International Institute for
Applied Systems Analysis
Schlossplatz 1
A-2361 Laxenburg, Austria

Tel: +43 2236 807 342
Fax: +43 2236 71313
E-mail: publications@iiasa.ac.at
Web: www.iiasa.ac.at

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Public R&D and Innovation: The Case of Wind Energy in Denmark, Germany and the United Kingdom

Ger Klaassen (klaassen@iiasa.ac.at)
International Institute for Applied Systems Analysis (IIASA)

Asami Miketa (miketa@iiasa.ac.at)
International Institute for Applied Systems Analysis (IIASA)

Katarina Larsen (larsen@infra.kth.se)
Royal Institute of Technology, Stockholm Sweden

Thomas Sundqvist (sundq@iiasa.ac.at)
International Institute for Applied Systems Analysis (IIASA)

Approved by

Leo Schrattenholzer (leo@iiasa.ac.at)
Project Leader, Environmentally Compatible Energy Strategies Project

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Abstract

This paper examines the impact of public research and development (R&D) support on cost reducing innovation for wind turbine farms in Denmark, Germany and the United Kingdom (UK). First we survey the literature in this field. The literature indicates that in Denmark R&D policy has been more successful than in Germany or the UK in promoting innovation of wind turbines. Furthermore, such studies point out that (subsidy-induced) capacity expansions were more effective in the UK and Denmark in promoting cost-reducing innovation than in Germany. The second part of the paper describes the quantitative analysis of the impact of R&D and capacity expansion on innovation. This is calculated using the two-factor learning curve (2FLC) model, in which investment cost reductions are explained by cumulative capacity and the R&D based knowledge stock. Time-series data were collected for the three countries and organized as a panel data set. The parameters of the 2FLC model were estimated, focusing on the homogeneity and heterogeneity of the parameters across countries. We arrived at robust estimations of a learning-by-doing rate of 5.4% and a learning-by-searching rate of 12.6%. The analysis underlines the homogeneity of the learning parameters, enhancing the validity of the 2FLC formulation.

Keywords: costs, innovation, learning, R&D, wind energy

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About the Authors

Ger Klaassen is a Senior Research Scholar at IIASA's Transboundary Air Pollution Project.

Asami Miketa is a Research Scholar at IIASA's Environmentally Compatible Energy Strategies Project.

Katarina Larsen is a Doctoral Student at the Department of Infrastructure at the Royal Institute of Technology. In 2000 she participated in IIASA's Young Scientists Summer Program. Her work was supervised by IIASA's Environmentally Compatible Energy Strategies Project.

Thomas Sundqvist is a Post-Doctoral Research Fellow at IIASA's Environmentally Compatible Energy Strategies Project. The research fellowship is financed by the Kempe Foundations.

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1. Introduction

The development of environmentally compatible energy technologies has been accelerated in response to the growing concern of the impacts from climate change. However, (liberalized) market circumstances are often unfavorable for those new technologies because they tend to be more expensive than existing but not necessarily environmentally benign technologies. Innovation that leads to cost reduction is therefore crucial for these environmentally benign technologies in order to gain larger market shares and policy interventions to initiate such innovations are called for. Such policy interventions can be justified on the basis of “technological learning”. “Technological learning” refers to the phenomenon that the cost of a technology decreases as the cumulative installation of the technology increases (Argote and Epple, 1990; Arrow, 1962; Dosi, 1988; Dutton and Thomas, 1984). Technology policies would stimulate innovation and higher up-front costs could be recovered in the long run after successful technological learning. Without proper policy measures for new technologies, current technologies would however maintain their competitive advantage and remain locked-in a situation relying on technologies that might not be environmentally friendly. In the past, technology-policies such as procurement subsidies and public R&D support have played a key role in promoting cost-reducing innovation of environmentally benign technologies.

In the conventional learning literature, focus is given on the effect of capacity expansion (possibly stimulated by procurement policy) of the cost-reducing innovation. The purpose of this paper is to extend the conventional analysis of the learning effects by including the effect of R&D, based on experience with wind energy in three European countries: Denmark, Germany, and UK.

We focus on wind energy, as it is currently one of the fastest growing energy sources and a carbon–free alternative for traditional fossil fuel based technologies. The selection of the three countries was based on the following arguments: Denmark is the largest global exporter of wind turbines and has the highest per capita levels of wind energy capacity installed. Germany has the highest capacity installed worldwide (BWE, 2001). The UK, in contrast to Denmark and Germany, promoted competition among different renewable energy forms through the introduction of a competitive bidding scheme for subsidies.

Although an abundance of theoretical literature exists on the effects of policy instruments on innovation, surprisingly little empirical research has been conducted (see Jaffe *et al*., 2001). Our analysis is empirical and based on a review of wind energy policy in the three countries and on technological learning concepts. This paper differs from the existing literature on the relation between policy instruments and innovation for wind energy (e.g., Hemmelskamp, 1999; Loiter and Norberg-Bohm, 1999, Mitchell, 1995 and 2000) since the focus is on the quantification of the impacts of policy instruments on innovation (i.e., public R&D).

The quantification was done based on a modified version of the two-factor learning curve (2FLC) model introduced by Kouvaritakis *et al*., (2000). The 2FLC is an extended version of the conventional learning curve (based only on cumulative capacity) in that it includes both cumulative capacity and knowledge stock (resulting from past R&D expenditures). This is a rather novel concept and its empirical validation has not yet been demonstrated successfully. One of the important contributions of this paper is thus to attempt to give a solid empirical foundation by using an econometric analysis using panel data for three countries. In addition, our version of the 2FLC refines the original knowledge stock concept, based on simple cumulative R&D, by introducing a concept of knowledge based on cumulative R&D adjusted by the depreciation of the knowledge stock as well as a time lag between actual timing of R&D expenditures and their addition to the R&D based knowledge stock.

Section 2 describes the different policies in the three countries to promote the diffusion of wind energy and summarizes the literature on the impacts of R&D and (policy-induced) capacity expansions on innovation in these countries. Section 3 introduces the two-factor learning curve model that is used to assess the impacts of policy instruments on cost reducing innovation. Section 4 summarizes the data for our panel analysis. Section 5 gives the results of the econometric analysis. Section 6 concludes and discusses the results obtained.

2. Policy Instruments for Promoting Innovation in Wind Energy

Progress in wind turbine technology can be attributed to R&D programs and accumulated experience in producing wind turbines. Capacity expansion leading to enhanced experience in producing wind turbines can partially be gained by financial incentives to increase demand such as subsidies. This section will have a closer look at R&D programs and demand-based incentives in three European countries for promoting the wind energy.

2.1. Denmark

The promotion of wind energy became important in Denmark in the mid-1970s. Already in 1991, wind turbines provided around 3% of the Danish electricity consumption. By the end of 1999, capacity had grown to 1771 megawatts (MW). The investment subsidy between 1979 and 1989 was instrumental in achieving such a rapid expansion of the capacity. This subsidy scheme offered 30% of the total investment cost for the installation of wind turbines that were approved by a test station (Olivecrona, 1995). From the mid-1980s, the Danish government provided another kind of incentive consisting of a partial refund for the energy and environmental taxes levied on electricity consumption in Denmark. This in effect consisted of the payment of a guaranteed tariff that was paid out to the wind farm operators by the energy supply companies for selling electricity to the electricity companies, which helped in expanding overall capacity. (Morthorst, 1999). A typical characteristic of the Danish system is that it combined market-stimulation incentives with national targets, resulting in the expansion of the domestic market for wind energy (Hemmelskamp, 1999).

A coordinated program of R&D support in all energy areas in Denmark started in 1976. The wind energy projects focused on the provision of information on the construction of large wind turbines involving Danish electricity companies, Risø National Laboratory and the Danish University of Technology. From 1976 to 1995, 10% of the total energy research program was spent on wind energy projects (Olivecrona, 1995). From 1983 to 1989, R&D support was mainly geared towards wind farms and large wind turbines. The percentage of R&D funds given to small wind turbine projects increased over time.

Evidence suggests that in Denmark R&D resulted in technically reliable wind turbines that were available at the end of the 1980s. After this development of the technological niche, subsidy schemes successfully paved the way for a market niche. In terms of R&D expenditures, the setting up of a test center that tested every wind turbine before being released on the market was relevant. R&D as well as demonstration projects in conjunction with investment subsidies (until the end of the 1980s) led to the development of reliable small wind turbines at the end of the 1970s. Part of the successful introduction at that stage was the shift of support away from the manufactures to the operators in order to stimulate further market introduction. Relevant in this context were the strong integration of the energy supply companies and the guaranteed feed-in tariff and the refunding of CO_2 and energy tax to wind turbine operators (Hemmelskamp, 1999). The careful balance and timing of R&D expenditures and procurement support have both played an important function in Denmark in promoting both innovation and diffusion of wind energy.

2.2. Germany

Germany has encouraged the use of wind energy since the 1970s. The major government instruments that led to the rapid diffusion of wind power capacity at the end of the 1980s consisted of: the 100/250 MW program, the feed-in law ("Stromeinspeisungsgesetz"), tax breaks, as well as the provision of low-interest loans (Hemmelskamp, 1999). The 100/250 MW program was the combination of the certification programs, i.e., requirements on technical quality guaranteed by test and research centers and investment subsidies. The feed-in law regulates the purchasing of renewable electricity by public energy supply companies. These companies are obliged to pay at least 90% of the average electricity price paid by the final consumers to the companies selling them wind energy. In addition, 80 to 90% of the companies building wind turbines received low-interest loans (1-2% points below the market rate). The various subsidies reduced the risk of investments and offered a secure basis. The feed-in law did not only induce demand but also provided an incentive to use efficient wind turbines (producing more electricity) in areas with favorable wind conditions and, perhaps more importantly promoted product and, in particular, process innovation. As a result, wind turbines can now operate profitably at locations with favorable wind conditions given the feed-in tariff and the low-interest loans from the government (Hemmelskamp, 1999). As a final point, investment costs could be written off against tax as capital or operating expenses, and initial losses incurred by the operators during the start up period can be used to reduce tax payments in future years when the wind turbine becomes profitable. In general, presently only the feed-in law tariff and the nationally supplied low interest loans are of major significance for the economic feasibility of wind energy (Hemmelskamp, 1999).

Regarding R&D support for wind energy, it started in 1974 with the Growian ("Grosswindanlage") project, which later ended in 1987. With a new focus for wind energy in the mid-1980s, R&D support was resumed again in Germany. This second wave included wind turbines with sizes of 640 to 1200 kilowatts (kW) as well as various projects concentrating on the development of small wind turbines. Some of the prototypes were later launched into the market in modified form. In Germany, the first R&D programs (in the 1970s) to develop large-scale wind turbines (using aerospace knowledge) were regarded a failure due to the considerable expenditures (Hemmelskamp, 1999). The progress of small wind turbines proved to be more successful as they were developed on the basis of engineering and shipbuilding knowledge. Knowledge spillovers did occur, in particular, small German windmill manufacturers were able to benefit from the Danish expertise.

2.3. United Kingdom

In the United Kingdom, the passing of the electricity act in 1989 marked the beginning of support for renewable energy. The act aims at promoting those forms of energy that are competitive. The government also set a target of 1500 MW of renewable energy capacity by the year 2000 (Hemmelskamp, 1999). The UK policy, created to stimulate the role of renewable energy (including wind), basically consists of a two-tier strategy. First, renewable energy policy is promoted through R&D and demonstration projects (Mitchell, 1995). The support budget for renewable R&D has been reduced by more than 50% between 1992-1993 and 1997-1998.

Secondly, with the privatization of the electricity sector in 1989 and 1990, R&D efforts were complemented by a guaranteed premium price per kilowatt hour (kWh) generated for those projects that successfully tendered for this subsidy through the so-called non-fossil fuel obligation (NFFO). Under the NFFO, a project that competes successfully, gets a contract to generate at a specified capacity, receiving its (index-linked) bid price for up to 15 years (DTI, 2000). The NFFO obliges public electricity suppliers or regional electricity companies (RECs) to buy a certain amount of renewable electricity. The difference between the premium price and the average monthly pool-purchasing price for electricity is in effect a subsidy (Mitchell, 1995). A typical element of the UK system is that the contracts awarded under the NFFO and the price paid for the renewable generation result from a process of competitive bidding within a (renewable) technology band on a pre-set date (Mitchell, 2000).

In the UK, the NFFO has been less successful in increasing the capacity of wind energy. This was mainly due to the lack of public acceptance in the spatial planning procedure, which, according to some authors, was related to the competitive pressure, which forced companies to invade profitable but sensitive sites (Elliott, 2000; Hemmelskamp, 1999; DTI, 2000). Mitchell (2000) finds that with respect to capacity expansion, the UK has not been as successful since the focus was on one single instrument such as the NFFO. The UK's NFFO is believed to have been successful though in reducing prices of renewable energy sources down to a level where they can compete (Mitchell, 2000; DTI, 2000). Part of the price reduction in the UK was related to importing technologies (mostly Danish), the prices of which have declined as a result of their domestic markets as well (Mitchell, 2000).

In the UK, R&D expenditures mainly supported large-scale wind turbines (above 3 MW) although this later changed to smaller-scale turbines whereas the NFFO supported medium-sized turbines (300 to 750 kW). R&D support was biased towards a few large-scale projects (Mitchell, 1995). Elliott (1996) finds that the NFFO subsidy scheme is reasonable for supporting near-market technologies but no substitute for R&D support for the longer-term development of technologies for which private R&D support is unrealistic.

In conclusion, the UK R&D expenditures for wind were insufficiently geared towards the type of turbines being installed. The UK NFFO has been successful in driving down costs but the downside of this was that not so much capacity has been installed.

2.4. Summarizing Policy Review for the Three Countries

In summary, we can conclude that:

- In Denmark, R&D as well as demonstration projects, in conjunction with investment subsidies, led to the development of reliable small wind turbines. The careful balance and timing of R&D and procurement support have both been important to promote both innovation and diffusion of wind energy;
- In Germany, the R&D programs (in the 1970s) aimed at developing large-scale wind failed but the development of small wind turbines was successful. The various subsidies (i.e., those under the feed-in-law) provided an incentive for product and process innovation but overlapping subsidies might have resulted in efficiency losses;
- In the UK, R&D expenditures for wind were insufficiently geared towards the type of turbines being installed. However, the UK subsidy scheme (NFFO) has been successful in driving down costs.

Concluding, the above evidence suggests that Denmark's R&D expenditures might have been more successful in promoting innovation than similar expenditures in Germany or the UK. The policy review also indicates that the UK scheme of (subsidy-induced) capacity expansion and the Danish procurement support might have been more effective in stimulating (cost-reducing) innovation than the German support schemes. In the next section, we describe the quantitative analysis for this study.

3. The Two-Factor Learning Curve

One measurable indicator of technological innovation is the cost reduction of technology. A number of studies have found an empirical relationship between cost reduction and cumulative capacity, and it is known as the “learning curve” (Argote and Apple 1990; Dutton and Thomas, 1984). Conventional learning curves include cumulative capacity as the explanatory factor for technology cost reduction.

The most commonly used formulation of the learning curve looks like:

$$SPC = A \cdot CC^{-\alpha} \tag{1}$$

where:

SPC	Costs of a technology per unit (specific cost)
CC	Cumulative capacity
-α	Learning index
A	Specific cost at unit cumulative capacity

The above formulation implies that for each doubling of capacity costs there is a constant percentage decrease, called the learning rate (calculated as $1-2^{-\alpha}$). Typical learning rates calculated for studies on wind turbines range from 4 to 32%. The range is dependent on the country/region studied and the indicator used (investment costs or production costs) to estimate the learning rate (McDonald and Schrattenholzer, 2001).

From a policy point of view, a shortcoming of the above conventional one-factor learning curve, which uses cumulative capacity as the only explanatory factor, is that the learning rate – and the learning process altogether – only depends on capacity expansion. Hence, only procurement policies, which increase demand and hence expand capacity, would play a role in reducing the costs of a technology. R&D, despite its popularity as a policy instrument and its obvious impact on innovation in especially in early development phases, has no place in it. Hence the traditional learning curve does not assist policymakers in the allocation of scarce resources over capacity expansion and R&D expenditures. This is remarkable since the use of cumulative R&D expenditures to estimate the impact of R&D expenditures on levels of output is well established in both macroeconomic and sector-specific studies (see for example Lieberman, 1984; Griliches, 1995; Nordhaus, 2002).

In response to this observation, Kouvaritakis *et al*. (2000) have proposed an extended learning-curve concept, the two-factor learning curve (2FLC), which includes cumulative R&D expenditures as the second factor, in addition to cumulative capacity to add a more direct policy variable in the learning curve model. We refined this original 2FLC by replacing the cumulative R&D with a more general knowledge stock concept, which takes into account the depreciation of the cumulative knowledge stock and adds a time lag between the actual R&D expenditures and their addition to the knowledge stock. Knowledge is then defined in the following way.

$$KS_t = (1-\delta) \cdot KS_{t-1} + RD_{t-x} \tag{2}$$

Where:

KS_t	R&D based knowledge stock at time t
RD_t	R&D expenditures
x	Time lag for adding R&D to the knowledge stock
δ	Annual knowledge stock depreciation rate

By doing this, we take into account the following two observations. First, the effect of R&D is not instantaneous. Money invested in research will only deliver tangible results (if at all) in some future time. Just as it takes some time for a paper to be written, reviewed and published. Second, knowledge depreciates (compare Griliches, 1995). The effect of successful past R&D – knowledge – gradually becomes irrelevant.

With this knowledge stock, the two-factor learning curve can now be formulated as:

$$SPC = A \cdot CC^{-\alpha} \cdot KS^{-\beta} \tag{3}$$

Where:

SPC	Costs of a technology per unit (specific cost)
CC	Cumulative capacity
KS	R&D-based knowledge stock
$-\alpha$	Learning-by-doing index
$-\beta$	Learning-by-searching index
A	Specific cost at unit cumulative capacity and unit knowledge stock

This model was estimated in a logarithmic form with an error term (ε).

$$\log(SPC) = \log(A) - \alpha \log(CC) - \beta \log(KS) + \varepsilon \tag{4}$$

4. Data

To analyze the quantitative relationship between the development of the investment costs over time on the one hand and cumulative capacity and the knowledge stock (based on R&D) on the other, we collected the following data:

- The (average) investment costs per kW (Figure 1)
- Cumulative capacity (Figure 2);
- Annual public R&D expenditures (Figure 3);

Figure 1 depicts the data collected on the investment costs. For Denmark and Germany, investment cost data for wind-farms installed were based on ISET (2000) and Durstewitz (2000). Data for the UK were based on Milborrow (2000). Note that, in contrast to other estimates, the investment cost data for the three countries cover all investment cost items, such as grid connections, foundations, electrical connections and not only the costs of the wind turbines (Rohrig, 2001; Varela, 2001). This is a significant difference since the non-turbine part of the investment costs might amount to 10 to 40% of the overall investment costs. Figure 1 shows that in all three countries the investment costs have declined, albeit not continuously. Data for 1992 for the UK are only for one project whereas data for the other years are generally averages of various projects.

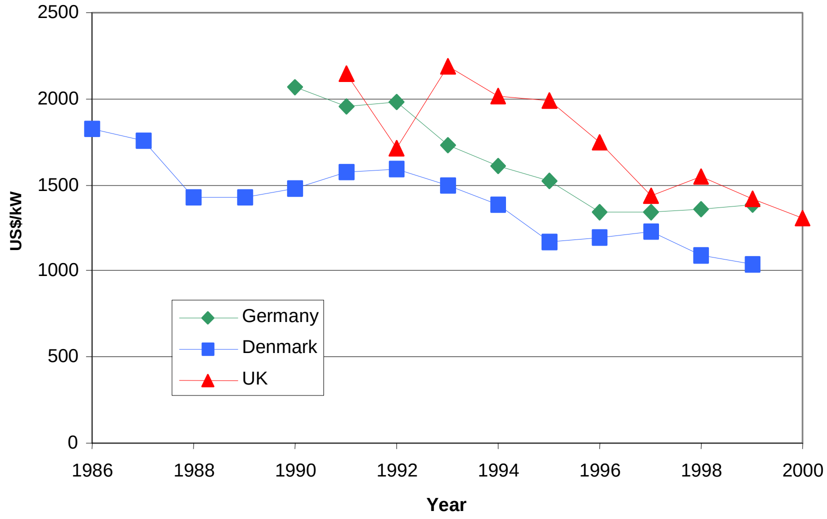

Figure 1: Data collected on the investment costs.

The data for the UK suggest a rapid decline in the investment costs after 1993 (the jump in costs for 1992 is probably due to the aforementioned data limitation). German data shows a regular though less sharp decrease over the whole period (1990–1998). Danish data suggest a gradual trend down from 1986 onwards with two periods of increasing costs. Differences in the level of the costs across the countries are not only related to country-specific factors but also reflect differences in the average size of the wind turbines installed.

The development of cumulative capacity in the three countries is shown in Figure 2. Clearly, Denmark started early whereas Germany and the UK expanded wind energy capacity only in the1990s. From 1994, German wind energy capacity exceeded Danish capacity and the German market has now twice the size of the Danish market and is nearly ten times bigger than the UK market.

Figure 3 shows the development of the annual public R&D expenditures on wind energy based on IEA data (2000). German expenditures have generally been higher than those for both other countries, with the exception of the period between 1983 and 1992. From the mid-1990s R&D expenditures in both Germany and the UK were cut significantly whereas Danish R&D outlays remained more or less stable.

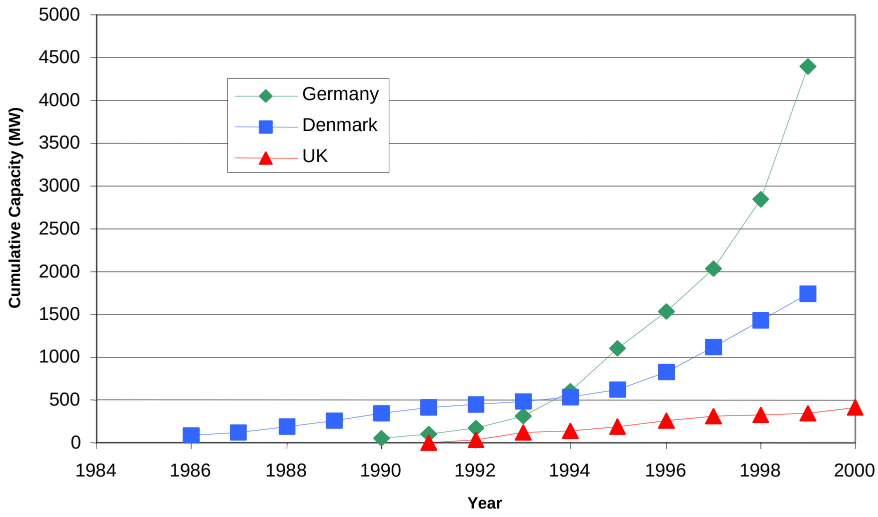

Figure 2: Development of (on-shore) wind energy capacity installed (MW). Sources: ISET, 2000; DWMTA, 2000; BWEA, 2000; BWE, 2001.

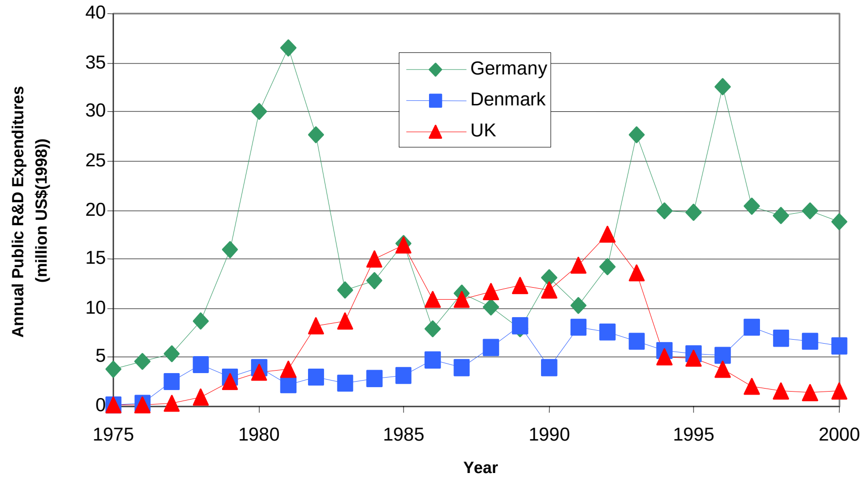

Figure 3: Public energy R&D expenditures for wind energy, IEA, 2000.

In order to translate these annual public R&D expenditures into the development of a knowledge stock, assumptions are needed on the time lag between R&D expenditures and their addition to the knowledge stock as well as the depreciation of the knowledge stock. Griliches (1998:27) suggests that for commercial R&D expenditures a time lag of 3 to 5 years might be appropriate and that depreciation would be so fast that hardly any of the private R&D spent 10 years ago would remain. This suggests an annual depreciation rate in excess of 10%. He also finds that for social (or public) R&D

expenditures, the data situation is much more difficult, but one would expect the social rates of depreciation to be lower than the private ones. Nordhaus (2002) indicates that the depreciation rates are variously estimated at 1 to 10%. IEPE (2001) uses a depreciation rate of 3% in calculating the R&D knowledge stock for a number of energy technologies. Watanabe (1999; 2000) finds a time lag of 2 to 3 years to be appropriate for R&D expenditures in the case of Japanese solar PV cells. Our own initial estimates of the time lag for solar PV and wind turbines on a global base indicated that time lags of 2 to 3 years and depreciation rates of around 5% lead to acceptable statistical results (Kobos, 2000). For this study we use a depreciation rate of 3% and a time lag of 2 years. We think the shorter time lags (2-3 years) are more appropriate for our work since they were derived for individual energy technologies (such as solar PV) rather than from studies with an industry specific or macroeconomic orientation (such as Griliches, 1998; Nordhaus, 2002).

Figure 4 depicts the result of this calculation of the knowledge stock. Clearly, the effect of reducing R&D expenditures in the UK since the beginning of the 1990s becomes noticeable and the depletion effect of old knowledge overweighs the creation of the new knowledge in the very recent years. This is not yet the case in Germany due to the time lags and the depreciation rate of public (R&D-based) knowledge.

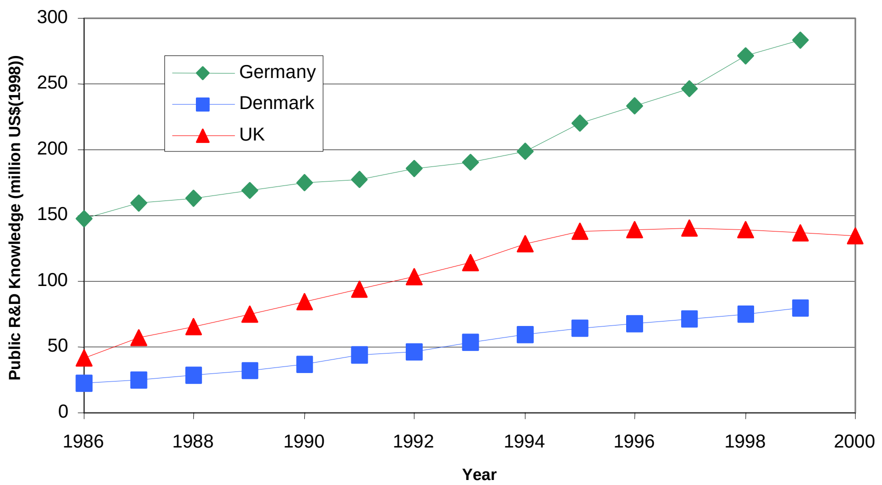

Figure 4: Development of the R&D based knowledge stock for wind power

5. Assessment of the Impact of R&D and Capacity Expansion

This section analyzes the effect of the cumulative capacity expansion and public R&D expenditures on the innovation of wind turbines in a quantitative way based on the above-introduced 2FLC. In this example, we used time-series data for the three countries, organized as a panel data set (a data set that combines time series and cross sections).

Analyzing a panel data set has several advantages over an analysis done based on time series of single country data. The first advantage is that the sample size increases and that we therefore obtain results that are more statistically reliable. Estimation of the learning curve for a relatively new technology such as wind is usually unreliable since sample sizes are typically limited to short time periods, i.e., insufficient degrees of freedom. For example, in our dataset, there are 14 data points for Denmark, and 10 for Germany and the UK each. By pooling the time series data and cross-section data, the number of observation points increases to 34, which gives us sufficient degrees of freedom for the statistical analysis.

The second advantage of a panel data analysis is the possibility to analyze cross-sectional variation, i.e., the homogeneity and heterogeneity across countries. The panel data analysis is suitable for testing whether the "learning" phenomenon, more specifically the capacity-related learning coefficient and the knowledge-based searching coefficient, has a technology-specific character or country-specific character.

5.1. Fixed-Effect Model: Common Slopes and Country-Specific Intercepts

Two possible error specifications of an econometric model with panel data are those of fixed and random-effects models. In this case, a fixed-effect specification is to be preferred since we are primarily interested in capturing within-country variations among the specific countries chosen for the study. The random-effects specification, however, would have been appropriate if we were drawing *N* countries randomly from a large population (Baltagi, 1995). The fixed-effects model assumes common slope coefficients and different intercepts across cross-sections (in our case they are countries). In the specific context of our two-factor learning curve estimation, all three countries are assumed to have common learning parameters but the specific costs at unit cumulative capacity and unit knowledge stock are different across the three countries. Note that we estimate the 2FLC in a logarithmic form (equation 4), thus the coefficients for the learning parameters become slopes and parameter *A* becomes the intercept of the model. The validities of these assumptions are then tested statistically.

Table 1 presents the result of our estimation of the two-factor learning curve based on the fixed-effect model. One common set of learning parameters is estimated for three countries and parameter *A* is estimated for each country. The important point to underline here is that all estimated parameters have the expected (negative) sign. In many cases with the estimation based on single time series, such estimates often result in counterintuitive positive signs, especially for the impact of cumulative R&D expenditures (compare Criqui *et al*, 2000; Kouvaritakis *et al*., 2000).

Note that panel analysis itself does not assure the improved result in terms of signs. However, there is an improvement compared with the result based on separate country estimations, given that the uncertainty in estimating the parameter *A* and the uncertainty in estimating the learning parameters are partially separated by the use of the fixed-effect model. What this means is that with an estimation based on single country data, country specifications are included in the estimated parameter and there is no way to separate them from the "pure" part of "learning parameter" which is assumed robust (by the formulation of the fixed-effect model) regardless of a selection of countries. With the fixed effect model formulation of the panel data, we can eliminate unobserved country-specific variation from the learning parameters estimation, and by doing it we can obtain more robust estimations of the learning parameters, which is of particular analytical interest for energy modeling purposes.

If we translate the estimated parameters into a learning-by-doing rate (based on cumulative capacity) of 5.4% and a learning-by-searching rate (based on the knowledge stock) of 12.6%, we also obtain results that fit well with ranges obtained in other studies (Kouvaritakis *et al*., 2000; McDonald and Schrattenholzer, 2001). The t-statistics for each variable also indicate that all of them are statistically significant. We also observe that the overall fit of the equation is reasonably good, showing an R-square of 0.75.

Table 1: The result of the 2FLC based on the fixed-effect model.

Variable	Coefficient	t-Statistic
LOG (Cumulative Capacity) (α)	-0.08	-3.68**
LOG (Knowledge Stock) (β)	-0.19	-2.22*
DK—C (A)	8.58	34.51**
DE—C (A)	8.94	23.34**
UK—C (A)	8.78	24.68**
R-squared (adjusted)	0.75 (0.72)	

Note: t-statistics marked with double asterisks (**) mean that the null hypothesis of the coefficient being zero is rejected at the 1-percent level of significance; those with a single asterisk (*) imply a rejection at a level of 5%.

5.2. Statistical Test of Cross-Country Variation

The fixed-effect model is built on two assumptions, (1) common slopes (common learning parameters) and (2) different intercept terms (different parameter *A*) across countries. The next step of this study was to test these two assumptions statistically. Such tests are carried out by formulating two alternative panel data models and compare the sums of their squared residuals with the fixed-effect model. One alternative panel data model is formulated with common slopes and a common intercept for all countries; the other consists of different intercepts and different slopes for each country. For ease of reference, they are numbered as follows:

(I) Common regression for all countries (Common slopes, common intercept)
(II) Different intercepts, common slopes (fixed-effect model)
(III) Different intercepts, different slopes

The test of different (country-specific) intercepts (parameter *A*) is performed by contrasting model I with model II. The test of common learning parameters (common slopes) is performed by contrasting model II with model III. Whether these assumptions are statistically accepted or not can be assessed by examining the F-statistics, which are calculated using the sum of the squared residuals (SSR) and the degrees of freedom (DF) in the estimation of two contrasted formulations. The exact formulation of the test statistics is as follows.

Null hypothesis for differential slopes:

***H₀*:** $\alpha_{Germany} = \alpha_{UK} = \alpha_{Denmark}$ **and** $\beta_{Germany} = \beta_{UK} = \beta_{Denmark}$

$$F = \frac{(SSR_{II} - SSR_{III})/(DF_{II} - DF_{III})}{SSR_{III} / DF_{III}} \sim F(DF_{II} - DF_{III}, DF_{III})$$

Null hypothesis for differential intercepts:

H_0: $A_{Germany} = A_{UK} = A_{Denmark}$

$$F = \frac{(SSR_{I} - SSR_{II})/(DF_{I} - DF_{II})}{SSR_{II} / DF_{II}} \sim F(DF_{I} - DF_{II}, DF_{II})$$

We performed ordinary least square estimations for the three models. The sum of the squared residuals and the degrees of freedom for the estimations are summarized in Table 2.

Table 2: The results of Model I - III.

Model	Sum of squared residual	Degrees of freedom
Common slope and common intercept (I)	$SSR_I = 0.427$	32
Common slope and different intercept (II)	$SSR_{II} = 0.319$	30
Different slopes and different intercept (III)	$SSR_{III} = 0.279$	28

Using the result of Table 2, the F-statistics were calculated (see Table 3). To summarize the results, the F-statistics for the common slope was insignificant and thus the null hypothesis is *not* rejected. Hence the evidence supports the existence of common learning parameters for each country. The F-statistics for the common intercept was significant and the null hypothesis was rejected at a 1% significance level. These tests of the model specifications thus support the formulation of the fixed effect model for the two-factor learning curve, whose results were presented in the previous section.

Table 3: F-statistics and probability.

Null-hypothesis	F statistics	Probability of rejecting the null hypothesis
Common slopes (learning indexes α and β) (II-III)	0.94	0.40
Common intercept (A) (I-II)	5.01	0.01

The t-test for the common slope showed that the specific cost at unit cumulative capacity and knowledge stock (*A*) appears to differ between countries. This does not strike us as surprise. There is no *a priori* reason that we can assume that they are identical, given the difference in price level in general and difference in country specific circumstances such as building codes and siting requirements prevailed in the three countries. The test for the common slope suggested that learning parameters are common to the three countries and "country effects" were not observed with these parameters. This implies that for the three countries and the wind technology we examined, "technological learning" seems to be a technology-specific phenomenon, rather than a country-specific one. The overall results enhance the validity of the 2FLC formulation as a technology specific phenomenon.

6. Conclusions and Discussion

This paper examined the impact of (subsidy-induced) capacity expansion and public R&D expenditures on cost reducing innovation for wind turbine farms in Denmark, Germany and the United Kingdom. In doing so, we used an extended version of the traditional learning curve that now incorporates both (public) R&D expenditures as well as cumulative capacity expansion as variables. We used panel data to estimate the learning curve.

Our survey of the literature suggests that in Denmark, R&D as well as demonstration projects, in conjunction with investment subsidies, led to the development of reliable small wind turbines and the careful balance and timing of R&D and procurement support promoted both innovation and diffusion of wind energy. In Germany, the R&D programs to develop large-scale wind failed but the development of small wind turbines was successful. The various subsidies provided an incentive for product and process innovation but overlapping subsidies might have resulted in efficiency losses. In the UK, R&D expenditures for wind were insufficiently geared towards the type of turbines being installed. The UK subsidy scheme (NFFO) has been successful in driving down costs. This suggests that R&D policy in Denmark was most successful in supporting innovation and capacity-promoting subsidies were most effective in Denmark and Germany in stimulating innovation.

The statistical analysis of the investment cost reductions of wind generation technologies in the three countries supported the validity of the two-factor learning curve formulation, in which the cost reductions are explained by cumulative capacity and the R&D-based knowledge stock. The analysis suggests that the learning parameters for the three countries are not found to be significantly different. In the fixed-effect specification of the panel data, learning parameters are common to the three countries but the initial parameter A differs for the three countries. In addition, all the estimated parameters were statistically significant and the learning parameters (which are 5.4% for learning-by-doing and 12.6% for the R&D based, learning-by-searching rate) have values in line with those found in the published literature.

In concluding, we would like to note a few points for further discussion. First, the analysis was restricted to the 1990s due to data limitations especially on investment costs. Secondly, the analysis was restricted to an evaluation of public R&D expenditures and did not take into account private R&D expenditures as a separate factor. Consequently, we might have overestimated the impact of public R&D expenditures. Global estimates of private R&D expenditures for wind energy based on sales and patent data from electricity generation equipment producers suggest that over the last 25 years (1974-1999) private R&D expenditures for wind energy might have been approximately 75% higher than public R&D expenditures (Criqui *et al.*, 2000). This is an area that requires more country-specific research.

Another area where more detailed country analysis might be warranted is the treatment of spillover effects between the three countries. More than 95% of the wind turbines installed in the United Kingdom were imported; around 80% of the installed capacity in the UK was imported from Denmark (BWEA, 2000; EUWINET, 2001). Nearly 40% of the wind turbine capacity installed in Germany was imported from Denmark, 0.5% was imported from the Netherlands and the rest came from domestic sources. In order to take this into account, we would need to refine the data and methodology we use.

Finally, our analysis was restricted to innovation in terms of investment costs reductions in three countries and it might thus be that differences in innovation between the countries have occurred in other areas such as operating & maintenance costs and efficiency improvements.

Bearing in mind these points, we believe that our approach based on the extended learning curve is a potentially powerful tool for policy makers to assess the impact of reducing or increasing R&D expenditures on technology costs and hence the diffusion of carbon-free wind turbines. It also offers a tool to start thinking on the appropriate level, as well as the optimal allocation of subsidies between procurement (such as feed-in tariffs and investment subsidies) and public R&D support so as to steer long-term technological development into the desired direction.

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