Audretsch (1990) and Geroski (1991) find a positive link between the rates of entry and innovation. Baldwin and Gorecki (1991) and Geroski (1989) document a productivity-enhancing effect of market entry on the industry level, and recently Aghion et al. (2009) claim that entry encourages incumbent innovation and productivity growth.

The degree of governmental regulation is crucial to lowering the barriers to entry by altering market structures. An overly strict regulatory environment will hamper new competitors. For this reason, we test the hypothesis that governmental barriers to competition lower R&D efficiency by distorting the incentives to innovate.

Our model specification follows the “knowledge production function” framework developed by Griliches (1979) and implemented by Pakes and Griliches (1984), Jaffe (1986), and Hall and Ziedonis (2001). According to Griliches (1979), innovative output is the product of knowledge generating inputs, similar to the production of physical goods. Some observable measures of inputs, such as R&D expenditures and the number of researchers, are invested in the knowledge production process and directed toward producing economically valuable knowledge. The process is seen as a continuum leading from R&D and human capital as inputs to some observable measure of innovative activity. Formally, it can be summarized using a knowledge production function:

$$I_c = f\left(R\&D_c, R_c\right)$$

where I_c is innovative output, $R\&D_c$ denotes R&D expenditures and R_c is the number of researchers. The unit of observation is the country (c) level.

Innovative output as the result of knowledge production can be difficult to capture. Therefore, we favor patent applications as a measure of the knowledge production process. By definition, they are related to inventiveness and based on an objective and relatively stable standard. Furthermore, data on patent application is widely available and provides additional information about the origin of the inventor and a detailed technological classification of the underlying invention. However, there are some drawbacks to their use as an indicator. Patent applications are often criticized for measuring only one component of the innovative output, since inventors may choose other protectionist strategies such as secrecy. The use of patents will thus underestimate real innovative activity. In addition, research has found that the value of patents is skewed to the right, with only some patents being highly valuable. This observation has been discussed by numerous authors, e.g. Scherer (1965), Pakes and Schankerman (1984), Pakes (1986), and Griliches (1990). Despite such drawbacks, patents are probably the most important indicator of research output and patent applications are extensively used in the literature (e.g. Hausman et al., 1984 and Kortum, 1997).

The empirical literature using a knowledge production function framework affirms the importance of level and dynamics of research personnel and R&D expenditures as input factors. However, only recently have empirical researchers emphasized the efficient usage of scarce resources. The relevant studies on R&D efficiency are summarized in Table 1.

This paper contributes to the extant literature in two important aspects: First, we measure R&D efficiency in OECD countries and consider R&D expenditures, distinguishing between public and private sources on the input side, as well as accounting for the possibility of multiple inventors on the output side. Secondly, we study the impact of product market regulation on R&D efficiency by applying a consistent two stage truncated regression approach proposed by Simar and Wilson (2007a).

Table 1: Literature Review of R&D Efficiency Studies

Authors	Data Sets	Methodology	Specification	Key results
Sharma and Thomas, (2008)	UNESCO Institute of Statistics data base, SCI Expanded data base of the web of science, WIPO Statistics data base	DEA approach with constant (CRS) as well as variable returns to scale (VRS).	Inputs: R&D expenditures, researchers, gross domestic product, population Output: patents granted, publications counts	Japan, Republic of Korea, China lie on the efficiency frontier with CRS, Japan, Republic of Korea, China, India, Slovenia and Hungary are found to be efficient with VRS
Wang and Huang, (2007)	WIPO Statistics data, MSTI data base, SCI expanded data base	DEA approach (VRS) and second stage Tobit Regression, Three stage approach according to Fried et al. (1999)	Inputs: R&D net capital stock, researchers, technicians, Output: patents granted, publications counts Environmental Variables: like the enrollment rate of tertiary education, the PC density and the English proficiency	About half of the countries are efficient in their R&D activities, higher education can explain variations in R&D input slacks, increasing returns to scale for two thirds of the countries
Wang, (2007)	WIPO Statistics data, MSTI data base, SCI expanded data base, World development indicators, economic freedom index	Stochastic frontier analysis (SFA), Battese and Coelli (1992, 1995) specification	Inputs: R&D net capital stock, researchers, technicians, Output: patents granted, publications counts Environmental Variables: the PC density, economic freedom index, percentage of R&D performed by the government	External factors affect R&D achievements, PC density and economic freedom index have a significant impact on efficiency differences
Rousseau and Rousseau, (1998)	EPO Patents, Science citation index, UNITED NATIONS, Statistical Yearbook,	DEA approach with CRS, different output and input weights	Inputs: GDP, active population and R&D expenditure Outputs: publications and patents	Switzerland was in 1993 the most efficient and effective country of Europe, closely followed by the Netherlands.
Rousseau and Rousseau, (1997)	EPO Patents, Science citation index, UNITED NATIONS, Statistical Yearbook,	DEA approach with CRS	Inputs : GDP, active population and R&D expenditure Outputs: publications and patents	DEA can be used as a tool to construct performance indicators for governments.

The empirical analysis is conducted in two steps. First, to measure R&D efficiency we follow the nonparametric DEA approach and assume a constant intertemporal frontier. Second, we analyze the influence of product market regulation on the differences in R&D efficiencies on the country level by applying the recently developed single bootstrap procedures proposed by Simar and Wilson (2007a). Due to unknown serial correlation among the estimated efficiencies, conventional approaches for drawing inferences are invalid.

The paper is organized as follows: Section 2 introduces the methodology of the two stage efficiency analysis and Section 3 presents our model specification and the data set. The empirical results of the efficiency analysis and the truncated regression are summarized in Section 4. Section 5 recapitulates the findings and concludes.

2 R&D Efficiency Analysis with DEA

To measure relative R&D efficiency and derive a ranking of countries by their achieved performance, we apply data envelopment analysis (DEA).[4]

The R&D technology frontier (efficiency frontier) is defined as the maximum output attainable by each input level (see Coelli et al., 2005). A particular country's distance from the technology frontier will depend on a mixture of exogenous, country-specific factors, such as governmental regulatory policies and barriers to entry. Our objective is to assess each country's efficiency level and then investigate the dependency on various indicators of the regulatory environment.

2.1 Stage 1: Estimation of relative R&D efficiency scores

Stage 1 uses the Farrell/Debreu-type output oriented efficiency measure:[5]

$$\mathrm{TE}\left(x^i, y^i\right) = \max\left\{\theta : \left(x^i, \theta y^i\right) \in \psi\right\},$$

where θ measures the radial distance between the input and output observation x^i, y^i and the technology frontier within the set. A value of $\theta = 1$ indicates that a country is fully efficient and thus is located on the frontier.[6]

[4] For an overview of the theoretical literature see Cooper et al. (2004).

[5] Farrell (1957) originally proposed estimating production efficiency scores in a nonparametric 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.

[6] 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 VRS assumption, a further convexity constraint $\sum\lambda=1$ must be considered. Within this framework, countries of similar sizes concerning the input requirements are compared.

We apply output orientation since it is reasonable to assume that countries desire to maximize their research output at a given level of R&D efforts. In the VRS model, the determination of the efficiency score of the i-th firm in a sample of size N is equivalent to the following equation (see Coelli et al., 2005):[7]

$$\psi = \Big\{(x,y) \in \Re_{+}^{p+q} :$$
$$\sum_{k=1}^{n} \gamma_k y_q^k \geq y_q, q = 1,\ldots,Q, \sum_{k=1}^{n} \gamma_k x_p^k \leq x_p, p = 1,\ldots,P; \gamma_k \geq 0; \sum \gamma_k = 1, k = 1,\ldots n\Big\},$$

We note that the identified efficient countries can also serve as peers to improve the performance of less-efficient countries via technology transfer, detailed process analysis, etc.

The DEA estimator belongs to the group of deterministic frontier models, which implies that all observations are assumed to be technically attainable.[8] As Simar and Wilson (2000, 2007b) show, these methods are sensitive to outliers and extreme values in the data. It is therefore important to assess ex ante whether outliers in the data inappropriately influence the performance measurements of the other countries. We apply the super-efficiency method proposed by Banker and Chang (2006) and Andersen and Peterson (1993) for outlier detection to identify and delete extreme values. Under this approach, decision-making units within the frontier can 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.[9]

2.2 Stage 2: Regulatory environmental indicators as determinants of efficiency?

Stage 2 represents an important step when deriving policy implications regarding a favorable regulatory, competitive and administrative environment while assuring R&D

[7] We are aware that the applied linear programming may not always identify all (efficiency slacks). The determination of an efficient frontier accounting also for the slacks (e.g. the second stage linear programming proposed by Ali and Seiford 1993 or the multi-stage method proposed by Coelli 1998) involve different problems of determining and interpreting the slacks (see e.g. Coelli at al. (2005)). Hence we concentrate upon the radial efficiency score provided by the first stage DEA linear programming.

[8] The model is deterministic in the sense of solving a linear programming problem; a stochastic component emerges when drawing inferences from it.

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

efficiency. We regress the efficiency scores on country-specific exogenous regulatory indicators. Our econometric model is based on Simar and Wilson (2007a) who propose a bootstrap procedure which permits valid inference in the second-stage regressions.[10] The model is specified as:

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

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

3 Model Specification and Data

The empirical DEA model, based on the notion of a knowledge production function, uses R&D expenditures and labor invested in R&D as inputs. We distinguish between R&D expenditures conducted by business enterprises,[11] by the government[12] and by higher education.[13] Such differentiation provides a more detailed picture compared to the conventional use of aggregate R&D[14] because the distribution of R&D expenditures over sources varies remarkably across countries.[15] The importance of public vs. private R&D

[10] Simar and Wilson (2007) show that conventional approaches for drawing inference in Tobit regressions, which have been widely applied in the past, are invalid when regressing non-parametric DEA scores on environmental variables in second stages. The inconsistency of simple second stage regressions is due to the complicated, unknown serial correlation among the estimated efficiencies.

[11] BERD in R&D terminology of MSTI

[12] GOVERD in R&D terminology of MSTI

[13] HERD in R&D terminology of MSTI

[14] GERD in R&D terminology of MSTI

[15] As Guellec and Van Pottelsberghe (2003) argue, high correlation between various types of R&D measures. However, as DEA is a linear programming methodology, this correlation does not affect our results. The DEA method derives an optimal set of input weights for each decision making unit. The obtained efficiency scores reflect the optimal combination for each observation relative to the frontier. Therefore we indirectly control for the potentially varying impact of different sources of R&D on efficiency. We distinguish between public and private R&D expenditures mainly to achieve a better fit of

is country-specific and should therefore be taken into account when measuring R&D efficiency. Furthermore, the productivity of R&D may vary across sectors; for example, a dollar invested in private R&D could increase a country's patent output more than a dollar invested in public R&D (see Wang, 2007). The distinction between private and public R&D is especially useful since the question of whether these are complements or substitutes has not yet been satisfactorily answered in the literature (David et al., 2000).

Another ongoing discussion in specifying knowledge 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 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 construct R&D stocks[16] using the perpetual inventory method suggested by Guellec and van Pottelsberghe (2001). Both approaches are tested by running separate DEA linear programming for each specification with comparable results. This is not surprising due to the high correlation between stocks and expenditures. Hence we follow a pragmatic approach and focus on R&D expenditures.

Data on human capital and R&D expenditures, which serve as inputs, are taken from the Main Science Technology Indicators published by the OECD. Manpower invested in R&D equals the number of researchers[17] per country. We use patents as an indicator of inventive output. A number of applications of DEA on R&D efficiency in the past also suggest the use of scientific publications as an additional output (see Table 1). However, recent studies reveal a number of measurement problems inherent in the publication counts, like co-authoring[18] and language bias (Rousseau and Rousseau, 1997), and therefore we also reject its usage (Sharma and Thomas, 2008).

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the technology frontier. The importance of public vs. private R&D is country-specific and should therefore be taken into account when measuring R&D efficiency.

[16] In line with the literature we assume a depreciation rate of 15%.

[17] Measured in full-time equivalents.

[18] The usage of all-author publication counts tends to overestimate the output of a country due to double counting when authors come from the same country.

Our analysis is based on a sample of 26 OECD member countries and two non-member countries (Argentina, China). The European Patent Office's Worldwide Patent Statistical Database (PATSTAT[19]) serves as the base of information on patent applications.[20]

Central to our exercise is the construction of patent aggregates by country and year. As de Rassenfosse and van Pottelsberghe (2009) argue, patent counts reflect – besides the widely discussed propensity to patent effect (Scherer, 1983) – a productivity component which justifies their usage as an indicator of research productivity. Counts are built by covering all patent applications filed with the European Patent Office according to their priority date between 1995 and 2004. We focus on EPO applications since an application to an international authority, in contrast to one made at the national level, e.g. at the German Patent Office, can be taken as a signal that the patentee believes the invention to be of high enough value to justify the expense of an international application. Furthermore, international filings are highly dependent on the productivity component while national filings tend to be driven more by the propensity component (de Rassenfosse and van Pottelsberghe, 2009).

The priority date is the date where the given invention is covered by a patent for the first time, no matter whether this first application is submitted to a national or an international authority. The first filing of a given invention mainly occurs at the national level, and therefore the majority of patent applications at the EPO are second- stage filings (de Rassenfosse and van Pottelsberghe, 2007). The priority date, then, is preliminary to the EPO application date in a considerable number of cases. Accordingly, we date patent applications using the priority date instead of the usual application date because it is closest to the date of invention and the decision to apply for a patent protecting the given invention (OECD, 2009). From an economic view, this is the only information of importance (Dernis et al., 2001).

When a variance exists between the country of the inventor and the applicant (as with multinationals), we assign patent applications to the country of the inventor. The

[19] Version 1/2008.

[20] The database maintained by the European Patent Office contains all national and international patent applications including inventors, applicants and their location, priority date and technological classification.

literature has until now usually considered only the first inventor's country of residence (e.g. Wang 2007, WIPO 2008) and thereby ignores research cooperation across 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 aggregation is conducted in two different ways:

1. We calcuate the unweighted sum over all inventors' countries of residence. This is by definition at least as large as the sum of all first inventors since patents with more than one inventor count more than once. Therefore, such an aggregation procedure might induce a bias due to double counting.
2. We derive 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's aggregate.

Empirical testing of the correlation between the first inventor and the multiple inventor output measures leads us to conclude that both can be used as an approximation of inventive output and will behave similarly in the empirical application. However, in the case of small countries, the conventional first inventor approach could lead to an underestimation of patent output when countries engage extensively in cross-border research cooperation. Therefore, we argue in favor of weighted patent aggregates as the appropriate output for the DEA application.

Consistent with recent literature (Sharma and Thomas, 2008 and Wang and Huang, 2007), we impose a lag structure of two years on inputs to account for the fact that R&D efforts do not immediately lead to innovative output (Hall et al., 1986). Table 2 illustrates the model specifications summarizing the input-output combinations.

Table 2: Model Specifications

Variables	Model 1	Model 2	Model 3
Inputs			
GERD			●
BERD	●	●	
HERD	●	●	
GOVERD	●	●	
Researchers	●	●	●
Outputs			
Weighted Patents	●		●
Unweighted Patents		●	

As mentioned Stage 2 of our empirical analysis evaluates the impact of barriers to entry caused by regulation on R&D efficiency. The regulatory environment is captured using the product market regulation indicators provided by the OECD in 1998 and 2003 (Conway et al., 2005). These indicators focus on the regulations which are potentially able to reduce competition in the areas of product markets. In the case of R&D efficiency, the regulations of considerable interest are those that influence the amount of competitive pressure by raising or lowering barriers to entry. A substantial amount of potential competitors are entrepreneurs which are either encouraged or deterrred from the prevalent degree of product market regulation. Table 3 shows the total number of barriers by country.

Information on regulation is collected from a questionnaire about specific policies applied by governments used by Conway et al. (2005). Numerous questions in various policy fields are summarized in an indicator system. The respondents are civil servants in national administrations who possess sufficient knowledge about the relevant policies to answer the questions. The information collected is then coded between 0 and 6 and increases with the restrictiveness of regulation.[21] Consistency checks are conducted by the OECD to further improve the quality of the data.

[21] The entire questionnaire and a detailed description of the construction are provided in (Conway et al., 2005).

In 1998, the countries with the highest level of regulation in this area were France, Italy, Mexico and Poland while in 2003 the Czech Republic ranked first. Nearly all countries reveal deregulation between 1998 and 2003.

Table 3: Barriers to Entrepreneurship[22]

Country	1998	2003
Australia	1.4	1.1
Belgium	1.9	1.6
Canada	1	0.8
Czech Republic	2	1.9
Denmark	1.4	1.2
Finland	2.1	1.1
France	2.8	1.6
Germany	2	1.6
Greece	2.1	1.6
Hungary	1.6	1.4
Iceland	1.8	1.6
Ireland	1.2	0.9
Italy	2.7	1.4
Japan	2.4	1.4
Korea	2.5	1.7
Mexico	2.7	2.2
Netherlands	1.9	1.6
New Zealand	1.2	1.2
Norway	1.5	1
Poland	2.8	2.3
Portugal	1.8	1.3
Slovak Republic	-	1.2
Spain	2.3	1.6
Sweden	1.9	1.1
United Kingdom	1.1	0.8
United States	1.5	1.2

Data Source: Conway et al. (2005)

[22] Calculation: composite indicator, two stages, pca.

Barriers to entrepreneurship encompass the following seven low-level indicators:

- Licenses and permit system: reflecting rules for obtaining and issuing licenses and permits (z1)
- Communication and simplification of rules and procedures: reflecting government's communication strategy to reduce administrative burdens (z2)
- Administrative burdens for corporations: depicts administrative burdens on corporation creation (z3)
- Administrative burdens for sole proprietor firms: depicts administrative burdens on sole proprietor firm creation (z4),
- Sector-specific administrative burdens: measures administrative burdens in transport and retail distribution (z5)
- Legal barriers: measures legal limitations on the number of competitors (z6)
- Antitrust exemptions: measures the scope for exceptions to competition law for public enterprises (z7).

The summary statistics for the years 1998 and 2003 of the low-level indicators are given in Table 4. A zero as the mean indicates that in at least one country the corresponding policies are not in place.

Table 4: Barriers to Entrepreneurship: Low-Level Indicators

Indicator		**1998**			**2003**	
	min	**max**	**mean**	**min**	**max**	**mean**
Licenses and permit system (z1)	0.0	6.0	3.4	0.0	6.0	2.1
Communication and simplification of rules and procedures (z2)	0.3	2.6	1.0	0.0	2.6	0.5
Administrative burdens for corporations (z3)	0.5	5.5	2.2	0.8	4.3	1.8
Administrative burdens for sole proprietor firms (z4)	0.3	4.3	2.2	0.0	4.0	2.8
Sector-specific administrative burdens (z5)	0.0	4.7	1.9	0.3	4.1	1.6
Legal barriers (z6)	0.3	3.5	1.8	0.3	2.3	1.5
Antitrust exemptions (z7)	0.0	3.7	0.6	0.0	3.5	0.5

Data Source: Conway et al. (2005)

In 1998, product market regulation via the license and permit system played a dominant role while administrative burdens became relatively more important in 2003. Nevertheless, all indicators, except z4, declined on average during the covered period.

4 Empirical Results

The empirical analysis is divided into two main sections. First, the relative R&D efficiency is determined by means of DEA to identify the OECD countries which perform efficiently. 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.[23] Country averages are then calculated over the observation period to obtain a ranking.

Second, we assess the impact of indicators of barriers to entry on yearly R&D efficiency scores by means of the truncated two-stage semi parametric regression proposed by Simar and Wilson (2007a).

4.1 Relative R&D efficiency

We assume an output orientation, thus countries aim to maximize R&D output given their exogenous inputs. We estimate both the constant returns to scale model (CRS, Charnes et al. 1978) and the variable returns to scale model (VRS, Banker et al., 1984). Within the CRS model, technical and scale efficiency are aggregated, whereas the VRS model measures the pure technical efficiency. Scale efficiency can therefore be determined by the difference between the results obtained from both specifications. The scale efficiency indicates if size and magnitude of the research production process in the countries is optimal.

[23] We are aware of the empirical problems assuming a constant intertemporal frontier. Recent research on inference in the nonparametric deterministic DEA framework underlines the importance of a large amount of data. Simar and Wilson (2007b) explicitly show by means of Monte Carlo experiments the curse of dimensionality problem: having a small data sample at hand results in large biases, large variances and wide confidence intervals. Ergo, we choose the maximum amount of data available.

Our sample includes East European countries, e.g. Poland, the Czech Republic and Slovakia, which underwent a transition period after 1989. To leave room for changes toward market-oriented structures, we start our observation period in 1995. Our sample excludes countries for which less than four years are available to ensure comparability across countries and years.[24] In total, we end up with 217 observations, which are representative for nonparametric estimation of relative efficiency by means of DEA under VRS and CRS assumptions.

To ensure a consistent and robust technology frontier we conduct ex ante outlier detection by means of super-efficiency analysis and apply the criterion outlined in Banker and Chang (2006) which defines outliers by an efficiency score greater than 1.2. Only three observations meet this criterion and are excluded from further calculations.[25] The small amount of outliers indicates that our frontier is not spanned by a number of unrealistic and extreme data points. Therefore, we claim the frontier being robust and consistent for the relative efficiency measurement of the remaining countries within the sample (214 observations).

We work with three model specifications as described in Section 3 (Table 2). The difference between Model 1 and Model 2 is the weighting scheme applied when deriving the patent counts. Model 1 uses weights for multiple inventors while Model 2 involves double counting. As expected the results are highly similar due to strong correlation and a rank correlation of about 0.97.

The ranking of countries only changes slightly in the midfield (for instance, Italy and Ireland) which could be caused by the different degree of engagement in cross-country research projects and country size.

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

[25] The deleted observations are Iceland (1996, 1999) and the Slovak Republic (1996). Due to significantly lower efficiencies in the rest of the time period we assume data problems for both countries in these years.

Table 5: Results for Different Model Specifications (VRS)[26]

Model 1		Model 2		Model 3	
Sweden	0.976	Sweden	0.982	Germany	0.945
Germany	0.966	Germany	0.957	United States	0.874
United States	0.874	United States	0.883	Netherlands	0.699
Belgium	0.854	Iceland	0.874	Finland	0.606
Netherlands	0.780	Belgium	0.870	Iceland	0.565
Finland	0.692	Netherlands	0.685	Japan	0.557
New Zealand	0.685	Ireland	0.679	Italy	0.540
Iceland	0.658	New Zealand	0.632	Belgium	0.487
Italy	0.650	Finland	0.620	Denmark	0.483
Ireland	0.573	Slovak Republic	0.613	Sweden	0.464
Denmark	0.565	Japan	0.608	France	0.373
Japan	0.557	Hungary	0.541	United Kingdom	0.331
Slovak Republic	0.556	Italy	0.509	Ireland	0.320
France	0.400	Denmark	0.497	New Zealand	0.314
United Kingdom	0.379	France	0.350	Norway	0.248
Hungary	0.339	United Kingdom	0.337	Hungary	0.209
Norway	0.289	Korea	0.288	Spain	0.196
Greece	0.274	Norway	0.248	Australia	0.169
Spain	0.260	Spain	0.233	Canada	0.167
Korea	0.259	Greece	0.211	Korea	0.156
Australia	0.238	Canada	0.207	Greece	0.119
Canada	0.202	Australia	0.205	Slovak Republic	0.089
Portugal	0.174	Portugal	0.144	Czech Republic	0.079
Argentina	0.145	Czech Republic	0.132	Portugal	0.063
Czech Republic	0.130	Argentina	0.127	Argentina	0.058
Poland	0.089	Poland	0.103	Poland	0.042
Mexico	0.069	Mexico	0.068	China	0.026
China	0.046	China	0.046	Mexico	0.023

Model 3 uses aggregated R&D expenditures as inputs instead of R&D expenditures by source. Compared to Model 1 we find a somewhat lower rank correlation (0.90) and small changes in the ranking; the major difference is that Sweden loses its top position.[27]

[26] Note, for the purpose of illustration we report average efficiency scores. However, second stage regressions are based on annual values.

Table 6: Efficiency Scores for Model 1 according to Different Approaches (CRS, VRS, scale efficiency)

Country	Average efficiency CRS	Average efficiency VRS	Average scale efficiency	Returns to scale[28]
Argentina	0.139	0.145	0.958	irs
Australia	0.237	0.238	0.996	irs
Belgium	0.839	0.854	0.982	irs
Canada	0.201	0.202	0.995	irs
China	0.046	0.046	0.994	irs
Czech Republic	0.114	0.130	0.878	irs
Denmark	0.552	0.565	0.977	irs
Finland	0.671	0.692	0.969	irs
France	0.400	0.400	1.000	crs
Germany	0.965	0.966	0.999	crs
Greece	0.258	0.274	0.943	irs
Hungary	0.324	0.339	0.957	irs
Iceland	0.369	0.658	0.561	irs
Ireland	0.441	0.573	0.770	irs
Italy	0.649	0.650	0.998	irs
Japan	0.431	0.557	0.774	drs
Korea	0.257	0.259	0.991	irs
Mexico	0.067	0.069	0.973	irs
Netherlands	0.777	0.780	0.996	irs
New Zealand	0.640	0.685	0.935	irs
Norway	0.285	0.289	0.989	irs
Poland	0.087	0.089	0.978	irs
Portugal	0.163	0.174	0.936	irs
Slovak Republic	0.165	0.556	0.296	irs
Spain	0.259	0.260	0.996	irs
Sweden	0.960	0.976	0.983	drs
United Kingdom	0.375	0.379	0.989	crs
United States	0.280	0.874	0.320	drs
Mean	0.391	0.453	0.898	
Median	0.305	0.389	0.978	
Standard deviation	0.268	0.286	0.192	

We argue in favor of Model 1 since we believe that disaggregating the inputs provides a more detailed picture of the research process in countries and adds potential useful information. Furthermore as known from the literature on author publication counts,

[27] Sweden is in particular efficient with respect to government expenditures on R&D. Aggregating over R&D by source eliminates the unique features with respect to different sources, thereby reducing Sweden's efficiency.

[28] Returns to scale are calculated for each observation at each point in time; exhibiting a property more than five times is our criterion for determining country-specific returns to scale.

double-counting of outputs overestimates efficiency. Hence, we prefer Model 1 to Model 2.

The difference between the CRS and VRS scores indicates scale efficiency. Table 6 shows that the majority of countries are not characterized by an optimal size of the research production process with respect to input allocation. Only Germany, France and the United Kingdom feature constant returns to scale, while Sweden, the United States and Japan show decreasing returns to scale.

The intertemporal frontier estimation exhibits an average technical efficiency of 0.39 in the CRS specification and 0.45 in the VRS specification. We note that these figures are relatively low compared to other studies. It indicates that large inefficiencies are present within the knowledge production process. We suggest that the low mean efficiency might also be explained by the fact that the sample includes low innovation- intensive countries like China or Korea from 1995 on. These countries only recently began to adapt their R&D expenditures to increase patent output. In addition, the intertemporal frontier is defined by the latest years in our sample, indicating that technological progress occurs over time.[29] Hence, it is not surprising that covering a larger time span lowers mean efficiency.

We calculate the mean annual efficiency from 1995 to 2004 by averaging over the individual efficiency scores of the countries per year. Implicitly we assume a constant intertemporal frontier and thereby consider the relative changes of the countries' positions towards the estimated DEA technology frontier. This is motivated by two 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, an unbalanced panel data set prevents comparing different frontiers for different years by means of e.g. Malmquist Indices (see Coelli et al., 2005).

[29] A pooled constant intertemporal frontier is not able to account for technological progress and to capture dynamic efficiency changes in the sample. The most recent frontier determines the benchmarks for previous years and we are not able to differentiate between different sources of efficiency changes (technological change, pure efficiency change and scale change). Our efficiency ranking incorporates only an aggregate performance measure over years.

Germany and Sweden are the most efficient OECD countries, followed by the United States and smaller countries like Belgium, the Netherlands and Finland. All could potentially serve as peers to help improve the performance of the least-efficient countries. Compared to other European regions, most Scandinavian countries are in the top third of the performance ranking. The high performance of the United States is remarkable, since European Patent Data are used which typically causes a home bias that would benefit European countries. We conclude that the United States is one of the leading and most efficient countries in global R&D. In light of this estimation bias, Japan is also worth noting because its performance is above average. We suggest this is largely due to Japan's leading role in communications and electronics as well as in the patent-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 mature economic system leads to higher R&D efficiency. The rankings for Poland, Mexico and China (which are characterized by a very low capacity of knowledge production) suggest that they are still in the phase of imitating and replicating existing technologies, and so far little effort has been expended on innovating at the world technology frontier.

4.2 The impact of regulatory environmental factors

In the second part of our empirical analysis, we analyze the influence of the regulatory environment on R&D efficiency using the semi-parametric two stage approach suggested by Simar and Wilson (2007a). We hypothesize that regulation reduces competition by raising barriers to entry and thereby lowering competitive pressure and the incentives to innovate efficiently.

Our econometric model regresses the output-oriented VRS technical efficiency scores obtained in the first stage on the seven low-level regulatory indicators:

$$\widehat{TE}_i = \beta_0 + \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3 + \beta_4 z_4 + \beta_5 z_5 + \beta_6 z_6 + \beta_7 z_7 + \varepsilon_i,$$

$\widehat{TE}_i$ represents the Farrell output efficiency scores ranging from 1 to infinity, with a value of 1 revealing full efficiency.[30] Hence, a positive beta-coefficient indicates an efficiency loss caused by the corresponding variable.

Our estimation results appear in Table 7. We find that the three low-level indicators, communication and simplification of rules and procedures, sector specific administrative burdens and antitrust exemptions, have a significant positive impact on efficiency scores as shown by the bootstrapped confidence intervals.[31] A positive impact implies that lowering the degree of regulation in these specific areas lowers barriers to entry and significantly increases R&D efficiency.

Table 7: Estimation Results

PMR Indicators	Variable	Lower bound	Estimated Coefficient	Upper bound
Licenses and permits system	z1	-2.396	-0.558	1.049
Communication and simplification of rules and procedures	z2	1.986	**8.446***	16.319
Administrative burdens for corporation	z3	-1.071	4.426	12.107
Administrative burdens for sole proprietor firms	z4	-12.756	-5.734	1.485
Sector specific administrative burdens	z5	1.211	**7.526***	15.893
Legal barriers	z6	-7.803	-3.193	2.821
Antitrust exemptions	z7	4.930	**8.494***	15.011

N=43, All estimation with constant, * significant at 10% level, i.e. 90% confidence intervals

The low-level indicator on communication and simplification of rules and procedures can be interpreted as summarizing the stumbling blocks related to the collection of information on start-up requirements, the enforcement of regulation and the treatment

[30] Note that this is in contrast to Tables 5 and 6 where we present the efficiency scores of the Shepard distance functions.

[31] A robustness check, which only evaluates the significant low-level indicators corroborates our findings from the previous estimations with slightly larger point estimates and confidence intervals.

of administrative burdens. Therefore, less regulation in this field suggests an emphasis by government on activities that facilitate innovation and entrepreneurship. This could be interpreted as a relevant factor stimulating competition by encouraging potential entrants to create a business.

In the case of sector-specific burdens, our results suggest that specific burdens being levied on the sector level reduce R&D efficiency significantly. This is probably mainly driven by country-specific heterogeneity since it depends on the economic importance and size of the sectors being regulated in each economy. Therefore, it implies that competitive barriers may play a larger role in specific economic sectors.

The third low-level indicator exhibiting a significant impact covers antitrust exemptions for public enterprises. This is not surprising since the incentive of public enterprises to strengthen their position by innovation is reduced when they are protected by governmental regulations. Hence, antitrust exemptions are accompanied by lower R&D efficiency since there is less pressure on companies to innovate and patent efficiently.

In summary, we find that the decision of potential entrants to start a business to a great extent depends on the regulatory environment, and that a highly regulated product market can dissuade entry by individuals and firms, thus reducing competition and the incentives to innovate and efficiently allocate the resources devoted to R&D.

5 Conclusions

This paper assesses the relative efficiency of public and private R&D expenditures in the OECD using the data envelopment analysis (DEA) approach. In times of globalization the efficient usage of the scarce resources a country invests in R&D becomes of great import. The purpose of our analysis is to highlight the R&D efficiency differences among OECD countries and their relationship to each country's regulatory environment.

We first estimated an intertemporal knowledge production frontier, followed by an investigation of the impacts of product market regulation on R&D efficiency via the consistent two stage truncated regression approach proposed by Simar and Wilson (2007a).

Our findings suggest that Sweden, Germany and the United States belong to the best-performing countries located on or close to the world technology frontier. These countries could also serve as peers to improve efficiency for less-efficient ones. The innovative capacity of advanced industrial countries is their most important source of prosperity and growth. Our results confirm the idea that a mature economic system leads to higher R&D efficiency compared to countries still developing their industry and technology pattern. Poland, Mexico and China are characterized by a very low rate of knowledge production, suggesting that they are still in the phase of imitating and replicating existing technologies, while only little effort is made to innovate at the world technology frontier.

Government policies aimed at encouraging R&D play a major role in ensuring a sufficient level of R&D spending. We hypothesize that regulation reduces competition by raising barriers to entry, thereby lowering competitive pressure and the incentives to innovate efficiently. Hence, we also assess the impact of the regulatory environment on R&D efficiency, via the single bootstrap procedures developed by Simar and Wilson (2007a). The regulatory environment is described using the indicator of product market regulation provided by the OECD.

Our estimation results show that the low-level indicators on communication and simplification of rules and procedures, antitrust exemptions and sector specific burdens have a significant impact, which suggest that greater degrees of regulation in these fields lower R&D efficiency. Overall, our results confirm the notion that high regulation in product markets dissuades potential entrants, especially entrepreneurs, by imposing barriers to entry, thereby reducing the competitive pressure for existing firms, and lowering R&D efficiency in a country's economy.

6 References

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