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1. General Introduction

1.1 Overview

Fostering innovation is crucial to sustain long-term growth and prosperity. Especially in the advanced countries of Europe, the United States and Japan, continuous technological innovation is of major importance as these countries determine the world technology frontier and are therefore no longer able to grow by imitating or adapting technologies developed elsewhere. An obvious to path to spur innovation would be to increase research and development (R&D) investment.

As Europe experienced on average a lower annual growth rate over the last decade than the United States (0.4 percentage points lower), the so-called Lisbon Agenda was launched in March 2000 to bolster innovation, growth and employment in the European Union (EU). In the Lisbon strategy, the governments of the member states established the goal transforming the EU into "the most competitive and dynamic knowledge-based economy in the world, capable of sustainable economic growth with more and better jobs and greater social cohesion" by 2010 [7]. One of the central ideas in this framework is that R&D investment in the EU is too low. As a result, the Lisbon strategy includes the goal of raising R&D expenditures to 3% of GDP. Faced with the reality of climate change and pollution, the initial Lisbon framework was amended at the European Council in Gothenburg in 2001 to include environment and sustainability [8]. At the current stage, we know that many EU countries are still far away from the spending goal of 3% even though the primal targets were supposed to be due in 2010. Consequently, the European Commission issued an "Agenda 2020" to sketch a vision of Europe for the 21st century, which again includes the 3% goal as a headline target [9].

Against this background, the motivation for this thesis arose from the need to gain a deeper understanding of the innovation process itself and the drivers of ideas generation. A question immediately crossing one's mind when talking about the Lisbon 3% target is: are we aiming at the right target? Do we employ resources devoted to R&D efficiently or could we increase innovation through improved performance? The first paper of this thesis offers an efficiency assessment of R&D to address on these questions. Given the fact that industries differ in their respective R&D intensities, it applies techniques developed in the field of productivity and efficiency analysis to benchmark innovation performance at the sector level across 17 OECD countries. The main distinction between previous literature on R&D efficiency and this paper is the emphasis of sector-specificity of innovation to account for industrial specialization patterns. Using patents as output and R&D expenditures and human capital as inputs for the efficiency analysis, frontier-determining industries turn out to include electrical and optical equipment, and machinery. We observe that only specific sectors in leading countries form the world technology frontier.

By fostering innovation, policy makers hope to revive productivity growth. As productivity growth is known to be the main determinant of economic growth, the relationship between innovative activity and productivity is of major interest. Therefore, the second paper analyzes how technological transfer affects productivity. Efforts devoted to R&D together with existing expertise on technologies and processes determine the productivity level. Besides own knowledge, ideas originating from other countries or sectors might spill over as technological externalities. The paper is one of few contributions on spillover channels at the sector level. It thereby distinguishes four channels over which knowledge can transcend boundaries and affect productivity: national and international, intra- and inter-sectoral respectively. Knowledge generation is approximated by the stock of patents in a certain industry. By applying recent estimation methods in the treatment of non-stationary panel data, we obtain results suggesting that total factor productivity growth is mainly driven by knowledge transfers within a certain industry, either taking place within national boundaries or flowing in from abroad.

After analyzing aspects of productivity and efficiency of innovation in the industrial sector, the third paper adopts a firm's perspective to study consequences of innovation strategies from panel data for the U.S. manufacturing sector. The empirical literature affirms the positive valuation of R&D and patents by financial markets but relatively little is known about the impact of the composition of the research portfolio that reflects the future strategic alignment of research and production. The portfolio can either be highly concentrated on certain technologies or relatively broad by providing access to many technologies. Based on an expanded Tobin's *q* approach, it shows that diversifying into new technologies implies a discount on the market value unless the new technologies are highly related to the ones already covered in a firm's portfolio.

Finally in the fourth paper, this thesis contributes to the "green growth" debate by identifying determinants of innovative activity in renewable energy technologies. Recently, the debate on the growth implications of climate change has gained considerable interest among policy makers and scientists [1], [2]. Even though innovation in green technologies is needed to adapt current and develop new technologies to master the challenges of climate change, actual performance is perceived to be insufficient [3]. The paper focuses on solar and wind technologies, two prominent and intensively studied technologies within the field of renewable energy generation. Each can be considered an emerging technology compared to more mature technologies (e.g. hydropower). The thorough analysis of innovation in wind and solar technology, traced by patent data, reveals that mainly spillovers and public R&D support spur the generation of new ideas. So far, the importance of knowledge transfers via different channels had been neglected in the empirical literature on green innovation.

A recurring theme of this thesis is the usage of patent data to measure and track innovative activity. Therefore, the following subsection provides a brief introduction to patenting procedure and statistics.

1.2 Usage of Patent Data

A crucial aspect in tracking innovative activity is its measurement, an issue that is discussed extensively in the literature on innovation. Even though a perfect indicator does not exist, three alternatives are frequently chosen in empirical research: R&D expenditures and the number of patents. , The third alternative, scientific publications, is less commonly used because of poor data availability.

While R&D data are issued annually for the OECD using a harmonized measurement methodology [13], we suggest that the use of patents offers far more flexibility to researchers due to their comprehensive information content. Patents are a powerful economic indicator, since, by definition, they involve truly new ideas. Patents share a common legal framework in that a group of intellectual property rights grants an owner a temporary monopoly over an invention. Exclusivity rights bar third parties from usage, production, sales or imports for a specified time, thereby generating a competitive advantage for the owner of the patent.

The owner of an invention has three options when applying for a patent: national, regional and international. National routes begin at a national patent office; usually the first filing takes place in the applicant's home country. Filing with a regional patent office such as the European Patent Office (EPO) obtains protection in the desired member states. The Patent Cooperation Treaty (PCT) allows a choice of convention countries should an owner wish to protect a new technology in more than one country. Upon receiving the filing, the respective patent office undertakes a rigorous examination. Is the suggested invention an inventive step and industrially applicable? When such criteria are satisfied, the patenting authority grants a patent.[1] An application is usually published 18 months after the initial filing.[2] Protection of a granted patent usually expires 20 years after filing, if the owner pays the annual maintenance fees.

Patent applications provide rich data such as:

- *List of claims*
  By listing the claims, the application summarizes the underlying invention and the intended patent coverage.
- *Technical classification*
  Patent applications are classified technically. A widely used classification scheme is the International Patent Classification System (IPC), a hierarchical system which codifies the subject of a patent. The information on technical classification can be exploited to assign patent applications to industries or certain technological fields, e.g. renewable energies.

[1] There is no clear rule on how long the examination takes; it largely depends on the underlying invention and the office in charge.

- *Priority date*

  The term "priority date" refers to the date when the underlying invention is protected by a patent for the first time, regardless of whether this first application was made at a national or an international authority. The first filing for an invention usually occurs at the national level and therefore the majority of patent applications at the EPO are second filings [5]. The priority date in a considerable number of cases precedes the EPO application date. Accordingly, patent applications are frequently dated using the priority date instead of the application date because it is closest to the date of invention and the decision to apply for a patent [14]. From an economic view, this is the only information of importance [6].
- *Cited patents*

  Cited patents are references to prior art, thereby helping to justify the novelty and the inventive contribution of the patent application. Furthermore, they are an indication of previous knowledge used in the inventive process.

When attributing patents to countries, researchers can classify them by:

- *Applicant's country of residence*

or

- *Inventor's country of residence*.

The choice will depend on the underlying research question. While the inventor's residence is more appropriate to study inventiveness of regions or innovation performance, applicant's residence is closely linked to the question of ownership and thereby economic appropriation.

Information gleaned from patent applications can be combined and exploited to track innovative activity by means of patent counts.[3] Due to the various aggregation opportunities, these counts can characterize inventiveness of countries, regions, firms or even individuals. Of special interest for new or emerging technologies is the

[2] Some exceptions exist at the United States Patent and Trademark Office (USPTO).
[3] Dernis et al. [6] discuss various dimensions of patent counts as measures of technology output.

description of globalization patterns. Patent data can also capture innovation dynamics by identifying research cooperation or patterns of diffusion.

The principal focus of this thesis is applications to EPO patents, since an application to a non-national authority can be taken as a signal that the patentee believes the invention is of sufficiently high value to justify the additional expense of a regional application. Furthermore, research concentration on a single authority ensures comparability with respect to timing, procedures and the legal framework. A potential problem with this focus is “home bias” which can emerge for non-European countries. Inventors in the United States or Asia may tend to seek initial patent protection in their home market and international protection at a later date. However, inventions that are valuable from an economic point of view and for which the market is thought to be international will usually be protected in the international domain.

Researchers should note three drawbacks to using patents as a proxy for innovative output [10]. First, the distribution of the value of patents is highly skewed to the right since only a few inventions are of remarkable economic value [11]. Second, the propensity to patent varies across countries and industries due to different legal and political environments [12]. Third, since an invention must be fully disclosed to obtain patent protection, some firms may prefer the strategic option of secrecy to prevent imitation [4].

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2. R&D Efficiency in Manufacturing: A Non-Parametric DEA Approach

Abstract

This paper discusses the measurement of R&D efficiency and identifies the best-performing countries. The principal industries determining the technology frontier are electrical and optical equipment, machinery, and chemical and mineral products. An analysis of 17 OECD countries between 2000 and 2004 shows that Germany, the United States, and Denmark have the highest R&D efficiency on average in total manufacturing. Sector-specific efficiency scores reveal substantial variation. We suggest that the return to R&D in terms of innovation growth can be enhanced by strategically increasing R&D investment in industries in which a country optimally performs.

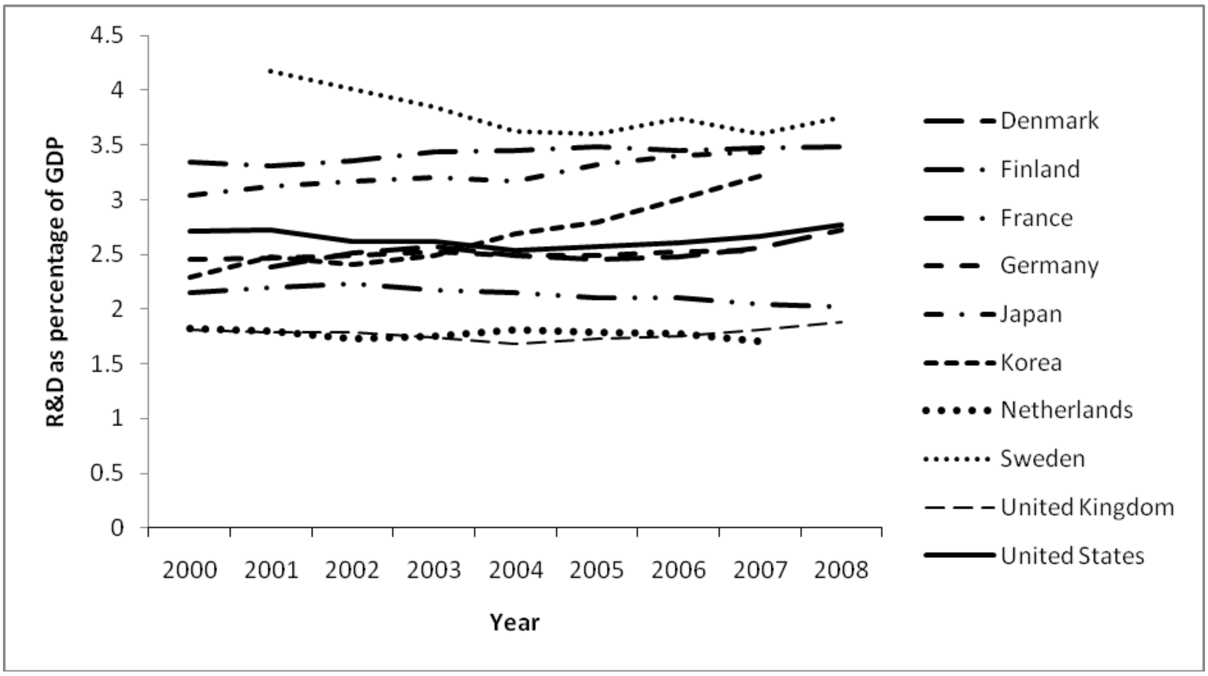
Keywords: R&D Efficiency, Data Envelopment Analysis, Manufacturing, Patents

JEL Classification: C14, L60, O31, O57

1 Introduction

The Lisbon Agenda for competitiveness included two targets for R&D: 1) R&D expenditures relative to 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%. My own 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 of Gross Domestic product (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 [41]. 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 [1], [2]. 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 [16] 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 patent production function framework [19] 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 and PATSTAT. We match EPO patent applications to the EU KLEMS industry-level data by using the concordance developed by Schmoch et al. [30]. 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 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 [5] 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 [36].

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 [15] and implemented by Pakes and Griliches [27], Jaffe [20] and Hall and Ziedonis [19], 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} is the number of high-skilled workers employed. The unit of observation is the country (c) industry (i) level. Innovative output is approximated by patent applications.[1]

[1] Some authors (e.g. [28], [29]) 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 [32]; 2) since detailed publication data are not available at the industry level, assigning publications to industries is problematic and would involve the

Based on the knowledge production function framework, the empirical literature confirms the importance of R&D capital to the knowledge creation process (e.g. [26], for an overview see [17]); however, far less attention has been paid to the importance of the efficient use of scare resources in this process.

Rousseau and Rousseau [28] 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 [29] 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 [21] 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 [43] 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

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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.

indicated a decrease in the number of efficient countries due to the external factors.

Recently, Sharma and Thomas [32] 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. [10] 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 [37]. 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 [36] and include outlier detection [5].

3 Methodology

As mentioned above, we employ DEA, a nonparametric approach[2] 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 [38]. 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 [7]), and variable returns to scale (VRS [6]). 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 [36]. 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 [8]:

[2] Another common nonparametric envelopment approach is free disposal hull (FDH [11]). In contrast to DEA, FDH relaxes the assumption of a convex production set and only presumes free disposability.

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

where λ is an $(N \times K) \times 1$ vector of constants and X and Y represent input and output vectors respectively. λ 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 [13]). 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 [36] have proposed a bootstrap procedure to overcome the problem of DEA techniques being deterministic.[3] 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. Then, the test statistic is the estimated ratio between the usual CRS and the VRS efficiency scores

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

Next, we project the observations (x_i, y_i) 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 [12] — is applied to generate pseudo samples. This procedure provides us with an empirical distribution of $(\hat{\omega}^*_b - \hat{\omega})$ which we use to determine the corresponding p-values.[4]

[3] Statistical inference is drawn based on the bootstrap methodology for estimating confidence intervals for efficiency scores [34].

[4] The empirical distribution resembles the unknown distribution of $(\hat{\omega}^*_b - \hat{\omega})$.

Note that our DEA estimator is a deterministic frontier approach, assuming that all observations are technically attainable.[5] The main drawback of such models is their high sensitivity to outliers and extreme values in the data [35], [38]. 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 [4] and Banker and Chang [5] 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 [5] 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[6] and Australia (AU), Japan (JP), South Korea (KR), and the United States (US) during 2000 and 2004.[7] Our unique dataset on input and output for the efficiency analysis derives from EU KLEMS[8] and PATSTAT[9] and covers 13 industries.

We estimate a cross-industry cross-country pooled frontier, where each observation is a

[5] We are aware that applied linear programming might not reveal all efficiency slacks. However, we follow Coelli et al. [8] who claim that "the importance of slacks can be overstated" when accepting the argument of Ferrier and Lovell [14] 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.

[6] 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).

[7] 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 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.

[8] A detailed description of the dataset is provided in [39], [40].

[9] European Patent Office Worldwide Statistical Database: PATSTAT version 1/2008.

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.[10] 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 [38] 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. [42], [44]).

Patents are assigned to industries based on the concordance developed by Schmoch et al. [30], who used expert assessments and micro-data evidence on the patent activity of firms in the manufacturing industry to link technologies to industry sectors.[11] The

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

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

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[12] 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.

However, further aggregation of NACE classes is needed to match the patent data to the input data sources.[13] 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.[14]

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 [24]. 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 [40]. 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 consolidates the sample statistics of the input and output variables in our

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[12] Nomenclature générale des activités économiques dans les Communautés européennes.
[13] A detailed description of the concordance appears in Appendix A.1.
[14] The depreciation rate equals 12%. The calculation of R&D stocks is explained in detail in [25]. Stocks are deflated using implicit PPPs at constant 2000 prices taken from the OECD [24].

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.

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

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. [32], [43]), we impose a two-lag structure for inputs to account for the fact that R&D efforts do not immediately result in innovative output [18].

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

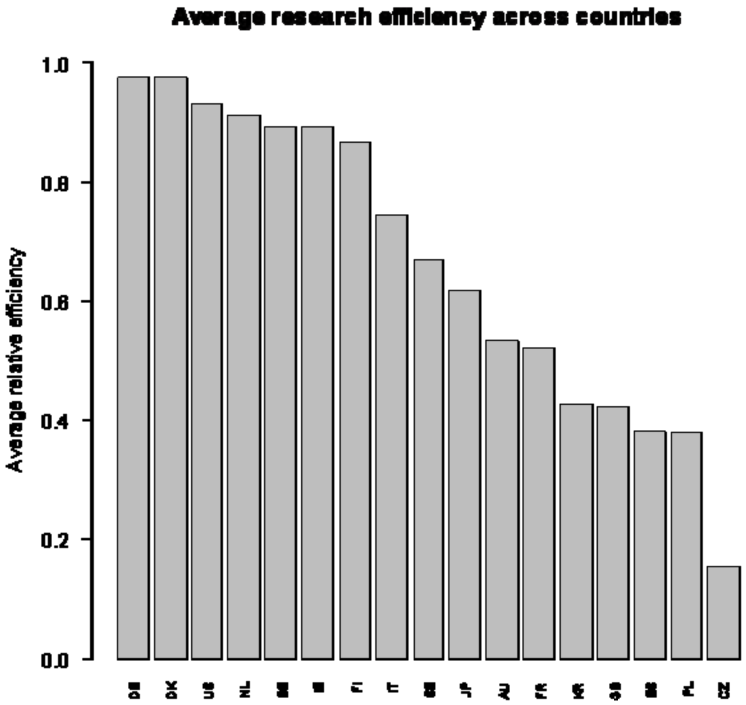
A first impression of R&D efficiency in manufacturing results from comparing the average efficiencies at the country level. We derive the averages by aggregating over sector-level data and then conducting a variable returns to scale[15] DEA analysis using these country-level aggregates. We implicitly assume a time-invariant technology frontier and focus on the distance of countries from the estimated frontier.[16] Figure 1

[15] As shown by Sharma and Thomas [32], most countries reveal increasing returns to scale, hence, a constant returns to scale technology is inappropriate.

[16] An alternative method would be to compare the technology frontiers of different years by means of Malmquist indices [8]. 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.

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.[17]

Figure 2
Average R&D efficiency in total manufacturing



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:

- *high efficiency*: Germany, Denmark, the United States, the Netherlands, Belgium, Ireland, Finland

[17] 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

- *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 [23]. 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

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countries tend to first seek patent protection in their home markets and expand protection globally only for valuable inventions.

— 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. [10] 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.[18] 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 [36] 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 [5].

Table 2 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.

[18] 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 in this respective industry, but not necessarily at the aggregate level.

Table 2

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.

Chemicals, pharmaceuticals, information and communication technology and machinery are among the most patent-intensive industries [33], a phenomenon possibly resulting from the different strategic motives for patenting in these industries [22], [31]. 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 3). 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[19] 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 3

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

[19] 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 [9].

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 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 4 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 4

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 5. 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 5

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.

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.

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.

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Appendix A

Table A.1

Concordance assigning IPC classes to European NACE[20]

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,

[20] Based on Schoch et al. [30].

		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, 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	942.25
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	534.94
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	440.43
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	369.24
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	3829.43
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	8119.92
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	454.91
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	8717.51
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	16722.28
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	1375.66
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	6761.01
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	1730.36
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	926.61
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	6002.40
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	24570.59

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	10637.8
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	11099.8
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

3. International Knowledge Spillovers and Productivity:
Applying Panel Cointegration to the Industrial Sector Level

Abstract

Using panel data for 14 OECD countries and 13 sectors for the period 1985-2004, this paper analyzes the significance of the linkage between channels of international knowledge spillovers and total factor productivity. We distinguish between domestic and international intra- and inter-sectoral spillover sources. Data on patent applications are exploited to estimate the contribution of technology transfer to industrial productivity. To account for technological distance, we weight foreign knowledge by bilateral technological proximity. By adopting estimation methods reflecting recent developments in the treatment of non-stationary panel data econometrics, we find that industry-specific knowledge both nationally and internationally mainly drives productivity in the respective sector.

Keywords: Knowledge Spillover, Total Factor Productivity, Manufacturing, Panel Cointegration

JEL Classification: C23, L60, O30, O40

1 Introduction

The transmission of technological knowledge to stimulate growth and productivity is an issue that is widely discussed in modern economics. The endogenous growth theory posits that technological progress is determined by innovative activity which in turn responds to economic incentives (e.g. [52], [1]). In this view, efforts devoted to R&D together with existing expertise on technologies and processes determine a country's productivity level. Empiricists argue that the seminal contribution of Coe and Helpman [12] and numerous subsequent studies (e.g. [37], [13]) confirm the importance of technology spillovers for a country's total factor productivity (TFP). In this view, a country's productivity is enhanced by its own R&D efforts first and then by foreign R&D capital.[1]

Unlike country-level studies, there has been little investigation of the role and channels of spillovers across sectors (e.g. [32], [41]). Nevertheless, the pattern of productivity of countries and industries has undergone remarkable changes by either transferring knowledge indirectly through trading intermediate goods, or directly through exchanging tacit knowledge at the micro level [58]. Being integrated into flows of knowledge tends to equalize the differences in productivity domestically across industries and internationally between countries whereas being cut off tends to aggravate existing differences and increase the danger of lagging behind. Analyzing the importance of knowledge spilling over within and between industries is relevant because it enables policy-makers to shape and refine appropriate policies. This paper contributes to the discussion by stressing the importance of inter- and intra-industry knowledge spillovers in explaining productivity growth.

The literature on the effects of spillovers on industrial TFP differentiates between domestic and foreign spillovers and between intra- and inter-sectoral sources [41], _– the four channels over which knowledge can transcend boundaries and affect productivity (e.g. [6]). Recent work can be traced to Keller [32] who analyzes whether knowledge transfers indirectly affect TFP via the international trade of goods. The

[1] Excellent surveys of the literature on R&D spillovers are [45], [11] and [33].

notion of trade as an influential factor was introduced by Coe and Helpman [12], who show that R&D spillovers take place through imported goods. Among others, Lichtenberg and van Pottelsberghe [40] generally confirm their findings, but point to the methodological concerns which have given rise to an alternative specification for foreign knowledge that is still based on trade flows. These measures are used in subsequent work on the analysis of technology transfer (e.g. [37], [38]) and, more recently, the contribution of institutional variables [13] and human capital (e.g. [14], [2]) to TFP.

In general, empirical studies on the role of knowledge spillovers for TFP growth mainly rely on two features: 1. the approximation of existing knowledge by R&D capital stocks; and 2. a weighting of foreign knowledge by the trading patterns of countries. Both aspects have been discussed critically. Griliches [20] suggests distinguishing between rent spillovers and pure knowledge spillovers. In his view, rent spillovers occur when an increase in the quality of intermediate goods is not accompanied by a proportionate increase in prices which causes knowledge to spill over from the supplier to the producer of the final good and results in efficiency gains. Hence, rent spillovers are assumed to depend on international trade flows. Studies using import shares for weighting purposes therefore focus on rent spillovers originating from economic transactions (e.g. [41], [32]).

On the contrary, pure knowledge spillovers are difficult to quantify since they are assumed to be mainly tacit [15]. However, it is not easy to separate pure knowledge from rent spillovers in theory and empirics [44]. Verspagen [59] and Los and Verspagen [42] exploit patent data to study this type of spillover and use a measure of technological proximity suggested by Jaffe [27] to quantify the ease of knowledge circulating between countries. Eaton and Kortum [16] argue that patent data can be interpreted as a more direct indicator of innovative activity compared to R&D because the data contain information about the origins of technologies and are legally related to invention and novelty. Using patents, Madsen [43] examines the impact of knowledge stocks on TFP for historical data and finds that international patenting has a substantial effect on TFP growth and convergence. To our knowledge, [2] Lach [35] has conducted the only patent-based analysis on the industry level to evaluate the impact of the patent stock on productivity growth in American manufacturing. He finds an output elasticity of knowledge of around 0.3, which is remarkably high compared to those found for R&D.

Related to the measure of innovative activity – R&D or patents – is the choice of a weighting scheme for foreign spillover sources. As mentioned above, focusing on trade structures is related to the analysis of rent spillovers. Studies on pure knowledge spillovers therefore apply the concept of technological proximity between countries, industries or firms – depending on the level of observation – to measure the technological distance from the spillover-receiver. Los and Verspagen [42] apply this methodology to study the effect of the two types of spillovers in U.S. manufacturing.[3] An update by Lee [36] casts further doubt on the importance of trade for the diffusion of knowledge by showing that the impact of import shares nearly vanishes when controlling for real knowledge spillovers.

To our knowledge, this paper is the first to study the channels of pure knowledge transfer on the industry level using patent data and applying the concept of technological proximity to ensure focusing on direct knowledge spillovers. We close the existing research gap by providing empirical evidence on the productivity and innovation linkage via an analysis of patent data for 14 OECD countries and 13 industries. We suggest that using patents as an indicator of innovative output highlights the robustness of previous results considering the different approaches of capturing knowledge.

Previous literature has partly neglected the time-series properties of the underlying variables. Referring to the work of Coe and Helpman [12], Kao et al. [30] emphasize the need to account for non-stationarity of data and suggest applying dynamic linear regression analysis. We conduct various panel unit root and recently developed panel

[2] For stylistic purposes, the plural form "we" is used in this single-authored paper.
[3] The patent-based measure of technological proximity is also combined with R&D data to stress the role of pure knowledge transfers: e.g. [22] uses this measure to study the impact of domestic R&D by sources of funding.

cointegration tests to investigate the time series properties of our variables. Estimations are presented for ordinary (OLS) and dynamic ordinary least squares (DOLS). Our results indicate that domestic and international intra-industry knowledge spillovers have significant impacts on TFP growth and that technologies originating from other sectors do not affect productivity. Our results indicate that intra-industry knowledge spillovers, domestically and internationally, have a considerable effect on TFP growth. Technologies originating from other sectors are not found to affect productivity.

The paper is organized as follows: Section 2 sketches the theoretical background and Section 3 introduces data sources and the construction of variables. Section 4 presents the econometric techniques and discusses the estimation results. Section 5 presents our conclusions.

2 Theoretical Background

The idea that externalities like knowledge spillovers affect productivity has an even longer history in the economic literature than the endogenous growth theory. In the early contributions, the main source of externalities is assumed to be "learning by doing" as suggested by Arrow [3]. The model still being used in empirical applications nowadays goes back to Griliches [20]. It transfers the early approaches on knowledge externalities to the field of R&D.

Generalizing the initial model to the country level, we assume that a country's output in industry j is given by the following Cobb-Douglas style production function:

$$Y_j = AS_j^{\delta} S_0^{\gamma} L_j^{\alpha} K_j^{1-\alpha}, \qquad 0 < \alpha < 1,$$

with L_j denoting manpower, K_j representing physical capital and A being a positive constant. Production is linked to technological capital via S, where S_j is the knowledge capital being specific to industry j. S_o stands for the state of aggregate technological knowledge outside the industry. The two major assumptions in this model are: 1.

constant returns to scale with respect to physical capital, and 2. labor and common factor prices to all firms within a certain industry.[4]

An aggregation of inputs to a conventional total input index

$$X_j = L_j^{\alpha} K_j^{1-\alpha}$$

leads to the common definition of TFP

$$TFP_j = \frac{Y_j}{X_j}.^{5}$$

Given the production function as specified above leads to the following linear equation relating productivity to knowledge inside and outside the industry:

$$\ln\left(TFP_j\right) = \ln\left(A\right) + \delta \ln\left(S_j\right) + \gamma \ln\left(S_0\right).$$

To adapt this theoretical framework to a multi-country and multi-industry setting, we follow previous studies and further distinguish between domestic and international knowledge to specify S_0. Therefore, we assume that the production of industry j in country i depends on knowledge within and outside the industry as well as on international knowledge inside and outside sector j:

$$\ln\left(TFP_{ij}\right) = \ln\left(A\right) + \delta\left(S_{ij}^{D}\right) + \gamma\left[\ln\left(S_{i-j}^{D}\right) + \ln\left(S_{ij}^{F}\right) + \ln\left(S_{i-j}^{F}\right)\right].$$

We thereby allow for four channels of spillovers: two intra-sectoral, national S_{ij}^{D} and international S_{ij}^{F}, and two inter-sectoral sources, S_{i-j}^{D} and international S_{i-j}^{F}.

Theoretically, the impact of inter-sectoral spillovers could also be estimated by treating all sectors in the sample as separate regressors in the estimation equation. However, sector-specific knowledge pools reveal a high degree of correlation leading to the problem of collinearity. Griliches [21] mentions this empirical issue and points to the problem of “wrong” signs and insignificant test statistics. Other authors choose only a few. However, this still incurs the danger of omitted variable bias and therefore is sometimes combined with certain restrictions (e.g. [5]). We circumvent the problem by separating spillovers only into intra- and inter-sectoral components.

[4] Relaxing these assumptions leads to the inclusion of further terms, which reflect e.g., how productivity alters as the firm structure of an industry changes.

3 Data and Variables

The econometric analysis is based on a balanced panel of 14 OECD countries[6] and 13 industries from the manufacturing sector over the period 1985-2004.[7] The analysis begins with the construction of variables for TFP and knowledge spillovers.

3.1 Total Factor Productivity

Calculating the measure of TFP derives from a homogenous Cobb-Douglas technology using the EU KLEMS[8] growth and productivity accounts which combine an extended historical time series with a detailed breakdown at the industry level.[9] TFP in the industry sector j for country i is defined as:

$$TFP_{ij} = \frac{Y_{ij}}{L_{ij}^{\alpha} K_{ij}^{1-\alpha}}$$

where Y_{ij} indicates value-added in the respective industry, K_{ij} denotes physical capital input and L_{ij} labor service inputs in terms of hours worked. TFP in this context is modeled as the ratio of an output quantity index of value added to the weighted sum of quantity indices of capital and labor inputs where α, the average annual share of labor compensation in value added, serves as weight.[10] All variables are indexed such that 1995 equals 100.

TFP reveals an upward trend over the period 1985-2004, even though substantial variation is present across countries and industries. The different sectors show remarkable differences in average productivity growth rates (Table 1), which vary between -2.2% for coke, petroleum and nuclear fuel and +5.8% for electrical and optical equipment.

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[5] In the absence of measurement error.

[6] Australia (AUS), Austria (AUT), Belgium (BEL), Denmark (DNK), Finland (FIN), France (FRA), Germany (GER), Italy (ITA), Japan (JPN), Netherlands (NLD), South Korea (KOR), Spain (ESP) United Kingdom (UK), United States (USA).

[7] Only in the case of South Korea, one industry (Wood) must be dropped due to insufficient patenting activity.

[8] EU KLEMS database, March 2008, see [56] for a short overview and [57] for a detailed description of the underlying methodology.

[9] Most of the previous studies are based on the OECD STAN database. The advantages of the EU KLEMS database are the harmonized methodology in calculating capital stocks and the use of additional data sources to expand coverage [46].

[10] EU KLEMS uses Tornqvist indices for aggregation.

Table 1

Cumulative average annual growth rates of TFP (1985–2004)

Industry description	TFP growth rate
Food products, beverages, and tobacco	0.14
Textiles, textile products, leather, and footwear	1.32
Wood, products of wood and cork	1.43
Pulp, paper, paper products, printing, and publishing	0.34
Coke, refined petroleum products, and nuclear fuel	-2.23
Chemicals and chemical products	2.16
Rubber and plastics products	3.14
Other nonmetallic mineral products	1.44
Basic metals and fabricated metal products	1.23
Machinery	1.93
Electrical and optical equipment	5.79
Transport equipment	2.17
Manufacturing NEC, recycling	0.47

Notes: Averages are calculated over countries. Growth rates in %.
Source: EU KLEMS database. Own calculations.

Figures A.1-A.4 (Appendix) display the evolution of TFP in the R&D-intensive industries chemicals and chemical products; machinery; electrical and optical equipment; and transport equipment for selected countries. We find a positive trend in all sectors, with the growth of TFP highest in electrical and optical equipment, especially in the United States and Finland. Compared to this expansive growth, the average productivity increase in machinery is moderate, with the exception of France. In chemicals and chemical products, Germany shows the largest growth when comparing the initial with the final level, whereas France exhibits relatively weak progress. Transport equipment provides a mixed picture concerning the relative positions of countries, but overall reveals an upward trend.

3.2 Technological Proximity

Foreign spillover pools are constructed as the sum of foreign countries' established knowledge weighted by bilateral technological distance, which is supposed to reflect the ease of knowledge transcending boundaries. Technological proximity are calculated according to Jaffe [27], [28] who compares countries' positions in technology space. The potential to benefit from foreign R&D is affected by bilateral distance: the closer countries' profiles the more they will spur each other's research activities.

Initially, Jaffe's measure was developed to derive weights for potential spillover pools on the firm level. Subsequent studies applied it to the country level to characterize the similarity of innovative activities in countries (e.g. [37], [23]).[11] There are two main assumptions: 1. all countries possess an equal ability to appropriate knowledge [28], and 2. technology can flow directly without the need of letting goods circulate [22]. This second assumption is an important distinction to the approach suggested by Coe and Helpman [12], which relies on tradable goods and therefore focuses on rent spillovers.

We first identify the areas of innovative activity across technologies using technology areas defined by Schmoch et al. [54].[12] Formally, a vector covering the shares in patenting behavior over well-defined technological fields summarizes the technological position of a country. The number of elements in the vectors equals 44, one element for each field n in country i at time t:

$$F_{it} = \left(F_1 \quad \dots \quad F_{44}\right) = \left(\frac{P_{it1}}{\sum_{n=1}^{44} P_{itn}} \quad \dots \quad \frac{P_{it44}}{\sum_{n=1}^{44} P_{itn}} \right).$$

where P_{itn} is the number of patent applications filed in field n and F_{it} reflects the corresponding frequency distribution.

Using the angular separation of vectors of country i and k, the proximity measure PM_{ikt} is derived as:

$$PM_{ikt} = \frac{F_{it} F_{kt}'}{\sqrt{\left(F_{it} F_{it}'\right)\left(F_{kt} F_{kt}'\right)}}.$$

Intuitively, the measure is calculated as the uncentered correlation between two vectors of technological position. It is therefore bounded by 0 and 1, with a value of 1 indicating identical technological patterns of innovative activity. A proximity of 0 implies

[11] An application at the industry level is [42].
[12] The 44 technological fields are in Appendix A.2.

orthogonal positions in technology space with no potential to benefit from each other's research activities. The technological distance is calculated for every year and thereby underlies certain dynamics. Unlike the Euclidian distance, this approach is not sensitive to the length of vectors.

Table 2 displays the average pattern of technological similarity. In terms of technological distance, the United States and the United Kingdom are quite close. Overall, Japan and South Korea exhibit the lowest proximity on average to European countries, which reflects a slightly different pattern of specialization that might reduce their ability to benefit from European technological externalities.

Table 2

Average technological proximity (1985–2004)

	AUS	**AUT**	**BEL**	**DNK**	**ESP**	**FIN**	**FRA**	**GER**	**ITA**	**JPN**	**KOR**	**NLD**	**UK**	**USA**
AUS	1													
AUT	0.867	1												
BEL	0.841	0.805	1											
DNK	0.912	0.794	0.828	1										
ESP	0.892	0.882	0.817	0.870	1									
FIN	0.628	0.634	0.591	0.572	0.610	1								
FRA	0.914	0.899	0.859	0.833	0.901	0.718	1							
GER	0.859	0.909	0.865	0.780	0.865	0.660	0.949	1						
ITA	0.870	0.930	0.858	0.825	0.915	0.625	0.908	0.937	1					
JPN	0.741	0.690	0.744	0.616	0.673	0.608	0.846	0.792	0.715	1				
KOR	0.659	0.588	0.603	0.583	0.637	0.583	0.723	0.624	0.607	0.814	1			
NLD	0.818	0.764	0.806	0.723	0.756	0.697	0.887	0.824	0.788	0.918	0.778	1		
UK	0.943	0.841	0.887	0.898	0.882	0.692	0.955	0.888	0.873	0.841	0.737	0.885	1	
USA	0.899	0.766	0.866	0.846	0.801	0.645	0.908	0.842	0.810	0.889	0.754	0.901	0.962	1

Notes: Displayed is the average proximity over years (1985-2004).

3.3 Knowledge Stocks

In line with previous literature, we distinguish between intra- and inter-sectoral knowledge spillovers. The reasoning is that research carried out in other countries but within the same sector might stimulate certain local innovative activities more than those in other sectors due to the same underlying technology set. This requires the calculation of four distinct technological variables covering domestic externalities within the sector and from other sectors as well as international externalities, again in- and outside the sector.

We use patent applications as measures of innovative output to approximate existing knowledge. The information on patent applications made between 1985 and 2004 is taken from the European Patent Office's Worldwide Patent Statistical Database.[13] Applications are dated using the priority date.

The assignment of patents to industries covered by EUKLEMS is based on a concordance developed by Schmoch et al. [54], who use expert assessments and micro-data evidence on the patent activity of firms in the manufacturing industry to link technologies to industries. The technological classes contained in the patent application are linked to technological fields and then aggregated to industries based on the NACE code.[14]

We construct domestic and foreign knowledge stocks to model potential pools for spillovers. The domestic knowledge stock of country i originating from industry j at time t is denoted by S^{D}_{ijt}. It is indexed such that 1995=100 and calculated using the perpetual inventory method, which depreciates knowledge at a constant rate.[15] Compared to the evolution of TFP, the increase in S^{D}_{ijt} in the R&D-intensive industries is larger and smoother over time (Appendix Figures A.5-A.8). Especially in the chemicals and chemical products sector, we observe a uniform upward trend across all countries.

[13] PATSTAT 1/2008, maintained by the European Patent Office (EPO).

[14] The entire concordance of International Patent Classification (IPC) classes and NACE industries is given in Appendix A.1. A patent counts for each sector covered by its IPC classes.

[15] We assume a depreciation rate of 15% and an initial growth rate of 20% which is common in the literature.

The same holds for machinery; overall the domestic knowledge stocks rise on average by 50% between 1995 (our base year) and 2004, which is slightly less than in the chemical industry. Finland experiences a drastic knowledge increase in its electrical and optical equipment sector; the stock quadrupled in the second half of our estimation period. Finland is followed by Germany which doubles its domestic industry-specific stock. Transport equipment shows Germany and Japan in the lead while the other countries reveal a relatively lower but steady growth.

Knowledge potentially spilling over from other sectors in the economy is summarized by

$$S^{D}_{i-jt} = \sum_{m \neq j} S^{D}_{imt} \text{ ,}$$

which is simply the sum of the domestic stocks in country i, except for industry j. International knowledge stocks are constructed as the weighted sum over foreign knowledge stocks where bilateral technological distance serves as the weighting scheme. In the case of international intra-sectoral spillovers, i.e. within one industry, the corresponding variable is given by

$$S^{F\ prox}_{ijt} = \sum_{k \neq i} PM_{ikt} S^{D}_{kjt} \text{ .}$$

Accordingly,

$$S^{F\ prox}_{i-jt} = \sum_{k \neq i} \sum_{m \neq j} PM_{ikt} S^{D}_{kmt}$$

defines the inter-sectoral foreign knowledge available to country *i* and sector *j* originating from other countries and sectors.

To further control for the impact of the weighting scheme, we derive unweighted spillover variables as follows. Let the unweighted international spillover pool be denoted by S^{F}_{ijt} being the sum of foreign knowledge (available to country i) produced in industry j, and therefore representing international intra-sectoral spillovers. In the same manner, the inter-sectoral (other than sector j) foreign stock available to country i can be derived and is denoted by S^{F}_{i-jt}. Again, we transform all explanatory variables into index values with base year 1995. This ensures comparability by the freedom from units of measurement and erasing the industry- or country-specific differences in levels.

Tables 3 displays the summary statistics for the dependent and the explanatory variables used.

Table 3

Summary statistics: (1985–2004)

Variable	Description	Mean	S.D.	Min	Max
$\ln(TFP)$	Value-added based TFP growth, constructed as index with 1995=100	4.586	0.298	-0.252	7.157
$\ln(S_j^D)$	Domestic stock of patent applications in industry j, constructed as index with 1995=100	4.558	0.564	0.469	7.017
$\ln(S_{-j}^D)$	Domestic stock of patent applications in all industries, except j, constructed as index with 1995=100	4.569	0.604	1.718	6.811
$\ln(S_j^{F\,prox})$	Foreign stock of patent applications in industry j, countries weighted by technological proximity, constructed as index with 1995=100	4.579	0.360	2.815	5.390
$\ln(S_j^F)$	Foreign stock of patent applications in industry j, constructed as index with 1995=100	4.584	0.341	3.591	5.381
$\ln(S_{-j}^{F\,prox})$	Foreign stock of patent applications in all industries, except j, countries weighted by technological proximity, constructed as index with 1995=100	4.594	0.383	3.070	5.262
$\ln(S_{-j}^F)$	Foreign stock of patent applications in all industries, except j, constructed as index with 1995=100	4.598	0.367	3.893	5.231

4 Empirical Analysis

4.1 Estimation Model

To estimate the effect of different channels of knowledge spillovers on productivity in a multi-country, multi-industry setting, we use the model described in Section 2:

$$\ln\left(TFP_{ijt}\right) = \alpha_i + \beta_1\left(\frac{S^D_{ijt}}{S^D_{ij1995}}\right) + \beta_2 \ln\left(\frac{S^D_{i-jt}}{S^D_{i-j1995}}\right) + \beta_3 \ln\left(\frac{S^F_{ijt}}{S^F_{ij1995}}\right) + \beta_4 \ln\left(\frac{S^F_{i-jt}}{S^F_{i-j1995}}\right) + u_{ijt}$$

with $i = 1,...,14 \quad j = 1,...,13 \quad t = 1985,...,2004$.

We thereby allow for dissimilar coefficients of the knowledge stocks and country-specific fixed effects α_i, which cover determinants not included in our model. Note that each estimated coefficient could be interpreted as an elasticity of TFP with respect to the variable of interest. Because we cannot exclude the possibility of non-stationarity of our variables, we could face the spurious correlation problem when running regressions on this equation. Therefore, before estimating the model and interpreting the coefficients as reflecting the long-run relationship between knowledge stocks and productivity, we turn to the analysis of the stochastic properties of the underlying time series.[16]

4.2 Cointegration Preliminaries

The first step is to pre-test all variables to find whether they contain a unit root. Several procedures for testing the presence of unit roots in case of panel data have been suggested in the literature.[17] All approaches try to combine the time-series with the cross-sectional dimension of the data to improve inference on unit roots and cointegration. Given this background, a persisting problem is the asymptotic behavior of the test statistics as N and T both tend to infinity.

[16] Granger and Newbold [19] introduce the notion of spurious regression. Based on simulations, they show that regression analysis based on non-stationary data series produces statistically significant results that have no economic meaning except for the case of cointegration.

[17] Breitung and Pesaran [8] review recent developments in this field. Concerning the first generation of tests, see Banerjee [4].

Table 3 presents the results for four different unit root tests: Levin et al. [39], Breitung [7], Im et al. [26] and Hadri [24]. Levin[18] et al. [39] were one of the first to develop a panel unit root test, which tests the hypothesis of non-stationarity of all time series against the alternative of stationarity of all series. The hypothesis of non-stationarity cannot be rejected by the Levin et al. [39] test for all variables. Breitung [7] suggests a slightly different approach that conducts an adjustment before running the regression. Thereby, bias correction is no longer necessary. Also the Breitung [7] test cannot reject the null hypothesis that all panel members reveal a unit root. Im et al. [26] suggest a more flexible framework by allowing for heterogeneity in the autoregressive parameters. Hence, we can still hypothesize that all series are non-stationary under the null, but under the alternative only a fraction needs to be stationary. However, we find no evidence for stationary processes.

Table 4

Panel unit root tests (1985–2004)

Variable	**Levin, Lin and Chu**	**Breitung**	**Im, Pesaran and Shin**	**Hadri**
$\ln(\mathrm{TFP})$	5.116	1.790	0.098	43.089***
$\ln(S_j^D)$	8.358	1.113	-1.203	66.352***
$\ln(S_{-j}^D)$	31.203	2.898	5.788	78.012***
$\ln(S_j^{F\,prox})$	5.862	4.120	5.817	84.216***
$\ln(S_j^F)$	17.460	6.307	18.462	88.497***
$\ln(S_{-j}^{F\,prox})$	26.315	-1.159	-0.838	73.28***
$\ln(S_{-j}^F)$	12.902	2.749	17.515	96.126***

Notes: Significance levels of 10%, 5%, and 1% for the one-tailed tests are indicated by *, ** and ***. The null hypothesis of a unit root is rejected if the test statistic is significant in case of Levin et al. [39], Breitung [7] and Im et al. [26]. On the contrary, Hadri [24] tests the null of stationarity. Variables are demeaned to mitigate the impact of cross-sectional dependence. Lags are specified such that the Akaike information criterion is minimized.

[18] The test is often referred to as the Levin and Lin test because it started circulating as a working paper in 1992. Chu joined the co-authors in the published version.

If it can be argued that we are interested in showing that our variables are stationary, it might be more appropriate to test the null hypothesis of stationarity against the alternative of non-stationarity. As Hadri [24] points out, classical hypothesis testing tends to accept the null hypothesis unless the data series exhibits strong evidence for the alternative. He proposes a Lagrange multiplier-based test on the null of stationarity. We find that the hypothesis of stationarity can be rejected for all dependent and explanatory variables at the 1% level. As all tests rely on the assumption of cross-sectional independence, we demean all time series when conducting the panel unit root tests to mitigate the impact of dependence being prevalent in the data as suggested by Levin et al. [39].[19]

Having established that all variables exhibit a unit root, i.e. are non-stationary, we next conduct a panel cointegration test to ensure that a long-term relationship exists. Note that we consider panel cointegration as the long-term relationship between our dependent and explanatory variables being present in the countries and sectors. This is in sharp distinction to the concept of cross-member cointegration where the dependent variables of panel members are cointegrated.

Methods of testing for panel cointegration are receiving more attention, especially in empirical applications. The most influential contribution is Pedroni [47] [48] who develops several panel cointegration tests based on the residuals of the estimated regressions.[20] A weakness of this type of test is its dependence on a common factor restriction: long-run cointegrating vectors (with variables in levels) are supposed to equal the short-run adjustment parameters (for variables in differences). As a consequence, a number of studies, e.g. [25], fail to reject the null hypothesis of no-cointegration even in cases where it is predicted by economic theory. The explanation is that these tests lose significant power when the common factor assumption is violated [34]. For these reasons, Westerlund [61] suggests four additional cointegration tests that explicitly relax this assumption by focusing on short-run dynamics.[21] Starting from

[19] An alternative would be to use "second generation" panel unit root tests which relax the assumption of cross-sectional dependence, e.g. Chang [9] or Pesaran [50].
[20] Notable contributions to the literature are Kao [29] and Westerlund [60].
[21] The test is implemented using a STATA code provided by [49].

an error-correction representation of the data generating process, the coefficient of the error-correction term is used to test the null hypothesis of no-cointegration:

$$\Delta y_{it} = \delta_i' d_t + \alpha_i \left(y_{i,t-1} - \beta' x_{i,t-1} \right) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta x_{i,t-j} + \varepsilon_{it} .$$

Error-correction in this setup occurs if $\alpha_i < 0$, and therefore x_{it} and y_{it} are cointegrated. Accordingly, cointegration does not exist if $\alpha_i = 0$, which implies the corresponding specification of the null hypothesis (of no-cointegration).

Concerning the alternative hypothesis, two different kinds of statements are possible: one assumes that $\alpha_i = \alpha < 0$ for all i, or $\alpha_i < 0$ for at least one i. The first type of test is termed panel tests and the second group-mean tests. We choose one test out of each group to test for the existence of a cointegrating relationship between productivity and knowledge spillovers. As Westerlund [61] shows by means of Monte Carlo simulations, these tests outperform both their counterparts and Pedroni-style tests in terms of power even in the presence of cross-sectional dependence.

Table 5 displays the tests where the null of no-cointegration is firmly rejected by the panel-type test at the 1% significance level. The group-mean test also mostly rejects the null, especially when controlling for a deterministic trend in the cointegrating relationship. Evidence for cointegration is strongest for the specification including domestic intra- and inter-sectoral spillover sources and international intra-sectoral knowledge, weighted by technological proximity, which is the preferred specification in our estimations. Taken together, we find evidence for the existence of a long-run relationship between productivity and international knowledge spillovers.

Table 5

Panel cointegration tests (1985–2004)

Variable	Panel test		Group-mean test	
	No trend	Time trend	No trend	Time trend
$\ln(TFP), \ln(S_j^D), \ln(S_j^F)$	-9.901***	-10.495***	-1.365	-11.795***
$\ln(TFP), \ln(S_j^D), \ln(S_j^{Fprox})$	-10.441***	-35.841***	2.171	-7.493***
$\ln(TFP), \ln(S_j^D), \ln(S_{-j}^D)$	2.467	-5.647***	5.081	-8.897***
$\ln(TFP), \ln(S_j^D), \ln(S_{-j}^D), \ln(S_j^{Fprox})$	-4.253***	-4.703***	-2.006**	-10.938***
$\ln(TFP), \ln(S_j^D), \ln(S_{-j}^D), \ln(S_j^F)$	-25.715***	-43.727***	2.421	-4.505***
$\ln(TFP), \ln(S_j^D), \ln(S_j^{Fprox}), \ln(S_{-j}^{Fprox})$	-3.961***	-4.763***	-1.479*	-10.817***
$\ln(TFP), \ln(S_j^D), \ln(S_{-j}^D), \ln(S_j^F)$, $\ln(S_{-j}^F)$	-6.835***	-18.762	-4.721***	-3.448***
$\ln(TFP), \ln(S_j^D), \ln(S_{-j}^D), \ln(S_j^{Fprox})$, $\ln(S_{-j}^{F\,prox})$	-5.245***	-1.742**	0.977	-7.051***

Notes: Error-correction-based cointegration test developed by Westerlund [61]. The null hypothesis is absence of cointegration. Significance levels of 10%, 5%, and 1% for the one-tailed test are indicated by *, ** and ***. Lags are specified such that the Akaike information criterion is minimized.

4.3 Estimation Results

Having shown that the regressions will not be spurious, we now turn to the estimations. The two econometric methods applied to estimate the effect of knowledge spillovers are ordinary least squares (OLS) and dynamic ordinary least squares (DOLS). In case of cointegration, the standard OLS estimator is “super consistent”, i.e. estimated coefficients converge faster to the true value. Table 6 presents panel estimations with stepwise expanding specifications derived by means of OLS. Starting with the impact of domestic spillovers, we find a significant influence of both intra- and inter-industry spillovers (Model 1). Model 2 shows the alternative where we begin by focusing on the sectoral perspective and therefore only include national and international industry-specific knowledge stocks. Again a clear impact is observed for both spillover channels. Evidently, concentrating exclusively on either the sectoral or the national perspective is misleading, since both specifications seem to suffer from omitted variable bias. As a consequence, Model 3 encompasses both perspectives. Here we find that existing domestic knowledge is no longer significant when allowing for international spillovers within the industry. The coefficients of domestic and international sectoral channels remain robust and comparable in size relative to Model 2.

So far, we have used foreign knowledge stocks adjusted for technological bilateral distance since the emphasis of our analysis is on direct knowledge and not on rent spillovers. Wanting to know the sensitivity of the results to a change in the weighting pattern, we reestimate Model 3 with the unweighted sector-specific knowledge stocks S_j^F. The only difference occurring is the slight decrease in coefficient size of the respective variable, while domestic knowledge remains fairly stable. So far, knowledge from other countries within the same sector has a substantially larger impact on TFP than technological development in the national arena. To check whether international spillovers from other sectors also affect productivity, we include them together with national and international intra-sectoral knowledge (Model 5) and then in the full model specification (Model 6) as derived in Section 2. Again, domestic industry-specific spillovers are robust to these changes. International flows originating outside the industry turn out to be insignificant. The picture is slightly different for international intra-sectoral spillover sources: the corresponding coefficient only remains significant at the 10% level even though it increases substantially in magnitude. Its non-significance could be caused by the problem of collinearity. As Griliches [20] notes, estimations on international spillovers are often hampered by this type of obstacle, because the different series are usually closely related. This problem is frequently discussed in the empirical literature when assessing spillover channels on both the country-wide- and sector-levels (e.g. [41]). In our dataset, the correlation coefficient is highest – almost 0.9 – for the two foreign knowledge stocks whether or not we use the weighted or the unweighted type. Nevertheless, Lee [37] argues that since no clear criterion for determining the presence of collinearity exists, even correlations above 0.8 do not cause serious problems in this context.

Table 6

Estimation results OLS

	Model 1:	Model 2:	Model 3:	Model 4:	Model 5:	Model 6:
$\ln\left(S_j^D\right)$	0.108***	0.080***	0.081***	0.084***	0.082***	0.082***
	(0.019)	(0.015)	(0.020)	(0.020)	(0.014)	(0.014)
$\ln\left(S_{-j}^D\right)$	0.047***		-0.002	0.014		0.014
	(0.017)		(0.020)	(0.019)		(0.026)
$\ln\left(S_j^{F\,prox}\right)$		0.138***	0.139***		0.221*	0.228*
		(0.020)	(0.023)		(0.131)	(0.140)
$\ln\left(S_j^F\right)$				0.114***		
				(0.020)		
$\ln\left(S_{-j}^{F\,prox}\right)$					-0.082	-0.099
					(0.137)	(0.157)
Number of groups	181	181	181	181		181
Observations	3620	3620	3620	3620		3620

Notes: 1. Dependent variable: ln(TFP), 1985–2004.
2. Robust standard errors are given in parentheses below the coefficient estimates.
3. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.
4. All estimated models include unreported country-level fixed effects.

Even though OLS estimates are "super consistent" in the presence of cointegration, a shortcoming is their non-normal distribution due to the finite sample bias which arises in the cases of endogeneity of regressors or serial correlation in the error terms. Therefore, the usual t-statistics could be misleading. Chen et al. [10] compare the finite sample properties of OLS with its bias-corrected counterpart and fail to reveal substantial improvements. More promising alternatives are the fully modified OLS (FMOLS) (e.g [48], [51]) and the DOLS estimator (e.g. [53], [55]). Kao and Chiang [31] study the asymptotic distributions of OLS, FMOL and DOLS and conduct Monte Carlo simulations to compare the finite sample properties. Their results illustrate that FMOLS does not outperform OLS and that DOLS is superior to both OLS and FMOLS in terms of bias reduction.

Even though the DOLS estimator shares the limiting distribution of the FMOLS estimator, the obtained coefficients may vary remarkably. To avoid the bias of OLS, the DOLS estimator expands an OLS approach by lead and lag terms of first differences of the explanatory variables to control for endogeneity.[22] As Kao and Chiang [31] show, the estimated coefficients of DOLS depend on the chosen number of leads and lags. We follow the suggestion of Kao et al. [30] by including two lags and one lead of first differenced explanatory variables.

Table 7 presents the coefficient estimates of DOLS. With respect to statistical significance, the results corroborate our findings from the OLS estimations.[23] Comparing the size of the coefficients of Model 3 for OLS and DOLS, we observe that DOLS delivers a higher elasticity of the industry-specific international knowledge spillovers at the expense of a slightly lower effect of domestic stocks. While the estimated coefficient of $\ln\left(S_j^{Fprox}\right)$ is 0.139 for OLS, it increases to 0.157 for DOLS.

Overall, we find an effect of $\ln\left(S_j^{Fprox}\right)$ nearly twice as large as the domestic one in the DOLS estimations. The elasticity of foreign knowledge originating within the industry remains surprisingly stable (0.154) when replacing the technology proximity weighted stock by the unweighted one (Model 4). We therefore do not observe a substantial effect of the weighting scheme in our analysis, possibly due to the fact that technological distance is a bilateral concept, varying only over countries but not over industries. Estimating the full model again confirms the importance of local knowledge with an elasticity of TFP of 0.07. As in all specifications including international spillovers, we never find evidence for a linkage between TFP and domestic inter-sectoral spillovers. The inclusion of both international spillover stocks leads to insignificant coefficients, but as already discussed, the issue of collinearity might influence the results for this certain specification. Therefore, Model 3 becomes our preferred specification.

[22] Serial correlation is accounted for in the calculation of standard errors.
[23] Models 1 and 2 are provided to re-emphasize the importance of covering sectoral and international spillover sources.

Table 7

Estimation results DOLS

	Model 1	Model 2	Model 3	Model 4	Model 5
$\ln\left(S_j^D\right)$	0.104***	0.082***	0.074***	0.081***	0.071***
	(0.022)	(0.018)	(0.022)	(0.022)	(0.025)
$\ln\left(S_{-j}^D\right)$	0.038*		0.011	0.012	-0.014
	(0.021)		(0.027)	(0.023)	(0.042)
$\ln\left(S_j^{F\,prox}\right)$		0.152***	0.157***		0.192
		(0.025)	(0.026)		(0.168)
$\ln\left(S_j^F\right)$				0.154***	
				(0.025)	
$\ln\left(S_{-j}^{F\ prox}\right)$					-0.033
					(0.191)
Number of groups	181	181	181	181	181
Observations	3258	3258	3258	3258	3258

Notes: 1. Dependent variable: ln(TFP), 1985–2004.
2. Robust standard errors are given in parentheses below the coefficient estimates.
3. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.
4. All estimated models include unreported country-level fixed effects.
5. For the DOLS estimation, two lags and one lead of first differenced independent variables are included.

Our findings are in line with the empirical literature when stressing the importance of international knowledge spillovers. Initially, Coe and Helpman [12] provided evidence on the role of international R&D for enhancing productivity growth. Subsequent studies cast doubt on the results by raising methodological concerns, e.g., Kao et al. [30] reject the effect of foreign R&D to TFP by using panel cointegration techniques while Edmond [17] claims the relationship is unstable across alternative specifications.

We address the sector specificity of knowledge by distinguishing between inter- and intra-sectoral channels. Thereby, we are able to show that foreign knowledge is conducive to TFP growth, but only within industries and it may explain why the country-level evidence is mixed. Previous studies on R&D spillovers at the industry level also corroborate our finding that foreign knowledge spurs productivity (e.g. [41], [18]). Numerically, even though we adopt a different measurement approach by relying on patent data together with technological proximity to focus on pure knowledge spillovers, our elasticities of TFP concerning intra-sectoral spillovers take a similar direction: Frantzen [18] reports a value of 0.095 for domestic and 0.079 for international R&D stocks. Even though our results are of course not directly comparable, the domestic effect is surprisingly close, but our influence of knowledge originating from other countries is substantially higher. With Braconier and Sjöholm [6], we share the result of non-significance of knowledge within the country being generated in other sectors.

5 Conclusion

The theoretical and empirical literature suggests that knowledge transcending national boundaries contributes positively to productivity growth in other regions. Until recently, however, few studies focused on differences in technology transfer across sectors. The purpose of this paper was to assess the importance of different channels of spillovers at the industry level by distinguishing between domestic and international intra- and inter-sectoral technological externalities, clearly focusing on pure knowledge spillovers. Using patent data as a measure of innovative output to capture generated knowledge, we estimate the contribution of existing knowledge to industrial productivity. To account for technological distance between countries, we weight foreign knowledge by bilateral technological proximity.

The analysis is based on 14 OECD countries and 13 industries between 1985 and 2004. By adopting estimation methods reflecting recent developments in the treatment of non-stationary panel data econometrics, we find that industry-specific knowledge, both nationally and internationally, mainly drives productivity in the respective sector. By contrast, knowledge flows from other sectors of the economy prove to be ineffective channels for knowledge transmission. Cross-border flows from other countries and sectors also turn out to have no productivity-enhancing effect.

Our results confirm the notion that the international flow of ideas is an influential factor for productivity growth. However, the investigation of the different channels of spillovers shows that policies designed to enhance the flow of knowledge must be targeted to the industry level. Based on our results, we suggest that policies accounting for sector-specific differences will be more beneficial for stimulating technological innovation and increasing productivity – the two important challenges posed by the Lisbon Agenda for the European Union.

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Appendix A

Table A.1

Concordance assigning IPC classes to European NACE[24]

NACE[25] (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	B21C, B21G, B22D, C21B, C21C, C21D, C22B, C22C, C22F, C25C, C25F, C30B,

[24] Based on Schoch et al. [54].

[25] Nomenclature générale des activités économiques dans les Communautés européennes

	products	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, 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

Table A.2

Technological fields[26]

Number	Field	Number	Field
1	Food	23	Agricultural machinery
2	Tobacco	24	Machine-tools
3	Textiles	25	Special machinery
4	Wearing	26	Weapons
5	Leather	27	Domestic appliances
6	Wood products	28	Computers
7	Paper	29	Electrical motors
8	Publishing	30	Electrical distribution
9	Petroleum	31	Accumulators
10	Basic chemicals	32	Lightening
11	Pesticides	33	Other electrical
12	Paint	34	Electronic components
13	Pharmaceuticals	35	Telecommunications
14	Soaps	36	Television
15	Other chemicals	37	Medical equipment
16	Man-made fibre	38	Measuring instruments
17	Plastic products	39	Industrial control
18	Mineral products	40	Optics
19	Basic metals	41	Watches
20	Metal products	42	Motor vehicles
21	Energy machinery	43	Other transport
22	Non-specific machinery	44	Consumer goods

[26] Based on Schmoch et al. [54].

Figure A.1
TFP growth, 1995=100

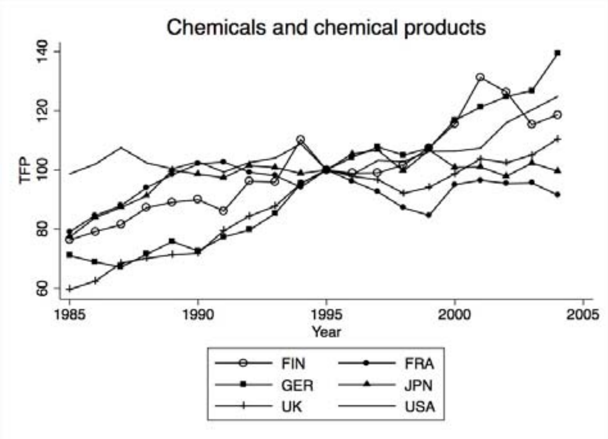


Figure A.2
TFP growth, 1995=100

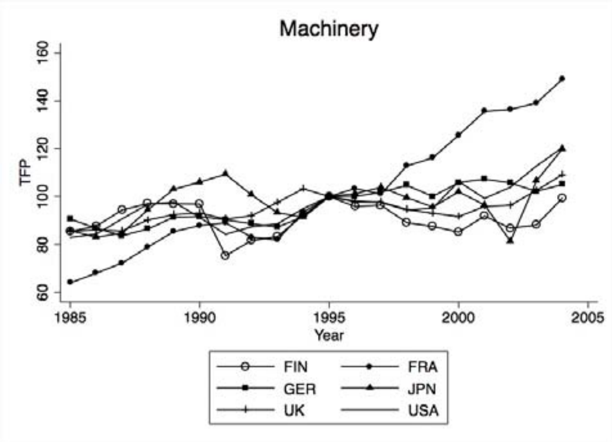


Figure A.3
TFP growth, 1995=100

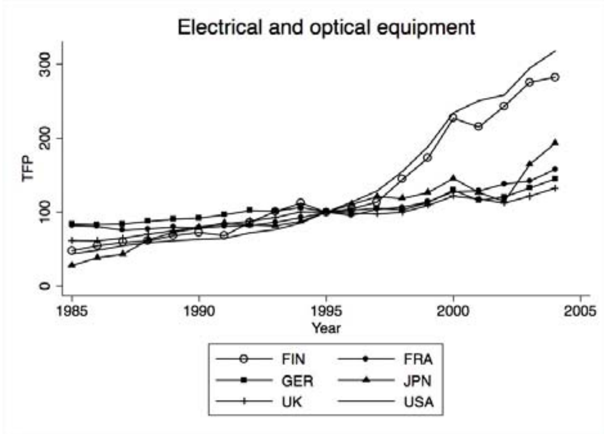


Figure A.4
TFP growth, 1995=100

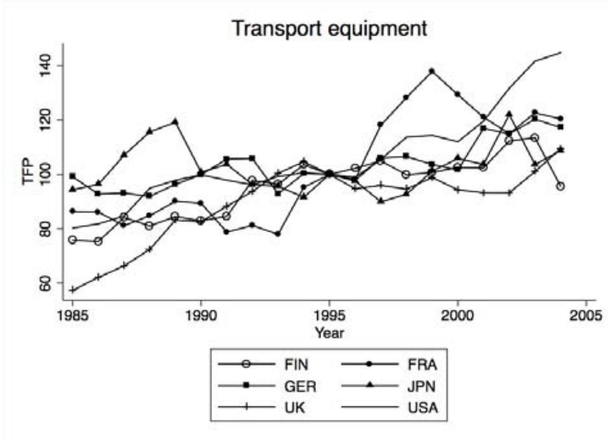


Figure A.5
Industry-specific domestic knowledge stock, 1995=100

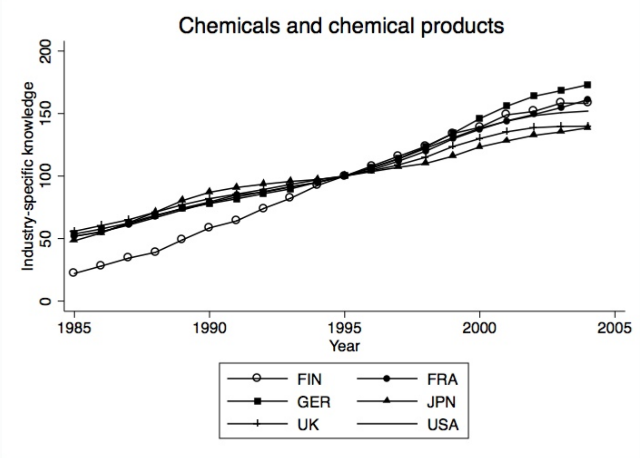


Figure A.7
Industry-specific domestic knowledge stock, 1995=100

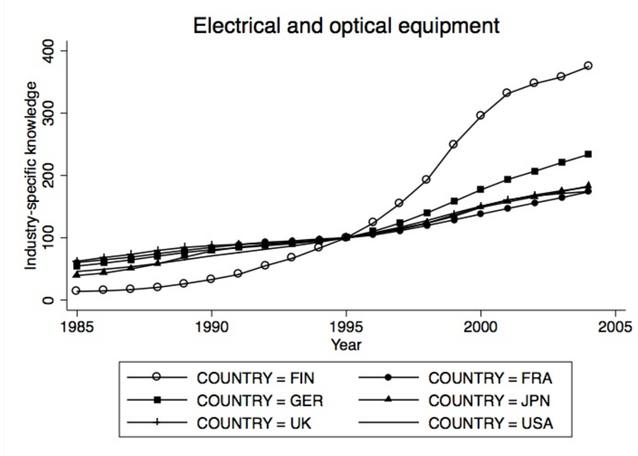


Figure A.6
Industry-specific domestic knowledge stock, 1995=100

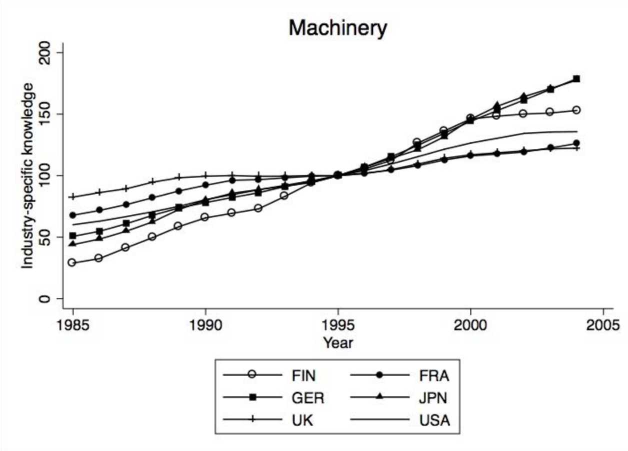
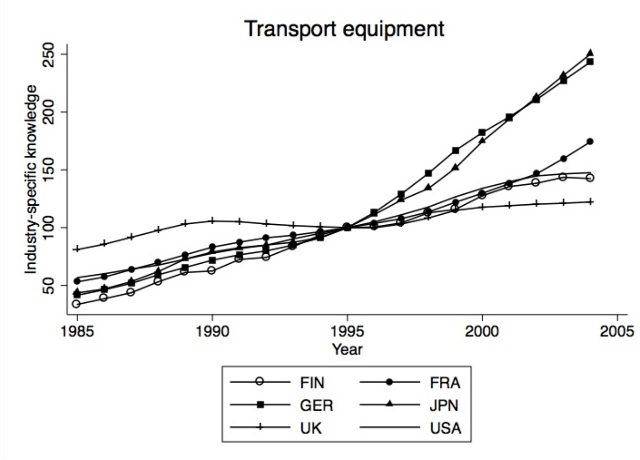


Figure A.8
Industry-specific domestic knowledge stock, 1995=100



4. Technological diversification and market value: An empirical analysis of U.S. manufacturing firms

Abstract

This paper analyzes the linkage between technological diversification and stock market valuation in order to identify the impact of technological relationship. We use U.S. manufacturing firm-level data on tangible and intangible assets and innovative activity between 1983 and 1995. Based on an expanded Tobin's *q* approach, we find that diversification implies a discount on the market value unless the new technologies are highly related to the existing ones. The estimated elasticity of technological diversification considering Tobin's *q* is 6%, but the discount drops to 4% for the 75% quartile of the relatedness distribution. We study the possibilities that diversification reduces the potential to benefit from economies of scale and that in cases of diversification additional spillovers can be received when a firm enters related technologies.

Keywords: Technological Diversification, Relatedness, Tobin's q, Patents, Knowledge Assets

JEL Classification: L25, 031, O32

1 Introduction

Most empirical research has evaluated the impact of knowledge assets such as R&D expenditures and patents on the market value of a firm, yet little has been published about the actual relationship between the range of a firm's innovative activity and its valuation by financial markets. Firms can either focus on a few key technologies or spread their activities over numerous fields, i.e. they are technologically diversified. A diversified firm must manage a portfolio of technologies when developing new products and services, but specialization suggests focusing on competencies [4], [23].

The impact of technological diversification on firm performance is mainly driven by economies of scale and scope [19], [34]. Firms acquire a specific technology portfolio, i.e. the range of technologies covered, which is then used as an input for future research projects. A firm's technology portfolio can either be highly concentrated on specific technologies, or provide access to a broad range of technologies [23]. Thus, an individual structure of a firm's technology portfolio determines its potential to exploit economies of scale and scope in future research.

While specialization in certain technologies generates economies of scale (e.g by learning effects [8]), technological diversification enhances the possibility of technological spillovers within and across firms [9]. Spreading the resources might enable firms to better make use of new technological opportunities or evolutions [28]. Furthermore, the transfer and application of knowledge to completely new technological fields becomes easier. Another argument used to promote diversification is risk reduction. As Scherer [35] notes, only 50% of all R&D projects are successful, implying that diversification could reduce the variance of returns to R&D, especially for large firms. Focusing on only a few technologies might leave firms with the risk of technological lock-in, implying that firms become trapped in their current technologies [38].

Recently, the concept of coherence has gained researchers' attention. The concept is that firms usually reveal some type of coherent pattern when diversifying, either at the product or at the technological level [24], [40]. Scott [36] argues that firms' activities generally follow purposiveness. Breschi et al. [4] illustrate that knowledge-relatedness is an important factor in shaping firms' technological diversification decisions. Empirical evidence reveals that relatedness to established technologies has a significant impact on observed diversification patterns. Nesta and Saviotti [29] suggest a measure of coherence of the knowledge base using patent data and find it an influential factor in explaining innovative performance. They even claim that the role of scope and coherence of the knowledge base is becoming increasingly important over time.

Despite the abundance of literature on technological diversification and relatedness, the impact of these two factors on the market value of a firm has been largely ignored. The only attempt we found that links knowledge assets, including coherence, to stock market valuation, is Nesta and Saviotti [30] for biotechnology firms. They use an aggregated integrated knowledge stock based on the measure of technological relatedness and observe a positive and significant impact of the adjusted knowledge stock on the market value. We include technological diversification, relatedness and size of knowledge assets separately in our expanded Tobin's q model on the theory that the market —depending on diversity and relatedness of the technology portfolios — can value two firms with equivalent tangible and intangible assets quite differently. Economies of scale and scope in R&D influence the cost structure of a firm and the related current and future cash flows.

Knowledge assets can be circumscribed using the knowledge creation process as suggested by Hall et al. [15]: R&D expenditures lead to innovations and thereby to patenting activities since patents can be interpreted as a measure of inventive output [31]. Citations being received by patents are then used as a method to approximate the economic value of individual patents [41]. Thus, we approximate knowledge assets using the three stock variables R&D, patents and citations, and amend the specification by the corresponding degree of technological diversification and relatedness. To determine technological diversification we exploit patent data since patents can be assigned to technologies which define the future range of action.

Some scholars suggest using product diversification measures instead (e.g. [39]). For our purposes, this is inappropriate, because product and technological knowledge belong to different stages of the value chain. Furthermore, Fai and von Tunzelmann [7] show that product and technological diversification are only directly connected in history while today's technological diversification is usually greater due to the far more complex technological environment [9]. The contribution of this paper is to elaborate on the influence of technological diversification, which is assumed to also anticipate the evolution of product and market diversification [33] on market valuation.

The remainder of the paper is organized as follows: Section 2 presents the theoretical framework. Section 3 introduces our measures of technological diversification and relatedness. Section 4 describes the data sources and Section 5 discusses the econometric specification and results. Section 6 summarizes our findings.

2 Value of Innovation

In an ideal world, the private returns to innovation would be measured directly. However, in the real world we only observe demand for goods and services but not for certain kinds of innovation. Therefore, market valuation serves as a proxy for the private returns to innovative efforts since public markets for these assets do not exist. Relating the measures of knowledge assets to the market value establishes their marginal contribution assuming that valuation by financial markets depends on the set of assets a firm possesses [13].

The market value encompasses all assets that will likely influence expected future cash flows and profits [6]. Obviously, changes in these assets will alter the expectations about uncertain future cash flows and hence the present value of the firm's expected revenue stream. The market value under simplifying assumptions should immediately react to changes in this stream and reflect the new revaluations. Predominant in the literature is the division of assets into tangible ones, i.e. plant, equipment and inventories, and intangible ones i.e. knowledge assets, usually approximated by R&D

expenditures, patent counts and patent citations.[1] Empirical studies on the relationship of intangible knowledge stocks and stock market valuation mainly conclude that financial markets reward innovative efforts (e.g. [15]).

However, we would argue that current measures of knowledge assets do not fully reflect all of the characteristics that affect market valuation. In fact, when assessing the potential for future performance, the number of technological fields and their relatedness add much useful information for shareholders and market operators. New technologies developed in the innovation process influence the market value and current knowledge assets serve as an input for future research projects and thereby determine the cost structure. Inputs like researchers, equipment and codified knowledge can be devoted to several technological areas but at varying costs. A widespread technology portfolio, i.e. the coverage of many technologies, may generate economies of scope in research. Future research in those fields will be less costly when the corresponding knowledge base is already established [39]. In contrast, specialization in certain technologies gives rise to economies of scale as firms benefit from learning effects [7].

The simple representation of a firm's market value can be traced back to Griliches [10] and is based on hedonic Tobin's *q* equations:

$$\mathrm{V} = \left[\mathrm{A} + \gamma \mathrm{K}\right].$$

In this typical model of the value function, the market value V is assumed to be a function of physical A and intangible knowledge assets K.[2] The firm invests continuously in its various assets to maximize its market value. The variable *q* can be interpreted as the current market valuation coefficient of a firm reflecting its monopoly position, differential risk and overall costs of capital adjustment.

We extend the standard version of the value function to capture technological diversification. Within this framework, the variable D denotes the technological fields where a firm can utilize its assets productively and generate future cash flows. We also

[1] Various approximations of intangible assets can be found in the empirical literature, e.g. [15], [3] and [37]

[2] We assume constant returns to scale of the value function.

allow the impact of technological diversification to vary with the degree of technological relatedness (R) between the technologies. R captures the amount of common knowledge across distinct technologies and thereby influences the potential to make use of economies of scope:

$$V = q\left[\left(A + \gamma K\right)D^{\theta+\delta R}\right].$$

The term δR adjusts the response of the market value to technological diversification (θ) by accounting for relatedness. Accordingly, this effect is either reduced or enhanced with this modification depending on the expected parameters of the model and the measure of relatedness.

To derive our hypothesis, we refer to the following arguments. Firms reduce their ability to exploit economies of scale when they diversify their technology portfolio. This is linked to the idea of economies of scale developed by Baumol et al. [2]. In contrast, the benefits generated by economies of scope depend on the amount of relatedness within the portfolio since it will be less costly to enter related technologies with the given knowledge base. Wernerfelt and Montgomery [42] argue that transferring technological knowledge to new fields might lead to a reduction in economic efficiency since factors of production contain a firm- and thereby field-specific component. Accordingly, the rent generated by these factors depends on the closeness of the current field and the newly created ones. Firms may still decide to spread their economic activity because of excess R&D capacity even though they then face a lower rent on their factors of production. The decision to cover many technologies can further be interpreted as an indicator for the degree of risk aversion of the decision-makers. Future returns of technological improvements are uncertain and diversification can reduce the variance of these returns. Mansi and Reeb [25] therefore argue that the negative impact of technological diversification can be interpreted as reflecting a risk premium.

In other words, we argue that technological diversification is valued negatively, i.e. causes a discount on the market value. This effect discount can be counterbalanced when diversification takes place in technologically related fields.

3 Measurement of Technological Diversification and Relatedness

To test our hypothesis, we measure technological diversification and the corresponding degree of relatedness in a firm's portfolio. In particular, we use the weighted and unweighted number of technological fields to capture diversification since we define diversification as innovative activities that span more than one technology. We suggest an index to approximate the degree of relatedness between technologies based on Teece's [40] approach of measuring corporate coherence.

3.1 Diversification

To capture technological diversification, we can use an unweighted count measure, which simply counts the areas of innovative activity, or weight them by economic relevance. We empirically test both alternatives. From an economic view, the simple count measure has the shortcoming of neglecting the unequal importance of technologies. Therefore, we also employ an entropy[3] measure to calculate the degree of technological diversification [21], which accounts for both the number of technologies and the distribution of innovative activity across them, and finds how concentrated a firm's activities are by weighting with relative importance.

Suppose all technologies are classified into N fields; we then use the share of the patenting activity S_j in each field *j* with patent count pc_j as weight:

$$S_j = \frac{pc_j}{\sum_{j=1}^{N} pc_j}$$

The weighting scheme mirrors the relative sizes of technological fields within a portfolio. It is obvious that the entropy measure assigns a lower contribution to total entropy to fields with small shares compared to the unweighted count measure. The total entropy of firm i's portfolio can be derived using the common formula

$$E_i = \sum_{j=1}^{N} S_{ij} \ln\left(\frac{1}{S_{ij}}\right), \qquad 0 \le E_i \le \ln(N).$$

The entropy takes on the value of zero in case of complete concentration in one field and is maximized at ln(N), when innovative activity is distributed equally across all technologies.

To make the entropy measure comparable to the unweighted count measure, we use a special variant of the entropy measure called its number-equivalent[4] counterpart, which is derived by:

$$NE_i = \exp\left(\sum_{j=1}^{N} S_{ij} \ln\left(\frac{1}{S_{ij}} \right) \right), \qquad 1 \le NE_i \le N.$$

1 and N, the total number of technologies, bound the number-equivalent entropy measure. Practically, the upper bound is defined by the technology classification scheme in use. NE_i equals 1 when a firm specializes completely in one technology. Only in cases of equal distribution of innovative activity across technologies, will its value equal the simple field count; otherwise it will be lower. Hence, a firm with a number-equivalent entropy of 5 — and actually serving seven fields — is seen as being as diversified as another firm engaged in five fields having 20% of their patents in each field.

3.2 Relatedness

Since we posit that the discount for technological diversification can be counterbalanced when a firm spreads its activities in related fields, we need a measure that will describe the degree of relatedness within the firm's portfolio. A first attempt to measure coherence in portfolios is conducted by Teece et al. [40] who argue that "activities which are more related will be more frequently combined within the same cooperation". Their assumption is based on the idea that inefficient combinations of activities will be erased by competition. This measure, sometimes termed the survivor measure of relatedness, studies the phenomena of corporate coherence by comparing the existing combinations of activities with random expectations. Nesta and Saviotti [29] adapt this concept to the coherence of a firm's knowledge base by exploiting patent

[3] The term entropy originally comes from thermodynamics. It captures the degree of organization within systems. There are applications in information theory as well as in corporate diversification, e.g. [20] and [32].
[4] Baldwin et al. [1] suggest using the number-equivalent entropy.

data.[5] Applying it to patents implies that patent classes exhibit technological relatedness if patents are assigned more often to the same combination of technological classes than expected. Instead of using patent classes, we conduct our analysis on the level of technological fields to determine the relatedness across technologies. The information on the relatedness of technologies is then used to calculate the coherence of a firm's technology portfolio as follows.

Suppose the total number of patents applied for by all firms is H and these H patents can be assigned to one or more technological fields according to the patent classification classes mentioned in the initial patent document. Let the variable P_{hj} take on the value of 1 if patent h is assigned to technology field *j* and 0 otherwise. Stacking this information across all patents (with N fields) gives us an $H \times N$ matrix containing only 0s and 1s:

$$P = \begin{pmatrix} P_{11} & \cdots & P_{1j} & \cdots & P_{1N} \\ \vdots & \ddots & & & \vdots \\ P_{h1} & \cdots & P_{hj} & \cdots & P_{hN} \\ \vdots & & & \ddots & \vdots \\ P_{H1} & \cdots & P_{Hj} & \cdots & P_{HN} \end{pmatrix}.$$

The observed number of joint occurrences of two technologies (l and j) is then given by the generic cells O_{lj} in the square matrix:

$$\Omega = P'P = \begin{pmatrix} O_{11} & \cdots & O_{1j} & \cdots & O_{1N} \\ \vdots & \ddots & & & \vdots \\ O_{l1} & \cdots & O_{lj} & \cdots & O_{lN} \\ \vdots & & & \ddots & \vdots \\ O_{N1} & \cdots & O_{Nj} & \cdots & O_{NN} \end{pmatrix}.$$

The next step compares the count of joint occurrences to its expected value under the hypothesis of randomness. Note that O_{lj} can either be affected by the relatedness of technologies l and j or the number of patents assigned to them. We therefore define a variable X_{lj} for the number of co-occurrences under the assumption of random joint

[5] A similar approach is found in Piscitello [34] and Breschi et al. [4], where the number of firms patenting in two or more fields is used to determine technological relatedness. In contrast, Leten et al. [23] compare the observed number of co-citations with its expectation.

occurrence, i.e. independence of technologies. X_{lj} is supposed to follow a hypergeometric distribution[6] with mean

$$\mu_{lj} = E\left(X_{lj} = x\right) = \frac{C_l C_j}{K}$$

and variance

$$\sigma_{lj}^2 = \mu_{lj}\left(\frac{K - C_l}{K}\right)\left(\frac{K - C_j}{K - 1}\right).$$

If the actual number of joint occurrences O_{lj} in technologies l and j exceeds its expected value μ_{lj}, we assume they are related. Of course, the opposite holds: if the actual number is small compared to the expected, we assume that the technologies are barely related. The measure of relatedness is thus based on the following test statistic:

$$t_{lj} = \frac{O_{lj} - \mu_{lj}}{\sigma_{lj}},$$

which can also be used to calculate p-values to test the significance of relatedness under the null hypothesis of random joint occurrence [4]. Calculating t_{lj} for all combinations of technologies leads to a symmetric $N \times N$ relatedness matrix.

Next, we proceed to the firm level and use this matrix to calculate a measure of coherence of the firm's technology portfolio. We derive the weighted average relatedness of technology j to all other technologies covered by firm i's portfolio:

$$WAR_{ij} = \frac{\sum_{l \neq j} t_{lj} pc_{il}}{\sum_{l \neq j} pc_{il}}.$$

WAR_{ij} shows the relatedness of technology j is weighted by the share of patents to all other technologies in the portfolio. Next, the weighted average relatedness vector is collapsed to a single measure of portfolio coherence

[6] K denotes population, C_l number of successes and C_j the sample size.

$$
\mathrm{COH}_i = \begin{pmatrix} ps_{i1} & \dots & ps_{ij} & \dots & ps_{iN} \end{pmatrix} \begin{pmatrix} \mathrm{WAR}_{i1} \\ \vdots \\ \mathrm{WAR}_{ij} \\ \vdots \\ \mathrm{WAR}_{iN} \end{pmatrix} \text{ with } ps_{ij} = \frac{pc_{ij}}{\sum_{j=1}^{N} pc_{ij}} .
$$

A positive value of COH_i suggests a generally high relatedness or complementarities between the technologies covered in the portfolio of firm i, while a negative value reveals poor relatedness. Changes in portfolio coherence can either occur because of modifications in the portfolio composition or because of alterations in the relatedness pattern.

4 Data and Descriptive Statistics

To estimate a market value equation, we need firm-level information on Tobin's *q*; data on knowledge assets such as R&D, patent and citations stocks; and our measures of technological diversification and relatedness.

We merge two datasets, the NBER Patent Database [14] and the Manufacturing Sector Masterfile [12], to create our unique database. The NBER Patent Database contains all patents granted by the United States Patent and Trademark Office (USPTO) between 1965 and 1996 and the corresponding patent citations. We exploit these data to calculate firm-specific patent and citation stocks using the perpetual inventory method.[7]

The Manufacturing Sector Masterfile contains firm-specific data which are based on the Compustat Annual Industrial Files. Firms are publicly traded on the American Stock Exchange and belong to the U.S. manufacturing sector. The Masterfile provides information on market value, book value of physical assets, and R&D investment. We calculate firm-specific R&D capital stocks, again derived according to the perpetual inventory method.

[7] We impose an initial growth rate of 20% to approximate the initial stock and a depreciation rate of 15%, which is common in the literature (e.g. [11]).

Firm-level data are linked to patent data by means of a match file provided by Hall et al. [14]. We caution that the problem with matching patent applications to firms is that while patents can be applied for under a variety of names, the Masterfile only contains one firm name. The so-called CUSIP match file resolves the problem by establishing unique linkages between firm names and patent applications.

To measure technological diversification and relatedness, we use the USPTO patent classification scheme[8] to define technological fields. Each patent is assigned to these fields based on the U.S. patent classes given in the application. Hence for each firm we have a complete description of its innovative activity: the number of patent applications in each technological field, the number of technologies covered — either weighted or unweighted — and the corresponding technological relatedness across technologies. Both measures, technological diversification and relatedness, are calculated as three-year moving averages since yearly data would be too volatile [30]. Hence, we assume that technology portfolio changes are at least medium-term decisions.

Merging our datasets (cleaning and dropping all companies with less than two patents in our observation period), gives us an unbalanced panel of 1700 firms for the period 1969 to 1995. The analysis is conducted using a sample from 1983 onward. Several important changes took place in the U.S. legal environment in the early 1980s, which enhanced the ability of patent holders to enforce their patents and led to increasing patenting activities of companies [22], [17]. The used version of the CUSIP match file only covers assignee names up to the year 1995; therefore our sample period ends at that year.

Table 1 displays the summary statistics for the estimation period 1983-1995. On average, the market value exceeds the book value by a factor of 1.8. Comparing mean and median of Tobin's *q*, we observe as expected a distribution skewed to the right. The average value of the R&D/asset ratio shows that R&D efforts of patenting companies are considerably higher compared to their assets.

Table 1

Summary statistics (1983-1995)

Variable	Description	Mean	Median	S.D.	Min	Max
Tobin's q	Market value	1.79	1.37	1.34	0	8.29
R&D/ Assets	Ratio of stock of R&D expenditures (deflated) to the book value of assets	0.35	0.17	0.70	0	19.45
Patents/ R&D	Ratio of patent stock to R&D stocks	1.01	0.55	5.11	0	333.33
Citations/ Patents	Ratio of patent citations to patent stock	12.99	10.20	10.09	0	179.01
Number Equivalent Entropy	Weighted number of technological fields covered by a firm's patent portfolio, measure of technological diversification	5.0	3.99	3.72	1	20.98
Number of Fields	Number of technological fields covered by a firm's patent portfolio, measure of technological diversification	8.28	5.00	7.97	1	39.00
Relatedness	Technological relatedness of fields within a firm's patent portfolio	8.87	5.35	13.65	-35.46	108.19

Notes: **Tobin's *q*** is derived as the sum of the common stock, the preferred stock, the long-term debt adjusted for inflation, and the short-term debt excluding assets. **R&D** stocks are deflated [12].

Turning to technological diversification, we find that firms are on average engage in 8 fields. Using the number equivalent entropy reduces this number to 5. No observed company is active in all fields. The maximum portfolio size equals 39 technologies, but the number drops to 20 when the number equivalent entropy is applied, since there are numerous fields of minor importance. Figure 1 shows the kernel densities of weighted and unweighted measures of technological diversification to illustrate their distribution. The majority of firms include up to 6 fields within their technology portfolios, but seldom more than 10 fields.

[8] The USPTO classification scheme is in Appendix 1.

Figure 1

Kernel densities (Epanechnikov) for weighted and unweighted number of technological fields

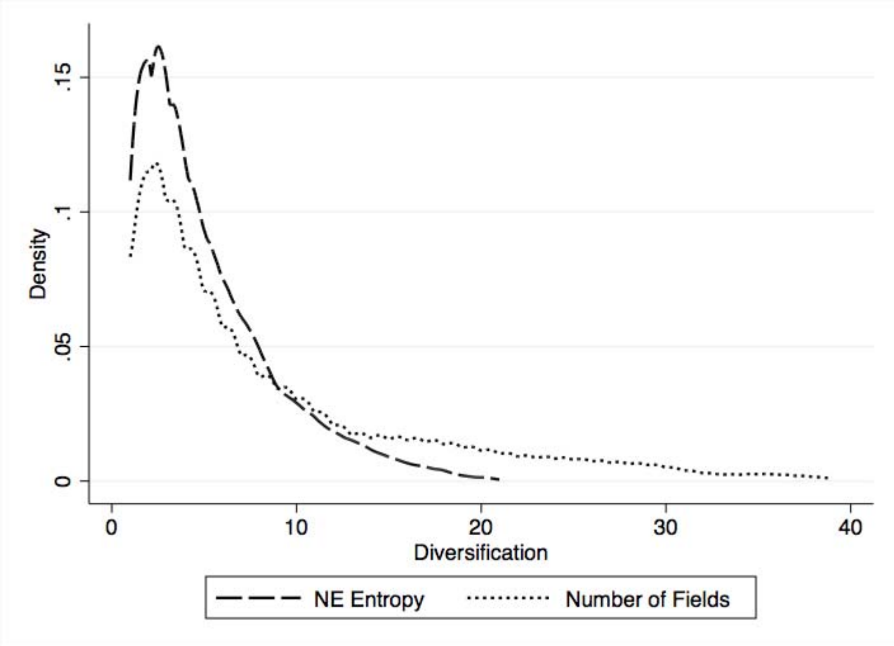
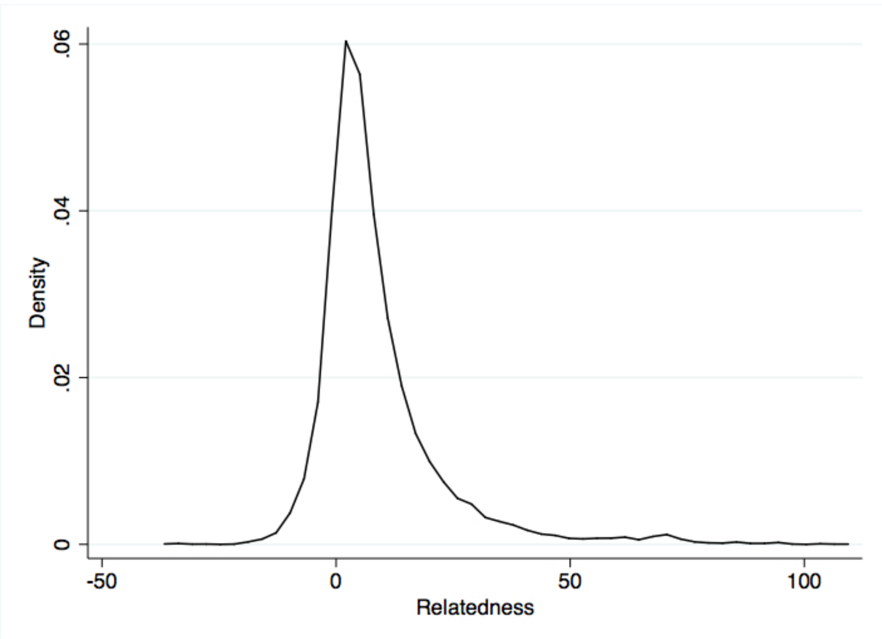


Figure 2

Kernel density (Epanechnikov) for technological relatedness



The measure of technological relatedness ranges from -35.46 (less-related than expected) to 108.19 (more-related than expected). Figure 2 shows the corresponding estimated kernel density. The distribution is centered around 0 with a median value of 5, and suggests that the majority of firms exhibit a related technology portfolio. This result might be the first indication of a strategic alignment focusing on expansion into related technologies.

5 Empirical Analysis

5.1 Methodology

After our theoretical model, moving the book value $\left(A_{it}\right)$ to the left side and taking logs leads to our fundamental estimation equation, which has the conventional Tobin's *q* (of firm i at time t) as the dependent variable:

$$\ln\left(Q_{it}\right)=\ln\left(\frac{V_{it}}{A_{it}}\right)=\ln\left(q_t\right)+\ln\left(1+\gamma\frac{K_{it}}{A_{it}}\right)+\theta\ln\left(D_{it}\right)+\delta\ln\left(D_{it}\right)R_{it}+u_{it}.$$

The deviation of Tobin's *q* from unity thus depends on the ratio of intangible capital to assets, technological diversification $\left(D_{it}\right)$, relatedness $\left(R_{it}\right)$ and a constant $\left(\ln\left(q_t\right)\right)$, which captures its current market valuation coefficient. We note that by taking the logarithm we are left with the usual entropy measure in our estimation equations. For explanatory purposes, we refer to the number-equivalent entropy in the upcoming discussion of the results, since the estimated coefficient together with the relatedness adjustment equals the elasticity of the market value with respect to the number of technological fields.

There are two different approaches in the literature regarding the treatment of the non-linear term $\ln\left(1+\gamma\frac{K_{it}}{A_{it}}\right)$. Approximating[9] the term by $\gamma\frac{K_{it}}{A_{it}}$ leads to linearization of the estimation equation. The accuracy of the approximation depends on the magnitude of $\frac{K_{it}}{A_{it}}$, and generally speaking, the smaller the term the better the approximation. Even though a non-linear estimator avoids committing an approximation error, it reveals a major shortcoming because it restricts us to the use of a pooled model without controlling for unobserved heterogeneity. However, firms are likely to exhibit various inter-firm differences such as unmeasured capital components, monopoly power or market characteristics that influence the magnitude of Tobin's *q*. Still, it is possible to claim that the high correlation between individual heterogeneity and slowly changing R&D intensities leads to an over- correction of R&D effects [15], [26]. We argue instead that the correlation between individual effects, explanatory variables and existing inter-firm differences creates biased coefficient estimates, unless we control for them. Therefore this leaves only the risk of a bias due to the approximation of the non-linear logarithmic term. Approximating and defining q_{it} by

$$q_{it} = \exp\left(\eta_t + m_i + u_{it}\right),$$

with time effects η_t and unobserved heterogeneity m_i, leads to:

$$\ln\left(Q_{it}\right) = \gamma \frac{K_{it}}{A_{it}} + \theta \ln\left(D_{it}\right) + \delta \ln\left(D_{it}\right) R_{it} + \eta_t + m_i + u_{it}.$$

The empirical literature on innovation suggests various approaches to specify the knowledge assets $\left(K_{it}\right)$ of a firm. We follow Hall et al. [15] who define the knowledge creation process as a continuum starting with R&D, proceeding with patents and ending with citations. Every step adds further information about the value of innovations. R&D exhibits the commitment of a firm to promote innovation; patents are interpreted as the corresponding output indicator; and citations measure the extent to which these innovations turn out to be "important" and valuable for the firm [41], [18]. Instead of dividing all three measures by physical assets which would introduce the problem of collinearity, we include ratios according to the relative positions in the knowledge creation process. Our linear estimation equation is therefore:

$$\ln\left(Q_{it}\right) = \left(\gamma_1 \frac{R\&D_{it}}{A_{it}} + \gamma_2 \frac{Pat_{it}}{R\&D_{it}} + \gamma_3 \frac{Cit_{it}}{Pat_{it}}\right) + \theta \ln\left(D_{it}\right) + \delta \ln\left(D_{it}\right) R_{it} + \eta_t + m_i + u_{it}.$$

A first look at the correlation matrix reveals the expected positive correlations between R&D intensities and citations per patents and the logarithm of Tobin's *q* (Table 2). The magnitude of correlations with Tobin's *q* differs substantially, from 0.3 with citations

[9] Approximation: ln(1+x)=x if x is small.

per patents to 0.02 with patents per R&D. In line with our hypothesis, our measures of technological diversification — the number equivalent entropy measure and the number of technologies — are negatively correlated with Tobin's q.

Table 2

Correlation matrix (1983-1995)

Variable	**Log (Tobin's q)**	**R&D/ Assets**	**Patents/ R&D**	**Citations/ Patents**	**Num. Equ. Entropy**	**Number Fields**
Log (Tobin's q)	1					
R&D/ Assets	0.19	1				
Patents/ R&D	0.02	-0.05	1			
Citations/ Patents	0.30	0.17	0.01	1		
Number Equ. Entropy	-0.14	-0.12	-0.01	-0.15	1	
Number of Fields	-0.07	-0.09	-0.01	-0.09	0.85	1
Relatedness	0.14	0.07	0.01	0.02	-0.29	-0.17

5.2 Results

A first impression of the stock market valuation of technological diversification is gained by comparing the average Tobin's q across different portfolio sizes. Figure 3 displays the averages for different degrees of diversification measured by the number-equivalent entropy. We observe that the average q is maximal for firms covering roughly 2 or 3 fields. The average q of firms concentrating on one field is lower which could indicate that the market appreciates reaching a minimum threshold of technological diversification. After the second and third fields, the average q steadily declines until the seventh field, where q is about 0.4 lower compared to a firm engaged in two technologies. Overall, we find the first descriptive evidence for a negative relationship between the degree of technological diversification and the market value.

Figure 3

Mean Tobin's *q* at different degrees of technological diversification

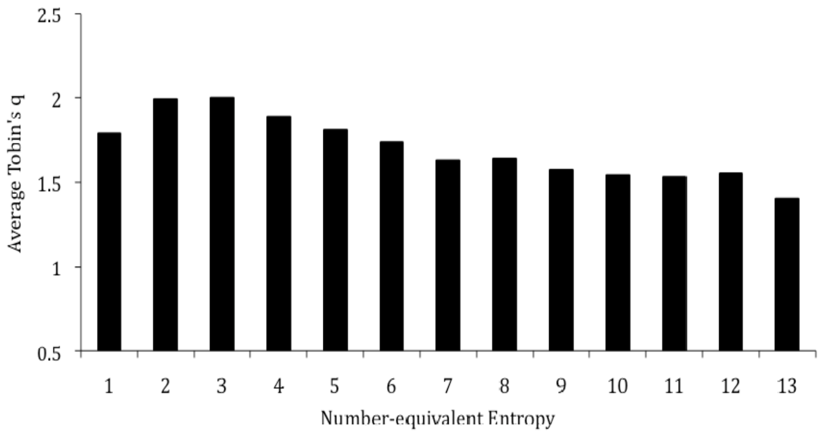


Table 3 presents the estimation results under the linear approximation of the term encompassing the knowledge assets. Starting with the simplest approach to approximate knowledge including patents, citations and R&D, the specification is expanded stepwise by including technological diversification and relatedness.

The specification in Model 1 is our benchmark model, covering the whole knowledge creation process with R&D, patents and citations. Applying a pooled OLS estimator, we find that R&D, patents and citations reveal a stable, positive and significant impact on a firm's market value. Model 2 exploits the panel structure of the data by using a fixed effects estimator. An F-test on the significance of individual effects indicates the presence of unobserved heterogeneity. The Hausman-test rejects the null hypothesis of zero correlation between individual effects and explanatory variables; therefore, a fixed effects approach is used. However, the impact of R&D, patents and citations still remain positive and significant, even though the coefficients become substantially smaller, which is not surprising due to the exploitation of within variance. Knowledge stocks are known to change only slowly over time and in particular R&D expenditures remain rather stable. The largest drop occurs in the case of citations per patents where the coefficient reduces to less than half of the pooled one.

Table 3

Estimation results of the linear model

	Model 1: OLS	Model 2: FE	Model 3: FE	Model 4: FE	Model 5: FE	Model 6: FE
R&D/Assets	0.094***	0.050**	0.048**	0.046**	0.052*	0.046
	(0.018)	(0.021)	(0.021)	(0.021)	(0.030)	(0.031)
Pat/R&D	0.005***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Cit/Pat	0.017***	0.007***	0.007***	0.007***	0.007***	
	(0.002)	(0.002)	0.002	(0.002)	(0.002)	
Entropy			-0.060***		-0.074***	
			(0.018)		(0.024)	
log(Number Fields)				-0.059***		
				(0.016)		
Entropy*Related					0.002**	
					(0.001)	
Entropy (corr.)						-0.069***
						(0.024)
Entropy*Related (corr)						0.002**
						(0.001)
log(Sales)						-0.040
						(0.028)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	0.410***	0.204***	0.292***	0.618***	0.620***	0.807***
	(0.035)	(0.031)	(0.041)	(0.042)	(0.051)	(0.197)
Observations	7826	7826	7826	7826	7084	7084
Firms	1007	1007	1007	1007	950	950
R-squared (overall)	0.163	0.142	0.139	0.123	0.175	0.163

Notes: 1. Dependent variable: logarithm of Tobin's *q*, 1983-1995.
2. All models include a dummy for non-reported R&D.
3. Robust standard errors are calculated by clustering at the firm level. Standard errors are given in parentheses below the coefficient estimates.
4. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Introducing the entropy measure (Model 3) which captures technological diversification shows a negative and significant influence with a coefficient of -0.06. This corresponds to an elasticity of the weighted number of technological fields (D) with respect to the market value of minus 6%. Hence, a firm with equivalent tangible and intangible assets and with a second field in its technology portfolio (compared to another firm with one field only) experiences a discount in its market value of 6%. The coefficients of the other knowledge stock variables are not affected.

Model 4 uses the logarithm of the simple count measure instead of the entropy measure to control for the impact of the weighting scheme. Again we find a negative and significant impact with a coefficient being absolutely similar in size. This is not surprising since the number-equivalent entropy is bounded from above by the unweighted count measure; the number of technologies will generally be at least as large as the corresponding weighted measure. The point estimate of -0.06 implies again an elasticity of the size of the technology portfolio with respect to Tobin's q of 6%. Our estimations therefore reveal no remarkable difference between the two measures of technological diversification. However, we believe that weighting according to economic relevance is a meaningful task and therefore experimented with a Herfindahl index of diversification, obtaining similar results even though the interpretation is not as straightforward since the Herfindahl index lies between 0 and 1.

Model 5 introduces the measure of technological relatedness which helps to distinguish between the different effects of economies of scale and scope. Only companies with large portfolios, i.e. at least two technologies, can exhibit technological relatedness. The analysis is therefore restricted to firms engaged in a minimum of two fields. The parameters summarizing the knowledge stocks remain stable compared to the other models. All parameters exhibit a positive influence on Tobin's q and are mainly significant at the 5% level. As suggested by our hypothesis, the coefficient of the interaction term is negative, suggesting a counterbalancing effect in the case of large and related technology portfolios. Evaluated at median relatedness and entropy, we find a discount of 6%. This discount reduces to 4% for the 75% quartile of the distribution of relatedness, implying that highly related technology portfolios experience smaller losses. Hence, stock market valuation strongly depends on the perception of whether or not firms diversify into technologically-related areas. We believe this relationship is firms' ability to exploit economies of scope drops when enlarging their portfolios to unrelated technologies and that spreading into related areas increases the possibility to benefit from economies of scope, which in turn can reduce the costs of R&D and increase future profits.

As a robustness check, Model 6 contains a size-corrected entropy measure constructed by regressing the entropy and the interaction term on the logarithm of sales and utilizing the residuals. We develop Model 6 because it is often argued that portfolio size is mainly driven by firm size. We further include sales as an explanatory variable. The coefficients of technological diversification and relatedness are hardly affected by this correction, which is more evidence for the robustness of our results and the absence of a size effect in our analysis.

Now, we compare the linear estimation results with the exact non-linear specification of the model (Table 4). In contrast to the linear specification, the parameters of R&D, patents and citations in the non-linear pooled model exceed those of pooled OLS and fixed effects (Table 3). The difference in size between pooled OLS and pooled non-linear is caused by the linear approximation of the logarithm.

As expected, the coefficients of the entropy measure and the relatedness interaction term are comparable in size to the linear model, probably because they are outside the non-linear part of the equation (Table 4, Model 1). However, the coefficient of the relatedness adjustment term becomes substantially larger, which emphasizes the importance of diversifying into related technologies. In contrast, the coefficient of the number of technologies — the entropy measure — becomes smaller. In total, this will lead to a reduction in the corresponding elasticity. The elasticity of technological diversification with respect to Tobin's q — evaluated at mean entropy — is minus 4% at the 25% quartile of the relatedness distribution. At the median, it reduces to 0.6%. For high levels of relatedness, we find a positive elasticity, e.g. 5% for the 75% quartile. This implies that firms could even benefit from diversifying into technologically-related fields by exploiting economies of scope via a common knowledge base.

Table 4

Estimation results of the non-linear estimations

	Model 1: NL OLS	Model 2: NL OLS	Model 3: NL OLS
R&D/Assets	0.291***	0.306***	0.166***
	(0.034)	(0.036)	(0.020)
Pat/R&D	0.018***	0.023***	0.013***
	(0.004)	(0.004)	(0.002)
Cit/Pat	0.045***	0.047***	0.034***
	(0.004)	(0.004)	(0.003)
Entropy	-0.051**		-0.043*
	(0.022)		(0.022)
Entropy*Related	0.006***		0.007***
	(0.001)		(0.001)
Entropy*Related (25%)		-0.056**	
		(0.023)	
Entropy*Related (50%)		-0.054**	
		(0.023)	
Entropy*Related (75%)		-0.041	
		(0.028)	
Entropy*Related (100%)		0.022	
		(0.035)	
High-Tech			0.100*
			(0.53)
Stable Tech (long run)			-0.115**
			(0.057)
Stable Tech (short run)			-0.002
			(0.074)
Year dummies	Yes	Yes	Yes
Observations	7084	7048	7084
R-squared	0.438	0.429	0.450

Notes: 1. Dependent variable: logarithm of Tobin's *q*, 1983-1995.
2. Robust standard errors are calculated by clustering at the firm level. Standard errors are given in parentheses below the coefficient estimates.
3. **High-Tech** and **Stable-Tech** denote dummy variables. The classification scheme is - in Table A.2 of the Appendix.
4. **Entropy*Related (x%)** denotes an interaction term of the entropy and dummy variables for the x-quartiles of the relatedness distribution.
5. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

To allow for a varying impact of technological diversification at different degrees of relatedness, we generate interaction terms of diversification and dummy variables indicating the quartiles of the relatedness measure distribution (Model 2). Firms revealing a low degree of relatedness in their portfolios, the 25% percentile, exhibit a significantly negative impact. This corresponds to an average discount for firms with unrelated portfolios of nearly 6% for an additional technology. The coefficient for the second quartile — again portfolios with a degree of relatedness smaller than the median — is also negative, significant and comparable in size. In the upper 50% of the distribution the results are less compelling. Even though we observe larger coefficients which are in line with our argument, they are no longer significant. This result still indicates that the negative impact on the market value diminishes as the relatedness within the portfolio rises, since a significant discount occurs in the case of unrelated portfolios.

Finally, we include industry effects according to segments developed by Chandler [5] as a last robustness check (Model 3). The segments are based on technological dynamics and distinguish between high-tech, stable-tech and low-tech industries. The results show that some sort of technological fixed effect does not drive the coefficients of technological diversification and relatedness. As expected, firms in high-tech industries experience a significantly higher Tobin's q on average. In contrast, no systematic difference occurs in the market value of stable-tech industries.

6 Conclusion

This paper analyzed the impact of technological diversification on stock market valuation. We showed that in addition to the common knowledge stocks used to describe intangible assets — R&D, patents and citations — two additional properties of intangible assets significantly affect the market value of a firm: technological diversification and the degree of relatedness within the technology portfolio. The range over which a firm spans its innovative activities affects its ability to benefit from economies of scale and scope in innovation and thereby affects future profits. Based on a theoretical framework using an expanded Tobin's q approach, we found evidence for a negative influence of technological diversification on market value. This discount can be counterbalanced partly when the relevant fields share a common technological base, which is approximated by the degree of relatedness.

In the linear version of our model, we found a diversification discount, evaluated at median relatedness and entropy, of 6% per additional field. This discount reduces to 4% for the 75% quartile of the distribution of relatedness, implying that highly related technology portfolios experience a smaller loss. The picture changed slightly when a nonlinear estimator was applied. We observe a discount of 4% at the 25% quartile of the distribution, evaluated at mean entropy. At the median, this reduces to 0.6%. For high levels of relatedness, we even find a positive elasticity, e.g. 5% for the 75% quartile. Hence, it might occur that a firm benefits from additional technologies.

Generally speaking, enlarging the technology portfolio in unrelated fields negatively influences the market value of a firm, because it reduces the ability to exploit economies of scale and scope. Our results suggest that under the objective of value maximization, the composition of the technology portfolio plays an important role for valuation by financial markets. This aspect should be taken into consideration when deciding to expand research activities into new areas, and the relatedness of the current technologies and the targeted new field or fields should be analyzed as well. We conclude that a properly designed diversification pattern can substantially influence future profits and market value.

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Appendix A

Table A.1

Classes within the U.S. classification system (December 2006)

Field	Description
1	Superconductor technology: Apparatus, material, process
2	Nanotechnology
3	Life and agricultural sciences and testing methods
4	Stock materials; articles
5	Compositions and synthetic resins; chemical compounds
6	Chemical processing technologies: processes and apparatus
7	Calculators, computers, or data processing systems
8	Information storage
9	Measuring, testing, precision instruments
10	Electricity, heating
11	Electro-mechanical systems
12	Electricity: Subsystems, components or elements
13	Ammunition, weapons
14	Body treatment care, adornment
15	Apparel and related arts
16	Plant and animal husbandry
17	Teaching
18	Amusement devices
19	Foods and beverages: apparatus
20	Heating, cooling
21	Buildings
22	Receptacles
23	Supports
24	Closures, partitions, panel
25	Textiles
26	Earth working and agricultural machinery
27	Check-actuated control mechanisms
28	Dispensing
29	Material or article handling
30	Fluid handling
31	Vehicles
32	Motors, engines, pumps
33	Coating, printing, and printed material; stationary, books
34	Manufacturing, assembling, including some correlative miscellaneous products
35	Cutting, comminuting, and machining
36	Miscellaneous treating
37	Handling or storing sheets, webs, strands, and cable
38	Machine elements or mechanism
39	Miscellaneous hardware
40	Tools
41	Joints and connections
42	Fastenings

Table A.2

Technology segments according to [5], [16]

Segment	Industry code (SIC) Description	Industry code (SIC)
High-tech (1)	Electronic computing equipment	3570-3573 3575 3576 3577
	Calculating machines excl. comp.	3578
	Refrigerating & heating equip.	3580-3582 3585 3589 3596
	Power distribution & transformers	3612
	Switchgear & switchboard apparatus	3613
	Motors, generators & industrial controls	3600 3620 3621 3622 3625
	Electronic & electric coils & connectors	3524 3677
	Household refrigerators & freezers	3630 3631 3632 3633 3635 3639
	Lighting fixtures & equipment	3640 3641 36425 3646 3647 3648
	Primary & storage batteries	3691 3692 3693
	Engine elctrical equipment & misc	3694 3699
	Electronic & electric connections	3643 3644 3678
	Electronic signaling & alarm systems	3669
	Radio & TV broadcasting sets	3663
	Radio & TV receiving sets	3651
	Records, magnetic, &optical recording	3652 3690 3695
	Communication equipment	3661 3662 3669 4810 4812 4813
	Electron tubes	3671
	Semiconductors & printed circuit boards	3672 3674 3675 3676
	Electro. components, computer acc.	3670 3679
	Engineering scientific instruments	381x
	Measuring & controlling devices	382x
	Aircraft parts & engines	3720 3721 3724 3728
	Ship & boat building & repairing	373x 3795
	Railroad equipment	374x
	Complete guided missiles, aerospace	376x
	Optical instruments & lenses	3827
	Dental equipment & supplies	3843
	Surg. & med. inst., appliances, & supplies	3840 3841 3842
	X-ray apparatus	3844
	Photographic equipment & supplies	3861
	Electromedical apparatus	3845
	Pharmaceuticals	283x
	Opthalmic goods	3851

Stable-tech (2): long horizon	Industrial inorganic chemicals	281x
	Plastic materials & resins	282x
	Paints & allied products	285x
	Industrial organic chemicals	286x
	Fertilizer	287x
	Explosives & misc. chemicals	289x
	Asphalt, roofing & misc coal/oil prods	2950 2951 2952 2990 2992 2999
	Petroleum & refining	291x 1311 1389
	Steelworks, rolling & finishing mills	331x
	Iron & steel foundries	332x
	Primary metal products	339x
	Prim aluminum smltg, reg, roll, &draw	3334 3353 3354 3355
	Primary smeltg & refing (non-ferrous)	3330 3331 3332 3333 3339
	Secondary smeltg & refing (non-fer.)	334x
	Rolling, drawing, & extruding of nonferr.	3350 3351 3356
	Drawing & insulating of nonfer. wires	3357
	Nonferrous metal casting	336x
	Turbines, generators, & combustion eng.	351x
	Lawn, garden & farm mach. & equip.	3523 3524
	Const. & mining mach. & equip.	3530 3531 3532
	Oilfield machinery	3533 3534
	Conveyors, ind. trucks&cranes, monorails	3535 3536 3537
	Mach. tools, metalworking eq. & acc.	354x excl. 3548
	Special industrial machinery	3550 3559
	Food prods & packaging machinery	3556 3565
	Textile machinery	3552
	Wood & paper industry machinery	3553 3554
	Printing trades machinery & equip.	3555
	Pumps & pumping equip.	3561 3586 3594
	Ball & roller bearings	3562
	Compressors, exhaust., & ventilation fans	3563 3564 3634
	General industrial machinery	3560 3568 3569 359x
	Ind. high drives, changers & gears	3566
	Industrial process furnace ovens	3567 3558
	Scales & balances excl. laboratory	3596
	General office machines	3579
	Motor vehicles	3711 3713 3715 3799
	Motor homes	3716 3792
	Motorcycles & bicycles	3751 3790

Stable-tech (3): short horizon	Tires & innertubes	301x
	Plastic products	307x 3080 3084-3089
	Unsupported plastics, films &sheets	3081 3082 3083
	Packing & sealing dev. & fab. rubber nec	3050 3051 3052 3053 3060 3061 3069
	Glass & glass products	321x 322x 323x
	Cement	324x
	Structural clay products	325x
	Pottery & related products	326x
	Concrete, gypsum & related prods	327x
	Abrasive asbestos & mineral wool	329x
	Metal cans & containers	3411 3412
	Cutlery & hand tools	342x
	Heating equipment & plumbing fix.	3430 3431 3432 3433 3437 3467
	Fabricated structural metal	344x
	Screw machine products, bolts, nuts	345x
	Metal forgings, plating & coating	346x 347x
	Wire springs & misc. metal prods.	3495-3499
	Ordnance & accessories	348x
	Valves & pipe fittings	3490 3491 3492 3493 3494
	Perfumes & toilet prods.	2844
	Soaps & cleaning products	2840-2843
	Motor vehicle parts & accessories	3714

Low-tech (4)	Meat products	2010 2011 2013 2015 2016
	Dairy products	2020 2021 2022 2023 2024 2026
	Canned & frozen foods	2030-2032 3037 2038 2053 3091 3092
	Processed fruits & vegetables	2033 2034 2035 2068 2096
	Breakfast cereals	2043
	Animal feed	2047 2048
	Grain mill products	2040 2041 2044 2045
	Wet corn milling	2046
	Bakery products	2050 2051 2052
	Sugar chocolate & cocoa prods.	2060-2067
	Fats & oils	207x
	Malt & malt beverages, alcoholic bev.	2082 2083 2084 2085
	Soft drinks & flavourings	2080 2086 2087
	Miscellaneous preproduced food	2090 2095 2098 2099
	Tobacco products	21xx
	Textile mill products	22xx excl. 2270 2273
	Rugs	2270 2273
	Apparel	23xx 3965
	Footwear, rubber & leather	3021 314x
	Leather & leather products	310x-313x 315x 316x 317x 319x 3961
	Logging & sawmills	241x 242x
	Millwork, veneer & plywood	243x 2450 2451 2452
	Wood products	244x 249x
	Household furniture	251x
	Office furniture	252x
	Shelving, lockers, office & store fixtures	253x 254x 259x
	Pulp, paper & paperboard mills	261x 262x 263x
	Industrial paper & paper products	2600 264x 265x 266x
	Converted paper - household use	267x
	Commercial printing	275x 2796
	Printing & publishing	27xx excl. 275x 2796
	Musical instruments	3931
	Sporting & athletic goods	3949
	Dolls, games & toys	3942 3944
	Pens, pencils, & other office & artists mat.	395x
	Misc. manufacturing industries	399x
	Jewelry & watches	3873 3910 3911 3914 3915 396x

5. Innovative Activity in Wind and Solar Technology: Empirical Evidence on Knowledge Spillovers

Abstract

This paper studies technological change in renewable energies, providing empirical evidence on the determinants of innovative activity with a special emphasis on the role of knowledge spillovers. We investigate two major renewable energy technologies — wind and solar — across a panel of 21 OECD countries over the period 1978 to 2004. Spillovers may occur at the national level, either within the same technology field or economic sector (intra-sectoral spillovers) or in related technologies or sectors (inter-sectoral spillovers), or at the international level. We find that innovation is strongly driven by knowledge spillovers, especially those occurring at the national level. Wind and solar technologies exhibit distinct innovation characteristics: both are stimulated by intra-sectoral spillovers, but respond differently to inter-sectoral spillovers, which are only significant in the case of wind technology. We also find evidence that public R&D stimulates innovation, particularly in solar technologies.

Keywords: Technological Change, Renewable Energy, Patents, Knowledge Spillover, Climate Change, Innovation

JEL Classification: 031, Q42, Q55

1 Introduction

Technological progress is generally viewed as a key answer to sustainable and less carbon-intensive energy use. In this context, Acemoglu et al. [1] recently emphasized the need to switch to green innovation. Increased awareness of the likely impacts and costs of climate change have spurred interest in power generation from renewable sources so as to reduce greenhouse gas emissions. Various forms of this technology exist, but they are usually not yet competitive with the use of fossil fuels. Their larger-scale use is dependent reducing their cost by means of technological innovation and improvements. We know very little, however, about the determinants of innovation in these technologies. This paper seeks to fill this research gap by empirically investigating the determinants of innovative activity with a special emphasis on the role of knowledge spillover in two major renewable energy technologies — wind and solar — across a panel of 21 OECD countries over the period 1978 to 2004.[1]

Our point of departure is the observation that knowledge spillovers have had a considerable impact on technological advances for energy saving technologies. Our study focuses, first, on renewable energy technologies and, second, on analyzing different sources of knowledge spillovers: on the one hand, at the national and international level and, on the other hand, within and between sectors.

Generally speaking, knowledge spillovers occur when one inventor's original idea "spills over" to competitors, other sectors of the economy, or other countries, thereby enriching the available stock of knowledge and stimulating the development of further ideas without the recipient having to pay for it. This phenomenon may occur at the national level, either within the same technology field or economic sector (intra-sectoral spillovers) or in related technologies or sectors (inter-sectoral spillovers). In fact, such inter-industry spillovers have occurred in the solar photovoltaic technology sector, which is strongly entwined with the semiconductor industry, particularly in Japan, using its silicone by-products for solar cell manufacturing and taking advantage

[1] Countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Great Britain, Greece, Hungary, Italy, Japan, Netherlands, Norway, Portugal, South Korea, Spain, Sweden, Switzerland, United States.

of its process know-how. However, the distinction between inter- and intra-sectoral spillovers has so far been neglected in other studies on innovation in renewable energy or environmental technologies.

Knowledge that spills across international borders is also expected to be a critical channel for advancing new technologies. The emerging Spanish wind industry, for instance, acquired valuable expertise via technology licensing from the Danish wind industry in the mid 1990s and has further assimilated this know-how for its own wind technology innovations. We therefore investigate the relative importance of inter-sectoral spillovers and intra-industry spillovers in the innovation process of wind and solar technology. It is, moreover, crucial to distinguish between national and international sources of knowledge. Additionally, we account for the fact that solar and wind technologies each involve their own distinct innovation process. Even though both are evolving and dynamically growing technologies, they are characterized by significant differences in the underlying technical principles and are therefore characterized by different innovation dynamics. We therefore allow for different processes by estimating separate regressions for each technology.

Methodologically, we use a knowledge/ideas production function framework to model the relationship between innovative output, as measured by the number of patent applications in wind or solar technology, and knowledge-generating inputs such as R&D expenditures, human capital, policy instruments, and spillover sources. The input variables for national, international, intra- and inter-sectoral spillovers are also constructed from counts of patent applications. Furthermore, public support contributes to the innovation process of renewables as this technology still operates at a cost disadvantage. Renewables rely, first, on support to spur their development, as evidenced by public R&D funding, and, second, on incentives for technology adoption and subsequent power production.[2]

[2] The latter incentive schemes fall into one of two categories. In a price-based scheme, a tariff is guaranteed per unit of renewable power supplied (feed-in tariff). A quantity-based scheme requires a particular quantity or share of energy to be produced from renewable sources (obligation). Recently, certificate trading systems have also been set up, under which renewable power generators can sell power on the market and sell certificates on the green certificates market [25],[19].

The empirical literature on innovation in energy or environmental technologies does not systematically examine the role of various sources of spillovers, but there is one strand of this work that uses patent data to analyze innovation in these fields. By legal definition, obtaining a patent requires novelty and inventiveness and they are thus a strong and frequently employed source of data for measuring innovation. To our knowledge, the only studies explicitly on innovation in renewable energy technology are Johnstone et al. [22].[3] The authors analyze the impact of various policy instruments, including obligations, tariffs, and tradable certificates, on the number of patent applications in wind, geothermal, solar, ocean, biomass, and waste technologies. Policy instruments are found to induce innovation in renewables, but the particular choice of an instrument matters. There are important differences between the technologies: obligations and tradable certificates work well for wind power innovations, which the authors explain by noting that wind is the most cost-competitive technology and hence development efforts focus on this less expensive field to meet regulatory obligations. Innovation in more costly technologies such as solar power, on the other hand, is more responsive to feed-in tariffs.

Articles with a broader technological scope include Popp [31] on energy-saving innovations and Verdolini and Galeotti [36] on energy-efficient technologies. Popp [31] examines how energy prices and the existing knowledge influence energy-saving innovations.[4] Results confirm a strong stimulating effect of energy prices and, moreover, establish the knowledge stock as a crucial driver for patenting in energy-saving technologies. Verdolini and Galeotti [36] study which supply and demand factors induce innovation in energy-efficient technologies. Using U.S. patent data from between 1975 and 2000, energy prices and externally available knowledge are confirmed to be strong drivers of innovative activity in these technologies. Results also reveal that the

[3] Some researchers also study diffusion of renewable energy technologies by using patent data, e.g., [32],[10].

[4] Innovation is measured by the number of patents in diverse energy-saving technologies, for instance, fuel cells, or renewables, compared to the overall number of patents in the United States. The knowledge stock serves as a proxy for the supply of ideas. It is measured by the aggregate of *all* U.S. patents or, alternatively, by a quality-controlled aggregate of the latter where patent citations are used to obtain the quality weightings.

closer countries are in terms of technology or geography, the more knowledge flows between them.[5]

Our work deepens the understanding of innovation in renewable energy technologies by, first, emphasizing the importance of knowledge spillovers for technological change and, second, studying the impact of various spillover sources. We find substantial evidence that innovation is driven by knowledge spillovers, especially at the national level. Hence, knowledge spillovers are predominantly a domestic phenomenon; international spillovers are found to have a negligible influence. Wind and solar technologies exhibit distinct innovation characteristics: both are stimulated by intra-sectoral spillovers, but respond differently to inter-sectoral spillovers, which are only influential in the case of wind technology. We also find evidence that public R&D stimulates innovation, particularly in solar technologies.

The paper proceeds as follows: Section 2 introduces the database and discusses the use of patent data to measure innovative activity. Section 3 outlines our model of innovative activity using a knowledge production function framework and describes the estimation approach. Section 4 presents the results of the analysis; Section 5 concludes.

2 Data and Descriptive Statistics

The econometric analysis is based on a balanced panel of 21 OECD countries over the period 1978 to 2004.[6] We focus on solar and wind technologies, two prominent and intensively studied technologies within the field of renewable energy generation. Each can be considered an emerging technology compared to more mature technologies such as hydropower. In the OECD, wind accounted for 5.81% of gross electricity generation from renewable sources in 2005 [21]. Wind energy generation is close to being cost competitive — at least in very favorable sites (see, e.g., [27]). Solar energy is still

[5] A number of studies investigate the link between environmental regulation, often measured by pollution abatement expenditures, and innovation (e.g., [3],[5]). In contrast to our work and that of Johnstone et al. [22], these scholars focus on the United States and rely on national firm- or sector-level data.
[6] To compile a representative sample for innovative activity in renewable energies, we imposed the restriction that any form of public R&D last for at least in one year and that domestic inventors applied for at least five patents in wind and solar technology.

expensive and its relative contribution to electricity generation is small (0.13% in 2005) [21], but its potential is enormous [27].

2.1 Usage of Patent Data

A crucial aspect in tracking innovative activity is its measurement, an issue that is discussed extensively in the literature on innovation. Given this paper's research focus, — studying the role of knowledge spillovers in "green innovation" — patents are a powerful indicator, since, by definition, they involve truly new ideas and have a common legal framework within each patenting authority. They thus assure comparability across countries and over time. In addition, patent applications contain detailed information on inventors, technological classification, timing of the invention, and protection coverage that can be exploited to track innovation in wind and solar technologies.

We use all patent applications filed with the European Patent Office (EPO) having a priority date between 1978 and 2004. EPO applications, in contrast to those made at a national authority, can be taken as a signal that the patentee believes the invention to be of high enough value to justify the expense of an international application. By exploiting patent applications, we assume that the knowledge they contain diffuses as soon as the patent application is published, which usually happens 18 month after the filing date [34].

We use these patent data to determine our output variable — innovation in wind and solar technology — by using a classification scheme developed by Johnstone et al. [22]. In addition, patent data are used to construct our key exogenous variables: the sources of spillovers are obtained by building four different types of knowledge stocks for solar and wind technology — existing knowledge in the specific technology (wind or solar) and existing knowledge in related technologies, distinguished according to whether the inventor is domestic or foreign (see Appendix A for details).

2.2 Other Explanatory Variables

Other exogenous variables in our ideas-generation framework are R&D expenditures, policy instruments, and human capital. Annual data on publicly funded R&D in solar and wind energy are from the IEA Energy Technology Research and Development Database [20]. Data on private R&D energy expenditures are not easy to obtain, a common problem faced by energy or climate researchers [28]. However, in the context of energy technology projects, governments are often heavily involved via publicly funded research or demonstration programs [16].

Information on the number of R&D personnel involved in renewable technologies is not directly available for use in measuring the human capital input in knowledge production. We can at least approximate the research potential present in a country by an intensity measure relating the general number of researchers to the total labor force. Even though researchers are no doubt working in various fields, their knowledge or innovations may have the potential to spur technological development in renewable energies, especially in case of basic research. Data on researchers per 1,000 employees in a country are from the Main Science Technology Indicators published by the OECD [29]. Since information on researchers is available only from 1981 onward, we are restricted to the time frame of 1981 to 2004 when including this variable in our estimations.

Johnstone et al. [22] find that policy instruments play a substantial role in encouraging innovation in renewable energy technologies. Such promotion schemes fall into one of two categories: price-based systems (feed-in tariffs)) or quantity-based systems (obligations and certificates) [9]. Similar to Johnstone et al. [22], we follow the categorization of IEA [19] and introduce time dummies that indicate the time period during which any of the three policies were in effect in a country. The policy dummies provide a somewhat narrow picture of the support schemes; it would be preferable to have more elaborate data to evaluate the relative effectiveness of these policy schemes, such as international rankings of the renewable support schemes. However, such information is not available and cannot be easily compiled.[7]

[7] Support schemes are comprised of several elements that are critical to their functioning and credibility. For instance, feed-in-tariffs vary not only by technology and tariff level, but also by the period over which

2.3 A First Look at the Data

Tables 1 and 2 display the summary statistics for the variables of interest in wind and solar technologies, respectively. The average amount of (real) public R&D expenditure is roughly $6.3 million for wind and $24 million for solar technologies, with substantial country-level variation. The 1970s oil shocks markedly intensified research into power generation from alternative sources. Government R&D spending — particularly in the United States — was high afterwards, at levels unprecedented until now. Wind R&D support peaked around the beginning of the 1980s at about $300 million and — apart from a small upward trend around 1995 — stayed at a much lower level of about $100 million (Appendix Figure A.1). Solar technologies underwent a similar dynamic, though at a higher overall level (Appendix Figure A.2). Support was highest, at $1,200 million, at the beginning of the 1980s and has been significantly lower ever since (around $400 million). The oil crises of the 1970s substantially increased political awareness of issues of energy security, and substantial funds were allocated for research on alternative, nonfossil fuel technologies by governments worldwide. However, in the face of lower energy prices from the 1980s on, political interest in alternative energy technologies projects declined.

In the case of solar energy, patenting dynamics mirror, in part, R&D support: an early peak at the beginning of the 1980s, followed by a trough lasting until 1989. Then, from 1990 onward, we observe a steady increase in innovative activity in solar technology until 2004. Patenting activities of the main applicants of interest are shown in Figure A.4 (Appendix). Since the early 1990s, Japan and Germany have played the leading roles in solar technology, although the United States appears to be catching up. The United States was a strong market for solar energy applications up to the beginning of the 1980s, but the substantial decline in public support under the Reagan administration appears to have severely dampened U.S. technology developments in this field. Only when Japan and Germany began their large-scale support schemes, did solar innovation increase again. Japan concentrated its renewable energy technology efforts on solar

the tariff is granted, design (fixed tariff versus premium on the electricity price), size, and location of applicability. This information is neither well documented nor easy to obtain and requires a consistent approach to compile the data and evaluate the characteristics of the national support schemes in a comparable standard for each technology. Currently, we are not aware of any such quantitative attempt in the literature.

technology to take advantage of knowledge already developed in the integrated circuit and consumer electronics industry.

In contrast, patent applications in wind technology were filed at a steady, fairly low level until 1995 (Appendix Figure A.3). After that year, we observe a boom in wind technology patenting that continues to the present day. The age of modern wind technology started in the aftermath of the 1970s oil crises. California experienced a major boom in wind power installations; however, the turbine technology and other components were largely imported from Denmark. While the U.S. interest in wind technology faded during the 1980s, European countries such as Germany, the Netherlands, and Denmark spurred technology development with major research and, especially, demonstration projects from the 1980s on. In Japan, wind technology development has usually had low priority due to little domestic expertise in this field and in an effort to avoid reliance on imports of this technology.

Germany dominates innovative activity in wind technology. The United States and Spain have only recently improved their performance in this domain. Spain is a late starter in this field, not even starting technology until the 1990s, at which time it actively pursued a strategy of encouraging foreign manufacturers to establish plants in Spain and form joint ventures with local partners.

Summary statistics for patent applications in wind and solar technology show that patenting activity is rather infrequent, leading to a large number of zero observations combined with low mean values of slightly more than 2 in the case of wind technology (Table 1) and about 5.5 for solar technology (Table 2). This pattern is mainly driven by the fact that the classification identifying relevant inventions in wind and solar is quite narrow and technologically specific (see Johnstone et al. [22]).

Table 1

Summary statistics: wind technology (1978–2004)

Variable	Description	Mean	S.D.	Min	Max
Patent_Wind	Patent applications in wind technology	2.240	8.220	0	114
R&D	R&D expenditures in mio. U.S. dollars, 2008 prices and PPP	6.313	14.254	0	156.836
Human_capital	Researchers per 1,000 employees	5.530	2.670	1.013	17.713
Wind_stock	Stock of patent applications in wind technology, domestic inventors	9.060	22.988	0	318.374
Wind_rel_stock	Stock of patent applications in wind-related technology, domestic inventors	1074.329	2505.399	0	20698.110
Int_Wind_stock	Stock of patent applications in wind technology, foreign inventors	181.019	148.353	20	731.927
Int_Wind_rel_stock	Stock of patent applications in wind-related technology, foreign inventors	21479.750	14743.550	1123.750	54948.520
Feed-in Tariffs	Policy instrument, dummy	0.349	0.477	0	1
Obligations	Policy instrument, dummy	0.233	0.423	0	1
Certificates	Policy instrument, dummy	0.072	0.259	0	1

Notes: ***Human-capital*** is only available from 1981 onward.

Table 2

Summary statistics: solar technology (1978–2004)

Variable	Description	Mean	S.D.	Min	Max
Patent_Solar	Patent applications in solar technology	5.485	12.584	0	116
R&D	R&D expenditures in mio. U.S. dollars, 2008 prices and PPP	24.019	70.261	0	859.348
Human_capital	Researchers per 1,000 employees	5.530	2.670	1.013	17.713
Solar_stock	Stock of patent applications in solar technology, domestic inventors	26.615	53.637	0	404.447
Solar_rel_stock	Stock of patent applications in solar-related technology, domestic inventors	5337.713	11838.390	0	64453.970
Int_Solar_stock	Stock of patent applications in solar technology, foreign inventors	531.579	231.913	106.75	1196.473
Int_Solar_rel_stock	Stock of patent applications in solar-related technology, foreign inventors	106720.700	71807	5186.75	254810.500
Feed-in Tariffs	Policy instrument, dummy	0.289	0.454	0	1
Obligations	Policy instrument, dummy	0.219	0.414	0	1
Certificates	Policy instrument, dummy	0.072	0.259	0	1

Notes: ***Human-capital*** is only available from 1981 onward.

3 An Empirical Model of Innovative Activity in Renewable Energy Technologies

3.1 A Knowledge Production Function Framework

Following the framework developed by Griliches [11], we estimate a knowledge production function to discover the determinants of innovative activity in wind and solar technology. Innovation is assumed to be the product of knowledge-generating inputs, comparable to the process of physical goods production. The vector of determinants usually encompasses the quantity of human capital or R&D expenditures and the total stock of knowledge available to researchers. Hence, the productivity of new knowledge is assumed to be strongly dependent on existent stock of ideas [33], the "standing on shoulders" effect (e.g., [2]).

Formally, knowledge production in technology j and country n can be summarized as follows:

$$I_{nj} = f\left(H_{hj}, K\right),$$

where I_{nj} is innovation in technology (j) (wind or solar), H stands for human capital, and K is the overall knowledge stock available to researchers. To enrich our understanding of the knowledge-production process, we further distinguish between domestic and international knowledge spillovers. The latter could be an especially important channel of knowledge transfer for smaller countries whose existing knowledge base is narrow or highly specialized.

To fully understand the externalities of national and international technological knowledge, empirical work on R&D spillovers often distinguishes between intra- and inter-sectoral spillovers by referring to sector-country observations (e.g., [24]). We transfer this approach to the field of renewable energies and study not only the impact of domestic and international spillovers in wind and solar technology (intra-sectoral level), but also knowledge externalities in related fields (inter-sectoral level). Our specification can be expressed as follows:

$$I_{nj} = f\left(H_{nj}, K_{nj}, K_{n-j}, K_{-nj}, K_{-n-j}\right),$$

where K_{nj} stands for the knowledge stock available in the same technology in the same country, K_{n-j} is knowledge in the same country but in related technologies, K_{-nj} is the stock in other countries in the same technology, and K_{-n-j} is knowledge from related technologies in other countries. In short, K_{nj} and K_{n-j} represent domestic spillover, whereas K_{-nj} and K_{-n-j} proxy international knowledge spillover.

3.2 Econometric Approach

As explained in Section 2, we measure innovative activity in wind and solar technology by the number of patent applications. The resulting dependent variable is a nonnegative-integer-valued variable with many zeros and small values, especially at the beginning of our estimation period. Thus, in the specification of our econometric model we follow the seminal work of Hausman et al. [17] and assume a Poisson process with parameter λ_{nj} for the number of patents applied for in country n in technology j:

$$E\left(I_{nj}\right) = \lambda_{nj} = \exp\left(X_{nj}'\beta\right)$$

$$P\left(I_{nj} = i_{nj}\right) = \frac{\exp\left(-\lambda_{nj}\right)\lambda_{nj}^{N}}{i_{nj}!}.$$

Again, I_{nj} is the number of patents in country n related to technology j and the vector X_{nj} encompasses R&D expenditures, human capital, our constructed knowledge stocks, and additional explanatory variables such as policy measures, year dummies, and a time trend. Time effects are often neglected in the empirical literature on “green innovation” but are important for capturing general changes in the propensity to patent and strategic patenting behavior across countries. R&D expenditures, human capital, and knowledge stocks are measured in logarithms;[8] hence the estimated coefficients can be interpreted as elasticities.

The most critical part of the Poisson model is the implicit assumption of conditional mean and variance both being equal to λ_{nj}. If this assumption is violated by the dataset, the model will produce misleading predictions of zeros and large counts [7], a

[8] Hall and Ziedonis [15] suggest using logarithms when estimating a knowledge production function.

phenomenon known as overdispersion. The mean-variance equality rarely holds in empirical applications on patenting behavior (e.g., [18]). One option is the application of a negative binomial estimator, which allows for flexibility in the parameterization of the mean-variance relationship. The negative binomial density is obtained by combining the Poisson distribution with a gamma distribution for the unobserved heterogeneity in the parameter λ_{nj}.

Our dataset raises a more pressing concern; we need to handle a considerable number of zero patent counts, roughly 50%.[9] This kind of problem occurs more often in the case of firm-level micro data where one is always confronted with certain firms that do not appear to innovate at all. In the case of wind and solar technology, we need to tackle this issue at the country level because there is only a very small number of innovations in these fields and we therefore do not observe relevant patenting activity for all countries and years. This paucity of observations could be due, on the one hand, to some countries never innovating at all in a certain technology and, on the other hand, to other countries that may have tried to innovate but failed. This leads to a different data generating process and a standard Poisson model cannot be used to describe it. We hence apply a zero inflated Poisson (ZIP) model as proposed by Lambert [23]. Assuming that the probability of not innovating is given by *p* and, accordingly, the likelihood of innovating is $1-p$, the ZIP model can be summarized as follows:

$$P\left(I_{nj}=i_{nj}\right)=\begin{cases} p_{nj}+\left(1-p_{nj}\right)\exp\left(-\lambda_{nj}\right), & i_{nj}=0 \\ \left(1-p_{nj}\right)\exp\left(\lambda_{nj}\right)\dfrac{\lambda_{nj}^{N}}{i_{nj}}, & i_{nj}=1,2,3,... \end{cases}.$$

The probability of exhibiting zero patents is modeled using the logistic distribution:

$$p_{nj}=F\left(Z_{nj}'\gamma\right)=\frac{1}{1-\exp\left(-Z_{nj}'\gamma\right)},$$

where we model the choice of not innovating as a function of public R&D support in the technology. The compound distribution is then maximized by means of maximum likelihood estimation. Conditional on R&D support, the rate of innovation is given by:

$$I_{nj}=\exp\left[\alpha+\beta_1\ln\left(R\,\&\,D_{nj}\right)+\beta_2\ln\left(K_{nj}\right)+\beta_3\ln\left(K_{n-j}\right)+\beta_4\ln\left(K_{-nj}\right)+\beta_5\overline{X}_{nj}\right],$$

[9] The portion of zero counts in wind technology is slightly above 50%; that of solar slightly below.

where $\overline{X}_{nj}$ contains additional control variables such as human capital and policy and time measures. Note that we omit the knowledge stock stemming from related technologies in other countries. As could have been predicted, the various knowledge stocks are correlated to a certain extent and the high correlation of above 0.75 between the two international stocks make this omission necessary.[10] Furthermore, this type of knowledge stock is by far the most diffuse since it flows from numerous locations and several technologies.

Additionally and consistent with recent literature on innovative activity, a lag structure on inputs is imposed to account for the fact that R&D efforts do not immediately lead to innovative output [13]. Therefore, we lag all inputs — except the policy dummies — by two periods. In line with Johnston et al. [22], we do not lag the policy dummies because the legislative process takes time and rational innovators are likely to start research activity during the political decision-making process, instead of waiting until the policy becomes legally effective [26]. In Section 4.3, we also account for individual heterogeneity and apply a negative binomial panel data estimator.[11]

4 Empirical Findings

A key aspect of our work is to explore the role of knowledge spillovers in the knowledge-production process in two renewable energy technologies, wind and solar. We look at three sources of knowledge spillovers — first, domestic spillovers originating from the domestic knowledge stock within the same technology; second, domestic spillovers from closely related fields in the economy; and third, international spillovers from either wind or solar technology. Our empirical results are presented in three parts. We begin by discussing the findings for innovation in wind energy technologies, followed by those for solar energy. In the last part we discuss the robustness of our results.

[10] The correlation between the other stocks is considerably smaller and ranges between 0.06 and 0.6.
[11] For details on the negative binomial panel estimator see e.g., Cameron and Trivedi [4]. A ZIP panel data estimator is not yet available.

4.1 Determinants of Innovative Activity — The Case of Wind

We start with a base specification that includes public R&D expenditures, human capital, policy support instruments, and the stock of existent domestic knowledge in wind technology (Table 3, Model 1).[12] The domestic spillover variable (Wind_stock) has a significant and positive coefficient in the model — preliminary evidence in favor of the relevance of knowledge spillovers in the innovation process of renewable energy technologies. An increase in the national knowledge stock of 1% induces a growth in wind patent counts of 0.83% on average. A second important driver of the wind innovation process is public R&D. Such a link might not be as clear-cut in the case of renewable energies as we proxy R&D by public funding.

Governments tend to fund basic or risky research projects that are less likely to result in innovative outputs such as patents. Nonetheless, we find that government R&D appears to be directed to research activities that result in patenting output or that at least increase the productivity and innovation output.[13] The human capital variable is not significant. Hence, there is no evidence that the overall national innovative capacity is critical to innovative developments in wind technology.[14] We also control for time effects by including a trend. As expected, its estimate shows that the number of patent applications follows a strong growth path over time.

The model also includes policy measures: these include demand-side schemes aimed at inducing the installation of the technology for power production, but that may also have a stimulating effect on technology development via learning-by-doing effects [26]. In contrast to Johnstone et al. [22], we find no evidence of a significant link between any of the support measures and innovative activity. Note, however, that these policy dummies measure only a certain aspect of the renewable support scheme, i.e., the period of time during which obligations, feed-in tariffs, or certificates were in effect. They do not take

[12] All estimations apply robust standard errors, which have been adjusted by clustering at the country level.
[13] For a more detailed discussion on the relationship between private and public R&D expenditures, see David et al. [6].
[14] Although the variable is not significant in this first estimation, we retain it in the specification to, first, be consistent in the usage of the knowledge production function framework, which would be susceptible to an omitted variable bias if differences in the national human capital/researcher endowment are not controlled for. Second, we next extend our specification for the various sources of spillover, which might affect the role of human capital due to different conditional expectations.

other important elements into consideration (e.g. fixed tariff versus premium) and therefore may provide only a narrow picture of the support mechanisms in place.

Model 2 now extends the analysis to study in addition the impact of knowledge originating from technologically closely related fields. We find support for the hypothesis that national inter-sectoral sources are an important factor affecting knowledge generation in wind technology by providing an additional opportunity for know-how transfers. The inclusion of this variable (Wind_rel_stock) results in small reductions in the magnitude of the R&D and domestic wind spillover coefficient estimates, but overall results remain robust. The inter-sectoral stock is, as would be expected, less influential than the direct wind spillover source, with the size of the coefficients differing by a factor 4. Anecdotal evidence suggests that knowledge in wind technology field itself has a higher effect on innovation output than state-of-the-art technology of related industries.

Model 2 is consistent with our notion of knowledge creation in renewable energy technologies — spillovers are critical drivers of innovation: Wind developers are exploiting and learning from technological know-how originating in the domestic wind "area"/sector itself and from knowledge gleaned from closely related sectors in the economy, such as machinery. Some key players in the wind industry have historical roots in established industries such as agricultural equipment or the steel industry. However, the role these long-established sectors of an economy play in innovation in wind technology has rarely been made explicit in empirical analyses.

As discussed in Section 3, a serious weakness of the Poisson model is that it fails to account for excess zeros in the dependent variable. We accordingly reestimate the previous model with ZIP (Model 3). There are some minor changes in the size of estimates but, again, we find a strong link between each of the two domestic spillover sources and innovative activity. Our analysis clearly suggests that the exclusion of these knowledge spillovers omits an important element of the innovation process of wind technology.

The previous Poisson regressions found R&D to be accelerating innovative wind technology developments, but that link becomes nonsignificant in the main ZIP regression. Turning to the regression equation for the excess zeroes, however, public R&D is a significant determinant in the model predicting whether a country is an active innovator in wind technology (bottom half of Table 3).[15]

It is evident that public R&D funding is pivotal in explaining whether a country generates any innovation output. Using the Vuong test to compare the ZIP and Poisson models, we find a significant positive value of the test statistic, providing clear evidence in favor of the ZIP approach.

To this point, all models have included a trend as our time measure. Alternatively, year dummies can be used to control for the upward dynamics in wind patent applications (Model 4). The results are in line with the previous regressions — both types of domestic knowledge spillovers work are significant drivers of wind innovation even though the innovative response to the stock of domestic wind knowledge is to some degree smaller than in Model 3, whereas the impact of inter-sectoral spillovers appears to be somewhat stronger. We will further elaborate on time effects in Section 4.3, where we also cover subperiods of our sample. Overall, the inclusion of year dummies comes at the price of losing degrees of freedom, leading us to prefer a trend specification.

The wind technology business exhibits a strong export orientation and internationalization. Thus, we would expect a positive coefficient of the international wind knowledge stock (Int_wind_stock) in Model 5 (Table 3). Contrary to our hypothesis, knowledge spillovers across international boundaries do not seem to be an important driver of technological progress in wind. The elasticities of the domestic spillover variables remain significant and the coefficient of wind-related knowledge spillovers drops slightly.

[15] We experimented with several alternative specifications of the inflate equation (not reported). Potential candidates were all variables already being covered in the Poisson stage of the regressions. They turned out to be insignificant and did not affect our results. Additionally, we added a "demand-push" perspective and controlled for existing wind energy capacity in a country. Again, our specification and conclusion remained robust.

Table 3

Determinants of innovative activity in wind technologies

	Model 1: Poisson	Model 2: Poisson	Model 3: ZIP	Model 4: ZIP	Model 5: ZIP
R&D	0.244**	0.199**	0.074	0.056	0.074
	(0.095)	(0.100)	(0.114)	(0.110)	(0.106)
Human_capital	0.204	0.065	0.056	0.037	0.116
	(0.229)	(0.213)	(0.249)	(0.218)	(0.254)
Wind_stock	0.833***	0.728***	0.721***	0.713***	0.723***
	(0.072)	(0.076)	(0.078)	(0.073)	(0.070)
Wind_rel_stock		0.152**	0.150**	0.170**	0.130**
		(0.068)	(0.062)	(0.069)	(0.059)
Int_Wind_stock					-0.199
					(0.205)
Feed-in Tariffs	-0.026	0.068	0.041	0.090	-0.002
	(0.178)	(0.177)	(0.207)	(0.183)	(0.198)
Obligations	0.221	0.077	0.120	0.009	0.130
	(0.167)	(0.161)	(0.148)	(0.149)	(0.142)
Certificates	0.266	0.396**	0.236	0.283	0.273
	(0.179)	(0.200)	(0.232)	(0.214)	(0.251)
Trend	0.103***	0.104***	0.087***	-	0.101***
	(0.022)	(0.023)	(0.023)		(0.016)
Year dummies	-	-	-	Yes	-
Intercept	-3.746***	-4.253***	-3.377***	-2.659***	-2.614**
	(0.272)	(0.341)	(0.380)	(0.578)	(1.068)
Inflate regression					
R&D			-0.644***	-0.693***	-0.660***
			(0.193)	(0.201)	(0.187)
Trend			-0.112***	-0.098**	-0.104***
			(0.035)	(0.041)	(0.032)
Intercept			1.707**	1.242	1.554**
			(0.790)	(0.919)	(0.725)
Observations	254	253	253	253	253
Countries	19	19	19	19	19
Log-likelihood	-520.787	-506.684	-480.313	-450.218	-478.697
Vuong test			2.35***		

Notes: 1. Dependent variable: number of EPO patent applications in wind technologies, 1981–2004. Countries not included are Australia and Hungary.
2. Robust standard errors are calculated by clustering at the country level. Standard errors are given in parentheses below the coefficient estimates.
3. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

These findings lead us to conclude that although the market for the technology itself is international, research and technology development appear to predominantly occur in a domestic setting. A possible explanation for this is that the pool of knowledge available domestically is still large enough that acquiring knowledge from abroad is generally redundant. Though innovators have contact and are in exchange with international business and research communities, appropriation from foreign knowledge is likely to be more costly that that occurring through domestic knowledge.

Turning to policy relevance, our results suggest that if an innovation system is predominantly characterized by domestic spillovers, and has the opportunity and means to exploit its existing strong knowledge base, then a country that is a technology leader is likely to maintain that position. This may also imply that "late movers" will have difficulty stimulating innovation in wind technology as they lack their own knowledge base.

4.2 Determinants of Innovative Activity — Solar Technology

Solar energy is still in a relatively early phase of development. This sector faces the specific technological challenge of improving the efficiency of solar energy conversion while significantly reducing the manufacturing costs.

We start from the same base knowledge production specification using a Poisson estimation approach (Model 1, Table 4). The only difference is that the knowledge spillover stock now stems from the domestic solar industry (Solar_stock). The findings reveal a picture similar to that obtained for wind: domestic spillovers within the same technology, i.e., solar, and R&D are the main drivers of solar innovation output. As a comparison of the elasticity estimates reveals, domestic intra-industry spillovers are again superior to R&D in stimulating innovation. We also find that the effect of domestic intra-industry spillovers — relative to R&D — is less strong in the case of solar than for wind (the ratio of elasticities of spillover to R&D is about 2.1 in solar technologies and 3.4 in wind technologies). Other variables, such as human capital intensity and policy instruments, are not significant factors in explaining innovation.

Table 4

Determinants of innovative activity in solar technologies

	Model 1: Poisson	Model 2: Poisson	Model 3: ZIP	Model 4: ZIP	Model 5: ZIP	Model 6: ZIP
R&D	0.322***	0.312***	0.271***	0.209***	0.270***	0.269***
	(0.061)	(0.065)	(0.076)	(0.077)	(0.074)	(0.079)
Human_capital	0.252	0.194	0.363	0.383	0.367	0.331
	(0.292)	(0.273)	(0.294)	(0.292)	(0.296)	(0.311)
Solar_stock	0.682***	0.633***	0.688***	0.605***	0.688***	0.661***
	(0.078)	(0.115)	(0.126)	(0.103)	(0.126)	(0.092)
Solar_rel_stock		0.072	-0.052	0.126	-0.044	
		(0.109)	(0.138)	(0.109)	(0.133)	
Int_Solar_stock					0.064	0.091
					(0.450)	(0.451)
Feed-in Tariffs	-0.111	-0.111	-0.069	0.006	-0.071	-0.075
	(0.159)	(0.158)	(0.165)	(0.175)	(0.176)	(0.183)
Obligations	-0.237	-0.231	-0.242	-0.144	-0.258	-0.261
	(0.151)	(0.148)	(0.153)	(0.172)	(0.261)	(0.261)
Certificates	-0.020	0.001	0.023	0.133	0.023	0.031
	(0.067)	(0.075)	(0.085)	(0.164)	(0.084)	(0.080)
Trend	0.060***	0.055***	0.060***	-	0.057***	0.054***
	(0.008)	(0.010)	(0.013)		(0.012)	(0.012)
Year dummies	-	-	-	Yes	-	-
Intercept	-2.791***	-3.036***	-2.319***	-45.359*	-2.741	-3.071
	(0.392)	(0.704)	(0.873)	(24.469)	(2.938)	(2.759)
Inflate regression						
R&D			-0.902***	-1.592*	-0.902***	-0.886***
			(0.257)	(0.929)	(0.260)	(0.266)
Trend			-0.056	-0.010	-0.056	-0.056
			(0.051)	(0.146)	(0.051)	(0.050)
Intercept			0.900	-0.455	0.882	0.813
			(1.351)	(3.347)	(1.351)	(1.286)
Observations	260	260	260	260	260	260
Countries	21	21	21	21	21	21
Log-likelihood	-686.650	-685.759	-675.461	-575.617	-675.374	-675.579
Vuong test			1.33*			

Notes: 1. Dependent variable: number of EPO patent applications in solar technologies, 1981–2004.
2. Robust standard errors are calculated by clustering at the country level. Standard errors are given in parentheses below the coefficient estimates.
3. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Next, we include national knowledge that could flow to the solar industry from technologically closely related fields (Solar_rel_stock, Model 2). Interestingly, this factor contributes little to innovative activity in solar technologies, whereas it had a strong effect in the wind case. Possible explanations for this include, first, that solar technology is still in its infancy (compared to wind) and it is most especially the exchange of knowledge and expertise within the same technological field that is accelerating technology development. Second, solar technology is more complex than wind technology (for details see Section 3 and Appendix A). There are more and heterogeneous potential opportunities for innovational complementarities. This implies that it could be more difficult to measure how innovation responds to related knowledge because the related knowledge is so diverse.

Do these findings hold in a ZIP specification? The Vuong test indicates that the ZIP model is better suited to the data. The inflate regression is specified similarly to the wind case regression. Public R&D expenditures are again found to be a critical determinant in modeling the zero patenting outcomes.[16] The ZIP model shows that innovation production is only accelerated by absorption and utilization of knowledge available in the domestic solar industry; inter-sectoral effects are negligible. As a robustness check, we reestimate the model including year dummies instead of a trend (Table 4, Model 4). The time dummies are mostly significant and positive; their size, as expected, is increasing over time (see also Figure 2). Coefficient estimates remain otherwise robust.

A third factor hypothesized to spur innovation is international spillovers. We accordingly extend the analysis to investigate the role international knowledge spillovers plays in innovation performance (Model 5). Again, international spillovers do not affect innovation performance. The coefficient of Int_solar_stock is very small and insignificant. Our analysis suggests that knowledge embodied in domestic spillovers from the solar sector is superior in creating new knowledge compared to solar knowledge from abroad or from related fields in the economy.

[16] Again, we tested several specifications for the inflate equation (not reported). Additional variables were not significant and did not change our results.

We now examine another model to explore the robustness of the insignificant role of international spillovers in the knowledge-creation process in solar energy. As national related technology knowledge was previously found to be insignificant (Model 3 or 4), we estimate a model including domestic and international solar stocks to elaborate on the role of the specific solar knowledge base. The results show considerable support for our earlier observation: solar innovative activity is predominantly spurred by domestic spillovers within its industry and, to a lesser extent, by R&D, but is not stimulated by international knowledge transfers (Model 5). It is not possible to state whether this is due to international spillovers being less conducive to innovation or whether the lack of influence is due to an incapacity, for whatever reason, of countries to exploit international knowledge. For an evolving technology like solar, the learning opportunities within the home country and the same technology field still seem to be sufficiently large to foster technological advances. However, it could be that in the future, as the technology matures, international knowledge spillovers will be more influential.

4.3 Robustness

In this section we test the robustness of our results by applying panel estimation methods and considering different time periods. To this point, we adopted a pooled ZIP regression approach, but as this method is not able to account for country-level heterogeneity, we use a negative binomial (Negbin) panel data estimator (e.g., [22],[3]). Beginning with wind technology, Model 1 in Table 5 shows random effects and Model 2 the fixed effects results. The Hausman test clearly rejects the assumption that error terms are uncorrelated with the individual effects. Most coefficients in the fixed effects model remain similar in magnitude, but the one for domestic wind spillovers is about one-third smaller than that previously obtained. Knowledge from related sectors no longer has a significant impact on innovation; however, one should be wary of concluding that inter-sectoral spillovers do not matter in case of wind. As Hall et al. [14] argue, R&D and, consequently, knowledge accumulation usually changes slowly over time, implying that national spillover sources (stocks) could be highly correlated with the individual effect.

Table 5

Robustness checks — alternative model specifications and estimation methods

	Wind Model 1: Negbin RE Full sample	Wind Model2: Negbin FE Full sample	Wind Model 3: ZIP Subsample: 1982–1994	Wind Model 4: ZIP Subsample: 1995–2004	Solar Model 5: Negbin RE Full sample	Solar Model 6: Negbin FE Full sample	Solar Model 7: Negbin FE Full sample	Solar Model 8: Negbin FE Full sample	Solar Model 9: ZIP Subsample: 1982–1994	Solar Model 10: ZIP Subsample: 1995–2004
R&D	0.222***	0.196**	0.331	0.064	0.441***	0.460***	0.448***	0.485***	0.361**	0.155
	(0.077)	(0.097)	(0.289)	(0.118)	(0.082)	(0.106)	(0.107)	(0.106)	(0.140)	(0.095)
Human_capital	0.038	-0.241	-0.012	0.043	0.271	0.285	0.013	0.536	1.106**	0.149
	(0.270)	(0.459)	(0.723)	(0.268)	(0.263)	(0.439)	(0.515)	(0.460)	(0.495)	(0.253)
Wind|Solar _stock	0.532***	0.347***	0.629**	0.678***	0.433***	0.163	0.102	0.139	0.612***	0.723***
	(0.117)	(0.127)	(0.271)	(0.092)	(0.099)	(0.123)	(0.137)	(0.125)	(0.171)	(0.090)
Wind|Solar _rel_stock	0.136*	0.077	0.134	0.179**	-	-	0.153	-	-	-
	(0.080)	(0.137)	(0.300)	(0.078)			(0.157)			
Int_solar _stock	-	-	-	-	-	-	-	0.501*	-	-
								(0.302)		
Feed-in Tariffs	-0.136	-0.234	-0.634	0.241	0.142	0.022	0.022	0.054	-0.210	-0.079
	(0.188)	(0.208)	(0.387)	(0.221)	(0.162)	(0.199)	(0.198)	(0.200)	(0.322)	(0.138)
Obligations	0.022	-0.030	1.607*	0.047	-0.035	-0.029	-0.018	-0.135	0.716*	-0.281
	(0.176)	(0.193)	(0.830)	(0.165)	(0.147)	(0.166)	(0.166)	(0.179)	(0.425)	(0.230)
Certificates	0.314	0.375	dropped	0.338	-0.006	0.024	0.051	0.036	droppped	0.056
	(0.223)	(0.244)		(0.244)	(0.164)	(0.184)	(0.187)	(0.183)	-	(0.120)
Trend	0.109***	0.132***	0.122	0.102**	0.054***	0.068***	0.059***	0.050**	-0.023	0.052
	(0.019)	(0.024)	(0.117)	(0.048)	(0.014)	(0.018)	(0.020)	(0.021)	(0.028)	(0.039)
Intercept	-4.450***	-3.451***	-3.624***	-3.925***	-3.367***	-2.709***	-3.185***	-5.862***	-3.376***	-1.879**
	(0.490)	(0.719)	(1.009)	(1.077)	(0.426)	(0.605)	(0.759)	(1.991)	(0.458)	(0.802)

Inflate regression										
R&D			-0.195	-0.750***					-166.553***	-1.288***
			(0.324)	(0.252)					(9.196)	(0.355)
Trend			0.047	-0.239*					-6.321***	0.026
			(0.088)	(0.140)					(0.396)	(0.219)
Intercept			-0.794	4.599					89.748***	-0.724
			(1.601)	(3.226)					(5.308)	(5.165)
Observations	253	237	121	132	260	249	249	249	122	138
Log-likelihood	-406.552	-336.541	-134.525	-337.221	-526.225	-445.970	-445.503	-444.627	-251.058	-383.987
Hausman test		chi2(8): 22.92***					chi2(8): 3058.37***			

Notes: 1. Dependent variable: number of EPO patent applications in wind or solar technologies, respectively.

2. Robust standard errors are calculated by clustering at the country level. Standard errors are given in parentheses below the coefficient estimates.

3. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

4. Note that variable **Certificates** dropped due to lack of variation in the early subsample 1982-1994.

We also reestimated the solar innovation model using a panel Negbin setting. Using a fixed effects approach, we find a somewhat stronger effect of R&D on innovation output (Table 5, Model 6). Compared to the results of a ZIP approach, we no longer detect a significant role of domestic intra-sectoral spillovers, possibly because the country dummies capture all permanent heterogeneity in each country and, accordingly, the coefficient is determined by the remaining less pronounced within-country variation over time. In line with our earlier results (Table 4, Model 3), spillovers from closely related sectors still have no influence on innovation in solar technologies (Table 5, Model 7). Interestingly, a different picture emerges when we include international spillovers (Model 8). Here, international knowledge spillovers within the solar industry are found to induce innovation, whereas the domestic solar spillovers remain insignificant. Why this should be so is not immediately clear, but it should be kept in mind that the effect described previously is only weakly significant.

Both solar and wind technologies have been around for several decades, but it is only in the last decade that they have become the subject of renewed interest and rapid commercialization. We therefore investigate whether significant changes in the set of determinants and their relative strength for knowledge production can be observed. We reestimate our ZIP model for two subsamples of the data, one for the period of 1982 to 1994 and the other encompassing 1995 through 2004. Wind technology development in the earlier subsample is significantly driven by domestic knowledge spillovers within the wind industry and by obligations (Model 3). For the more recent period, we see that related-sector technology has become a stimulating factor (Model 4).[17]

Finally, a comparison between different time horizons for solar technologies reveals a very similar picture (Models 9 and 10). Domestic knowledge spillovers within the solar technology field have a major influence on innovation output. The magnitude of the effect is revealed to be even stronger in the subsample covering the last decade. One interesting difference is that R&D is significant in the early period only. Apparently, solar technology innovation went through a phase during which R&D and human capital were critical to innovative activity, but later on, when the knowledge base in the solar

[17] We also conducted estimations including year dummies (results not reported), the results of which are not in conflict with our previous findings.

industry expanded, innovation in this domain is chiefly the result of within-field knowledge spillovers.

5 Conclusion

Innovation is no panacea for mitigating climate change, but it is a crucial factor in reducing greenhouse gas emissions and limiting the costs associated with that task. This paper is one of the first to empirically study the channels through which innovative activity in solar and wind technologies is spurred. Our work contributes to the literature on innovation in renewable energy technologies by, first, emphasizing the importance of knowledge spillovers for technological change and, second, studying the impact of various spillover sources. A distinction is drawn between intra- and inter-sectoral spillover sources, as well as between domestic and international spillovers.

Our analysis yields several important findings. Knowledge spillovers are an important input in the knowledge-generation process of wind and solar technologies. Innovators in both wind and solar technologies absorb and utilize existing own-field knowledge in making technological advances. However, spillovers are predominantly a domestic phenomenon — i.e., they chiefly occur within a country; international spillovers play a negligible role. Another important finding from our estimation results is that wind and solar technologies have distinct innovation characteristics and thus should be considered separately in innovation analyses. Wind and solar technologies are both stimulated by intra-sectoral spillovers, but they respond differently to inter-sectoral spillovers, which are influential only in the case of wind technology.

Our results suggest that if an innovation system is predominantly characterized by domestic spillovers, and it has the opportunity and means to exploit its existing strong knowledge base, then a country that is a technology leader is likely to maintain that position. This implies that "late movers" will have difficulty in creating their own research in renewable energy technologies as they lack a corresponding knowledge base; international spillovers do not seem to be to sufficient for activating innovation. The use of renwable energy technologies in developing countries is expected to provide significant benefits at the global level in terms of climate change, and also at the local level for environmental sustainability and development. There is an important debate on how to best support a North-South technology transfer. An important lesson from our study on OECD countries is that international knowledge flows have to date played a negligible role and that successful technology development is currently contingent on a solid domestic knowledge base in the same technology or, to a lesser extent, in related sectors. This raises some concern over the ability of developing countries to develop, not to mention improve, their own renewable energy technology sector. It should be emphasized here, that we only analyzed the conditions for innovation in renewable energy technology, not for patterns of production. There other factors such as factor cost, particularly for labor, or commodity costs play a more prominent role. International policy commitment will be needed to bring renewable energy technologies to these countries. In some cases, increasing or building the capacity of these countries to absorb knowledge transfers and spillovers may be effective but, as our results reveal, the self-sustained development of renewable energy technologies will not come easily in developing countries. That international knowledge spillovers are so insignificant is additionally unfortunate as it could lead to a costly duplication of research effort if each country independently engages in developing renewable energy technologies.

Coordination of R&D efforts, priorities, and the exchange of failure and success stories could avoid such duplication and, moreover, accelerate overall technological progress. In this paper, we find that public R&D support stimulates innovation in renewable energy technologies, a result that is particularly robust for solar technologies.

The importance of knowledge flows between sectors has to date been mostly ignored in policy debates. If developers of clean technologies are able to learn from other sectors in the economy, it could well reduce the costs of innovation. However, it is not a priori clear whether policy intervention would in actuality enhance inter-sectoral knowledge transfer and, if it could, how it should be designed to work most effectively. There is still much to learn about the mechanisms of and incentives for absorbing and using external knowledge. In general spillover mechanisms are weakly understood and there is a great deal of room for further research on them. One extension of our work would be to construct measures of “proximity” in technology space case studies or geographical distance. Additionally, studies based on micro data (e.g., from firms in renewable energy technologies) could greatly expand our understanding of the underlying knowledge-generation process. A further extension of our study would be to include national patent data or make a detailed investigation of how knowledge flows across countries and technologies as evidenced by patent citations.

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Appendix A

Calculation of the Spillover Variables

To derive knowledge stocks, we use information on patent applications from the European Patent Office's (EPO) Worldwide Patent Statistical Database. This database contains all national and international patent applications. Note that patents often have more than one inventor from different home countries. In the empirical literature, the analysis is often restricted to the first inventor, which might be misleading, especially in case of transnational research collaborations. We allow for multiple inventors when calculating our patent counts. Given the possibility of affiliation with more than one country, our patent counts might be larger than the total number of patent applications at the EPO, e.g., a co-invention by a French and a German inventor counts twice, once in the count for Germany and a second time in the count for France.[18]

Patents in wind and solar technology are collected according to a classification scheme published by Johnstone et al. [22] that links technology classes, more specifically the International Patent Classification (IPC) classes, to renewable energy technologies. Methodologically, these relevant classes were determined by using a set of keywords related to technological developments in this area.

Domestic knowledge stocks in wind and solar technology are derived by applying the perpetual inventory method to the yearly patent applications in these fields in a certain country. Accordingly, the knowledge stock available at time t is determined by:

$$K_t = (1+\delta)K_{t-1} + pat_t .$$

Hence, the stock is equal to the stock at time $t-1$ K_{t-1}, minus depreciation δ,[19] plus patent applications in period t pat_t The initial stock is approximated using an initial growth rate of 20%. Foreign knowledge stocks in wind and solar are calculated as the sum of the domestic stocks minus those of the country of interest.

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[18] This approach helps to approximate the underlying value of innovative output since one might argue that international co-inventions are of higher economic value due to the origination of larger costs. We also experimented with first inventor patent counts in the estimations and it had very little influence on our results.

[19] We impose a depreciation rate of 15%, which is common in the literature (e.g., [12]).

Another influential factor in determining innovative activity is knowledge spillover from technologically closely related industries. To extract patent applications in related industries, we combine the classification on renewable energy technologies by Johnstone et al. [22] with a sectoral concordance provided by Schmoch et al. [35] that links industrial fields to IPC classes. Expert assessments and micro-data evidence on the patenting activity of firms in the manufacturing industry are used to link technology classes to industry sectors. Based on this concordance, we identify those fields that encompass the IPC classes defining innovation in wind and solar technology and denote them as being related to wind or solar energy (Table A.1 and A.2). According to Johnstone et al. [22], patents with IPC class "F03D" belong to the field of wind energy. The class "F03D" belongs to the industrial field "energy machinery."

We hence derive the patent stock in wind-related industries by summing over all applications belong to the field "energy machinery" except for those belonging directly to wind energy ("F03D"). In case of solar energy, the procedure is slightly more complicated because solar energy patents are found in five different fields: "mineral products," "metal products," "energy machinery," "electrical motors," and "electronic components." We perform the calculation in the same manner as for the case of wind. Detailed classifications for deriving related stocks are provided in the tables below. Foreign stocks are determined according to the method described previously.

Table A.1

Related wind technology

Field	**IPC Classes**	**Except for wind technology IPC Class**
Energy machinery	B23F, F01B, F01C, F01D, F03B, F03C, F03D, F03G, F04B, F04C, F04D, F15B, F16C, F16D, F16F, F16H, F16K, F16M, F23R	F03D

Table A.2

Related solar technology

Field	IPC Classes	Except for solar technology IPC Class
Mineral products	B24D, B28B, B23C, B32B, C03B, C03C, C04B, E04B, E04C, E04D, E04F, G21B	E04D 13/18
Metal products	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, F16B, F22B, F24J, G21H	F24J 2
Energy machinery	B23F, F01B, F01C, F01D, F03B, F03C, F03D, F03G, F04B, F04C, F04D, F15B, F16C, F16D, F16F, F16H, F16K, F16M, F23R	F03G 6
Electrical motors	H02K, H02N, H02P	H02N 6
Electronic components	B81B, B81C, G11C, H01C, H01F, H01G, H01J, H01L	H01L 27/142 & 31/04-078

Figure A.1
Innovative activity in wind technologies, EPO patent applications

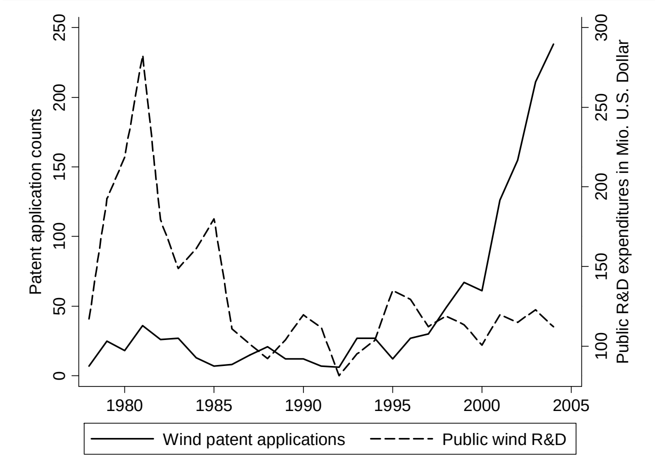


Figure A.2
Innovative activity in solar technologies, EPO patent applications

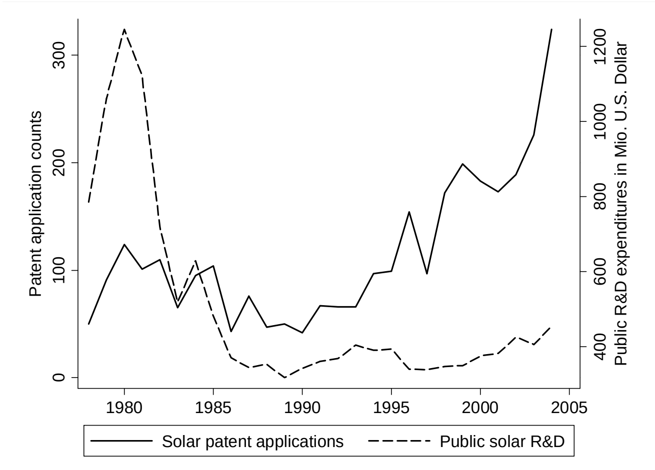


Figure A.3
Wind patent applications by major innovators, EPO patent applications

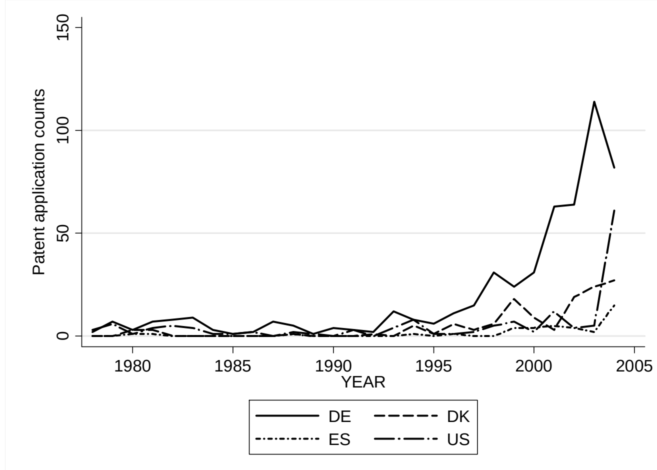
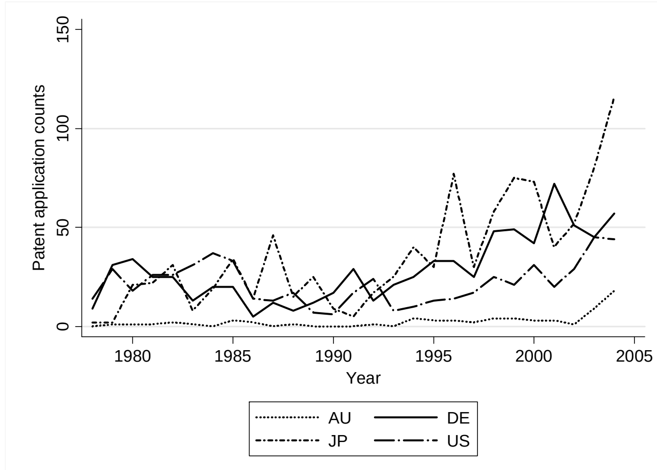


Figure A.4
Solar patent applications by major innovators, EPO patent applications



Zusammenfassung

Die vorliegende Arbeit besteht aus den folgenden wissenschaftlichen Beiträgen:

1 Forschungseffizienz in der verarbeitenden Industrie

Ein wesentlicher Aspekt der Lissabon Agenda ist die geplante Erhöhung der FuE Aufwendungen auf 3% des BIP zur Steigerung der Innovationstätigkeit. Die Erreichbarkeit eines höheren Niveaus von FuE und Innovation unterstellt erhöhte Effizienz der Forschung in Anbetracht knapper Ressourcen. Dieser Artikel identifiziert Länder und Industrien mit hervorragender Forschungseffizienz mit Hilfe der DEA Methodik und liefert erste Anknüpfungspunkte für Innovationsstrategien zur Steigerung der Forschungsleistung durch Hervorhebung von Stärken und Schwächen. Die Analyse von Industrien in 17 OECD Ländern in den Jahren 2000 bis 2004 ergibt, dass Deutschland, die USA, und Dänemark die höchste Effizienz im verarbeitenden Gewerbe haben. Es ergeben sich jedoch erhebliche Abweichungen, wenn branchenspezifische Effizienzwerte berechnet werden. Wesentliche Industrien, die die technologische Grenze bestimmen, sind Elektrik und Optik, Maschinenbau, Chemie und Mineralien.

2 Internationale Wissenstransfers und Produktivität

Dieser Artikel analysiert die Bedeutung internationaler Wissenstransfers für totale Faktorproduktivität anhand eines Paneldatensatzes für 14 OECD Länder und 13 Industrien im Zeitraum von 1985 bis 2004. Der Transfer kann durch nationale oder internationale und weiterhin innerhalb einer Industrie oder aus anderen Sektoren erfolgen. Zur Messung von Wissenstransfers werden Patentdaten verwendet, die im Falle von Transfers aus anderen Ländern mit der Nähe des technologischen Profils gewichtet werden. Unter Verwendung von Techniken aus dem Bereich der Kointegrationsanalyse für Paneldaten wird gezeigt, dass Wissenstransfers hauptsächlich innerhalb einer Industrie stattfinden, sowohl auf nationaler als auch auf internationaler Ebene. Transfers aus anderen Sektoren sind von untergeordneter Bedeutung.

3 Technologische Diversifikation und Marktwert: Eine empirische Ananlyse für das verarbeitende Gewerbe in den USA

Dieser Artikel untersucht die Beziehung zwischen technologischer Diversifikation und Marktwert und analysiert, ob der Grad der technologischen Nähe diese Beziehung beeinflusst. Die Analyse beruht auf Daten des amerikanischen verarbeitenden Gewerbes im Zeitraum von 1983 bis 1995. Basierend auf einem erweiterten Tobin's q Modell wird gezeigt, dass Diversifikation einen Abschlag auf den Börsenwert zur Folge hat wenn neue Technologien nicht in direktem Zusammenhang mit den bestehenden Kompetenzen stehen. Die geschätzte Elastizität im Hinblick auf technologische Diversifikation beträgt 6%. Dieser Abschlag reduziert sich auf 4% für das 75% Quartil der technologischen Nähe. Eine mögliche Erklärung ist, dass technologische Diversifikation die Möglichkeitenen reduziert, Skalenerträge und Verbundvorteile zu nutzen, während im Falle von Diversifizierung in verwandte Technologien von Wissenstransfers profitiert werden kann.

4 Innovationstätigkeit und Wissenstransfers im Bereich der Wind- und Solartechnologie

Dieser Artikel erforscht den technologischen Wandel in erneuerbaren Energien und analysiert Determinanten der Innovationsaktivität unter besonderer Beachtung der Rolle von Wissenstransfers. Wir untersuchen zwei wesentliche erneuerbare Energiequellen – Wind und Solar – über ein Panel von 21 OECD Ländern im Zeitraum von 1978 bis 2004. Wissenstransfers können nationalen Ursprungs sein, entweder innerhalb der Technologie (intra-sektoral) oder in verwandten Technologien (inter-sektoral). Alternativ können Transfers auch auf internationaler Ebene stattfinden. Es zeigt sich insbesondere auf nationaler Ebene, dass Innovationen stark von Wissenstransfers getrieben werden. Wind- und Solartechnologien weisen unterschiedliche Innovationscharakteristika auf: beide werden belebt durch intra-sektorale Transfers, reagieren aber unterschiedlich auf inter-sektorale Transfers, die nur für den Fall der Windtechnologie von Bedeutung sind.