DISCUSSION PAPER SERIES

No. 8579

INDUSTRIES AT THE WORLD TECHNOLOGY FRONTIER: MEASURING R&D EFFICIENCY IN A NON-PARAMETRIC DEA FRAMEWORK

Jens Schmidt-Ehmcke and Petra Zloczysti

INDUSTRIAL ORGANIZATION

Centre for Economic Policy Research

www.cepr.org

Available online at: www.cepr.org/pubs/dps/DP8579.asp

ISSN 0265-8003

INDUSTRIES AT THE WORLD TECHNOLOGY FRONTIER: MEASURING R&D EFFICIENCY IN A NON-PARAMETRIC DEA FRAMEWORK

Jens Schmidt-Ehmcke
Petra Zloczysti

Discussion Paper No. 8579
September 2011

Centre for Economic Policy Research
77 Bastwick Street, London EC1V 3PZ, UK
Tel: (44 20) 7183 8801, Fax: (44 20) 7183 8820
Email: cepr@cepr.org, Website: www.cepr.org

This Discussion Paper is issued under the auspices of the Centre's research programme in **INDUSTRIAL ORGANIZATION**. This paper is produced as part of the project Growth and Sustainability Policies for Europe (GRASP), a Collaborative Project funded by the European Commission's Seventh Research Framework Programme, Contract number 244725. Any opinions expressed here are those of the author(s) and not those of the Centre for Economic Policy Research. Research disseminated by CEPR may include views on policy, but the Centre itself takes no institutional policy positions.

CEPR Discussion Paper No. 8579

September 2011

ABSTRACT

Industries at the World Technology Frontier: Measuring R&D Efficiency in a Non-Parametric DEA Framework

This paper identifies the leading country-industry combinations that define the world technology frontier in manufacturing. Using a unique industry dataset compiled from EU KLEMS and PATSTAT, it explores which countries and industries reveal the most efficient innovation processes. We combine a traditional nonparametric frontier approach with super-efficiency and tests for return to scale properties using bootstrap procedures to derive consistent and robust efficiency estimates. Our analysis of 17 OECD countries and 13 industries between 2000 and 2004 shows that Germany, the United States, and Denmark have the highest R&D efficiency on average in total manufacturing. However, sector-specific efficiency scores reveal substantial variation across countries. The principal industries determining the technology frontier are electrical and optical equipment, machinery, and chemical and mineral products. Our results suggest that in case of limited resources, priority should be given to the industries that promise the largest output for the available amount of investment. Instead of generally increasing the R&D-to-GDP ratio--as suggested in the Lisbon Agenda--policymakers might target future R&D efforts to those industries that are economically important and reveal excellent performance.

JEL Classification: C14, L60, O31 and O57
Keywords: data envelopment analysis, manufacturing, patents, R&D efficiency and technology frontier

Jens Schmidt-Ehmcke

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=171191

Petra Zloczysti

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=171193

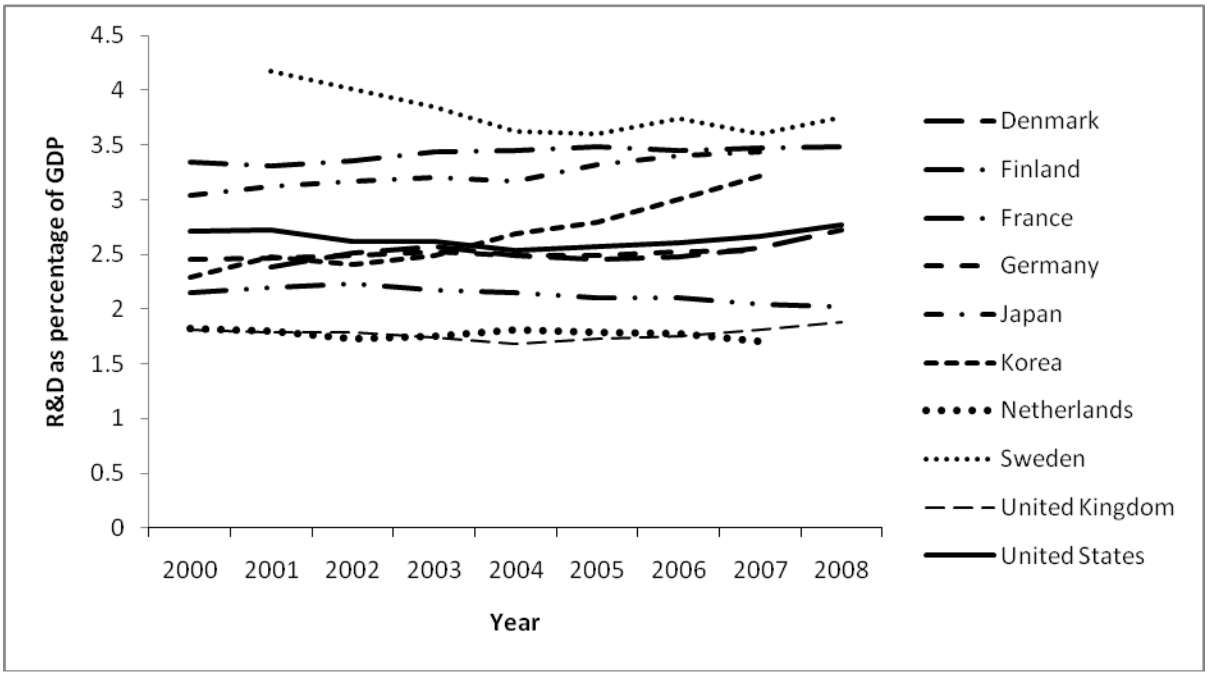
*This paper is produced as part of the project Growth and Sustainability Policies for Europe (GRASP), a Collaborative Project funded by the European Commission's Seventh Research Framework Programme, Contract number 244725. The research was conducted while the authors were in residence at DIW Berlin.

Submitted 5 September 2011

1 Introduction

The Lisbon Agenda for competitiveness included two targets for research and development (R&D): 1) R&D expenditures relative to gross domestic product (GDP) were expected to increase to 3% by 2010; and 2) the business sector would be responsible for about two-thirds of the expenditures. Despite the R&D target for 2010, only Finland, Sweden, Japan and South Korea achieved R&D above 3% (Figure 1); the worst performers were Italy, Spain and Poland. In 2008 Sweden had ranked first at 3.7%. Our analysis of 17 OECD countries raises questions about benchmarking all countries against the Lisbon Agenda's single common target. For instance, could another type of performance measure and assessment of R&D target a country's limited financial resources to achieve the highest possible levels of innovation?

Figure 1
R&D as a percentage of GDP



Notes: Total R&D (business and public) as percentage GDP.

Source: OECD Main Science and Technology Indicators.

Our goals are to identify the best-performing countries and industries for benchmarking and to gain insights about the strengths and weaknesses of innovation strategies that improve R&D efficiency. Although the extant literature generally focuses only on the country level, we suggest that the industry level is more useful. In fact, neglecting the importance of industrial specialization can skew performance rankings (van Pottelsberghe de la Potterie 2008). A country like Finland, which has specialized in information and communication technologies, will reveal a relatively high R&D intensity since this particular industry requires high R&D expenditures. On the contrary, specialization in low R&D industries like food, wood or paper will inevitably generate a low R&D to GDP ratio at the country level. Consequently, R&D efficiency will be affected as a rise in inputs necessitates growth in output to become or remain efficient. In other words, benchmarking at the industry level allows a finer-grained examination of countries' domains of specialization relative to the industries that occupy the technology frontier. In addition, a thorough analysis of R&D efficiency provides the opportunity to critically evaluate the creation of a European Research Area by increasing investment in R&D activities to 3% of GDP, since both the size and the efficient use of invested resources matter when planning future investment.

Furthermore, we suggest that countries with less-efficient industries could employ our findings to improve their own processes and performance. For example, the obtained efficiency scores could be used as an alternative measure for determining a country's distance to frontier in empirical applications. Until recently, research has focused on differences in labor productivity to capture frontier distance where the United States usually serves as the benchmark, implying that it marks the frontier (Acemoglu et al. 2006; Aghion et al. 2009). The advantage of efficiency scores is that they help us endogenously define the frontier without assuming a specific production function, lead country or industry.

In short, this paper identifies the country-industry combinations that define the world technology frontier in the manufacturing sector. It explores which countries reveal the most efficient industry-specific innovation processes. First, we derive efficiency estimates for the entire manufacturing sector at the country level. Second, we proceed to the industry level and identify those county-industry combinations that define the world technology frontier. Third, we focus on selected industries — those mainly defining the technology frontier — and conduct separate efficiency analyses to account for industry-specific production technologies.

We build on the empirical literature concerning the importance of level and dynamics of R&D expenditures for economic growth (Guellec and van Pottelsberghe de la Potterie 2001) which shows that countries utilizing their R&D resources inefficiently will be penalized with a growth discount. Based on the theoretical concept of an ideas/knowledge production function framework stemming from the endogenous growth literature, our efficiency assessment relies on the existing literature applying a knowledge/patent production function framework (e.g. Hall and Ziedonis 2001) and adapts it to evaluate the efficiency of the ideas generation process over countries and industries.

We assemble a unique industry dataset compiled from EU KLEMS[3] and PATSTAT[4]. We match European patent applications to the EU KLEMS industry-level data by using the concordance developed by Schmoch et al. (2003). We conduct our analysis using nonparametric efficiency measurement methods and identify the differences in the efficiencies on the country and industry levels using a traditional nonparametric frontier approach, i.e. data envelopment analysis (DEA). This method requires no specification of the

[3] A detailed description of the dataset is provided in Timmer et al. (2007, 2008).
[4] European Patent Office Worldwide Statistical Database: PATSTAT version 1/2008.

functional form of the ideas generation process, or any a priori information concerning the importance of inputs and outputs. Since DEA is a deterministic approach, extreme observations can have a strong influence on the calculated efficiencies. We circumvent this problem by using the super-efficiency approach of Banker and Chang (2006) to detect and then remove extreme observations from the sample to achieve a consistent and robust technology frontier. The unique dataset allows us to compare industries of varying economic size in our model. Since it is both statistically and economically important to determine whether the underlying technology exhibits increasing, constant, or decreasing returns to scale, we test the hypotheses of constant returns to scale using the bootstrap procedure proposed by Simar and Wilson (2002).

Our paper is organized as follows: Section 2 introduces the analytical framework and briefly summarizes the literature in this field. In Section 3, the methodology of DEA is introduced. Section 4 describes the model specification and data. The empirical results for total manufacturing and by industry are presented in Section 5. Section 6 summarizes the findings and concludes.

2 Measurement of R&D Efficiency

A knowledge production function is central to many endogenous economic growth models in which innovation plays a crucial role in sustaining long-term growth. Innovation becomes even more important to productivity growth when a particular national industry approaches the world technology frontier, because at that point, imitation, as opposed to true innovation, is less feasible. The resources available for the generation of new knowledge are often limited and thus must be used as efficiently as possible to sustain and promote long-term growth. We particularly focus on the economic process generating new knowledge which becomes manifest in inventions that can lead to cost reductions in the form of process innovations or to the development of new products or technologies. More specifically, we analyze whether there are substantial performance differences in ideas creation between countries and industries.

Our model follows the knowledge production function framework first articulated by Griliches (1979) and implemented by Pakes and Griliches (1984), Jaffe (1986) and Hall and Ziedonis (2001), among others. 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 expenditure, existing knowledge and high-skilled labor, are invested in knowledge production. These "inputs" are directed toward producing economically valuable ideas. The production process is viewed as leading from R&D and human capital (the inputs) to some observable output measure of innovative activity:

$$I_{ci} = f\left(R\&D_{ci}, HS_{ci}\right),$$

where I_{ci} is innovative output, $R\&D_{ci}$ denotes the R&D capital stock as a proxy for efforts and accumulated knowledge, and HS_{ci} captures human capital. The unit of observation is the country *(c)* industry *(i)* level. Innovative output is approximated by patent applications.[5]

Based on the knowledge production function framework, the empirical literature confirms the importance of R&D capital to the knowledge creation process (e.g. Mairesse and Mohnen 2004), for an overview see Hall and Mairesse 2006); however, far less attention has been paid to the importance of the efficient use of scare resources in this process.

Rousseau and Rousseau (1997) were the first to use a DEA approach. Using a sample of 18 developed countries, they applied an input-oriented, constant returns to scale model with two outputs — the number of scientific publications and the number of granted patents — and used GDP, along with population and R&D investment, as input factors. They concluded that in 1993, Switzerland was the most efficient country in Europe, followed closely by the Netherlands. Using the same framework, Rousseau and Rousseau (1998) extended their work by including the non-European countries, specifically the United States, Canada, Australia, and Japan. The authors reaffirmed that Switzerland, followed by the Netherlands, had the highest R&D efficiency.

Lee and Park (2005) measured R&D efficiency in 27 countries with a special emphasis on Asia. They expanded Rousseau and Rousseau's basic framework by using the technology balance of receipts as an additional output of the innovation process. In their basic model, Austria, Finland, Germany, Hungary, and Great Britain were found to occupy the technology frontier.

Wang and Huang (2007) proposed a three-stage approach to evaluating the relative technical efficiency of R&D across 30 OECD member and nonmember countries that controlled for cross-country variation in external factors, such as the enrollment rate in tertiary education, PC density, and English proficiency. A first stage applied an input-oriented DEA analysis with variable returns to scale where patents and publications served as outputs and R&D expenditure and researchers as inputs. They found that about half the countries in their sample were efficient in R&D activity. A second stage investigated the influence of external effects caused by environmental factors outside the efficiency evaluation. Using the results, they conducted an additional DEA which indicated a decrease in the number of efficient countries due to the external factors.

---

[5] Some authors (e.g. Rousseau and Rousseau 1997, 1998) suggest including publications as an additional output; we do not, for three reasons: 1) recent studies reveal a number of measurement problems inherent in publication counts, such as double-counting in the case of co-authoring (Sharma and Thomas 2008); 2) since detailed publication data are not available at the industry level, assigning publications to industries is problematic and would involve the difficult and probably not entirely objective task of matching journals to sectors; 3) publication counts have the potential to introduce a language bias in favor of English-speaking countries.

Recently, Sharma and Thomas (2008) measured the efficiency of the R&D process across 18 countries using a DEA approach that applied both constant and variable returns to scale production technologies. Their approach deviated from previous work in two ways: they considered a time lag between R&D expenditure and patents, and they included developing countries in their analysis. Their main findings indicated that when using the constant returns to scale approach, Japan, South Korea, and China occupied the efficiency frontier, whereas within the variable returns to scale framework, Japan, South Korea, China, India, Slovenia, and Hungary were efficient.

Cullmann et al. (2011) updated the measurement of R&D efficiency in the OECD using a DEA approach with variable returns to scale, including outlier detection by means of super-efficiency analysis. Efficiency scores were calculated using intertemporal frontier estimation for the period 1995 to 2004. They found that Sweden, Germany and the United States were located on or close to the technology frontier. The authors further analyzed the impact of the regulatory environment using a bootstrap procedure recently suggested by Simar and Wilson (2007a). The results showed that barriers to entry, aimed at reducing competition, actually reduced R&D efficiency by attenuating the incentive to innovate and to allocate resources efficiently.

This paper makes three important contributions. While previous studies focus on the aggregate country level, our point of departure is the manufacturing sector, which we then separate by industry in order to identify those having highly efficient research processes. In addition, we allow for industry-specific frontiers to investigate whether the countries defining the frontier at the country level also show excellent performance in selected industries. Methodologically, we test for the form of returns to scale by means of bootstrap (Simar and Wilson 2002) and include outlier detection (Banker and Chang 2006).

3 Methodology

As mentioned above, we employ DEA, a nonparametric approach[6] that measures the efficiency of a decision-making unit (DMU). This approach requires no assumption about the functional form of a production function or any a priori information on the importance of inputs and outputs. Central to DEA is the production frontier, defined as the geometrical locus of optimal production plans (Simar and Wilson 2007b). Using linear programming techniques, we construct a piecewise linear surface, or frontier, that envelops the data as a reference point. The individual efficiencies of each DMU relative to the production frontier are then calculated by means of distance functions. The distance to the frontier is thus a measure of inefficiency. There are basically two types of DEA models: those that maximize outputs, leaving the input vector fixed (output-oriented), and those that minimize inputs, keeping the output vector constant (input-oriented). We use the output-oriented approach, because when resources devoted to R&D are usually scarce, it is reasonable to assume that countries will seek to maximize their innovative output to foster long-term growth.

Different assumptions can be made regarding the underlying technology that defines the frontier. In this paper, we distinguish between the two types of technology, constant returns to scale (CRS, Charnes et al. 1978), and variable returns to scale (VRS, Banker et al. 1984). CRS assumes that all DMUs produce at their optimal scale, and VRS accounts for existing scale inefficiencies. Using the CRS specification when VRS is appropriate leads to technical efficiency scores being confounded by scale efficiencies. Hence, if we assume, a priori, a CRS technology without investigating the possibility that it is non-constant, we run the risk that our efficiency estimates will be inconsistent. On the other hand, if we assume VRS when, in fact, the technology exhibits global constant returns to scale, there may be a loss of statistical efficiency (Simar and Wilson 2002). Formally, the only difference between the CRS and the VRS specifications is the presence of an additional convexity constraint $\sum \lambda = 1$.

Formally, the efficiency score of the *i-th* industry in a sample of *N* industries and *K* countries in the VRS model is determined by the following optimization problem (Coelli et al. 2005):

$$
\begin{aligned}
&\max_{j,\lambda} \phi \\
&\quad \text{s.t.} \qquad\qquad , \\
&\quad -\phi y_i + Y\lambda \geq 0 \\
&\quad x_i - X\lambda \geq 0 \\
&\quad I1'\lambda = 1 \\
&\quad \lambda \geq 0
\end{aligned}
$$

where $\boldsymbol{\lambda}$ is an $(N \times K) \times 1$ vector of constants and **X** and **Y** represent input and output vectors respectively. $\boldsymbol{\lambda}$ further reflects the respective weights for inputs and outputs assigned to each firm. ϕ measures the radial distance between the observation (x_i, y_i) and the efficiency frontier, hence $1 \leq \phi \leq \infty$ (Farell-type efficiency scores, Farell 1957). In the empirical application, we give efficiency scores defined by $TE = \theta = \frac{1}{\phi}$ which vary between 0 and 1. A value of 1 indicates that an industry is fully efficient and thus located on the efficiency frontier, whereas DMUs with efficiency scores below 1 are assumed to be inefficient.

Simar and Wilson (2002) have proposed a bootstrap procedure to overcome the problem of DEA techniques being deterministic.[7] Thus, we apply their method and test the null hypothesis (H_0) of a global CRS production frontier against the alternative hypothesis (H_1) that the production frontier exhibits VRS.

---

[6] Another common nonparametric envelopment approach is free disposal hull (FDH, Desprins et al. 1984). In contrast to DEA, FDH relaxes the assumption of a convex production set and only presumes free disposability.
[7] Statistical inference is drawn based on the bootstrap methodology for estimating confidence intervals for efficiency scores (Simar and Wilson 1998).

Then, the test statistic is the estimated ratio between the usual CRS and the VRS efficiency scores

$$\hat{\omega} = \frac{\hat{\theta}^{\text{CRS}}_{\text{N}\times\text{K}}\left(\mathbf{x},\mathbf{y}\right)}{\hat{\theta}^{\text{VRS}}_{\text{N}\times\text{K}}\left(\mathbf{x},\mathbf{y}\right)}.$$

Next, we project the observations $\left(x_i, y_i\right)$ onto the respective frontiers and the distance between the two estimates forms the test statistic. The distribution of the test statistic $\hat{\omega}$ under H_0 is unknown and therefore bootstrapping — as suggested by Efron (1957) — is applied to generate pseudo samples. This procedure provides us with an empirical distribution of $\left(\hat{\omega}_{\text{b}}^{*} - \hat{\omega}\right)$ which we use to determine the corresponding p-values.[8]

Note that our DEA estimator is a deterministic frontier approach, assuming that all observations are technically attainable.[9] The main drawback of such models is their high sensitivity to outliers and extreme values in the data (Simar and Wilson 2000, 2007b). Outliers are the extreme observations that are often caused by errors in measuring inputs or outputs. It is therefore important to assess ex ante whether the data contain outliers that drive the location of the efficiency boundary, inappropriately influencing the performance estimations of the other DMUs in the sample. We use the super-efficiency method proposed by Andersen and Petersen (1993) and Banker and Chang (2006) to identify and remove extreme values ex ante. The concept is based on the idea of re-estimating the production frontier with different sets of observations from the sample. At every step, one of the efficient DMUs is excluded from the reference set to make it possible to obtain efficiency scores that exceed 1. If an efficient observation is an outlier, it is more likely to have an output level greater than other observations with similar input levels; such outliers are more likely to have a super-efficiency score greater than 1. Banker and Chang (2006) suggest that DMUs with efficiency scores larger than 1.2 should be considered outliers and removed from the sample before conducting the final DEA calculation.

4 Model Specification and Data

We assemble a sample of 13 EU-countries[10] and Australia (AU), Japan (JP), South Korea (KR), and the United States (US) during 2000 and 2004.[11] Our unique dataset on input and output for the efficiency

---

[8] The empirical distribution resembles the unknown distribution of $\left(\hat{\omega}_{b}^{*} - \hat{\omega}\right)$.

[9] We are aware that applied linear programming might not reveal all efficiency slacks. However, we follow Coelli et al. (2005) who claim that "the importance of slacks can be overstated" when accepting the argument of Ferrier and Lovell (1990) that slacks may essentially be viewed as allocative inefficiencies and that an analysis of technical efficiency can therefore reasonably concentrate on the radial efficiency scores.

[10] Belgium (BE), Czech Republic (CZ), Denmark (DK), Finland (FI), France (FR), Germany (DE), Ireland (IE), Italy (IT), Netherlands (NL), Poland (PL), Spain (ES), Sweden (SE), United Kingdom (GB).

[11]The truncation point is determined by the availability of patent applications, which are published 18 months after application. We further impose one restriction on the industry-specific country patent aggregates, namely, that at least 15 patents are applied for within a certain year, to ensure that sufficient

analysis derives from EU KLEMS and PATSTAT and covers 13 industries.

We estimate a cross-industry cross-country pooled frontier, where each observation is a single industry-country combination in time without considering the panel structure of the data. We are aware that a pooled intertemporal frontier is unable to capture technological change and dynamic efficiency changes. However, we believe it is reasonable to assume that the process of knowledge generation is not subject to short-term technology changes. Process improvements — as caused by environmental factors like deregulation or education — will lead to improvements only in the medium term.[12] Another reason for assuming a constant intertemporal frontier is the limited sample size at the industry level. In the empirical application, we provide efficiency estimates for selected industries to relax the assumption of a common frontier encompassing all industries. At this level, we are confronted with only 17 observations per year, and as Simar and Wilson (2007b) recently showed via Monte Carlo simulations, this would bias our results due to the curse of dimensionality problem. We therefore decide against estimating yearly frontiers and presume the knowledge production technology to be constant during 2000 and 2004.

R&D investment and manpower serve as inputs and patent applications approximate innovative output. Our information on patent applications is taken from the European Patent Office's database, because an application to an international authority, in contrast to one made to a national authority, can be viewed as a signal that the patentee believes the invention to be valuable enough to justify the expense associated with an international application. Central to our exercise is constructing patent aggregates by country, industry, and year, and we build the variable using all patent applications filed with the EPO with a priority date between 2000 and 2004. We assign the patent applications to the inventor's country, because it is more indicative of the invention's location. In line with the prior literature, we consider only the first inventor's country of residence (e.g. Wang 2007; WIPO 2008).

Patents are assigned to industries based on the concordance developed by Schmoch et al. (2003), who used expert assessments and micro-data evidence on the patent activity of firms in the manufacturing industry to link technologies to industry sectors.[13] The international patent classification (IPC) classes provided in the patent applications are grouped into 44 technological fields and then assigned to industries based on the NACE[14] code. Because patent applications usually contain more than one technology class and none can be interpreted as its main class, a weighting scheme is needed to avoid double-counting patents. Thus, we weight every class mentioned in an application by the reciprocal of the total number of classes.

patent activity is present in each sector of the countries covered. A relaxation of this restriction to 5 produced largely the same results, but introduced more noise in the estimation of averages.

[12] We also experimented with 3-year samples and found comparable results. However, this forced us to further reduce our sample coverage.

[13] The authors argue that patents are most widely used in the manufacturing sector to protect intellectual property.

[14] Nomenclature générale des activités économiques dans les Communautés européennes.

However, further aggregation of NACE classes is needed to match the patent data to the input data sources.[15] Human capital and R&D effort serve as the inputs in our model. R&D stocks provided by the EU KLEMS database approximate the R&D resources used in the innovative process at the sector level. From a theoretical point of view, R&D stocks are preferable to annual R&D expenditures, because they capture the amount of knowledge available in an economy although, in practice, assumptions must be made when calculating the initial stock. We build the R&D stocks in the EU KLEMS database according to the perpetual inventory method.[16]

Manpower invested in R&D is usually captured by the number of researchers per country published by the OECD in the Main Science and Technology Indicators (OECD 2008b). However, these data are not available at the sector level and so we approximate human capital input by the share of skilled workers, since it is plausible that researchers and support staff are mainly recruited from this group. The exact distinction between high-skilled and medium-skilled workers is somewhat vague due to differences in national educational systems (Timmer et al. 2007). In the case of high-skilled labor, we assume comparability only for bachelor degrees. Therefore, we include both high- and medium-skilled labor as inputs to control for heterogeneity across countries' educational systems, and our findings suggest that the main results are robust with respect to the use of skilled or only high-skilled labor. Data on high- and medium-skilled labor at the sector level are available from the EU KLEMS database.

Table 1

Summary statistics: (2000–2004)

Variable	**Description**	**Mean**	**S.D.**	**Min**	**Max**
	Output Variable				
Patents	Patent applications at the EPO, unit of observation: country-industry	885.71		16	17664
	Input Variables				
R&D	Stock of R&D expenditures, expenditures are deflated using PPPs of 2000, unit of observation: country-industry	12479.4	40855.95	1.13	370589.2
High-skilled	Number of high-skilled workers, country-level data	107.4	232.21	0.11	2008.9
Medium-skilled	Number of medium-skilled workers, country-level data	428.76	583.66	0.74	3355.31

[15] A detailed description of the concordance appears in Appendix A.1.

[16] The depreciation rate equals 12%. The calculation of R&D stocks is explained in detail in O'Mahony et al. 2008. Stocks are deflated using implicit PPPs at constant 2000 prices taken from the OECD (OECD 2008b).

Table 1 consolidates the sample statistics of the input and output variables in our analysis. On average, across countries, industries, and years, 886 patents have been applied for at the EPO, although there is much heterogeneity within this average, ranging from a minimum of 16 patents to a maximum of 17664. A similar pattern is observed in the R&D stocks. In line with expectations, the share of high-skilled workers is substantially smaller (one-quarter) than the share of medium-skilled workers.

The aggregated manufacturing-level data (Appendix Table A.2) show that the United States has the highest average number of patent applications at the EPO which is of interest considering the "home" bias of the European countries in our sample. Japan is third in patenting activity. In Europe, Germany is the most frequent patent applicant with an average R&D stock almost twice that of France. A remarkably low amount of patents originates from Spain, even though the average Spanish R&D stock is substantially higher than Finland, Denmark and Australia. There is considerable variation of high-skilled and medium-skilled workers across countries, e.g. the number of high-skilled workers in South Korea is more than four times that of Germany.

We calculate the industry-specific means of our input-output variables by averaging over years (Appendix Table A.3). The industries in our sample exhibiting the highest patent intensity are chemicals and chemical products, electrical and optical equipment, and machinery. Fewer inventions are patented in the wood and coke and petroleum sectors. Comparing these observations to the average R&D stocks reveals that the patenting-intensive industries are also R&D-intensive with the exception of the transport equipment sector which exhibits huge R&D stocks, but a relatively low patent-to-R&D ratio. Consistent with recent literature on R&D efficiency (e.g. Sharma and Thomas 2008; Wang and Huang 2007), we impose a two-lag structure for inputs to account for the fact that R&D efforts do not immediately result in innovative output (Hall et al. 1986).

5 Results

There are three steps in our empirical analysis:

1. Derive efficiency estimates for the manufacturing sector at the country level to deliver a first research performance assessment which can be compared to previous studies in this field.
2. Identify the efficient industries with respect to R&D efforts by proceeding to industry- and country-specific data, thereby accounting for patterns of industrial specialization and "allowing" countries to occupy the frontier only in certain industries.
3. Conduct separate efficiency analyses of the industries that define the frontier in step 2.

5.1 Cross-country comparison

A first impression of R&D efficiency in manufacturing results from comparing the average efficiencies at the country level. We derive the averages by aggregating over sector-level data and then conducting a variable returns to scale[17] DEA analysis using these country-level aggregates. We implicitly assume a time-invariant technology frontier and focus on the distance of countries from the estimated frontier.[18] Table 2 displays averages of the corresponding values for the period from 2000 to 2004. It shows that Germany, Denmark, the United States, the Netherlands, and Belgium are the most efficient with respect to innovative output in manufacturing. The high average efficiency of the United States, indicative of its strong position in the international context, is especially noteworthy due to our use of European patent data to approximate innovative output.[19]

Table 2

Average R&D efficiency in total manufacturing

Country	**R&D efficiency score**
Germany	0.975
Denmark	0.974
United States of America	0.930
Netherland	0.910
Belgium	0.892
Ireland	0.891
Finland	0.865
Italy	0.744
Sweden	0.668
Japan	0.618
Australia	0.534
France	0.521
South Korea	0.426
United Kingdom	0.422
Spain	0.381
Poland	0.378
Czech Republic	0.153

Notes: Output-oriented DEA with variable returns to scale.

Our results for total manufacturing can be summarized by grouping the sample countries according to their average R&D efficiency in manufacturing:

[17] As shown by Sharma and Thomas (2008), most countries reveal increasing returns to scale, hence, a constant returns to scale technology is inappropriate.

[18] An alternative method would be to compare the technology frontiers of different years by means of Malmquist indices (Coelli et al. 2005). This approach is impossible in the case of unbalanced panels and therefore not applicable to our dataset since we do not observe sufficient patenting activity across all years, countries, and sectors.

[19] The use of European patent data will tend to underestimate the output and thus the performance of non-European countries such as the United States, Japan, Australia, and South Korea. Inventors in these countries tend to first seek patent protection in their home markets and expand protection globally only for valuable inventions.

- *high efficiency*: Germany, Denmark, the United States, the Netherlands, Belgium, Ireland, Finland
- *medium efficiency*: Italy, Sweden, Japan, Australia, France
- *low efficiency*: South Korea, the United Kingdom, Spain, Poland, the Czech Republic.

Regarding the Lisbon Agenda, we observe that countries already reaching the 3% threshold — Finland, Sweden, South Korea and Japan — do not belong to the group revealing high efficiency with the exception of Finland. However, the United States and Denmark with R&D intensities of about 2.7% show excellent research performance in manufacturing. These findings suggest that high R&D intensities do not automatically imply high efficiency scores, since intensities they are mainly driven by a country's industrial structure. To undertake a thorough performance assessment we must compare individual positions of countries across industries at the industry level. Nevertheless, our results at this stage indicate that Finland, Denmark and the United States generally outperform at relatively high R&D- to-GDP ratios.

The small European economies, i.e. Denmark, Belgium, the Netherlands, Ireland, and Finland, show a significantly high level of R&D efficiency, whereas the United Kingdom, France, and Spain, lag behind. A possible explanation is that it is easier for smaller countries to link research conducted at universities to private business R&D activities due to the smaller number of large companies. We suggest that increasing R&D in such countries is an avenue for fostering innovation and growth.

Some of our findings should be treated with caution, e.g. the efficiency values for South Korea and Poland, because of the unavailability of data. Additionally, our patent data only extend to 2004. Since patenting is usually a result of R&D efforts, our efficiency assessment may simply be too "early" for South Korea, since very recent data show a drastic increase in Korean patent activity locally and at the international level (OECD 2008a). Poland has the lowest R&D intensity in our sample, an indication that it has not yet caught up. Another country with a low innovative capacity is the Czech Republic, which is only now entering the international patenting arena. The country has increased its R&D efforts to about 1.5% of GDP, making it an interesting candidate — as South Korea — for performance assessment in future studies when the data on innovative output for 2005 to 2009 become available to researchers.

Comparing our results to Cullmann et al. (2011) reveals considerable overlap: they also found that Germany, the United States, the Netherlands and Finland belong to the best-performing countries, while the Czech Republic and Poland lag behind. Overall, their R&D efficiency ranking confirms our findings.

5.2 Accounting for Industrial Specialization

The next step is to measure R&D efficiency across countries and industries by conducting DEA using a pooled sample of industry-country observations.[20] We identify industries that define the frontier and account for industrial specialization patterns of countries by considering sectors separately. As this is the first attempt to measure R&D efficiency at the industry level, we need to test whether the underlying technology exhibits constant or variable returns to scale, because previous evidence is not available. A p-value of 7.7 percent for the Simar and Wilson (2002) test statistic suggests rejecting the hypothesis of constant returns to scale. Hence, we allow for variable returns to scale in frontier estimation. The assumption of a constant technology frontier enveloping all industries will be relaxed in the next section when we conduct specific efficiency analyses for selected industries. To ensure the estimation of a consistent and robust technology frontier across countries and industries, we apply ex ante outlier detection by means of super-efficiency analysis (Banker and Chang 2006). Table 3 compares the average scores across industries. We observe that the estimation exhibits average technical efficiencies of between 0.11 and 0.64, which are relatively low compared to other empirical work. The low mean efficiencies are caused by the large within-sample variation in R&D efficiency across countries, which may also result from the different specialization profiles of countries. On average, the electrical and optical equipment sector obtains the highest efficiency scores followed by machinery, and chemicals and chemical products. Weak R&D performance appears in food and beverages, pulp and paper, and transport equipment.

Table 3

Average R&D efficiency at the industry level (2000-2004)

Industry description	**R&D efficiency score**
Food products, beverages, and tobacco	0.114
Textiles, textile products, leather, and footwear	0.232
Wood, products of wood and cork	0.250
Pulp, paper, paper products, printing, and publishing	0.175
Coke, refined petroleum products, and nuclear fuel	0.219
Chemicals and chemical products	0.531
Rubber and plastics products	0.542
Other nonmetallic mineral products	0.505
Basic metals and fabricated metal products	0.299
Machinery	0.591
Electrical and optical equipment	0.638
Transport equipment	0.216
Manufacturing NEC, recycling	0.454

Notes: Output-oriented DEA with variable returns to scale. Averages are calculated across countries and years.

[20] Poland and the Czech Republic are omitted due to insufficient data at the sector level.

The huge variation in average efficiencies emphasizes the need to conduct R&D performance assessments at the industry level. Otherwise, as mentioned earlier, efficiency rankings will be skewed since a country specializing in machinery will most likely appear to outperform a country specializing in the food sector at the aggregate level, but not necessarily in the respective industry.

Chemicals, pharmaceuticals, information and communication technology and machinery are among the most patent-intensive industries (Sheehan et al. 2004), a phenomenon possibly resulting from the different strategic motives for patenting in these industries (Noel and Schankerman 2006; Schneider 2008). We could argue that it is not surprising to find a higher average R&D efficiency in electrical and optical equipment, chemicals (including pharmaceuticals), plastics products, and machinery simply because these industries tend to seek patent protection more frequently. However, these industries also exhibit greater R&D intensities and thereby larger R&D stocks compared to others, as shown in our descriptive statistics in Section 4. Our results therefore suggest that the observable ideas generation process is simply more efficient in these industries and thus drives the technology frontier.

To gain further insights about the relationship of R&D performance assessment and industrial specialization, we are interested in the efficient country-industry combinations that suggest excellent research performance (Table 4). The electrical and optical equipment industry is efficient in the Netherlands, Germany, the United States, and Finland. Due to the underlying panel structure of our data, we usually observe industries in countries for five consecutive years. However, a certain country-industry combination does not necessarily have to be efficient every year to stay at the technology frontier, and that is exactly what we observe: country-industry combinations occupy the frontier for one or two years and lag slightly behind for the rest of the estimation period. An example is the German electrical and optical equipment industry, which is fully efficient only once but reaches an average efficiency of 0.93. This is the second-highest value in the cross-country comparison; only the United States outperforms Germany, with an average of 0.96 in the electrical and optical equipment industry. Hence, the high R&D efficiency in this industry is one of the driving forces behind the high overall U.S. efficiency score.

Other industries at the technology frontier include machinery, rubber and plastics, and mineral and chemical[21] products. Germany's chemical industry reaches the frontier in three out of five years. Germany also has large average efficiency scores of 0.93 and 0.89 for machinery and rubber and plastics, respectively. Our results further confirm that the small European countries, Finland, the Netherlands and Denmark, are some of the best-performing countries in terms of R&D efficiency, with special strength in specific industries. For example, Finland shows an excellent performance in rubber and plastics, mineral products and electrical and optical equipment, while Denmark plays a leading role in transport equipment. The Netherlands actually reaches the frontier in four industries: coke, rubber and plastics products, machinery, and electrical and optical equipment. Overall, we find electrical and optical equipment to be the most important industry when determining the technology frontier, followed by machinery, and mineral products.

Table 4

R&D-efficient country-industry combinations (2000-2004)

Industry description	**R&D-efficient countries**
Food products, beverages, and tobacco	-
Textiles, textile products, leather, and footwear	-
Wood, products of wood and cork	Italy (1)
Pulp, paper, paper products, printing, and publishing	-
Coke, refined petroleum products, and nuclear fuel	Netherlands (1)
Chemicals and chemical products	Germany (3)
Rubber and plastics products	Finland (1), Netherlands (1)
Other nonmetallic mineral products	Denmark (3), Finland (2), Italy (1)
Basic metals and fabricated metal products	-
Machinery	Italy (3), Germany (1), Netherlands (1)
Electrical and optical equipment	Netherlands (2), Denmark, Finland, Germany, United States
Transport equipment	Denmark (1)
Manufacturing NEC, recycling	Germany, Italy, Sweden

Notes: The number in parenthesis is the number of years a country has been on the technology frontier in the particular industry.

Compared to the R&D efficiency analysis in total manufacturing, we observe countries occupying the frontier in certain industries that do not belong to the generally highly efficient group. An example is Italy, which reaches the frontier mainly in machinery but also in mineral products and wood. Wood is known to be a low R&D intensity industry, which weakens the Italian position in terms of the Lisbon Agenda's target, even though this specific industry seems to have a relatively good research performance. This finding indicates that it might be useful to amend the evaluation of the Lisbon R&D goal with some type of performance assessment. Naturally, the economic relevance of the corresponding sectors must also be considered.

In summary, the return to R&D in terms of innovation growth could be enhanced by strategically increasing R&D investment in those industries in which a country exhibits excellent performance. The performance assessment should be conducted within the industry, relative to other countries, since R&D intensity and patenting activity vary substantially across industries. Note that excellent R&D performance

[21] Chemical products encompass the pharmaceutical industry, where patent protection has very strong effects because the process of research and development is so costly and time-consuming that firms need to ensure protection of their intellectual property via a temporary monopoly (Cohen et al. 2000).

according to our definition by no means necessitates high R&D intensities, but provides references for future public investment strategies.

5.3 Results for Selected Industries

Recognizing that our assumption of a commonly technology frontier across industries can be challenged, we now relax the assumption and conduct separate industry-specific frontier estimations to identify leading countries, as well as those lagging behind, for our selected industries: electrical and optical equipment, machinery, and chemical products.

Table 5 presents each industry's share of a country's gross output in total manufacturing. On average, these industries account for 32% of gross output. The distribution across countries provides insights about the respective specialization patterns. Again using Italy as an example, we observe a share of 12.3% of machinery in 2004, which is the second-highest in our sample. Recall that we also find Italy to be highly efficient in this respective sector, even though it ranges only in the midfield in total manufacturing R&D efficiency.

Table 5

Share in gross output of total manufacturing (in %) in 2004

Country	**Chemicals and chemical products**	**Machinery**	**Electrical and optical equipment**	**Σ**
Australia	7.61	5.48	3.25	16.34
Belgium	16.74	4.78	5.13	26.64
Denmark	10.90	12.52	11.51	34.93
Finland	6.39	11.63	19.51	37.54
France	11.64	6.92	9.54	28.09
Germany	9.51	12.58	12.74	34.83
Ireland	26.83	1.64	28.69	57.16
Italy	8.24	12.30	8.21	28.75
Japan	9.22	8.92	16.92	35.05
Netherlands	18.41	7.67	8.31	34.39
South Korea	10.76	7.04	22.34	40.14
Spain	8.46	5.51	5.78	19.76
Sweden	8.51	11.24	12.55	32.30
United Kingdom	11.29	7.50	10.08	28.87
United States	11.03	7.12	13.45	31.60

Source: EU KLEMS database, own calculations.

Conducting separate DEA analysis for the frontier industries generally corroborates our earlier findings as shown in Table 6. Germany and Denmark occupy the research frontier along with the United States and the Netherlands. In the case of the United States however, the machinery sector reveals a comparably low innovative capacity, given its R&D efficiency profile. Generally, we also observe a relatively weak performance on the part of South Korea, the United Kingdom, and Spain, indicating that these countries have the potential to raise output, given their levels of R&D efforts.

For electrical and optical equipment, Japan, Finland and Belgium join the group of leading countries, whereas Italy and Spain show the weakest performances. Returning to the subject of countries' specialization profiles, Finland is notable. Section 5.2 points out that Finland has already reached the frontier in this industry, which is confirmed in our sector-specific analysis. The share of gross output in total manufacturing of nearly 20% emphasizes the importance of this sector for the Finnish economy; hence, a high R&D intensity coincides with an excellent research performance and economic relevance.

Table 6

Average R&D efficiency scores for selected industries (2000-2004)

Country	**Chemicals and chemical products**	**Machinery**	**Electrical and optical equipment**
Australia	0.95	0.53	0.72
Belgium	0.77	0.94	0.81
Denmark	0.97	0.91	0.92
Finland	0.86	0.59	0.82
France	0.87	0.62	0.70
Germany	0.99	0.93	0.94
Ireland	0.72	0.96	0.56
Italy	0.77	0.99	0.40
Japan	0.52	0.36	0.83
Netherlands	1.00	0.94	0.81
South Korea	0.47	0.53	0.50
Spain	0.52	0.34	0.28
Sweden	0.54	0.52	0.56
United Kingdom	0.35	0.34	0.55
United States	0.99	0.44	0.96

Notes: 1. Output-oriented DEA with variable returns to scale.
2. Industry-specific frontiers are determined.
3. Averages are calculated across years.

Regarding the machinery industry, our earlier results show this sector as highly efficient in Italy, Germany, and the Netherlands. Italy's proficiency in this sector is again confirmed by the present estimation results. The group of highly efficient countries in machinery also includes Belgium and Ireland. Surprisingly, all other countries exhibit a sharp decline in R&D efficiency, with Japan, Spain, the United Kingdom, and the United States occupying surprisingly weak positions. Compared to other industries, the efficiency gap in machinery production most obviously separates our study countries into high and low performers.

In the chemicals and chemical products industry, the Netherlands, Germany, the United States and Denmark are again the dominant players. The industry-specific analysis confirms the already identified leading groups of countries, with Australia close behind. At the end of the distribution are South Korea, Spain, and Japan with a low average efficiency of about 0.5 and the United Kingdom with the lowest score of 0.35.

6. Conclusion

This paper analyzes R&D efficiency at the industry level in manufacturing for 13 European member and 4 nonmember countries between 2000 and 2004. We consider three inputs: knowledge stocks approximated by R&D expenditures and high- and medium-skilled labor to capture human capital.

Grouping the countries according to their average R&D efficiency score summarizes the results for total manufacturing:

- *high efficiency*: Germany, Denmark, the United States, the Netherlands, Belgium, Ireland, Finland
- *medium efficiency*: Italy, Sweden, Japan, Australia, France
- *low efficiency*: South Korea, the United Kingdom, Spain, Poland, and the Czech Republic

As R&D investment and efficiency depend on national industrial structures, the reasonable and useful level for performance assessments is the industry domain. We observe countries occupying the frontier in certain industries that do not belong to the generally highly efficient group, e.g. Italy in machinery, and mineral products, and countries determining the frontier for the aggregate being superior only in certain sectors, e.g. Finland in electrical and optical equipment and mineral products. Generally, we find electrical and optical equipment is the dominant industry when determining the technology frontier, followed by machinery, and mineral products.

Conducting separate DEA analyses for selected industries corroborates the results from the pooled estimation and provides further insights about the relative position of countries in economically-important industries. Again, we find support for the usefulness of industry-specific analyses as we observe country-specific R&D efficiency profiles with substantial variation across sectors, e.g. a relatively low score of the United States in machinery. Estimating distinct industry frontiers gives a clearer picture of national strengths and weaknesses. More specifically, it reveals the size of the gap between the efficient and less-efficient countries, since it no longer assumes that a common frontier envelops all industries.

We believe that our work can provide guidance to policymakers interested in improving innovative performance and ensuring long-term economic growth. When resources are limited, priority should be given to the industries that promise the largest output for the available amount of investment. Instead of generally increasing the R&D-to-GDP ratio, policymakers might target future R&D efforts to those industries that are economically important and reveal excellent performance. We caution that our findings should not be inappropriately over-generalized, particularly since our work is a first attempt to evaluate R&D performance at the industrial sector. A finer-grained sector classification and the use of efficiency measurements within industries to benchmark against international competitors could provide additional insights.

Acknowledgements

We thank for their helpful comments and support Astrid Cullmann, Irwin Collier, Christian von Hirschhausen, and Andreas Stephan and participants of the EWEPA 2011 in Verona for useful suggestions.

Funding

Growth and Sustainability Policies for Europe (GRASP); Collaborative Project funded by the European Commission's Seventh Research Framework Programme, (Contract number 244725).

References

Acemoglu, D., Zilibotti, F. & Aghion, P. (2006). Distance to frontier, selection and economic growth. *Journal of the European Economic Association*, 4, 37–74.

Aghion, P., Blundell, R., Griffith, R., Howitt, P. & Prantl, S. (2009). The effects of entry on incumbent innovation and productivity. *Review of Economics and Statistics*, 91, 20–32.

Aghion, P. & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60, 323–351.

Andersen, P. & Petersen, N. (1993). A procedure for ranking efficient units in data envelopment analysis. *Management Science*, 39, 1261–1264.

Banker, R.D. & Chang, H. (2006). The super-efficiency procedure for outlier identification, not for ranking efficient units. *European Journal of Operational Research*, 175, 1311–1321.

Banker, R.D., Charnes, A., & Cooper, W.W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30, 1078–1092.

Charnes, A., Cooper, W.W. & Rhodes, E. (1978). Measuring the inefficiency of decision making units. *European Journal of Operational Research*, 2, 429–444.

Coelli, T., Rao, P. & Battese, G.E. (2005). *An Introduction to efficiency and productivity analysis*, New York: Springer.

Cohen, W.M., Nelson, R.R. & Walsh, J.P. (2000). *Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent (or not)*. NBER Working Paper 7552.

Cullmann, A., Schmidt–Ehmcke, J. & Zloczysti, P. (2011). R&D efficiency and barriers to entry — A two stage semi-parametric DEA approach. *Oxford Economic Papers*, doi:10.1093/oep/gpr015.

Desprins, D., Simar, L. & Tulkens, H. (1984). Measuring labor efficiency in post offices. In M. Marchand, M. Pestieau & H. Tulkens (Eds.), *The performance of public enterprises: Concepts and measurement* (pp. 243-267). Amsterdam, North Holland: Elsevier Science Publishing.

Efron, B. (1979). Bootstrap methods: Another look at the jackknife. *Annals of Statistics*, 7, 1–26.

Farell, M. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, 120, 253–281.

Ferrier, G.D. & Lovell, C.A. (1990). Measuring cost efficiency in banking: Econometric and linear programming evidence. *Journal of Econometrics*, 46, 229–245.

Griliches, Z. (1979). Issues in assessing the contribution of R&D to productivity growth. *Bell Journal of Economics*, 10, 92–116.

Guellec, D. & van Pottelsberghe de la Potterie, B. (2001). *R&D and productivity growth*. OECD Science and Technology Working Papers 3.

Hall, B.H. & Mairesse, J. (2006). Empirical studies of innovation in the knowledge-driven economy. *Economics of Innovation and New Technology*, 15, 289-299.

Hall, B.H., Griliches, Z. & Hausman, J.A. (1986). Patents and R&D: Is there a lag? *International Economic Review*, 27, 265–283.

Hall, B.H. & Ziedonis, R.H. (2001). The patent paradox revisited: An empirical study of patenting in the U.S. semiconductor industry 1979–1995. *RAND Journal of Economics*, 32, 101–128.

Jaffe, A. (1986) Technology opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *American Economic Review*, 76, 984–1001.

Lee, H.-Y. & Park, Y.-T. (2005). An international comparison of R&D efficiency: DEA approach. *Asian Journal of Technology Innovation*, 13, 207–222.

Mairesse, J. & Mohnen, P. (2004). *The importance of R&D for innovation: A reassessment using French survey data*. NBER Working Paper 10897.

Noel, M. & Schankerman, M. (2006) *Strategic patenting and software innovation*. CEPR Discussion Paper 5701.

OECD (2008a). *Compendium of patent statistics*. Paris, France: OECD.

OECD (2008b). *Main science and technology indicators*. Paris, France: OECD.

O'Mahony, M., Castaldi, C., Los, B., Bartelsman, E., Maimaiti, Y. & Peng, F. (2008). *EU KLEMS — Linked Data: Sources and Methods*. Birmingham: University of Birmingham.

Pakes, A. & Griliches, Z. (1984). Patents and R&D at the firm level: A first look. In Z. Griliches (Ed.), *R&D, patents, and productivity* (pp. 55-72). Chicago: University of Chicago Press.

Rousseau, S. & Rousseau, R. (1997). Data analysis as a tool for constructing scientometric indicators. *Scientometrics*, 40, 45–46.

Rousseau, S. & Rousseau, R. (1998). The scientific wealth of European nations: Taking effectiveness into account. *Scientometrics*, 42, 75–87.

Schmoch, U., Laville, F., Patel, P. & Frietsch, R. (2003). *Linking technology areas to industrial sectors*. Final report to the European Commission, Karlsruhe: ISI.

Schneider, C. (2008). Fences and competition in patent races. *International Journal of Industrial Organization*, 26, 1348–1364.

Sharma, S. & Thomas, V.J. (2008). Inter-country R&D efficiency analysis: An application of data envelopment analysis. *Scientometrics*, 76, 483–501.

Sheehan, J, Martinez, C. & Guellec, D. (2004). Understanding business patenting and licensing: Results of a survey. In OECD (Ed.), *Patents, Innovation and Economic Performance: Conference Proceedings* (pp. 89–110). Paris, France: OECD.

Simar, L. & Wilson, P. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science*, 44, 49–61.

Simar, L. & Wilson, P. (2000). A general methodology for bootstrapping in nonparametric frontier models. *Journal of Applied Statistics*, 27, 779–802.

Simar, L. & Wilson, P. (2002). Non-parametric tests of returns to scale. *European Journal of Operational Research*, 139, 115–132.

Simar, L. & Wilson, P. (2007a). Estimation and inferences in two-stage, semi-parametric models of production process. *Journal of Econometrics*, 136, 31–64.

Simar, L. & Wilson, P. (2007b) Statistical inference in nonparametric frontier models: recent developments and perspectives. In H.O. Fried, C.A. Lovell & S.S. Schmidt (Eds.), *The measurement of productive efficiency and productivity growth* (pp. 421-521). New York: Oxford University Press.

Timmer, M., O'Mahony, M. & Van Ark, B. (2008). *The EU KLEMS Growth and Productivity Accounts: An Overview*. Groningen and Birmingham: University of Groningen & University of Birmingham.

Timmer, M., Van Moergastel, T., Stuivenwold, E., Ypma, G., O'Mahony, M. & Kangasniemi, M. (2007). *EU KLEMS Growth and Productivity Accounts, Version 1.0, Part I Methodology*. Groningen: University of Groningen.

van Pottelsberghe de la Potterie, B. (2008). Europe's R&D: Missing the wrong targets? *Intereconomics*, 43, 220–225.

Wang, E.C. (2007). R&D efficiency and economic performance: A cross-country analysis using the stochastic frontier approach. *Journal of Policy Modelling*, 29, 345–360.

Wang, E.C. & Huang, W. (2007). Relative efficiency of R&D activities: A cross-country study accounting for environmental factors in the DEA approach. *Research Policy*, 36, 260–273.

WIPO (2008). *World patent report — A statistical review*. Geneva, Switzerland.

Appendix A

Table A.1

Concordance assigning IPC classes to European NACE[22]

NACE (Rev. 1)	Industry description	IPC Classes
15t16	Food products, beverages, and tobacco	A01H, A21D, A23B, A23C, A23D, A23F, A23G, A23J, A23K, A23L, A23P, C12C, C12F, C12G, C12H, C12J, C13F, C13J, C13K, A24B, A24D, A24F
17t19	Textiles, textile products, leather, and footwear	D04D, D04G, D04H, D06C, D06J, D06M, D06N, D06P, D06Q, A41B, A41C, A41D, A41F, A43B, A43C, B68B, B68C
20	Wood, products of wood and cork	B27D, B27H, B27M, B27N, E04G
21t22	Pulp, paper, paper products, printing, and publishing	B41M, B42D, B42F, B44F, D21C, D21H, D21J
23	Coke, refined petroleum products, and nuclear fuel	C10G, C10L, G01V
24	Chemicals and chemical products	B01J, B09B, B09C, B29B, C01B, C01C, C01D, C01, C01G, C02F, C05B, C05C, C05D, C05F, C05G, C07B, C07C, C07F, C07G, C08B, C08C, C08F, C08, C08J, C08K, C08L, C09B, C09C, C09D, C09K, C10B, C10C, C10H, C10J, C10K, C12S, C25B, F17C, F17D, F25J, G21F, A01N, B27K, A61K, A61P, C07D, C07H, C07J, C07K, C12N, C12P, C12Q, C09F, C11D, D06L, A62D, C06B, C06C, C06D, C08H, C09G, C09H, C09J, C10M, C11B, C11C, C14C, C23F, C23G, D01C, F42B, F42D, G03C, D01F
25	Rubber and plastics products	A45C, B29C, B29D, B60C, B65D, B67D, E02B, F16L, H02G
26	Other nonmetallic mineral products	B24D, B28B, B28C, B32B, C03B, C03C, C04B, E04B, E04C, E04, E04F, G21B
27t28	Basic metals and fabricated metal products	B21C, B21G, B22D, C21B, C21C, C21D, C22B, C22C, C22F, C25C, C25F, C30B, D07B, E03F, E04H, F27D, H01B, A01L, A44B, A47H, A47K, B21K, B21L, B22F, B25B, B25C, B25F, B25G, B25H, B26B, B27G, B44C, B65F, B82B, C23D, C25D, E01D, E01F, E02C, E03B, E03C, E03D, E05B, E05C, E05D, E05F, E05G, E06B, F01K, F15D, F16B, F16P, F16S, F16T, F17B, F22B, F22G, F24J, G21H
29	Machinery	B23F, F01B, F01C, F01D, F03B, F03C, F03D, F03G, F04B, F04C, F04D, F15B, F16C, F16D, F16F, F16H, F16K, F16M, F23R, A62C, B01D, B04C, B05B, B61B, B65G, B66B, B66C, B66D, B66F, C10F, C12L, F16G, F22D, F23B, F23C, F23D, F23G, F23H, F23J, F23K, F23L, F23M, F24F, F24H, F25B, F27B, F28B, F28C, F28D, F28F, F28G, G01G, H05F, A01B, A01C, A01D, A01F, A01G, A01J, A01K, A01M, B27L, B21D, B21F, B21H, B21J, B23B, B23C, B23D, B23G, B23H, B23K, B23P, B23Q, B24B, B24C, B25D, B25J, B26F, B27B, B27C, B27F, B27J, B28D, B30B, E21C, A21C,

[22] Based on Schoch et al. (2003).

		A22B, A22C, A23N, A24C, A41H, A42C, A43D, B01F, B02B, B02C, B03B, B03C, B03D, B05C, B05D, B06B, B07B, B07C, B08B, B21B, B22C, B26D, B31B, B31C, B31D, B31F, B41B, B41C, B41, B41F, B41G, B41L, B41N, B42B, B42C, B44B, B65B, B65C, B65H, B67B, B67C, B68F, C13C, C13D, C13G, C13H, C14B, C23C, D01B, D01D, D01G, D01H, D02G, D02H, D02J, D03C, D03D, D03J, D04B, D04C, D05B, D05C, D06B, D06G, D06H, D21B, D21D, D21F, D21G, E01C, E02D, E02F, E21B, E21D, E21F, F04F, F16N, F26B, H05H, B63G, F41A, F41B, F41C, F41F, F41G, F41H, F41J, F42C, G21J, A21B, A45D, A47G, A47J, A47L, B01B, D06F, E06C, F23N, F24B, F24C, F24D, F25C, F25D, H05B
30t33	Electrical and optical equipment	B41J, B41K, B43M, G02F, G03G, G05F, G06C, G06D, G06E, G06F, G06G, G06J, G06K, G06M, G06N, G06T, G07B, G07C, G07D, G07F, G07G, G09D, G09G, G10L, G11B, H03K, H03L, H02K, H02N, H02P, H01H, H01R, H02B, H01M, F21H, F21K, F21L, F21M, F21S, F21V, H01K, B60M, B61L, F21P, F21Q, G08B, G08G, G10K, G21C, G21D, H01T, H02H, H02M, H05C, B81B, B81C, G11C, H01C, H01F, H01G, H01J, H01L, G09B, G09C, H01P, H01Q, H01S, H02J, H03B, H03C, H03D, H03F, H03G, H03H, H03M, H04B, H04J, H04K, H04L, H04M, H04Q, H05K, G03H, H03J, H04H, H04N, H04R, H04S, A61B, A61C, A61D, A61F, A61G, A61H, A61J, A61L, A61M, A61N, A62B, B01L, B04B, C12M, G01T, G21G, G21K, H05G, F15C, G01B, G01C, G01D, G01F, G01H, G01J, G01M, G01N, G01R, G01S, G01W, G12B, G01K, G01L, G05B, G08C, G02B, G02C, G03B, G03D, G03F, G09F, G04B, G04C, G04D, G04F, G04G
34t35	Transport equipment	B60B, B60D, B60G, B60H, B60J, B60, B60L, B60N, B60P, B60Q, B60R, B60S, B60T, B62D, E01H F01L, F01M, F01N, F01P, F02B, F02D, F02F, F02G, F02M, F02N, F02P, F16J, G01P, G05D, G05G, B60F, B60V, B61C, B61D, B61F, B61G, B61H, B61J, B61K, B62C, B62H, B62J, B62K, B62L, B62M, B63B, B63C, B63H, B63J, B64B, B64C, B64D, B64F, B64G, E01B, F02C, F02K, F03H
34t35	Transport equipment	B60B, B60D, B60G, B60H, B60J, B60, B60L, B60N, B60P, B60Q, B60R, B60S, B60T, B62D, E01H F01L, F01M, F01N, F01P, F02B, F02D, F02F, F02G, F02M, F02N, F02P, F16J, G01P, G05D, G05G, B60F, B60V, B61C, B61D, B61F, B61G, B61H, B61J, B61K, B62C, B62H, B62J, B62K, B62L, B62M, B63B, B63C, B63H, B63J, B64B, B64C, B64D, B64F, B64G, E01B, F02C, F02K, F03H

Table A.2

Summary statistics: country level (2000-2004)

Country	**Patents**				**R&D**				**High-skilled**				**Medium-skilled**			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Australia	988.73	396.14	120.00	1316.00	11475.31	731.60	10695.31	12383.88	233.67	25.12	187.79	265.04	912.41	23.81	873.58	942.2
Belgium	1791.46	513.58	703.00	2408.00	21247.66	691.09	20295.03	21869.15	100.09	2.44	96.31	104.06	500.09	27.46	451.92	534.9
Denmark	1008.82	322.45	292.00	1377.00	8068.75	737.58	7192.70	8924.98	26.56	3.53	20.86	30.81	416.68	19.29	377.02	440.4
Finland	1293.91	465.58	184.00	1756.00	12844.10	1342.51	11251.02	14380.25	185.62	16.26	155.60	205.53	346.51	19.14	311.06	369.2
France	8311.46	2627.65	1425.00	10909.00	126489.10	3404.08	122569.80	130383.50	417.88	34.32	379.91	505.69	3739.69	93.07	3543.70	3829.4
Germany	31328.55	10153.03	6738.00	40494.00	235506.10	7169.71	227042.00	243748.10	923.38	27.03	899.79	984.07	7594.50	265.25	7175.89	8119.9
Ireland	214.45	89.01	47.00	329.00	3149.89	153.26	2965.63	3322.22	65.04	16.89	40.53	91.21	428.75	24.28	393.41	454.9
Italy	4929.91	1409.71	1909.00	6488.00	42905.19	114.67	42765.27	43019.69	248.24	14.71	225.13	266.75	8513.60	153.87	8127.31	8717.5
Japan	21125.64	7292.83	2606.00	27615.00	486848.40	18084.60	465781.70	507609.80	4215.53	74.92	4058.65	4320.42	15395.44	943.06	14044.39	16722.
Netherlands	3431.82	1185.97	777.00	4747.00	24787.83	446.53	24222.00	25293.68	83.75	14.64	65.56	108.82	1319.26	55.68	1205.07	1375.6
South Korea	1719.91	1323.35	526.00	4548.00	69024.85	3494.39	66553.94	71495.76	2750.78	430.54	2317.89	3472.43	6073.16	397.72	5340.16	6761.0
Spain	937.64	362.05	441.00	1631.00	16832.96	1105.64	15624.49	18158.09	523.04	119.31	318.33	685.37	1441.02	230.98	995.70	1730.3
Sweden	2441.73	634.41	728.00	3008.00	36348.87	2820.43	32826.70	39345.42	116.89	27.35	84.87	165.36	870.20	30.12	835.65	926.6
United Kingdom	6117.46	1961.52	801.00	7673.00	97799.71	2146.41	95243.11	100233.10	781.08	69.20	660.10	851.81	5356.43	569.71	4325.81	6002.4
United States	33048.82	10558.20	3428.00	39608.00	880727.00	5370.19	873631.70	886484.20	7781.95	380.48	7083.66	8304.06	22283.02	2549.71	18570.38	24570.

Source: EU KLEMS database and PATSTAT, own calculations.

Table A.3

Summary statistics: industry level (2000-2004)

Industry	**Patents**				**R&D**				**High-skilled**				**Medium-skilled**			
	Mean	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**
Food products, beverages, and tobacco	1728.4	44.4	1688.0	1781.0	39514.3	2113.7	37416.1	41892.0	1466.1	45.6	1414.7	1539.0	8342.7	105.6	8240.3	8509.2
Textiles, textile products, leather, and footwear	1159.2	132.2	968.0	1311.0	10461.8	247.9	10109.2	10670.9	492.6	53.2	421.1	550.1	4409.0	502.6	3823.1	5084.7
Wood, products of wood and cork	178.4	40.5	139.0	229.0	3206.6	925.8	1838.5	3865.2	213.6	49.1	145.2	272.4	1888.6	265.7	1530.6	2236.2
Pulp, paper products, printing, and publishing	1211.8	81.1	1109.0	1290.0	24509.5	1870.3	22443.2	26875.3	2027.1	148.8	1836.7	2173.2	6162.9	306.4	5844.7	6595.8
Coke, refined petroleum products, and nuclear fuel	683.8	23.3	667.0	723.0	23958.7	1255.6	22586.2	25623.2	111.8	5.2	107.1	119.0	316.5	18.0	289.3	339.1
Chemicals and chemical products	28545.2	892.0	27214.0	29570.0	368141.9	13914.7	353882.7	384520.4	1586.9	30.7	1552.9	1628.1	3406.5	127.6	3261.5	3564.4
Rubber and plastics products	5617.4	106.9	5496.0	5734.0	37502.2	1949.3	35219.4	39634.4	928.7	31.4	893.7	962.9	4114.7	155.2	3984.6	4344.7
Other nonmetallic mineral products	3789.8	236.3	3487.0	4124.0	22539.5	245.4	22347.6	22865.9	526.8	9.0	518.7	538.9	2863.2	141.0	2713.2	3056.6
Basic metals and fabricated metal products	6307.6	128.1	6162.0	6455.0	62275.4	563.9	61605.1	62982.3	1798.8	46.2	1750.0	1869.9	10166.4	316.3	9891.5	10637.
Machinery, NEC	24701.8	686.5	24001.0	25828.0	144652.2	6548.6	137205.5	151711.5	1911.0	109.7	1812.0	2066.9	7989.2	489.9	7545.3	8633.6
Electrical and optical equipment	56945.4	1828.0	55674.0	60165.0	779547.2	38031.6	735008.9	816686.9	4081.3	138.4	3916.6	4249.4	9973.3	899.6	9080.8	11099.
Transport equipment	11288.0	802.7	10531.0	12345.0	502620.9	16632.0	488258.5	522170.6	2134.1	111.6	2049.3	2295.6	7145.6	157.9	7011.5	7367.8
Manufacturing, NEC	2256.8	65.4	2188.0	2343.0	15615.8	1050.5	14448.7	16803.1	695.6	22.8	669.9	721.5	3875.4	181.0	3721.8	4147.5

Source: EU KLEMS database and PATSTAT, own calculations