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TOWARDS AN EFFICIENT USE OF R&D – ACCOUNTING FOR HETEROGENEITY IN THE OECD

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ABSTRACT

Towards an Efficient Use of R&D – Accounting for Heterogeneity in the OECD

Expenditures devoted to research and development (R&D) are scarce and thus need to be used as efficiently as possible given the financial constraints countries are facing. This paper assesses the relative efficiency of R&D expenditures for 26 OECD member countries and 2 non-member countries. As countries differ in their national innovation systems and states of economic development and industrialization, e.g. transition economies in Eastern Europe vs. Asian countries vs. Anglo-Saxon countries, the measurement of R&D efficiency needs to consider differences in the technology of knowledge production. The existing empirical literature on R&D efficiency mainly builds on a homogeneous technology frontier neglecting the importance to account for country-specific heterogeneity. This paper models technological differences in knowledge production among countries using a stochastic frontier model for panel data. Applying a latent class model for SFA, we find empirical evidence for two technological classes, a `capital-intensive' and a `labor-intensive' one. Assuming a common knowledge production technology, as has been done so far in the empirical literature, thus results in biased efficiency estimates.

JEL Classification: C40, O31 and O57
Keywords: innovation, knowledge production function, latent classes, r&d efficiency and stochastic frontier analysis

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1 Introduction

Empirical literature affirms the importance of R&D expenditures for economic growth (Porter and Stern, 2000; Guellec and van Pottelsberghe, 2001). However, R&D resources available for the generation of new knowledge are limited due to financial constraints in the public and the private sector. Thus they need to be used as efficiently as possible, given the national innovation system consisting of local, institutional, organizational and legal factors. The related literature predominantly focuses on the level of R&D expenditures and new R&D investments while paying less attention to whether or not available resources being used in an efficient manner that maximizes innovative output (Wang and Huang, 2007). Nevertheless, this is of particular interest because additional R&D investments might not be helpful in promoting growth if resources are used inefficiently (Wang, 2007).

For this reason the analysis of efficient usage of knowledge generating inputs to create innovative output is becoming more and more important in the empirical literature (Wang and Huang, 2007). These empirical applications all build on the same knowledge production function proposed by Griliches (1979) and implemented by Pakes and Griliches (1984), Jaffe (1986), and Hall and Ziedonis (2001). Against this background, innovative output is the product of knowledge generating inputs, similar to the production of physical goods Griliches (1979). 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.

In this context nonparametric and parametric efficiency measurement techniques are used in the empirical literature to measure the relative R&D efficiency and derive a ranking of a set of observations with regard to their achieved performance.[1] R&D efficiency can be measured at the firm-level, industry-level, regional-level or in the empirical literature, the widely used the country-level. In this framework a production frontier is determined and then relative to this frontier the individual efficiencies of each country is estimated. The most widely used nonparametric method in this field is Data Envelopment Analysis (DEA), where the efficiency frontier is determined by means of linear programming methods (Charnes et al., 1978). Empirical studies (see e.g. Wang and Huang, 2007; Rousseau and Rousseau, 1997, 1998; Guan and Chen, 2012) point out that a significant potential for efficiency increases prevails within the knowledge production process. Other empirical applications (Wang, 2007) use the parametric efficiency analysis concept of stochastic frontier analysis (SFA) to measure the relative R&D efficiency. In this context cross-section or panel data econometric methods are

[1] For a detailed literature review on measurement of R&D efficiency we refer to Sharma and Thomas (2008).

used to construct the frontier covering the data. All parametric studies remain in the one dimensional output context, meaning that they are limited to one single output in the knowledge production function, usually patents.

To the best of our knowledge, the empirical applications in the empirical literature on R&D efficiency assume a common homogeneous frontier (world patent production frontier) for all countries. However, as one is faced with country-specific heterogeneity in the OECD and the world, assuming the same knowledge production function (frontier) is a rather limiting assumption. Country-specific characteristics, e.g. access to venture capital, degree of openness of the economy or national culture, influence the ideas generation process, and thus the underlying reference frontier. Some of these characteristics are observable and others are truly unobserved or too complex to be measured and modeled in the econometric model. Thus, unobserved factors might result, on the one hand, in biased technology estimations and therefore efficiency rankings and, on the other hand, in ambiguous and dubious policy recommendations.

We argue, that for R&D efficiency analysis at the country-level, it is important to account for heterogeneity to model national differences in the slope and shape of the knowledge production function because countries are so different in their national innovation systems, states of economic development, and industrialization. This seems evident when we compare e.g. transition economies in Eastern Europe vs. Asian countries vs. Anglo-Saxon countries. Thus, our modeling approach differs from previous empirical applications substantially by accounting for observed and unobserved heterogeneity. In our econometric model we aim to highlight that groups of countries exhibit different knowledge production functions capturing remarkable differences across the countries with respect to their national innovation systems. We apply a latent class stochastic production frontier model following Orea and Kumbhakar (2004) and Greene (2005). In this framework, countries are clustered in different classes with different knowledge production technologies and therefore frontiers. Simultaneously, estimates of a set of distinct knowledge production functions are obtained and countries are assigned to production functions (based on the class membership of countries). By means of this latent class model, we test and account for country-specific heterogeneity in knowledge production in order to obtain unbiased R&D efficiency estimates and rankings.

We conduct a parametric R&D efficiency analysis for 26 OECD countries and 2 non-member countries, Argentina and China, for the 1993-2007 time period. We contribute to the extant literature in two important aspects: First, we account multiple outputs by means of an econometric distance function. We argue that different types of outputs (patents and publications) should be considered in order to cover basic, fundamental and applied R&D output and to ensure correct parametric efficiency estimates (Thomas et al., 2011). Second, by applying a latent class stochastic frontier model we allow for country-specific heterogeneity in knowledge production and test different country-specific factors such as access to venture capital, national culture or trade openness having an impact in knowledge production. Section 3 describes our empirical model and Section 4 the data used. In Section 5 we discuss the empirical results. Section 6 summarizes and outlines our major conclusions.

2 Literature review

Empirical studies show that R&D promotes innovation at the firm-level (Griliches, 1986; Jaffe, 1986; Griliches, 1998), the industry level (Griliches and Lichtenberg, 1984) and across countries (Griliches and Mairesse, 1983; Mansfield, 1988).[2] Griffith et al. (2006) e.g. uses firm-level data from four European countries (France, Germany, Spain, and the UK) to describe the link between R&D expenditures, innovation output and productivity based on a structural model at the firm-level. A drawback underlined in the paper is that R&D expenditures, as a measure of input, do not explicitly take into account productivity and effectiveness of efforts.

Therefore measuring R&D efficiency analysis has become more and more important in the empirical literature. In this context we are faced with varying notions: Fu and Yang (2009) refer to patenting efficiency; Lee and Park (2005), Sharma and Thomas (2008) and Thomas et al. (2011) refer to R&D efficiency; Wang and Huang (2007) call the concept efficiency of R&D activities, whereas Halkos and Tzeremes (2011) refer to innovation efficiency and Hung et al. (2009) to academic productivity.

There is a wide range of application is the empirical literature with respect to the observation unit. R&D efficiency can be measured at the firm-level, industry-level, regional-level, or country-level: Zhang and Zhaoc (2003) investigate R&D efficiency in a sample of Chinese industrial firms with a special focus on the influences of ownership. Gantumur and Stephan (2010) concentrate on innovative efficiency and productivity in a firm-level panel based on the German Innovation Survey for the 1992-–2004 period, and analyze to what extent the acquisition of external disembodied technology affects the efficiency and productivity of technology acquiring firms. Thomas et al. (2011) refer to subnational levels of the United States. Guan and Chen (2010) build on a province-level panel dataset on R&D activities of 30 selected Chinese provinces while Li (2009) investigates the increasing disparity in regional innovation performance between Chinese regions. Another line of the literature analyzes national R&D efficiency, thus the aggregated unit of observation is the entire country. This is the approach we follow

[2]For a literature overview see Bos and Sanders (2011).

in our paper.

Sharma and Thomas (2008) examine the relative efficiency of the R&D process of 22 developed and developing countries in a nonparametric DEA framework, considering one single output (patents) and two inputs (gross domestic expenditures on R&D and the number of researchers). Wang and Huang (2007) use a three-stage DEA approach to evaluate the relative efficiency of R&D activities across 30 countries, controlling explicitly for the external environment, such as the enrollment rate of tertiary education and the PC density. Lee and Park (2005) measure R&D productivity at the national level to provide policy implications, especially for Asian countries. Further, Rousseau and Rousseau (1997, 1998) apply DEA to assess the efficiency and effectiveness of the R&D effort of European countries and conclude that DEA can be used as a tool to construct performance indicators for governments. Cullmann et al. (2011) updates the measurement of R&D efficiency in the OECD using a DEA approach. Efficiency scores were calculated using intertemporal frontier estimation for the period 1995 to 2004. They find that Sweden, Germany and the United States are located on or close to the technology frontier. The authors further analyze the impact of the regulatory environment using a bootstrap procedure suggested by Simar and Wilson (2007). The results show that barriers to entry, aimed at reducing competition, actually reduced R&D efficiency by attenuating the incentive to innovate and to allocate resources efficiently. Guan and Chen (2012) use a DEA model for measuring the innovation efficiency of national innovation systems for 22 OECD countries by decomposing the innovation process into a network with a two-stage innovation production framework, an upstream knowledge production process and a downstream knowledge commercialization process. In a second stage they examine the effects of policy-based institutional environment on innovation efficiency. They provide evidence that the overall innovation efficiency is subject to commercial efficiency performance. Thus, improving commercial efficiency should be the main focus in future innovation policy-making.

Wang (2007) considers 30 countries (23 OECD and 7 other) for the 1998-2002 period in a parametric framework. The analysis is based on a translog production model taking into account environmental factors that influence the R&D performance (ratio of government expenditures on R&D to total expenditures on R&D, density of personal computers, indicator of national economic freedom). Considering 21 OECD countries, Fu and Yang (2009) estimate a patent production frontier for the 1990-2002 period by means of SFA. Differences in patenting efficiency are explained by exogenous characteristics within the Battese and Coelli approach (Battese and Coelli, 1995). None of the empirical applications within the parametric framework modelled more than one output.

Previous empirical applications assume one common technology and, therefore, one common efficiency frontier for all countries. Fu and Yang (2009) add directly in the production function further variables in the traditional knowledge production function: total expenditures on education, and the value added shares of high tech industries relative to the total economy to account for differences in the expenditure and industry structure of the countries. Fritsch and Slavtchev (2011) define different slope parameters for different regions in Germany and aim to answer the question of what factors can explain differences in regional innovation system efficiency using (among others) SFA techniques. Teitel (1994) uses a parametric production function approach, but not within the frontier framework, in order to analyze the relationship between number of patents and four explanatory variables: R&D expenditures, number of scientists and engineers, per capita income and the population for the 1976-1985 period. The data set is split into four different subsets of countries (low income countries, middle income countries, high income countries and Latin America) in order to obtain better coefficient estimates. Some empirical applications define in a second stage efficiency clusters based on post-hoc comparisons (Lee and Park, 2005). In their paper they define four different groups of countries with respect to different efficiency dimensions (inventors, merchandisers, academics, duds). This is different to our approach. We assume, *a priori*, a different technology in producing innovative output to obtain more reliable and unbiased efficiency estimates. This also involves that the peers are different ones in different groups.

3 Model specification

3.1 Distance function approach

To measure the relative R&D efficiency within a knowledge production setting, the majority of applied parametric efficiency analyses uses the production function to describe the underlying technology of the countries' knowledge production. Single output Cobb-Douglas or translog functional forms are most widely assumed but become critical when more than one output is modeled (Coelli, 2000).[3] In this framework the majority of applied work manages the issue by aggregating the different outputs into a single index. Wang (2007) analyzes the relative efficiency of aggregate R&D activities in 30 countries based on a translog specification with one aggregated output index.[4]

[3]Within the nonparametric DEA, multiple outputs can be incorporated easily, which is not the case within parametric efficiency analysis.

[4]He aggregates four single outputs including the weighted sum of the number of patents (excluding new designs) granted by each selected country, the number of patents granted by the United States

His weighting scheme is based on the average amount of patents and papers in each year. He imposes, *a priori*, the relative weights to each output assuming the same relative impact within the knowledge production process. Imposing, *a priori*, weights is questionable without an empirical cost driver analysis to test empirically for the different impacts of the outputs.

Another approach to model multi-output production is the concept of parametric distance functions (Coelli, 2000). This approach is proposed by Shephard (1953, 1970), who derives a distance function representation of a multi-output technology as a primal alternative that requires no aggregation, price and cost information, or behavioral assumption.[5] To model the knowledge production process we apply a parametric frontier output distance function (in opposition to an input distance function) 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 of researchers (Wang and Huang, 2007). The output distance function is defined on the output set $P(x)$ as

$$d_o(x, y) = min\{\rho : (y/\rho) \epsilon P(x)\} \tag{1}$$

and considers how much the output vector y may be proportionally expanded by the scalar distance ρ with the input vector x held fixed (Coelli, 2000).[6] The term $d_o(x, y)$ will assume a value less than or equal to one if the output vector y is an element of the feasible production set $P(x)$. In addition, $d_o(x, y) = 1$ if it is located on the outer boundary of the production possibility set (Coelli and Perelman, 2000).[7]

Imposing homogeneity, we follow Lovell et al. (1994) and Coelli and Perelman (2000) who point out that homogeneity implies that for any $w > 0$

$$d_o(wx, y) = wd_o(x, y). \tag{2}$$

Therefore, one of the outputs may be arbitrarily chosen, such as the M-th output and

to each country studied, the annual number of papers published in the Science Citation Index (SCI) international journals, and the annual number of papers published in the Engineering Index (EI) international journals.

[5]See Coelli (2000) and Coelli and Perelman (2000) for a detailed description on the econometric estimation and advantages and disadvantages of the distance function representation.

[6]It is assumed that the technology satisfies the standard axioms: $d_o(x, y)$ is non-decreasing, positively linearly homogeneous and convex in y and decreasing in y (Coelli, 2000; Färe and Primont, 1995; Coelli and Perelman, 2000).

[7]Applications of this concept to estimate parametric distance functions using econometric methods is quite common in infrastructure and service sectors (Färe et al., 1993; Grosskopf et al., 1995; Saal et al., 2007) and in agriculture research (Brümmer et al., 2002, 2006).

set $w = 1/y_M$. This yields

$$d_o(x, y/y_M) = d_o(x, y)/y_M \tag{3}$$

The distance function can be approximated by a translog functional form (Färe et al., 1993), which is widely used in empirical application due to its flexibility for econometric estimation.

$$\ln d_o = TL(x, y, \alpha, \beta, \delta). \tag{4}$$

To obtain the frontier surface (the transformation function) one would set $d_o = 1$, so that the left side equals zero (Coelli and Perelman, 2000). Imposing homogeneity (see Equation 3) by dividing Equation 4 by an optional output and some rearranging the translog output distance function for the case of M outputs and K inputs is specified for the i-th country as

$$\begin{aligned}
-\ln y_{Mi} &= \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln(\frac{y_{mi}}{y_{Mi}}) + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{N} \alpha_{mn} \ln(\frac{y_{mi}}{y_{Mi}}) \ln(\frac{y_{mi}}{y_{Mi}}) \\
&+ \sum_{k=1}^{K} \beta_k \ln x_{ki} + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{L} \beta_{kl} \ln x_{ki} \ln x_{li} \\
&+ \sum_{m=1}^{M} \sum_{k=1}^{K} \delta_{mk} \ln(\frac{y_{mi}}{y_{Mi}}) \ln x_{ki} + \ln d_o
\end{aligned} \tag{5}$$

where $\ln d_o$ is a nonnegative variable that can be associated with technical inefficiency u_i. Given the stochastic error v_i, this model can be formulated in the common SFA form with the combined error term $v_i + u_i$ (see Section 3.2). Technical efficiency is the ratio of observed output to frontier output. A radial output-oriented measure of technical efficiency TE is then obtained by

$$TE = \frac{1}{d_o} = exp(-u_i). \tag{6}$$

The distance function provides a promising new solution to the single output restriction of the standard knowledge production functions.[8] The estimated distance

[8] One concern in the econometric estimation is potential regressor endogeneity, which may introduce possible simultaneous equation bias. Ratios on inputs appear on the right side of the estimating equation, which may involve simultaneous feedback problems because these input variables are assumed to be endogenous. Some authors propose instrumental variables estimation (see Sickles et al., 1996; Atkinson and Primont, 2002).

functions often fail to satisfy the concavity and quasi-concavity properties implied by economic theory (O'Donnell and Coelli, 2005). This sometimes leads to surprising conclusions regarding the effects of input and output changes on productivity growth and relative efficiency levels. Therefore, the starting point before any interpretation of inefficiencies is to check and to test for the properties.[9]

3.2 A latent class stochastic frontier model

To determine the relative R&D efficiency of the countries under consideration, we compare some measure of actual performance against a reference technology (the stochastic frontier). The distance to the frontier can be interpreted as a common measure of inefficiency. In the stochastic frontier framework, the error term in the econometric estimation of the production technology is divided into two uncorrelated components: a one-sided non-negative disturbance u_i, half-normally distributed, representing the inefficiency; and a symmetric disturbance v_i, assumed to be normally distributed, and capturing random noise in the sample (Greene, 2004). In our econometric model the distance d_o (see Equation 5) can be defined as the sum of the two uncorrelated components u_i and v_i.

In our econometric model we highlight that groups of countries exhibit different knowledge production functions capturing remarkable differences across the countries with respect to their national innovation systems. We therefore use a latent class framework for SFA that is able to account for specific technological characteristics of the countries in the sample. Countries are classified into a set of different technologies and efficiency distributions. However the specific classification is, *a priori*, unknown (Greene, 2004; Orea and Kumbhakar, 2004). In this model all parameters vary by class standing for the different technologies.[10]

For the output distance function (see Equation 5), the latent class stochastic frontier model is as follows

[9] Regularity conditions could also be imposed by estimating the model in a Bayesian framework (O'Donnell and Coelli, 2005).

[10] The latent class model for SFA is applied in a number of other fields see (Orea and Kumbhakar, 2004; Greene, 2005; Caudill, 2003; Corral and Alvarez, 2008). To our knowledge we are the first to model R&D efficiency by means of a latent class model.

$$
\begin{aligned}
-\ln y_{Mit}|_j &= \alpha_{0j} + \sum_{m=1}^{M} \alpha_{mj} \ln(\frac{y_{mit}}{y_{Mit}}) + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{N} \alpha_{mnj} \ln(\frac{y_{mit}}{y_{Mit}}) \ln(\frac{y_{mit}}{y_{Mit}}) \\
&+ \sum_{k=1}^{K} \beta_{kj} \ln x_{kit} + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{L} \beta_{klj} \ln x_{kit} \ln x_{lit} \\
&+ \sum_{m=1}^{M} \sum_{k=1}^{K} \delta_{mkj} \ln(\frac{y_{mit}}{y_{Mit}}) \ln x_{kit} + v_{it}|_j + u_{it}|_j
\end{aligned} \tag{7}
$$

where j indicates the class or regime. Class membership is unknown. One assumes that there is a latent sorting of the observations in the data resulting in a total number of J classes (Greene, 2007). Note, that the coefficients differ for each class, reflecting the differences in the technology for different groups of countries. For one specific observation from class j the model is characterized by the conditional density $g(.)$ determined by the class specific parameter vector Θ_j.

$$
g(y_{Mit}|\frac{y_{mit}}{y_{Mit}}, x_{kit}, class_j) = f(\Theta_j, \frac{y_{mit}}{y_{Mit}}, x_{it}) \tag{8}
$$

The contribution of the country i to the conditional likelihood (conditional on class j) is

$$
P(i|j) = \prod_{t=1}^{T} P(i,t|j) \tag{9}
$$

The unconditional likelihood for country i is an average over the J classes. It can be shown that the likelihood function can be expressed by (see Greene, 2005)

$$
logLF = \sum_{i=1}^{N} log(\sum P_{ij} \prod_{t=1}^{T} LF_{ijt}) \tag{10}
$$

The class probabilities can be parameterized by a multinomial logit model:

$$
P_{ij} = \frac{\exp(\delta_j' q_i)}{\sum_{j=1}^{J} \exp(\delta_j' q_i)} \tag{11}
$$

where q_i is a vector of country-specific but time-invariant variables. These variables, called separating or switching variables, are included to identify any regularity in classifying the sample by means of the estimated coefficients of latent class probability functions $\widehat{\Theta_j}$ (Greene, 2007). A positive sign of the coefficient suggests that the larger the variable the higher the probability that a country belongs to this class. Similarly, the significantly negative value of a coefficient indicates that the probability of membership in this class decreases when the variable increases.

Under the maintained assumptions, maximum likelihood techniques will give asymptotically efficient estimates of all parameters. Greene (2002, 2004) point out that both the technology as well as the probability to belong to a certain class are estimated simultaneously. All observations in the sample are used to estimate the underlying technology for each class. The estimated parameters can be used to compute the conditional posterior class probabilities. In addition, Greene (2004) suggests that the class probabilities apply unchanged to all years of the observation period.

In standard SFA for R&D efficiency measures, the individual efficiency is estimated to the common frontier, since all countries are assumed to operate under the same technology. The latent class specification estimates as many frontiers as the number of classes. To measure the efficiency level of an individual observation (see Orea and Kumbhakar, 2004, for a summary) technologies from every class are taken into account, weighted with the respective probabilities (Greene, 2002). To determine the number of J classes for the best model fit, we apply information criteria such as the Akaike Information criterion (Greene, 2007).

4 Data

Two sets of variables are required to estimate the latent class model. First, variables in the knowledge production frontier covering appropriate inputs and outputs are needed. Second, variables determining class probabilities that help classify countries into the different classes with different underlying knowledge production technologies are also needed.

4.1 Knowledge production function

Based on the notion of a knowledge production function framework (Griliches, 1979) we use as inputs

* Number of researchers ($x1$)
* R&D expenditures ($x2$)

and as outputs

* Patent applications ($y1$)
* Publications ($y2$)

Data on human capital and R&D expenditures are taken from the Main Science Technology Indicators published by the OECD. Human capital invested into R&D is proxied by the number of researchers per country. Consistent with the literature on R&D efficiency (Sharma and Thomas, 2008 and Wang and Huang, 2007), we impose a lag structure on inputs to account for the fact that efforts do not immediately lead to innovative output (Hall et al., 1986). Therefore, inputs are lagged by two years in the SFA application. Summary statistics and the exact definition of the variables, together with the source of the variables, are shown in Table 1 and Table 2.

Patent applications serve as our indicator of inventive output taken from the OECD patent statistics (see Table 2). We focus on PCT patent applications. The PCT procedure is a popular approach in filing international applications as it allows applications for patent protection in a large number of countries, thereby ensuring comparability across countries. Previous studies on R&D efficiency suggest amending the output side by scientific publications to consider basic and fundamental research output (Sharma and Thomas, 2008). We therefore add scientific and technical journal articles taken from the world development indicators as the second output dimension.

The data set covers 28 countries (26 OECD member countries and two non-member countries, Argentina and China for the 1993-2007 period, resulting in an unbalanced panel set of 428 observations. Countries are listed in Table 3, with the number of years observed respectively.

Besides the relations between direct inputs and outputs, countries might differ in the underlying technology of knowledge production due to observable or unobservable characteristics. To appropriately measure R&D efficiency, we allow for different technologies by assigning countries to the corresponding latent classes. Class membership is determined empirically by using switching variables that capture contextual factors shaping the environment in which innovation takes place.

4.2 Switching variables

Country-specific variables (q_i variables in Equation 11) are used to determine latent class probabilities in order to classify the countries within the sample. In line with the literature, the following variables are considered to be influential in identifying technological differences in knowledge production:

* Business expenditures on R&D per GDP (BEX_{RD})

In the existing literature (see e.g. Wang, 2007), it is argued that the distribution of R&D expenditures over sources (public and private) is country-specific and varies remarkably across countries. A dollar invested in private R&D might increase a country's patent

Variable	Mean	St.Dev.	Min	Max
Knowledge Production Function				
x1	142252.9	270734.0	676.0	1430551.0
x2	21346.2	47498.9	61.3	286341.7
y1	3141.5	7498.4	0.1	52441.6
y2	20622.0	38700.1	104.0	209694.7
Switching Variables				
VC	5.1	1.5	1.2	8.6
HTE_1	16.9	10.2	1.2	57.1
$OPENESS$	70.8	35.1	16.0	184.7
$EDUC$	5.4	1.0	2.6	7.1
NC	7.2	0.8	5.3	9.0
BEX_{RD}	0.984	0.696	0.059	3.199
HTE_2	0.038	0.048	0.001	0.329

Table 1: Descriptive statistics

Variable	Def.	Description	Sources
Knowledge Production Function			
PCT patents	y1	Patent applications filed under the Patent Cooperation Treaty (PCT)	OECD Patent Statistics
Publications	y2	Scientific and technical journal articles	WDI
Researcher	x1	Total researchers (FTE)	MSTI
R&D Expenditures	x2	Gross domestic expenditure on R&D	MSTI
Switching Variables			
Venture capital	VC	Venture capital is easily available for business development	IMD World Competitiveness Yearbook
High tech. exports (%Manufacturing)	HTE_1	High-technology exports (% of manufactured exports)	WDI
Trade	$OPENESS$	Trade % of GDP	WBDI
Education exp.	$EDUC$	Total education expenditure per GDP	WDI
National culture	NC	The national culture is open to foreign ideas	IMD World Competitiveness Yearbook
Business exp.	BEX_{RD}	Business expenditure on R&D per GDP	MSTI, OECD
High tech. exports (% GDP)	HTE_2	High-technology exports (% of GDP)	WDI

Table 2: Definition and sources of variables

Country	**Number of observed years 1993 - 2007**
Argentina	9
Australia	17
Belgium	16
Canada	17
China	15
Czech republic	11
Denmark	17
Finland	14
France	17
Germany	14
Greece	17
Hungary	15
Iceland	17
Ireland	17
Italy	17
Japan	17
Korea	11
Mexico	10
Netherlands	14
New zealand	17
Norway	16
Poland	12
Portugal	17
Spain	17
Sweden	17
Turkey	16
United Kingdom	17
United States	17

Table 3: Countries in the Sample

output more than a dollar invested in public R&D (Wang, 2007). We therefore include the share of business expenditures on R&D per GDP (BEX_{RD}) as one of the switching variables to control for the impact of private R&D.

* National culture (NC)

Recent empirical applications analyze the link between social and cultural factors and innovation performance (Halkos and Tzeremes, 2011). The assumption is that cultural factors have a direct impact on the efficiency of knowledge production. Our approach differs as we assume national culture (NC), measured by expert ratings collected in surveys, to have an impact on the technology itself (and its marginal products) and not on performance levels.[11]

* Total education expenditure per GDP ($EDUC$)

[11] The IMD World Competitiveness Yearbook (WCY) ranks countries annually according to their openness to foreign ideas, which in turn is used to derive the overall competitiveness of nations. A detailed description of the construction of that indicator can be found in IMD (2011).

Researchers can only be hired if a sufficient number of young people holds a university degree and choose to stay in academia or applied research. Therefore, the structure of the educational system influences the supply of human capital that is qualified for R&D. We thus include the total expenditure on education per GDP ($EDUC$) as a determinant of latent class probability. This can also be interpreted as an indicator of the involvement of universities in research (Fu and Yang, 2009).

* Trade per GDP ($OPENNESS$)

The empirical literature hypothesizes that openness to trade affects the knowledge generation of countries by enabling knowledge spillovers and easing the access to high-quality inputs (Fu and Yang, 2009). To proxy the degree of openness of an economy, the ratio of trade volume to GDP ($OPENNESS$) is tested as a potential switching variable.[12]

* Share of high technology exports (HTE_1) and (HTE_2)

Fu and Yang (2009) emphasize the influence of the industry structure, more specifically the share of high technology activity in an economy, on innovative performance. Evidence suggests a positive impact of the value-added share of the high-technology industry on the patenting capacity of a country. We therefore include the share of high technology exports in manufacturing exports (HTE_1) and the share of high technology exports per GDP (HTE_2) to test whether the industrial structure matters for the shape of the knowledge production function.

* Venture capital (VC)

The strength of venture capital markets influences the availability of resources that can be devoted to R&D at the business level. If venture capital is easily available for business development, high-risk projects can be developed that could not otherwise be undertaken. This is of special importance for small firms and entrepreneurs. Access to venture capital is, therefore, a key factor affecting innovation performance (Guan and Chen, 2012).

Summary statistics and the exact definition of the variables, together with the source of the variables, are shown in Table 1 and Table 2. As class membership is constant over time, switching variables are assumed to be time-invariant. Country-specific averages are therefore used in the estimation to capture systematic differences that could drive the shape of the frontier.

[12] Trade to GDP ratio is defined as (exports + imports)/(2*GDP).

5 Empirical results

5.1 Estimation results

We estimate a latent class model with two different classes to test whether different underlying knowledge production technologies are prevalent in our sample, caused by country-specific heterogeneity. The likelihood ratio test shows that the flexible translog functional form is appropriate, not the stricter Cobb-Douglas specification.[13] All variables are mean corrected to avoid outliers in the sample, which could have a large impact on the estimation outcome. Coefficients in this case can be interpreted as elasticities for the sample averages. Estimating a latent class model requires, *a priori*, determination of the number of classes. The Akaike information criteria (AIC) prefers the definition of two classes (-0.534) to a single class model (0.43).[14] Therefore, we use the two class specification. Given the small number of observations in each class and the number of parameters to be estimated for a translog output distance function, further segmentation up to three or more classes asks too much of the data (Schnier et al., 2006).[15] Table 4 shows the regression results of the maximum likelihood estimates of the distance function estimation for two classes (see Equation 7). In terms of the share of significant parameters, the output distance function appears to reasonably fit the observed data. The estimated coefficients of the first order terms have the expected signs (the normalized second output has a positive sign and both inputs have a negative sign) and are statistically significant. The prior class probabilities display a relatively equal latent sorting of the observations into both classes (class A = 60 per cent and class B = 40 per cent).

The first order elasticities α_{mj} and β_{kj} (see Equation 7) represent the output and input elasticities contribution to the production of the output y_1. The coefficients of the first order output α_{2A} and α_{2B} and input variables β_{1A}, β_{1B} and β_{2A}, β_{2B} differ significantly in both classes.[16] With respect to outputs, the homogeneity restriction allows us to calculate the share of both outputs in knowledge production as the output coefficients sum up to one. The share of scientific publications (α_{2A}, α_{2B}) is equivalent to 0.843 in class A and 0.890 in class B. Accordingly, the share of patents in total

[13] We estimate the unrestricted translog and the restricted Cobb-Douglas model and obtain a likelihood ratio test statistic of 275.65 favoring the unrestricted translog model.

[14] Following Orea and Kumbhakar (2004) and Greene (2007), the AIC can be used to compare models with different number of classes. The appropriate model has the lowest AIC.

[15] Empirical results with more than two classes did not converge to a meaningful solution within the maximum likelihood estimation. The econometric estimation problems might be due to a high degree of within-class multicollinearity.

[16] Controlling for time variation, including a linear time trend and/or time dummies in different model specifications did not reveal significant trending behavior.

knowledge production equals 16.7 per cent in class A and 11.0 per cent in class B. The larger share of publications is consistent with the primary data, where the number of publications is generally higher than the number of patent applications. Estimation results show that the marginal rate of transformation of patents and publications generated relative to the output mix differs slightly in both classes, indicating the presence of two underlying technologies with a slightly higher patenting activity in class A.

With regard to the input side, the estimated elasticities (R&D expenditures and number of researcher) differ significantly in both classes. In class A, the larger elasticity with respect to R&D expenditures (β_{2A} = -0.609) reflects its increasing share relative to the other input: the number of researchers (β_{1A} = -0.201) in the knowledge production function. On the contrary, in class B the elasticities of the two input variables are relatively similar (β_{1B} = -0.428 and β_{2B} = -0.448), reflecting their equal shares in the knowledge production distance function. Comparing the two classes we therefore label class A as 'capital-intensive' as the corresponding elasticities of R&D expenditures is three times larger than the elasticity of labor input. We respectively label class B as 'labor-intensive', given its equal input shares in the distance function.

The second-order elasticities reflect complementary/substitution effects of the inputs or the outputs in the overall production (Ogundari and Brümmer, 2010; Grosskopf et al., 2004). Negative input elasticities β_{kj} reflect substitution effects between respective inputs (x_1, x_2) to the production of output (y_1). Accordingly, positive input elasticities indicate complementary effects of inputs. Class A shows significant evidence for input substitution effects between R&D expenditures and the number of researchers. For constant patent and publication output, resources can either be used to hire researchers or devoted to R&D labs, equipment, materials or personnel. On the contrary, for class B we neither find a significant substitution nor complementarity effect between both inputs.

Empirical evidence suggests that overall parameter heterogeneity prevails in our model. The corresponding likelihood ratio test (unrestricted vs. restricted) clearly rejects with a test statistic of 256.5 the Null hypothesis of equal parameter estimates. Our results show that the two classes of countries, the 'capital-intensive' and the 'labor-intensive' one, as identified by the latent class specification are characterized by different knowledge production frontiers. Estimating a common frontier without controlling for parameter heterogeneity, as often conducted in previous empirical literature on R&D efficiency, leads to biased estimates and therefore inconsistent individual efficiency estimates and country rankings.

Variable		'Capital-intensive' Class A Coeff.	St.Error		'Labor-intensive' Class B Coeff.	St.Error
Constant		-0.506	0.036		-0.090	0.047
y2	α_{2A}	0.843	0.023	α_{2B}	0.890	0.029
x1	β_{1A}	-0.201	0.056	β_{1B}	-0.428	0.057
x2	β_{2A}	-0.609	0.048	β_{2B}	-0.448	0.050
y2y2	α_{22A}	0.095	0.010	α_{22B}	0.310	0.035
x1x1	β_{11A}	0.854	0.221	β_{11B}	-0.013	0.139
x2x2	β_{22A}	0.645	0.173	β_{22B}	-0.255	0.144
y2x1	δ_{21A}	-0.165	0.067	δ_{21B}	0.049	0.048
y2x2	δ_{22A}	0.096	0.055	δ_{22B}	0.037	0.048
x1x2	β_{12A}	-0.760	0.190	β_{12B}	0.180	0.142
T	ηA	-0.001	0.003	ηB	-0.003	0.003
Sigma	σ_A	0.300	0.021	σ_B	0.288	0.017
Lambda	λ_A	3.834	1.140	λ_B	10.342	4.405
$Constant$		-10.745	7.927		Fixed	Parameter
VC	γ_{1A}	10.093	4.348		Fixed	Parameter
BEX_{RD}	γ_{2A}	-1.085	1.039		Fixed	Parameter
$OPENESS$	γ_{3A}	-2.028	1.959		Fixed	Parameter
HTE_2	γ_{4A}	-0.773	0.724		Fixed	Parameter

Table 4: Estimation results Model 1

5.2 Class-specific efficiencies

The reliability and consistency of the classes determined is controlled for by defined switching variables. Table 4 displays coefficient estimates of latent class probability functions $\hat{\delta}$ (see Equation 11). Including switching variables tests whether they deliver useful information in classifying the sample, more specifically if they provide useful information to determine the probability of a country belonging to a certain class.

Based on the empirical literature on R&D efficiency, we test seven switching variables reflecting common systematic differences in the innovative environment. In our baseline Model 1, venture capital (VC), business expenditures on R&D per GDP (BEX_{RD}), trade per GDP ($OPENESS$) and the share of high technology exports per GDP (HTE_2) serve as switchers.[17] Table 4 shows that only venture capital has a significant impact in all specifications. We conclude that the positive sign on the coefficient of VC in class A suggests that the better the availability of venture capital, the greater the probability of a country to belong to class A. In contrast to venture capital, the share of business expenditures, trade openness and the share of high technology exports are not found to have a significant contribution to the classification of the sample. Additionally, neither national culture (NC) nor education expenditure per GDP ($EDUC$) drive class probabilities (see Table 5). The evidence on the share of

[17]The complexity of the model means that we can only test 4 switchers at the same time, due to the limited number of degrees of freedom. We therefore conducted different estimations of model variations with respect to switchers, see Table 5 and Table 6.

Variable		'Capital-intensive' Class A Coeff.	St.Error		'Labor-intensive' Class B Coeff.	St.Error
Constant		-0.506	0.036		-0.090	0.047
y2	α_{2A}	0.843	0.023	α_{2B}	0.890	0.029
x1	β_{1A}	-0.201	0.056	β_{1B}	-0.428	0.057
x2	β_{2A}	-0.609	0.048	β_{2B}	-0.448	0.050
y2y2	α_{22A}	0.095	0.010	α_{22B}	0.310	0.035
x1x1	β_{11A}	0.853	0.223	β_{11B}	-0.013	0.139
x2x2	β_{22A}	0.645	0.174	β_{22B}	-0.255	0.144
y2x1	δ_{21A}	-0.165	0.067	δ_{21B}	0.049	0.048
y2x2	δ_{22A}	0.096	0.055	δ_{22B}	0.037	0.048
x1x2	β_{12A}	-0.760	0.191	β_{12B}	0.180	0.142
T	ηA	-0.001	0.003	ηB	-0.003	0.003
Sigma	σ_A	0.300	0.021	σ_B	0.288	0.017
Lambda	λ_A	3.834	1.140	λ_B	10.342	4.405
Constant		-3.106	11.245		Fixed	Parameter
VC	γ_{1A}	11.154	5.253		Fixed	Parameter
NC	γ_{5A}	-0.728	5.476		Fixed	Parameter
HTE_1	γ_{6A}	-3.300	1.535		Fixed	Parameter
$EDUC$	γ_{7A}	-2.804	3.456		Fixed	Parameter

Table 5: Estimation results Model 2

high technology exports per manufacturing exports is mixed, while the corresponding coefficient is not found to be significant in Model 1, it becomes significant in Model 2. Results suggest that large high technology exports increase the probability of a country to belong to class B.

Referring to the 'capital'- and the 'labor-intensive' classes, we observe that the capital-intensive class encompasses many European countries such as Germany, United Kingdom, Netherlands, Spain, Italy, Greece, Finland, Sweden and Denmark. It also includes Non-European Anglo-Saxon countries like the United States, Australia, Canada and New Zealand. Eastern European countries, usually formerly socialist countries (Czech Republic and Hungary) share the labor-intensive technology, together with small Western European countries like Belgium, Portugal, Iceland, Ireland, Norway and Non-European developing countries (Argentina, China, Mexico). Japan and Korea, the only Asian Countries considered here, also belong to class B.

Empirical evidence shows that the modeling of inefficiency is appropriate for this setting, as the total variance of the composed error $\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$ results to the largest part from the inefficiency component σ_u and not from the unsystematic error term σ_v. [18].

The sample statistics for the estimated efficiencies for the whole sample and for each estimated class are illustrated in Table 7. As opposed to nonparametric DEA, in the

[18]as $\lambda = \sigma_u/\sigma_v = 3.834$ is significant and larger than one (see Table 4)

Variable		'Capital-intensive' Class A Coeff.	St.Error		'Labor-intensive' Class B Coeff.	St.Error
Constant		-0.506	0.036		-0.090	0.047
y2	α_{2A}	0.843	0.023	α_{2B}	0.890	0.029
x1	β_{1A}	-0.201	0.056	β_{1B}	-0.428	0.057
x2	β_{2A}	-0.609	0.048	β_{2B}	-0.448	0.050
y2y2	α_{22A}	0.095	0.010	α_{22B}	0.310	0.035
x1x1	β_{11A}	0.852	0.233	β_{11B}	-0.013	0.140
x2x2	β_{22A}	0.644	0.178	β_{22B}	-0.255	0.144
y2x1	δ_{21A}	-0.165	0.069	δ_{21B}	0.049	0.048
y2x2	δ_{22A}	0.096	0.056	δ_{22B}	0.037	0.048
x1x2	β_{12A}	-0.759	0.199	β_{12B}	0.180	0.142
T	ηA	-0.001	0.003	ηB	-0.003	0.003
Sigma	σ_A	0.300	0.021	σ_B	0.288	0.017
Lambda	λ_A	3.833	1.140	λ_B	10.342	4.405
Constant		7.793	8.410		Fixed	Parameter
VC	γ_{1A}	18.779	9.449		Fixed	Parameter
HTE_1	γ_{6A}	-4.616	2.347		Fixed	Parameter
$OPENESS$	γ_{3A}	-4.668	3.001		Fixed	Parameter
$EDUC$	γ_{7A}	-3.978	3.706		Fixed	Parameter

Table 6: Estimation results Model 3

parametric stochastic efficiency framework no country is fully efficient. The efficiency estimates vary between 0.382 and 0.991 with the mean R&D efficiency being relatively high: 0.853. In comparison to other nonparametric R&D efficiency studies (see e.g. Sharma and Thomas, 2008), this can be explained by the fact that in our approach deviation from the frontier are not only due to technical inefficiency, but also due to noise (random error) in the data. However, in comparison to other SFA R&D efficiency studies, our model leads to higher mean efficiencies (Fu and Yang, 2009; Wang, 2007). If there is more than one knowledge production frontier embodied in the data, the latent class model is able to capture the different technologies and disentangle heterogeneity from inefficiency. Thus, larger inefficiencies within the knowledge production process found in other empirical studies need to be interpreted with caution.

Within the latent class framework, we no longer assume a common technology and frontier for all the countries, but two different ones, thus countries of the 'capital-intensive' class A are benchmarked against the frontier of class A and countries of the 'labor-intensive' class B respectively to the frontier of class B.[19] We observe a slight difference in the performance levels of the latent classes (0.86 vs. 084).

Regarding the overall mean efficiencies over the observation period (1993-2007) in Table 8 we observe that the United Kingdom is ranked highest together with other

[19] In fact, as explained in Section 3.2 both frontiers are taken into account weighted with the relative probability. The posterior probabilities of class membership where clear for all the countries meaning near by 1 for one class and zero probability for the other class.

	Obs	Mean	Std.Dev.	Min	Max
Total	428	0.853	0.102	0.382	0.991
Class A	240	0.863	0.089	0.551	0.981
Class B	188	0.842	0.115	0.382	0.991

Table 7: Summary Statistics of efficiency Scores

Anglo-Saxon countries such as New Zealand, Australia and Canada. This result is stable over our observation period. The Netherlands obtain a high efficiency score in providing R&D research output, while Germany and the US are both ranked in the middle. Small Scandinavian countries, such as Denmark and Finland, are among the lowest ranked countries in class A. Turkey is scored last when considering the mean efficiency, but catching up over time and finally ranked in the middle range together with Australia and Spain in 2006. In class B Ireland, France, Belgium and Norway are most efficient, while Korea, Mexico and Portugal are among the less efficient countries in research and development worldwide, so little effort has been made in innovation at the technology frontier. Mexico has remained at the bottom of the rankings, illustrated by the low efficiency score in 2006, while Portugal has increased its R&D efficiency over time. It is remarkably that China, starting with a low efficiency score in 1996 undertook much effort and has increased its R&D efficiency significantly. In 2006, China was already the most efficient country in class B.

6 Summary and conclusions

This paper analyzes the R&D efficiency level of 26 OECD and 2 Non-OECD countries over the 1993-2007 period. Comparing the performances of countries, researchers and policy makers are faced with a high degree of cross-country heterogeneity regarding the national innovation systems. The heterogeneity might manifest in different industrial or financial structures, different national cultures or educational systems. Only parts of this heterogeneity is observable in the data and can be accounted for in the econometric model. What we noticed in the empirical literature on R&D efficiency is that usually one uniform homogeneous knowledge production technology is assumed for all countries with the same input and output intensities, marginal products and elasticities. However, if more than one type of production frontier is embodied in the data, unobserved factors might be interpreted as inefficiency. To avoid such types of misspecification we argue in favor of a latent class stochastic frontier model reflecting country-specific production patterns. This new modeling approach in the literature

Country	Class	1993-2006	1996	2001	2006
Argentina	B	0.880	na	0.968	0.841
Australia	A	0.909	0.910	0.930	0.880
Belgium	B	0.909	0.959	0.842	0.923
Canada	A	0.890	0.914	0.858	0.846
China	B	0.820	0.813	0.821	0.977
Czech Republic	B	0.839	na	0.827	0.905
Denmark	A	0.814	0.838	0.800	0.740
Finland	A	0.766	0.843	0.738	0.691
France	B	0.943	0.964	0.956	0.914
Germany	A	0.840	na	0.878	0.904
Greece	A	0.880	0.854	0.823	0.959
Hungary	B	0.836	0.764	0.947	0.842
Iceland	B	0.814	0.924	0.803	0.719
Ireland	B	0.947	0.967	0.960	0.954
Italy	A	0.837	0.801	0.930	0.962
Japan	B	0.838	0.832	0.818	0.850
Korea	B	0.633	na	0.651	0.803
Mexico	B	0.652	0.658	0.640	0.570
Netherlands	A	0.942	0.948	0.940	0.944
New zealand	A	0.946	0.961	0.957	0.926
Norway	B	0.897	0.928	0.919	0.925
Poland	A	0.865	0.772	0.792	0.955
Portugal	B	0.803	0.644	0.793	0.948
Spain	A	0.861	0.882	0.908	0.896
Sweden	A	0.838	0.905	0.836	0.784
Turkey	A	0.728	0.655	0.686	0.860
United Kingdom	A	0.962	0.970	0.970	0.969
United States	A	0.846	0.866	0.854	0.902

Table 8: Efficiency Changes in time

on R&D efficiency improves the empirical results (efficiency scores and rankings) because it simultaneously estimates a set of distinct production functions disentangling heterogeneity from inefficiency. Unobserved production differences are explained more appropriately by alternative production functions and not technical efficiency.

Our hypothesis of heterogeneous groups of countries is confirmed. We identify two different latent classes being prevalent in the data: a more capital-intensive one and a relatively labor-intensive one, according to the size of the estimated input elasticities in the two classes. This is reflected by the significant different marginal products (input and output elasticities) in the estimated output distance function. Differences in the obtained efficiencies in comparison to other empirical studies are caused by the underlying benchmarking approach: different frontiers for the different classes are determined. We argue, that assuming a uniform homogeneous knowledge production frontier for such different countries results in ambiguous and questionable parameter estimates and therefore biased efficiency estimates and rankings.

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