SCALE IN TECHNOLOGY AND LEARNING-BY-DOING IN THE WINDMILL INDUSTRY

by

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Abstract: This paper examines the remarkable development of technology and the fast learning-by-doing in the windmill industry since it emerged in the beginning of the 1980s. Based on time series of prices of windmills a dynamic cost function for producing windmills is tested. The estimations verified that learning-by-doing in the Danish windmill industry has contributed significantly to improve the cost efficiency of the producers. The technological development has been stimulated both by process and product innovations as the capacity of the individual mills has increased. The learning effect created by early subsidies from the government has consolidated the competitive advantages of the windmill cluster in Denmark and preserved the first mover advantages at the world market. The article concludes that the industry probably will enter into a matured phase in the future with more modest technological growth.

Key words: Learning-by-doing, scale in technology, process and product innovations
JEL Classification: D2, L6

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1. Introduction

The windmill industry has grown rapidly during the 1990s. Calculated on the basis of the productive capacity of the installed windmills, the production has increased more than ten-fold. Since the 1980s, the Danish windmill producers have gained a leading position in this new industry, which is illustrated by the impressive fact that at present the Danish producers satisfy around half the world demand for windmills. This rapid growth in production has triggered considerable improvements in productivity and hence a substantial fall in the costs of producing electricity by windmills.

The reason for this spectacular development of the windmill industry is the endeavours at the political level of increasing the production of electricity from renewable energy sources after the first oil crisis in the mid-seventies. Since the early 1980s, production of electricity from windmills in Denmark has been stimulated by various environmental policy motivated state aid schemes among which the most important has been a price guarantee per produced kWh (kilowatt-hour) to the producers of wind energy, i.e. the windmill owners (Morthorst, 1999). Without these subsidies, windmills as suppliers of electricity would not have been competitive compared to traditional power plants and hence the producers of windmills would not have got foothold in the Danish industry. This is also illustrated by the development in demand where a large part of the windmills produced in the pioneering years in the 1980s were sold domestically whereas exports made up a substantial part of sales in the 1990s.

The Danish windmill industry represents an industrial cluster consisting of comparatively few independent companies taking advantage of their imminence on the World market. The advantages for the companies might be due to strong demands from local customers, inter-firm diffusion of technological knowledge, common access to high quality production factors, active rivalry between the firms in the industry and strong motivation and opportunity to compare performance, see Porter (1990). The early support for alternative energy sources from the Danish government created a big home market for windmills and gave the Danish producers first mover advantages. However, an important condition for a successful outcome of such first mover advantages is the existence of learning-by-doing within the industry, which could further reduce the production costs and consolidate the competitive advantages of the industry.

The paper therefore looks for evidence of experience accumulation within the windmill industry, which may have contributed to the formation of the cluster. The papers test a dynamic cost function in the windmill industry taking into account the time-dependent development in technology and the increase over time in the scale or capacity of the windmills. The paper is organised as follows. Section 2 looks at the earlier industrial studies of learning-by-doing, Section 3 introduces the available data used and Section 4 presents the evidence of learning-by-doing in the Danish windmill industry. Section 5 concludes the paper.

2. Previous results on learning-by-doing

Learning-by-doing is demonstrated in the pioneer work of Wright (1936) who studied the development in labour productivity in the US airframe industry. Wright shows that the number of man hours required to produce an aeroplane body declines with the cumulative number of aeroplanes produced. An early theoretical contribution to the learning-by-doing hypothesis is given in Arrow (1962) who incorporates learning effects associated with cumulative investments into a macroeconomic growth model. Later on, dynamic scale economies have been analysed in large number of empirical and theoretical analyses. Recent empirical contributions are given by a.o. Zimmerman (1982), Irwin and Klenow (1994) and Benkard (1999). Of the theoretical contributions may be mentioned Dasgupta and Stiglitz (1988), who investigate for the implications of learning-by-doing on the market structure, Lucas (1988, 1993), Stokey (1988) and Young (1991, 1993) who continue the Arrow tradition of including learning-by-doing in macroeconomic growth models.

It is the firm or the plant that generates experience through its day-to-day operations. This learning effect may be internal and external. If the firm for example is capable of keeping all knowledge about production for itself then the learning effect is a pure internal process (internal dynamic scale economies). In this case the dynamic marginal costs are less than the static current marginal costs with an amount equal to expected present value of future cost reduction due to experiences from current production in the firm (Irwin and Klenow, 1994). As the dynamic externality is appropriated by the firm itself in this case, internal dynamic scale economies influence the strategic behaviour at the firm level and the long-term market structure at the industry level (see e.g. Dasgupta and Stiglitz, 1988).

In case of knowledge spillovers between firms, e.g. through labour turnover, the learning process reflects external dynamic scale economies. In the special case where there is a large number of firms and where diffusion of knowledge between firms in the same industry is perfect, the level of production in the individual firm has only a negligible impact on total learning. What matters in this case is total production in the industry i.e. the dynamic scale economies are external and hence static and dynamic marginal costs coincide at the firm level.

The relation between production costs and the cumulative production is usually specified by the following dynamic cost function:

$$c_t = \alpha Q_{t-1}^{\beta} \quad ; \alpha > 0, \ \beta > 0 \tag{1}$$

where c_t is the production costs per unit of output in period t, Q_{t-1} is the lagged cumulative output, α a scale parameter illustrating the unit costs of producing the first unit and β a parameter for the learning elasticity i.e. the percentage decrease in unit cost by one percentage increase in lagged cumulative output. Empirical analyses often include several other explanatory variables in the cost function such as capacity utilization (internal static scale economies), number of product generations and time (exogenously given technological progress). The studies usually report a high R^2. Table 1 lists the main results of the estimated learning parameter in earlier industry studies. Beside the estimated learning parameter β, the learning rate is often reported i.e. the percentage decline in unit production costs in case of a doubling of production, see the last column of the table.

Table 1. Industry studies of learning-by-doing

Industry	Author	Dep. variable	Control for		Learning	
			scale	time	elasticity	rate, %[1]
US Aircraft	Wright, 1936	# labour hours	NO	NO	-0.32	20
	Mishina, 1999	# labour hours	YES	YES	-0.29	18
	Benkard, 1999	# labour hours	YES	NO	-0.29	18
Global Semi-conductor	Webbink, 1977[2]	Selling price	NO	NO	-0.4	24
	Gruber,1992	Selling price	YES	YES	-0.15	10
	Irwin and Klenow, 1994	Selling price	NO	YES	-0.32	20
US Chemicals	Liberman, 1984	Selling price	YES	YES	-0.18[3] -0.44[4]	12 26
EU Electricity Technology	Williams and Terzian, 1993[5]	Selling price	NO	NO	-0.29	18
	Neij, 1999[5]	Selling price	NO	NO	-0.06	4

Notes: 1) The learning rate expresses the relative decline in production costs with a doubling of the cumulative production calculated as $1\text{-}2^{\beta}$. 2) The study is quoted in Irwin and Klenow, 1994. 3) Inorganic products. 4) Synthetic fibres. 5) The study is quoted in OECD/IEA, 2000.

The estimated learning parameter (measured by elasticity or rate) varies quite a lot between the different studies. The reported learning elasticity's for all studies fall in the range from -0.06 to -0.44. One reason for this variation is the different estimation methods used in the studies. Over time new technologies reduce the unit costs and controlling for this effect by introducing a time trend in the regression, they reduce the learning parameter. Also the advantages of scale economies reduce unit costs, and this effect is normally controlled for by introducing the size of the yearly production in the regression. The studies controlling for these effects have lower estimates of the learning elasticity.

All studies from the aircraft industry are based on plant-level data and measure the development in costs with the development in unit direct labour cost of output. The studies within the other industries (semiconductor, chemicals and electricity) are based on firms within the industry and use the average selling price within the industry as a proxy for unit costs of production. Available studies on electricity production (including windmills) as shown in the last two rows of Table 1 are based on very aggregate data with short time series. Accordingly, the available estimates on learning-by-doing in this industry are quite suggestive.

Besides these industrial studies, Bahk and Gort (1993) examine new firm startup for a sample of 2150 new firms or plants in 41 industries. They decompose the internal learning in the plants into organization learning, capital learning and manual task learning, and they find that organizational learning appears to continue over a period of at least 10 years following the birth of a plant while capital learning disappears after 5 to 6 years. They also incorporate the industry wide learning in their study, but it seems to be connected to the technological development as the effect disappears when they control for embodied technical changes in the capital stock.

3. The data

The primary political objective of producing windmills is to increase the supply of electricity from renewable sources. This goal arose as a response to the first energy crisis in the beginning of the 1970s. But first from the late 1970s an actual market for windmills emerged making a larger scale of production possible. The data used in this study has been obtained from the Danish Wind Turbine Manufacturers' Association in Copenhagen and from EM Data in Aalborg. The Danish Wind Turbine Manufacturers' Association yearly publishes data for production and sales of Danish windmills in "Windpower Note" whereas EM Data conducts a survey among Danish windmill investors collecting information on investment expenditure and first year production.

Table 2 illustrates the yearly production of windmills since 1983 in Denmark measured either by the number of produced windmills or by total effect measured in MW (megawatt). The effect in MW measures the capacity defined as the produced quantity of electricity per hour under circumstances of optimal wind. At very low wind speeds, the windmill goes out of production and also at high wind speeds production is discontinued to protect the mill from breakdown. Hence optimal wind conditions exist for an interval of wind speed where the windmill produces at its maximum effect.[1] Measured by effect, the annual production of windmills has increased from 117 MW in 1984 to 1900 MW in 1999. The average effect of a windmill has increased from 31 kW in 1983 to 698 kW for windmills sold in 1998. This fact

[1] The technology has improved during the investigation period so that the interval of the optimal wind has increased. Hence, for given effect new vintages of windmills produce more electricity during a year compared to older vintages for given conditions of wind.

points at a trend in the underlying technologies with production of windmills with larger effect (production capacity).

Beside these annual data, this study also has access to a micro data set with investment and production information for a sample of 833 new windmill instalments. The sample is conducted by EM Data in Aalborg in the period from 1980 to 1999, and it is a representative sample of prices of new windmills in Denmark. Column 5 in Table 2 lists the average real price, i.e. investment expenditure on the purchase of a windmill, quoted in kW. It appears from the table that price per unit capacity has fallen to below half the price per unit capacity of a mill purchased back in 1981.

Table 2. Production, effect and prices for Danish windmills, 1983 - 1998

Year	No. of mills	Effect in MW	Effect per mill in kW	Price per mill in DKK/kW, 1980 prices	Export share
1983	1279	40	31	6846	0.28
1984	1694	117	69	6287	0.93
1985	3812	243	64	5598	0.91
1986	2246	212	94	5176	0.84
1987	767	88	115	4845	0.59
1988	597	102	171	3978	0.23
1989	754	136	180	4082	0.38
1990	723	162	224	4323	0.54
1991	778	166	213	4482	0.54
1992	712	165	232	4343	0.71
1993	689	210	305	4132	0.83
1994	1144	368	322	3882	0.88
1995	1530	574	375	3369	0.87
1996	1360	726	534	3433	0.69
1997	1644	968	585	3328	0.69
1998	1742	1216	698	3191	0.74

Source: Danish Wind Turbine Manufacturers' Association (1999): "Danish wind energy 4th quarter 1998", *Windpower Note*, no. 22, April 1999. EM Data, Aalborg.

Note: Calculations in fixed prices are based on the deflator for gross factor income for the period 1983-93 and gross domestic product for 1993-98.

This substantial fall in the price has brought the Danish producers of windmills at the forefront of the competitive edge with first mover advantages. The export share of the industry is well above 75% for most of the years as shown in the last column of Table 2 and this gives the Danish producers a dominant position at the world market. For 1998, the total worldwide installing capacity was 2,597 MW, which gives the Danish windmill industry a world market share of around 50% according to BTM (2000) report.

The scale in technology for windmills has changed dramatically over this period which is further highlighted in Table 3 where the windmills from the survey are classified according to their capacity. The number of windmills in the sample is clustered around some standard capacities and it is seen from the last column that mills with a large scale are much more cost efficient than the smaller mills. Scale in technology is therefore very important to take into account when evaluating dynamic cost function in the windmill industry. However, column 3 shows that the average year of installment also increase with mill capacity so the higher cost efficiencies of the large mills could also be a result of either the general development in technology over time or the learning-by-doing in the industry. In the following section we will try to disentangle these different effects.

Table 3. Capacity, installment age and prices for Danish windmills, 1983 - 1998

Mill capacity In kW	No. of mills	Average year of installment	Price per mill in DKK/kW, 1980 prices
10	1	83.00	6818
11	4	96.50	7931
15	1	85.00	3693
18	1	84.00	6571
22	2	93.00	5400
55	34	84.62	4938
65	3	84.33	5051
75	20	85.40	4084
80	5	86.40	4252
81	1	85.00	4421
90	7	86.71	2999
95	27	86.89	4081
99	39	87.26	3927
100	3	89.33	3273
130	7	88.29	3159
150	212	90.49	3749
160	6	88.67	3283
175	2	90.00	3004
180	4	87.75	3007
200	38	90.37	3242
225	67	91.93	3371
250	43	90.16	2778
270	1	91.00	2742
300	24	92.88	2969
400	4	93.00	3737
450	6	91.17	2811
500	26	95.12	2839
550	10	96.90	2673
600	98	96.72	2749
660	4	98.00	2941
750	29	97.72	2446

Source: EM Data, Aalborg and own calculation.
Note: Calculations in fixed prices are based on the deflator for gross factor income for the period 1983-93 and gross domestic product for 1993-98.

4. Estimation of the learning effects

The following empirical analysis estimates the total learning effect at the industry level no matter whether it is a result of firm-specific learning or a result of knowledge spillovers between the firms. We therefore explain the experience accumulation in the industry by the total cumulative production in the industry. However, the average effect per mill increases during the investigated period and it is an open question whether learning-by-doing is triggered by production of windmill capacity (Q) or by number of windmills (N). We leave it to the estimation to judge between the two alternative explanatory variables for learning. Since no data is available on the unit costs of producing windmills, the price of the mill is used as a proxy for the unit costs.[2] Implicitly it is therefore assumed that the price-cost margin is either constant or at least does not change according to a specific trend during the period of investigation. More exactly, the price is specified as the real investment expenditure on the purchase of the mill.

An aggregate time-series model

We estimate the learning model on the aggregate time-series data in Table 1 and use the following logarithmic transformation of the learning model in equation (1):

$$\ln P_t = \ln\alpha + \beta \ln N_{t-1} + \mu \ln \Delta N_t + \lambda_t + \varepsilon_t \qquad (2)$$

where t is the time period, P_t is the average windmill price per kW in fixed prices, N_{t-1} is the accumulated experience measured by cumulative number of mills produced up to the last period (t-1), ΔN_t is the number of mills produced in year t, λ_t is a time trend to capture the exogenously given productivity growth rate and ε_t is a random, normally distributed error term. Due to economic of scale at the industrial level μ is expected to be less than zero. To take account of changes in the demand conditions of windmills, the export share is used in the estimation and we also use an alternative proxy for experience accumulation: the cumulative production measured in effect (Q_{t-1}).

[2] It is quite common to use the price as a proxy for unit costs, e.g. when estimating learning curves in other industries. See for example Gruber (1992) and Irwin and Klenow (1994) for estimations of learning curves in the semiconductor industry.

Table 4 shows the estimation results. The estimated parameter for the learning elasticity has the expected sign and is highly significant no matter the specification of the model. The estimated models (2) and (3) further control for the exogenously time-dependent increase in productivity by introducing a time trend. The time-dependent growth in productivity is significant and 2.6% per year. However, the learning elasticity is reduced considerably to a level of -0.15, although it is still very significant.

Table 4. Aggregate time-series estimates of the learning effect, 1983 - 1998

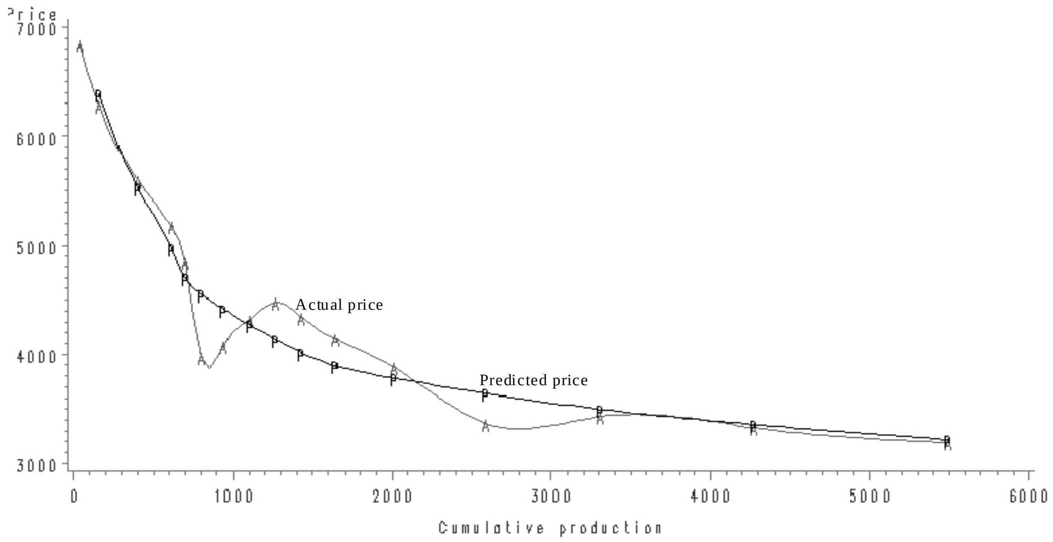
	Dependent variable: $\ln P_t$			
	Model (1)	Model (2)	Model (3)	Model (4)
Intercept	11.7851** (0.3221)	12.8259** (0.3782)	13.2500** (0.4171)	10.8501** (0.5854)
$\ln N_{t-1}$ Cum. production	-0.2912** (0.0348)	-0.1449** (0.0486)	-0.1713** (0.0400)	
$\ln Q_{t-1,}$ Cum. production				-0.1305** (0.0306)
λ_t, time trend		-0.0264** (0.0075)	-0.0266** (0.0059)	-0.0086 (0.0090)
$\ln \Delta N_t$, production year t			-0.0495 (0.0379)	
$\ln \Delta Q_{t,}$ production year t				-0.0484 (0.0375)
Export share			0.2790** (0.0910)	0.2881** (0.0820)
R^2 (Adjusted)	0.8216	0.9023	0.9403	0.9478
Observations	15	15	15	15

Notes: Numbers in brackets are standard error of the coefficient. * denotes that the estimated coefficient is significant at the 5% level, ** at the 1% level.

The level of the actual production within the industry has a negative but not significant effect on the prices of the mills, so no significant economy of scale at the industry level is identified. The data does not allow for a detailed analysis of the role of demand. An increase of demand might increase the price-cost margin and hence delink the price variable from unit cost. As an indicator of demand conditions the export share has been used. The result shows that the export share has a significant positive effect on the price of windmills and correcting for these demand conditions and the production level in the industry increases the elasticity considerably to –0.17. In model (4) we measure cumulative production at the industry level with their capacity instead of the number of windmills. This alternative measure produces a lower but still significant estimate of the learning elasticity. However, the estimated coefficient of the time-dependent increase in productivity is also reduced. The reduced size of the estimated parameter is properly a result of the considerable change in technology over the period with a tenfold increase in the average size of the installed windmills. In the panel estimations below we control for scale in mill capacity.

Figure 1 illustrates the development in actual and estimated average windmill price per kW along the cumulative production. The estimated price model is based on the learning effect and a general time trend. The model fits the actual decline in the average price of a windmill in this period very well and a learning-by-doing hypothesis is therefore consistent with the illustrated evidence. However, the figure also illustrates how the collapse of the world market demand in 1986-89 put a heavy pressure on the prices of windmills an effect which is picked up by the introducing the export share in the model.

Figure 1. Actual and estimated price levels against cumulative production of mills



A panel data model

The development of still larger windmills is an integrated part of the observed productivity improvements, and thus the fall in price per kW might be caused both by process innovation (productivity improvements in the production of a given type of windmill) and product innovation (production of new, larger and more efficient mills). To separate these two determinants of the price development, the learning effect is estimated on the representative sample of individual windmill projects where it is possible to take into consideration how either type of technological innovation has affected the historical development of the price of a windmill.

The panel model is estimated with the following logarithmic transformation of an expanded version of equation 1:

$$\begin{aligned}\ln I_{i,t} = \ln\alpha + \beta \ln N_{t-1} + \mu \ln \Delta N_t + \delta \ln E_{i,t} + \gamma \ln A_{i,t} \\ + \phi_j F_j + \lambda_t + \varepsilon_{i,t}\end{aligned} \tag{3}$$

where $I_{i,t}$ is the total price or investment expenditure for windmills in project i delivered in period t, N_{t-1} is the accumulated experience, ΔN_t is the number of mills produced in the industry in year t, $E_{i,t}$ denotes the installed effects of windmills in project i, $A_{i,t}$ is the number of windmills in project i (note that for most observations A=1). F_j are dummies for the largest manufacturers of windmills correcting for heterogeneity among the producers, λ_t is a time trend to capture the exogenously given productivity growth rate and $\varepsilon_{i,t}$ is a random, normally distributed error term.

The investment expenditure on a windmill is expected to rise less than proportional with the size of the mill since windmills with larger effect reflect better technology, i.e. $0<\delta<1$. As scale in wind technology is very important for cost efficiency as Table 3 shows, we also estimate a fixed-effect model controlling for heterogeneity among the different mill capacities. Also, the investment expenditure is expected to rise less than proportional with the number of mills in the park since it is reasonable to expect that a discount is given when several mills are purchased at the same time, i.e. $0<\gamma<1$.

Results for this extended model are reported in Tables 5 and 6. The dependent variable now expresses the total price of the windmill no matter its size I_t and we therefore have to correct for scale in technology in the models. Table 5 presents four different models for the estimation of the learning effect where mill capacity measured in kW is used as a scale variable. The capacity variable is very significant in the first three models with a coefficient around 0.8, implying as expected that the price of a mill increases less than proportional to the size of the mill. The last model controls for scale in technology by using fixed effects in the estimating procedure. Also the coefficient to the number of mills purchased per project is very significant and stable across the different models. The coefficient of 0.95 suggests a 5% price discount when the purchases of windmills are doubled.

Table 5. Panel estimation of the learning effect with different scale in technology, 1983 -1998

	Dependent variable: $\ln I_t$			
	Model (1)	Model (2)	Model (3)	Model (4)
Intercept	9.2948** (0.1931)	9.3830** (0.2323)	8.7528** (1.0216)	
$\ln N_{t-1}$, Cum. production	-0.1252** (0.0275)	-0.1109** (0.0288)	-0.0855 (0.0785)	-0.1353** (0.0383)
ln E, mill capacity	0.7718** (0.0136)	0.7775** (0.0137)	0.8892** (0.2176)	
ln A, # of mills purchased	0.9580** (0.0275)	0.9580** (0.0274)	0.9577** (0.0275)	0.9699** (0.0261)
$\ln \Delta N_t$, production year t		-0.0006 (0.0179)		0.0191 (0.0244)
Export share		0.0994* (0.0478)		0.1946** (0.0515)
$\ln N_{t-1} * \ln E$			-0.0122 (0.0225)	
λ_t, time trend	0.0133** (0.0036)	0.0099** (0.0038)	0.0151** (0.0048)	-0.0171** (0.0055)
R^2 (Adjusted)	0.9379	0.9383	0.9380	0.9525
Observations	727	727	727	727

Notes: Numbers in brackets are standard error of the coefficient. * denotes that the estimated coefficient is significant at the 5% level, ** at the 1% level.

In these models, the size of the industrial learning-by-doing effect is estimated on the cumulative number of windmills produced and the effect is significant in models (1) and (2) representing a traditional specification used in most of the earlier studies surveyed in Table 1. Model (3) examines the interaction between learning-by-doing and the scale in technology and it finds a negative but insignificant relationship. The results show a tendency to a larger impact on prices from learning-by-doing on windmills with a large capacity. One interpretation of this result could be that the log specification of the scale effect in technology is inadequate and we therefore proceed in model (4) by estimating a fixed effect model controlling for heterogeneity in technology. This model is the preferred one as the explanatory power of the model is higher and it works better in disentangling the correlation between the variable for mill capacity, accumulated production and the time trend.

To test for the existence of an economic of scale effect on mill prices within this industry, the number of mills produced in the same year is introduced as an explanatory variable in model (2) and (4). However, the estimated elasticity is not significant, implying no economic of scale at the industry level. On the other hand, the coefficient to the export share is highly significant and the results from model 4 predict a rise in windmill prices of 0.19 % when the export share increases with 1 %.

The estimated size of the learning elasticity is considerably less in this panel estimations compared with the estimate from the time-series model above where a 1% increase in the cumulative production of windmills reduces the price with 0.135 % (model 4, Table 5) against 0.171 % (model 3, Table 4). The main reason for these differences is, that scale in technology is very important for the price of a windmill as verified by Table 3 and the scale effect on the price is mixed up in the aggregate time series for mill prices. This gives an upward biased estimate of the learning coefficient in the time series models. Controlling for the scale effect in the panel estimation also reduces the time-dependent increase in productivity from 2.66 % (model 2, Table 4) to 1.71% (model 4, Table 5) per year. Therefore, of the actual fall in the prices for windmills of about 50% in the period from 1983 to 1998 more than 30% are caused by the sevenfold increase of scale in technology.

Some differences may also exist among the producers in their capability of adapting the learning process, and to test for such heterogeneity among the largest manufacturers in their price setting behaviour we estimate models adding fixed effect for producers in Table 6. The results suggest that in general the four largest manufacturers are marketing their windmills at lower prices than the small producers. Especially, the prices of windmills from Bonus and Nordtank are significantly under average prices at the market with a discount of 15% and 7%, respectively.

Table 6. Estimation of the learning effect with fixed effect for technology and firms, 1983-98

	Dependent variable: ln I_t		
	Model (1)	Model (2)	Model (3)
ln N_{t-1}, cum. production	-0.1353** (0.0382)	-0.1107** (0.0363)	-0.0551 (0.0448)
ln A, # of mills purchased	0.9699** (0.0261)	0.9765** (0.0249)	0.973** (0.0251)
ln $\Delta N_{t,}$ production year t	0.0191 (0.0244)	0.0349 (0.0232)	0.0286 (0.0233)
Export share	0.1947** (0515)	0.2228** (0.0489)	0.2122** (0-0486)
$\lambda_{t,}$ time trend	-0.0171** (0.0055)	-0.0215** (0.0052	-0.0192** (0.0055)
BONUS		-0.1597** (0.0180)	1.1082* (0.6277)
MICON		0.0080 (0.0281)	-0.8944 (1.1424)
NORDTANK		-0.0723** (0.0193)	1.3831** (0.4345)
VESTAS		-0.0264 (0.0211)	0.6962* (0.3301)
ln N_{t-1} * BONUS			-0.1347* (0.0656)
ln N_{t-1} * MICON			0.0889 (0.1176)
ln N_{t-1} * NORDTANK			-0.1549** (0.0463)
ln N_{t-1} * VESTAS			-0.0778* (0.0355)
R^2 (Adjusted)	0.9525	0.9579	0.9588
Observations	727	727	727

Notes: Numbers in brackets are standard error of the coefficient. * denotes that the estimated coefficient is significant at the 5% level, ** at the 1% level.

The last mentioned results might reflect that learning varies over manufacturers and that large manufacturers are able to reap more benefits from internal and external dynamic scale economies than small producers on the Danish market. Almost three fourth of the windmills sold in Denmark are produced by the four largest Danish manufacturers, and this high level of concentration may reflect that the learning effects are mostly internalised among these four producers. In model 3 of Table 6 we therefore proceed the estimation but with individual values of parameters for learning for each of the four largest manufacturers.

The results show significantly different learning capabilities among the main manufacturers of windmills with a significantly higher learning effect in Bonus and Nordtank whereas Micon has a significantly positive coefficient to the cross product. However, the estimate for Micon may be unreliable due to a lack of time observations as the company has only existed in the last part of the period. According to these estimates, three of the companies experience a larger learning effect (reducing their prices relative to other producers) compared to other producers. But now the average price of a windmill offered from these manufacturers deviates positively from the average price as estimated with the separate intercepts.

5. Conclusions

The paper analyses the rapid growth of the Danish windmill industry in the period from 1983 to 1998. The growth has been followed by a fast increase in productivity and the study finds that learning-by-doing has a significant influence on the growth in productivity in this period. While past studies on learning-by-doing in this industry have been rather suggestive, our study shows consistent estimates of a learning rate between 11 and 13% across models based on aggregate time series data and panel data, respectively.

The learning rate for the windmill industry found in this study is on average at the lower end compared to historical data on other industries such as aircraft and semiconductor. This lower learning rate could in part be explained by the constant launching of new prototype windmills of larger size during the period of study. Although this study has tested for this scale effect, continuous introducing of new models may reduce the learning capability. At the same time the exact size of the learning rate is an empirical question and may vary across different industries and over time depending on general factors such as e.g. technological opportunity, demand conditions, the nature of markets, national and international rivalry.

In the past, the Danish windmill industry has benefited from both strong process and product innovations. In the future, the windmill industry will probably develop into a more mature phase of technological growth. If future output is similar to the past production with an average of about 1400 windmills cumulated per year, it will double the next 16 years. Applying the estimated learning elasticity at -0.135, the price will decrease by only 13.5% due to process innovations. In the past, product innovations have mostly been related to a substantial increase of the capacity of the individual windmills. It is doubtful whether the future will show a similar trend of sizes. Diminishing returns of cost efficiency of windmills with respect to sizes and in particular logistic problems of transportation of the windmill frames from the producer to the site where the mills are to be raised seem to cause a dinosaur syndrome, which ultimately limits the maximum sizes of the mills.

However, the emerging utilization of wind power from off-shore windmills seems promising because of the more abundant wind energy at seaside A major technological break-through for off-shore windmill technology might initiate a new wave of product and process innovations and if this is the case, the prophecy of an imminent mature phase for industry has been delivered too early

References

Arrow, K.J. (1962): "The Economic Implications of Learning-by-Doing", *Review of Economic Studies*, vol. 29, June 1962, pp 155-173.

Bahk, B-H. and M. Gort (1993): "Decomposing Learning by Doing in New Plants", *Journal of Political Economy*, vol. 101, no. 4.

Benkard, C. L. (1999): "Learning and forgetting: the dynamics of aircraft production", *NBER Working Papers*, no. 7127, Massachusetts: National Bureau of Economic Research.

BTM Counsult Aps.(2000): *International Wind Energy Development, Forecast 2000-2004.*

Danish Wind Turbine Manufacturers' Association (1999): "Danish wind energy 4th quarter 1998", *Windpower Note*, no. 22, April 1999.

Dasgupta, P. and J. Stiglitz (1988): "Learning-by-Doing, Market Structure and Industrial and Trade Policies", *Oxford Economic Papers*, vol. 40, no. 2, pp 246-268.

Gruber, H. (1992): "The Learning Curve in the Production of Semiconductor Memory Chips", *Applied Economics*, vol. 24, no. 8, pp 885-894.

Irwin, D.A. and P.J. Klenow (1994): "Learning-by-Doing Spillovers in the Semiconductor Industry", *Journal of Political Economy*, vol. 102, no. 6.

Liberman, M. B. (1984): The learning curve pricing in the chemical industries. *Rand Journal of Economics*, vol. 15, pp. 213-228.

Lucas, R. E. (1988): "On the Mechanics of Economic Development", *Journal of Monetary Economics*, vol. 22, pp 3-42.

Lucas, R. E. (1993): “Making a Miracle”, *Econometrica*, vol. 61, pp 251-272.

Mishina, K. (1999): Learning by New Experiences: Revisiting the Flying Fortress Learning Curve. In (eds. N. R. Lamoreaux, D. M. G. Raff and P. Temin) *Learning by doing in markets, firms and countries*. National Bureau of Economic Research: US.

Morthorst, P. E. (1999): “Capacity development and profitability of wind turbines”, *Energy Policy*, vol. 27, pp 779-787.

OECD/IEA (2000): *Experience Curves for Energy Technology Policy*. Organisation for Economic Co-operation and Development and International Energy Agency, Paris.

Porter, M. E. (1990): “The Competitive Advantages of Nations”. The Free Press, New York.

Stokey, N.L. (1988): “Learning by Doing and the Introduction of New Goods”, *Journal of Political Economy,* 96, pp 701-717.

Wright, T.P. (1936): “Factors Affecting the Cost of Airplanes”, *Journal of the Aeronautical Sciences*, vol. 3, pp 122-128.

Young, A. (1991): “Learning by Doing and the Dynamic Effects of International Trade”, *Quarterly Journal of Economics,* 106, pp 369-405.

Young, A. (1993): “Invention and Bounded Learning by Doing”, *Journal of Political Economics,* 101, pp 443-472.

Zimmerman, M.B. (1982): “Learning Effects and the Commercialization of New Energy Technologies: The Case of Nuclear Power”, *Bell Journal of Economics,* vol. 13, no. 2, pp 297-310.