Technical Change Theory and Learning Curves: Patterns of Progress in Energy Technologies

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Abstract

Better understanding of the role of learning by doing and learning by research at different stages of technical progress is important for development of a theory of innovation and designing effective technology policies. This paper presents a comparative analysis of energy technology learning and progress within the framework of Schumpeter's invention-innovation-diffusion paradigm. We estimate learning by doing and research rates for a range of energy technologies in four stages of technical progress. We find learning patterns that are broadly in line with the perceived view of the process of technical progress. Emerging technologies respond slowly to research and development (R&D) and capacity expansion. Evolving technologies exhibit high learning by doing and research rates. Reviving technologies exhibit considerable response to learning by research although they do not face significant market constraints. Mature technologies exhibit similar learning characteristics to emerging technologies. The results point to relative importance of R&D in the process of technological progress. We generally find higher learning by doing than learning by research rates but do not find any development stage where learning by doing alone is the dominant driver of technical change. Also, high capital intensity and market constraints appear to slow down the pace of progress of emerging and evolving technologies. We find little scope for potential substitution between learning by doing and learning by research across the technologies and different stages of their development path. It remains crucial to understand how a technology can be supported in its transition from the emergence stage to a self-sustaining growth path.

Key words: Energy technology, electricity, technical change, learning curves

JEL Classification: O3, Q4

1. Introduction

The importance of technological progress as a driving force behind factor productivity and economic growth has been recognised in the economic literature for some time. The main focus of the early literature on science and technology was, however, on the effect and measurement of technological change on output and growth. A common feature of this literature was their treatment of technical change as a phenomenon exogenous to the economy. By default, such view of technical progress poses clear limitations for economic and policy analysis of technology.

Since the 1960s, the focus of the literature has shifted toward the role of economic factors on technical change (Thirtle and Ruttan, 1987). The new paradigm views technical progress as an endogenous to the economy and the determinants of the change process. This shift originated from renewed attention to the role of technological change and the desire to influence the course and rate of the change through policy. The new paradigm emphasizes how such induced technical change can be achieved. The notion of induced technological progress is particularly relevant for energy and environmental technology issues where the economic, social, and social stakes are high (Criqui et al., 2000; Grubb et al., 2002).

It is, therefore, important to enhance our understanding of the effect of learning on technical change and different stages of development. Innovation theory and cross-technology analysis using learning curves can identify the learning characteristics of the stages of the process of technical change. It is also of interest to improve the process of learning and identify those technologies that are likely to achieve most progress during the foreseeable future. Further, it is important to determine whether resources allocated to promotion of a given technology are better spent on research and development (R&D) or capacity promotion policies.

This paper presents a comparative analysis of technical progress in a range of energy technologies representing different stages of the technical innovation and change process using the learning curve approach. The paper uses simultaneous two-factor learning curves and diffusion models to estimate learning for the technologies and finds comparable patterns of learning characteristic among the main categories of technologies. The next section reviews relevant literature and concepts of technical change and technology learning curves. Section 3 describes the methodology and data used in the paper. Section 4 presents the results of the analysis. Section 5 is conclusions and policy implications.

2. Induced technical change and learning curves

Technical change is generally conceptualized as a gradual process that involves different stages. The process and stages have been described in various ways. The most established of these is the model based on the paradigm that is often referred to as the Schumpeterian trilogy of invention, innovation, and diffusion (Schumpeter, 1934; 1942). Within this framework, invention is viewed as the generation of new knowledge and ideas. In the innovation stage, inventions are further developed and transformed into new products. Finally, diffusion refers to widespread adoption of the new products.

The relationship between the stages of technical progress is no longer thought to be linear. Rather, the process of technical change is non-linear and encompasses feedback loops between the model components (Stoneman, 1995). These inter-relations and feedback in the innovation process are, however, not well understood and despite numerous attempts, to this date, a coherent theory of the determinants of technical change and innovation remains illusive. The concepts and characteristics of the stages and process of technical change are also relevant for economic analysis of energy technologies (Jensen, 2004).

Research and development (R&D) activities are among the main drivers of technological progress. There is a degree of correspondence between the process of technical change and the type of R&D activities in basic research, applied research, and development activities. Basic research is broadly related to the invention and early stages of conception of a technology. As the technology matures, applied research and development activities are generally associated with the innovation and diffusion stages of technical progress. As noted, R&D is present in all stages of development of a technology although the nature of the activity is subject to change. However, R&D is not the only source of technical change. Knowledge gained in the process of manufacturing, scale of production, and utilization is also recognized as a significant source of technological advancement. There is also reason to believe that the relative importance of R&D in technical progress can vary in different stages of development of technology.

At early stages of development, technical progress is likely to be achieved through R&D. This is partly due to the fact that, in the absence of commercial viability, growth in installed capacity remains limited. Installed capacity does not begin to grow until cost improvement and/or public policies ensure commercial viability. While market size and conditions are constrained, R&D will play the leading role in achieving technical progress. Commercial prospect and supportive policies attract R&D and capacity expansion. As the technology develops and gradually reaches maturity the effect of additional amounts of both R&D and capacity will tend to diminish.

R&D and installed capacity are important sources of cost reduction and progress in new energy technologies (Skytte et al., 2004; Criqui et al., 2000). However, it can take a long time before a technology evolves from invention to innovation stage and ultimately becomes fully commercialised. It is, therefore, important to study the relative importance of technology push and market pull factors and, in particular their role in different stages of technological development (see Grübler et al., 1999). This will not only enhance our understanding of the stages and process of technical changes but also will help to formulate better informed and targeted technology policies.

2.1 R&D and technology policy

The notions of induced technical change and learning curves imply that the direction and rate of technical progress and the stages in the innovation process can be influenced. It then follows that targeted policies can be devised to mitigate market failure for evolving and emerging energy technologies. A typology of policies, consistent with the invention, innovation, and diffusion paradigm outlined in the above divides these into supply push and demand pull policy measures.

R&D activities are often subject to three main types of market failure namely indivisibility, uncertainty, and externalities (Ferguson and Ferguson, 1994). The aim of technology push measures is to overcome such barriers and to promote generation of the knowledge base and development of evolving and emerging technologies. In turn, market or demand-pull measures are devised to promote technical change by creating demand and developing markets for new technologies and products. Different technologies are at different stages of the development process. Government R&D and promotion schemes are initially more important at the basic research and development stage. As the technology matures policies supporting demand pull will gradually be more effective in promoting technical progress.

2.2 Learning curves

One approach to measure technical change that has recently received renewed attention is based on the notion of learning curves and the estimation of the learning effect. Learning curves are used to measure technical change in the form of cost improvement in technologies as a result of innovative activities. The concept of the learning effect as a distinct source of technical change was presented in Wright (1936) and Arrow (1963) and is often termed as "learning-by doing". The learning effect of a technology is generally derived from learning curves where technical change is measured in terms of reduction in the unit cost (or price) of a product as a function of experience gained from an increase in its cumulative capacity or output.

Although, the notion of learning curves has been known for a long time, the pressing need for innovation in energy and environmental technology and policy instruments has been an important source of interest in this area of research. The early applications of learning curves, between 1930s and 1960s, were mainly production orientated (Wrigt 1936; Alchian, 1963; Arrow, 1962; Hirsh, 1952). In 1970s and 1980s, the learning curves were also applied in the context of business management, strategy, and organisation studies (BCG, 1970; Dutton and Thomas, 1984; Hall and Howell, 1985; Lieberman, 1987; Spence, 1986; Argote and Epple, 1990). Since 1990s, learning curves have attracted considerable interest for the purpose of technology and policy analysis in general and for application to energy technologies in particular (Papineau, 2006; McDonald and Schrattenholzer, 2001; Criqui et al., 2000; IEA, 2000).

In their most common form, learning curves define the cost or price of a technology as a power function of a learning source in cumulative form such as installed capacity, output, or labour. The learning curve for a given technology is defined as in Equation (1). The learning effect of capacity increase on the cost of technology is then generally expressed as learning rate measured in terms of the percentage cost reduction for each doubling of the cumulative generation capacity or production as in Equation (2).

$$C = \alpha * K^{\varepsilon} \tag{1}$$

$$LR = 1 - 2^{-\varepsilon} \tag{2}$$

where:

C unit cost of technology

K cumulative capacity (or production, etc.)

ε learning elasticity

LR learning rate

2.3 Issues with single-factor learning curves

The usefulness of the simple specification of learning curves in Equation (1), originally developed in the context of manufacturing and mature industries, to technical change in evolving and emerging technologies is uncertain. The endogenous view of and proactive approach to technical progress implies that, in order to induce technological progress, both push and pull instruments should be used.

Therefore, the use of simple single-factor specification of learning curves in the context of change in energy technologies poses has known limitations. An important shortcoming of single-factor curves is that that they do not take the effect of R&D on cost reduction into account. From a policy point of view, single-factor learning curves can only lead to capacity-oriented recommendations while ignoring the role of R&D in technical change. In addition, in the absence of explicit inclusion of R&D in the models, they are likely to produce inaccurate estimates of learning by doing rates.

Single-factor learning curves are often intended for the analysis of innovation process. However, there is likely to be a possible endogeneity between cost reduction and capacity expansion i.e. reductions in the cost of a technology are also likely to increase the adoption of that technology. Therefore, within the framework of the invention, innovation, and diffusion paradigm, single-factor learning curves amount to leaving out the main aspect of the technology diffusion. Moreover, by including only cumulative capacity, they only indirectly refer to the diffusion stage of technological development. Consequently, single-factor learning curves are not appropriate for analysis of evolving and emerging energy technologies where the innovation stage of the technological process is generally of most interest.

2.4 Two-factor learning curves

In some recent studies, the notion of learning effect has been extended to incorporate “learning-by-researching” where R&D is assumed to enhance the technology knowledge base, which in turn leads to technical progress. The learning effect of R&D is accounted for in “two-factor learning curves” that incorporate cumulative R&D spending or number of patents as proxy for stock of knowledge (Kouvariatakis, 2000). As a policy analysis tool, two-factor learning curves incorporate a role for R&D and, in effect, for technology policy in promoting and achieving induced technical progress.

The notion of two-factor learning curves was first proposed in Kouvariatakis et el. (2000) where cumulative R&D and cumulative production are assumed to be the drivers of technology cost improvement. Despite their relative advantages, however, there are few examples of application of two-factor learning curves. Klassen et al. (2002) and Cory et al. (1999) have applied two-factor learning curves in analysis of innovation in wind energy. Also, Miketa and Schrattenholzer (2004) and Barreto and Kypreos (2004) have used two-factor learning curves in bottom-up optimization models of energy technologies. The effect of R&D on the technology cost reduction is illustrated in Figure 1.

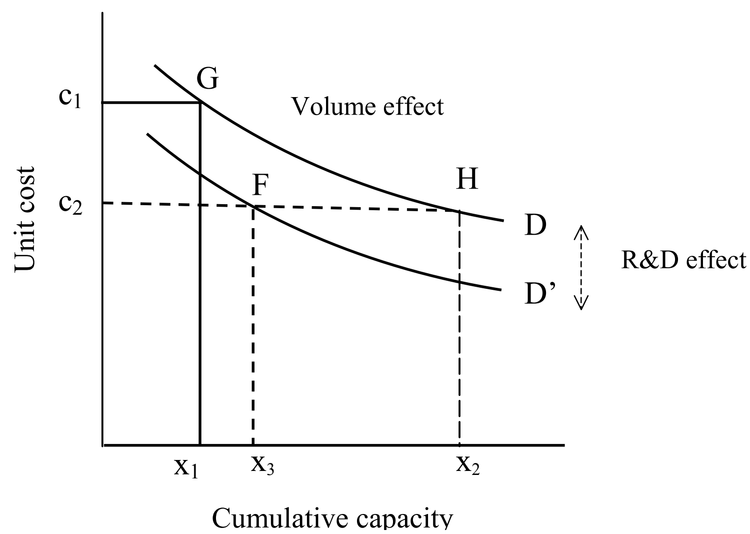


Figure 1: Cost reduction effects of learning by doing and learning by research

The learning by doing effect from the increase in cumulative capacity is represented by the decreasing curve D showing the volume effect. The effect of learning by research is through technological improvement and causes a shift in the trajectory of learning curve of the technology to D'. For example, a reduction in the cost of a given technology from c_1 to c_2 is attainable either by an increase in cumulative capacity x_2, or a capacity increase to x_3 combined with a shift in the learning curve to D' induced by R&D. From the point of view of technology policy, it is of considerable interest to understand the relative effectiveness of R&D and capacity for a given technology at different stages of the process of technical change. This can, for example, to more efficient allocation of scarce resources earmarked for promotion of energy technologies.

3. Method and data

3.1 Method

Energy generation technologies produce a rather homogenous output in terms of effect and energy. The disciplinary and knowledge base among technologies can vary greatly. There are environmental variations across technologies such as differences in market-related conditions, policy, and the regulatory framework within which the technologies evolve. In addition, technologies can be at different stages of development. It then follows that the progress path of energy technologies can exhibit differences. Consequently, it is unlikely that there exists one standard learning model for all technologies that will produce the best estimates of learning rates.

In addition, there is not an absolute or unique learning rate for a given technology. Rather estimated learning rates can be context-dependent and driven by model specification, variables, aggregation level, and time-period. Indeed, there is considerable variation in the empirical estimates of learning rates for some energy technologies (see e.g. McDonald and Schrattenholzer, 2001; Ibenholt, 2002). Moreover, estimated learning rates can vary over different time periods (Claeson Colpier and Cornland (2002). Also, due to the underlying differences, estimations of learning rates for different technologies may lend themselves, in terms of statistical significance, to different models and specifications. This can partly be expected as the technological characteristics of different energy technologies can vary.

Also, models used for the estimation of learning rates should take the effect of learning by researching on reducing the cost of technology into account. As suggested in Söderholm and Sundqvist (2003), inclusion of R&D spending in learning curves not only adds a controllable or policy variable but also reduces the problem of omitted variables bias that would attribute some cost reduction achieved by R&D to cumulative capacity. In addition, learning rate estimations need to take into account the endogeneity of cumulative capacity and unit cost of technology. The notion of endogeneity suggests that while increased cumulative capacity can result in unit cost reduction, the cost reduction can in turn lead to market diffusion and encourage policies that lead to higher cumulative capacity.

A system of simultaneous equations incorporating R&D and endogeneity of capacity and cost i.e. diffusion, transforms single-factor learning curves from a partial learning function to a learning-innovation-diffusion models that reflects the main elements and feedback in the invention, innovation, and diffusion paradigm. To our knowledge, the only example of such approach is reported in Söderholm and Klassen (2003) which uses simultaneous learning and diffusion equations to estimate the effect of promotion policies for wind energy in the UK, Spain, Denmark, and Germany. The study finds evidence of a diffusion effect i.e. significant positive effect from cost reduction on cumulative generation capacity as well as the effect of policy type and design on cost development of wind power.

The general specification used for estimation of the two-factor simultaneous learning-diffusion model (Model-I) is represented by Equations (3) and (4) using the three-stage least-square (3SLS) estimation method. We estimate the model for each technology separately where the unit cost of a given technology *C* and the cumulative installed capacity *Cap* are treated as endogenous/instrumental variables. Other variables such as cumulative R&D spending *RD* and the time variable *Y* (when significant) are used as exogenous variables. Additionally, the cumulative number of patents for that technology *Pat* is used as additional instrumental variable. Those technologies for which Model-I do not return significant results we use two-factor learning model specification (Model-II). For these we use two-stage least squares (2SLS) estimations as specified in Equation (3) only together with cumulative patents *Pat* or time variable *Y* as instruments.

Two-factor learning equation:

$$LogC_{nt} = \alpha_n + \beta_n * LogRD_{nt} + \kappa_t * LogCap_{nt} \tag{3}$$

Diffusion equation:

$$LogCap_{nt} = \mu_n + \omega_n * LogC_{nt} + \chi_t * LogY_{nt} \tag{4}$$

$$Endogenous\ variables: LogC_{nt}, LogCap_{nt}$$

$$Exogenous\ variables: LogRD_{nt}, LogPat_{nt}, LogY_{nt}$$

where:

C	total unit cost of technology (€1999/KW)
RD	cumulative private and public R&D spending (mill. €1999)
Cap	cumulative installed generation capacity (MW)
Y	time variable (years)
Pat	cumulative number of technology patents
n	technology
t	learning period (*1, …, t, …w*)

Figure 2 summarises the theoretical, practical, and policy conceptualisation of technical change and how these relate to different models of learning curves discussed in this section. As shown in the figure, single-factor learning curves (1-FLC) only reflect a particular aspect of technical change process i.e. the effect of diffusion or market pull on technology cost. Two-factor learning curves (2-FLC) incorporate the effect of innovation through R&D and technology push. The two-factor learning-diffusion models (2-FLDC) also incorporate the diffusion effect of technology/cost improvement and thereby reflect the main tenets of the Schumpeterian theory and model of technical change as depicted in dashed arrows.

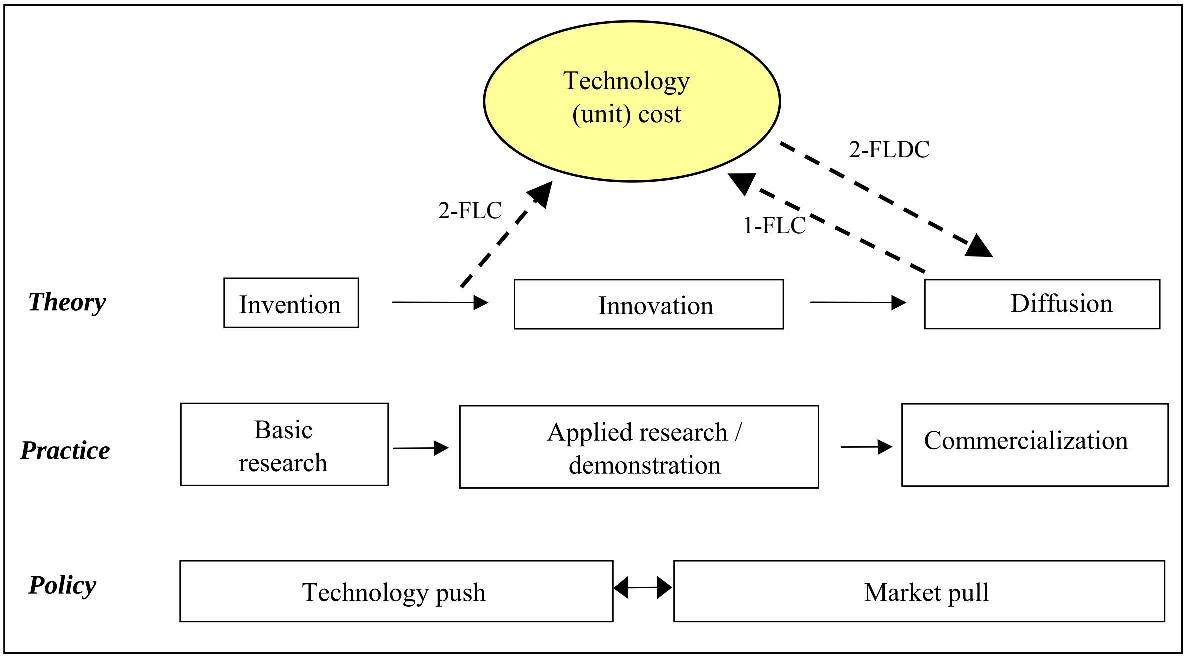


Figure 2: Technical change concepts and models of learning curves

We also calculate the elasticity of substitution between cumulative R&D spending and capacity expansion for the technologies studied here. Elasticity of substitution is a unit-neutral measure of the ease with which the input factors can substitute each other. In a Cob-Douglas specification, the elasticity of substitution can be calculated from Equation (5).

$$\sigma = \frac{\beta_n}{\kappa_n} * \frac{Cap_{nt}}{RD_{nt}} \qquad (5)$$

An elasticity measure equal to unity represents the case of constant returns to scale. At the same time, the degree to which the elasticity deviates from unity show the degree of difficulty with which input factor can substitute each other.

3.2 Data

Any attempt to estimate technology learning rates is faced with the choice of level of data aggregation. The appropriate level of analysis is dependent on the purpose of the study. For example, country or regional-level studies allow for examination of the effect of policies and local circumstances on technology cost. This paper aims to examine high-level patterns of technical change. Therefore, we utilize aggregated global data for a broad view of technological progress and to reflect the effect of unobservable factors such as spillover effects on costs. Table 1 summarises the technologies and time periods that are examined in this study.

Table 1: Technologies and data summary (mean values)

	Technology	Year	Unit cost of capacity ($99/kW)	Cumulative installed capacity (MW)	Cumulative R&D (mill. $99)	Cumulative patents (number)
1	Pulverized fuel supercritical coal	1990-1998	1,493	19,034	7,461	495
2	Coal conventional technology	1980-1998	1,308	650,512	35,452	-
3	Lignite conventional technology	1980-2001	1,275	105,120	7,877	-
4	Combined cycle gas turbines	1980-1989	573	1,524	15,438	3,324
		1990-1998	509	62,301	25,448	7,634
5	Large hydro	1980-2001	3,426	452,558	17,881	-
6	Combined heat and power	1980-1998	920	31,084	14,913	47
7	Small hydro	1988-2001	2,431	23,708	1,171	-
8	Waste to electricity	1990-1998	3,528	11,338	18,928	5407
9	Nuclear light water reactor	1989-1998	3,090	328,391	97,211	13,198
10	Wind - onshore	1980-1998	2,094	2,913	7,099	1,634
11	Solar thermal power	1985-2001	4,990	256	4,498	-
12	Wind – offshore	1994-2001	2,066	82	261	-

We examine the learning effect in thirteen different energy technologies. The choice of technologies studied here have been driven by availability of suitable data i.e. the key variables that allow derivation of learning rates using simultaneous two-factor learning and diffusion models. However, this preferred model specification has had the effect of limiting the number of years for which some of these technologies could be analysed. The data for the technologies used for the purpose of this analysis were compiled based on the information available in the database of the POLES model.[1] The unit cost and R&D spending figures for the technologies are expressed in 1999 US dollars. The R&D data comprise estimated government and private spending. The technology patent data are from the European Patent Office.

4. Results

In this paper, we allow for the possibility that the underlying differences among technologies can result in different suitable models for estimation of learning rates. We use two alternative model specifications to a set of technologies in the following order of preference. Where possible, we estimate simultaneous two-factor learning and technology diffusion equations (Model-I). In those cases where the first approach does not yield significant and reasonable results, we have estimated the simpler single-equation models of two-factor learning curves (Model-II) and where suitable used together with exogenous variables.

As discussed in the above, moving from single-factor learning curves to two-factor learning-diffusion models is methodologically preferable. However, this may pose certain empirical issues. While the former always return some significant result, the latter models do not necessarily do so. Technology learning rates are based on econometric estimations of often relatively short time-series data where all the series generally exhibit strong trends. The results of regression analysis can, therefore, be spurious and the R-squares can overestimate the relationship between the dependent and independent variables. Moreover, it is possible that some estimated coefficients can be statistically insignificant or even have the wrong sign.[2]

In the following we present the results for estimation of technology learning rates in four categories (mature, reviving, evolving, and emerging technologies) which are broadly in line with their perceived level of maturity and stage of development as discussed in the previous section(s). We also point to contextual similarities and differences across these

[1] The TECHPOL database has been kindly provided by the LEPII-EPE, Grenoble, France. This database has been assembled in the framework of the SAPIENT project (DG Research) to inform the world energy simulation model, POLES.

[2] Cory et al. (1999) estimate two-factor learning curves for wind turbines in the United States between 1981 and 1995 find the unintuitive result of positive sign for the coefficient of number of turbines. They suggest that this can be the results of large changes in the market growth and find plausible results by splitting the data into two separate periods.

technologies such as capital intensity, unit size, and market opportunities. In addition, we calculate elasticity of substitution for the technologies over the period under the study as measure of substitution possibility between and independence of the effect of learning by doing and learning by researching on cost reduction.

4.1 Mature technologies

The first category of technologies discussed here comprises a set of established and mature generation sources in our sample (Table 2). The technologies in this category have been developed and utilised over a long period of time and have had a major role in the expansion of electricity sectors worldwide. As shown in the results, the mature technologies have similar learning characteristics and exhibit low learning by research and learning by doing rates.

Table 2: Learning elasticities and rates for "mature" technologies

		Learning Model				Diffusion Model		Inst./ Exogen.
Technology	Method	Capacity Elasticity	Learning by Doing	Research Elasticity	Learning by Research	Diffusion	Year	Var.
Pulverized fuel supercritical coal	Model-I	-0.0551*	3.75%	-0.0897	6.03%	-11.05***	0.045***	RD, Y, Pat
Coal conventional technology	Model-I	-0.1909***	12.39%	-0.0182	1.25%	-2.33***	0.15***	RD, Y
Lignite conventional technology	Model-II	-0.0842***	5.67%	-0.0250*	1.72%	-	-	-
Combined cycle gas turbine 1990-98	Model-I	-0.0321***	2.20%	-0.0347***	2.38%	-16.465	0.601	RD, Y, Pat
Large hydropower	Model-II	-0.0285***	1.96%	-0.0384*	2.63%	-	-	-
*** 5% significance ** 10% significance * 15% significance								

Due to their mainstream position and widespread use, these technologies has meant that they have faced less market constraints in terms of commercial and expansion opportunities than other technologies. The mature technologies are, per unit of capacity, also relatively less capital intensive than the newer technologies. This is partly due to the relatively large size of the units.

A notable exception is the conventional coal technology, which shows a somewhat higher learning by doing rate. While the learning coefficients are statistically significant, the reasons for this are not immediately clear. However, given the existing high levels of installed capacity for established technologies, a doubling of capacity and further cost improvements can take place rather slowly and over a long period of time.

4.2 Reviving technologies

The second category of technologies comprises a set of "reviving" generation sources. The technologies in this category have been utilised for a relatively long time and as such they do not represent radical innovations (Table 3). The results find also common learning characteristics among the technologies. They exhibit low levels of learning by doing while showing a fairly high degree of learning by research. The rate of research by doing achieved in these fairly established technologies is significant. The learning rates for the technologies suggest that there is limited scope for future cost reductions through learning by doing. At the same time, the learning by research rates show considerable potential for further cost reductions. The existing high levels of installed capacity for these technologies suggest that they have limited scope for more cost reductions. Although, the extent to which that such learning rates can sustain in the future is uncertain.

Table 3: Learning elasticities and rates for "reviving" technologies

		Learning Model				Diffusion Model		Inst./ Exogen.
Technology	Method	Capacity Elasticity	Learning by Doing	Research Elasticity	Learning by Research	Diffusion	Year	Var.
Combined cycle gas turbine 1980-89	Model-I	-0.0094***	0.65%	-0.2815***	17.7%	-8.451	0.227	RD, Y, Pat
Combined heat and power	Model-I	-0.0033***	0.23%	-0.1351***	8.9%	-26.23***	-	RD, Pat
Small hydropower	Model-II	-0.0070***	0.48%	-0.3333***	20.6%	-	-	-
*** 5% significance ** 10% significance * 15% significance								

During the periods studied here, the reviving technologies have achieved technical progress which, combined with their environmental advantages, have created favorable policies and market opportunities. Small hydropower benefited from increased research as a result of a strong drive to develop renewable sources. Availability of smaller and more efficient combined heat and power units have expanded the market for this technology by facilitating industrial and commercial applications of this technology. Combined cycle gas turbines achieved technical progress in increasing the efficiency and reducing the cost effective size of turbines.

Another shared characteristic among the reviving technologies is that R&D and technical change has lowered the efficient size threshold and has enabled them to be built in smaller and economic units. Further, similar to mature technologies, the technologies in this category are not highly capital intensive. Therefore, the required initial capital investments in these technologies have decreased which, in the liberalised electricity markets, has given an additional comparative advantage to these technologies.

4.3 Evolving technologies

The third category of technologies comprises "evolving" generation resources. The technologies in this category consist of nuclear power (light water reactor), waste to electricity, and wind energy. These technologies have existed for a shorter time than the reviving technologies and have experienced improvements during the period under consideration. The estimated learning rates for these technologies show that they share the characteristics of rather high levels of learning by doing as well as learning by research (Table 4).

Table 4: Learning elasticities and rates for "evolving" technologies

		Learning Model				Diffusion Model		Inst./ Exogen.
Technology	Method	Capacity Elasticity	Learning by Doing	Research Elasticity	Learning by Research	Diffusion	Year	Var.
Nuclear power (light water reactor)	Model-I	-0.6517***	36.3%	-0.4485***	26.7%	-0.910***	-	
Waste to electricity	Model-I	-0.7738***	41.5%	-0.8286***	43.7%	-0.762***	-	RD, Pat
Wind energy	Model-I	-0.2021***	13.1%	-0.4502**	26.8%	-3.458***	-	RD, Pat
*** 5% significance ** 10% significance * 15% significance								

Nuclear power has not been a priority area in energy policy and environmental concerns with accidents and radioactive waste has significantly reduced the market opportunities for the technology. Wind energy has enjoyed a favorable policy environment in many countries and, as a result of various promotion schemes, has shown considerable growth in recent years. However, due to its reliance on public subsidies and lack of full cost competitiveness in relation to established conventional technologies, wind technology still faces market constraints in reaching a significant share of electricity resource mix. Waste to electricity technology is in a middle position. Environmental concerns associated with emissions and siting constraints have meant the technology has not been priority area and has not become a major energy source. Moreover, the trend toward liberalisation of the electricity sectors in many countries has further limited the market potential for the evolving technologies, as these have not been the obvious choice for private investors operating in competitive markets.

As noted, the evolving technologies have been evolving under the condition of market constraints that has limited their growth potential. It is, therefore, plausible that these technologies still poses significant potential for further cost improvement through learning by doing through, for example, increase in manufacturing scale and design standardisation. Also, their existing moderate and low levels of installed capacity suggest that these technologies still have further scope for significant capacity increases and cost reductions through learning by doing.

Moreover, the estimated learning by research rates shows considerable potential for cost reduction. Nuclear power and wind energy are capital intensive technologies and the required initial capital investments in these technologies are comparatively higher than those of fossil fuel based technologies. As a result, the main potential for further cost improvements in these technologies is likely to be from learning by research and in the form of lowering the capital investment requirements.

4.4 Emerging technologies

The final category of technologies examined is “emerging” generation sources and includes thermal solar power and offshore wind energy. The emerging technologies have existed for a relatively short time and have achieved a lesser degree of technical progress during the period under consideration. The estimated learning rates for thermal solar power and offshore wind show low levels of learning by doing and learning by research for both technologies (Table 5).

Also, both technologies examined here have clear environmental advantages and have benefited from promotion policies. However, limited progress in technical change and cost effectiveness relative to other technologies has limited the market opportunity and diffusion for these technologies. This is also reflected in our results as, due to lack of capacity responsiveness to cost improvement, learning-diffusion models did not return results that were acceptable. As a result of market constraints and lack of cost competitiveness, the diffusion of emerging technologies has been slow and they are yet to gain a noticeable share of energy mix.

Table 5: Learning elasticities and rates for "emerging" technologies

		Learning Model				Diffusion Model		Inst./ Exogen.
Technology	Method	Capacity Elasticity	Learning by Doing	Research Elasticity	Learning by Research	Diffusion	Year	Var.
Solar power – thermal	Model-II	-0.0320***	2.2%	-0.0779***	5.3%	-	-	-
Wind energy – offshore	Model-II	-0.0151	1.0%	-0.0720***	4.9%	-	-	Cap, Y
*** 5% significance ** 10% significance * 15% significance								

Similar to evolving technologies, the liberalisation of the electricity sectors has increased the dependence of the emerging technologies on public R&D and promotion schemes. In the light of the existing low levels of installed capacity and presence of market constraints, the emerging technologies are likely to have significant potential for cost improvement through learning by doing and learning by research. Another similarity to evolving technologies is that emerging technologies are capital intensive and as a result, the main potential for further cost improvements in these technologies, from learning by research and learning by doing, is likely to come in the form of reductions in investment requirements.

As mentioned earlier, single-factor learning curves not only do not reflect the effect of R&D on technical change but can also misestimate the effect of learning by doing that they aim to measure. Table 6 shows the learning by doing rates for the same technologies and dates examined in the above using simple single factor learning curve specifications as in Equations (1)-(2). As shown in the table, the learning by doing rates estimated by single-factor learning curves are higher than those estimated by two-factor learning curves and two-factor learning-diffusion curves. Moreover, the overestimation tends to be larger for evolving and emerging technologies, which are of particular interest to current technology and energy policy debates. An implication of devising policies based on overestimated learning by doing rates such as those shown here is that they can shift scarce innovation resources from more productive R&D activities and to less productive and perhaps more costly capacity-promotion policies.

Table 6: Learning by doing rates using single-factor curves

	Technology	Learning by Doing Elasticity	Learning by Doing Rate
1	Pulverized fuel supercritical coal	-0.071	4.8%
2	Coal conventional technology	-0.237	15.1%
3	Lignite conventional technology	-0.117	7.8%
4	Combined cycle gas turbines (1980-89) Combined cycle gas turbines (1990-98)	-0.040 -0.046	2.8% 3.3%
5	Large hydro	-0.042	2.9%
6	Combined heat and power	-0.030	2.1%
7	Small hydro	-0.041	2.8%
8	Waste to electricity	-1.247	57.9%
9	Nuclear light water reactor	-1.048	51.6%
10	Wind - onshore	-0.247	15.7%
11	Solar thermal power	-0.368	22.5%
12	Wind – offshore	-0.126	8.3%

Table 7 summarizes the main results and characteristics of the four technology categories. The results indicate that emerging technologies can initially experience a relatively long period during which they respond slowly to R&D and capacity expansion and as a result their technical progress evolves rather slowly. In the next development stage, evolving technologies exhibit both high learning by doing and learning by research. It is noteworthy that reviving technologies only show considerable potential for technical improvement through learning by doing although they do not face significant market constraints. At the final development stage, mature technologies exhibit rather similar learning characteristics to emerging technologies in the form of low learning by doing and learning by research rates.

Table 7: Technology development stage, learning rate, capital intensity, and market

	Learning by Doing	Learning by Research	Capital Intensity	Market Opportunity
Mature technologies	Low	Low	Low	High
Reviving technologies	Low	High	Low	High
Evolving technologies	High	High	High	Low
Emerging technologies	Low	Low	High	Low

As expected, some of the results show that unit cost reductions tend to increase diffusion and adoption of technologies. However, we only find high rates of learning by doing in the evolving technologies. With a view to a stylized technical progress and diffusion path, high capital intensity and limited market opportunities can constrain the pace of technical change in emerging and evolving technologies.

An interesting technology policy question is the extent to which learning by doing and learning by research may substitute each other and whether such substitution is dependent on the stage of the development of a technology. Such knowledge would be useful in allocation of government technology promotion funds between technology push and market pull measures. Figure A1 in the Appendix exhibits the elasticity of substitution and its development over time for the same set of technologies and for the same periods as those used to derive the learning rates. As shown in the figure, the results generally deviate from unity and thus only indicate weak substitution possibility between learning by doing and learning by research across the technologies. A notable exception is, however, wind energy technology where we find evidence of ease of substitution between innovation input factors.

5. Conclusions

A better understanding of the role of learning by doing and learning by research at different development stages of technologies is important for developing a theory of innovation and designing more effective technology policies. This paper presents a comparative analysis of energy technology learning and progress within the framework of invention, innovation, and diffusion paradigm. Some conclusions and lessons can be drawn form the empirical analysis towards this aim.

We estimated the learning by doing and learning by research rates for a range of energy technologies in four stages of technical progress. Overall, the observed patterns of learning by doing and learning by research are broadly in line with the perceived view of the process of technological progress and diffusion. We find that emerging technologies experience a period during which they respond slowly to R&D and capacity expansion. Evolving technologies exhibit both high learning by doing and learning by research. Reviving technologies show considerable potential for technical improvement through learning by research although they do not face significant market constraints. Mature technologies exhibit similar learning characteristics to emerging technologies.

The relative importance and the relationship between R&D and capacity expansion is a rather important question and, at the same time, little understood aspect of technical change. The results generally point to the relative importance of R&D in the process of technological progress. We generally find higher learning by doing rates (although not always statistically significant). In addition, we did not find any development stage where learning by doing alone was the dominant driver of technology cost improvement.

At the same time, we found little scope for potential substitution between learning by doing and learning by research across the technologies as well as in different stages of their development path. The effects of learning by doing and learning by research on technology cost improvement can be regarded as independent from each other.

A crucial question, in terms of technology learning, is how technologies pass from one stage of development to another. This is in particular important in the passage from the “emerging” to “evolving” technology stage. There remains an ample need for more extensive and accurate data on energy technologies. Better data will enable more elaborate models of technology learning. This will in turn enhance the contribution of empirical studies towards the formulation of theories of innovation.

References

Alchian, A. (1963). Reliability of progress curves in airframe production, *Econometrica*, Vol. 31, No. 4.

Argot, L. and Epple, D. (1990). Learning curves in manufacturing, *Science*, New Series, Vol. 247, No. 4945, Feb. 23, 920-924.

Arrow, K. (1962). The economic implications of learning-by-doing, *Review of Economic Studies*, Vol. 29, 155-173.

Barreto, L. and Kypreos, S. (2004). Endogenizing R&D and market experience in the "bottom-up" energy-systems ERIS model, *Technovation*, Vol. 24, No. 8, August, 615-629.

BCG (1970). Perspectives on experience, Boston Consulting Group, Boston, MA.

Claeson Colpier, U., and D. Cornland (2002). The Economics of the combined cycle gas turbine – An experience curve analysis, *Energy Policy*, Vol. 30, 309-316.

Cory, K. S., Bernow, S., Dougherty, W., Kartha, S., and Williams, E. (1999). Analysis of wind turbine cost reductions: The role of research and development and cumulative production, paper presented at AWEA's WINDPOWER '99 Conference, Burlington, VT, June 22.

Criqui, P., Martin, J.-M., Schrattenholzer, L., Kram, T., Soete, L., and Van Zon, A. (2000). Energy technology dynamics, *International Journal of Global Energy Issues*, Vol. 14, Nos. 1-4, 65-103.

Dutton, J. and Thomas, A. (1984). Treating progress function as a managerial opportunity, *Academy of Management Review*, Vol. 9, No. 2.

Ferguson, P. R. and Ferguson, G. J. (1994). *Industrial Economics: Issues and Perspectives* (2nd ed.), Macmillan: London.

Grubb, M., Kohler, J., and Anderson, D. (2002). Induced technical change in energy and environmental modeling: Analytic approaches and policy implications, *Annual Review of Energy and Environment*, Vol. 27, 271-308.

Grubler, A., Nakićenović, N., and Victor, D. G. (1999). Dynamics of energy technologies and global change, *Energy Policy*, Vol. 27, Issue 5, May, 247-280.

Hall, G. and Howell, S. (1985). The experience curve: The economist's perspective, *Strategic Management Journal*, Vol. 6, No. 3, 197-212.

Hirsh W. Z. (1952). Manufacturing progress functions, *Review of Economics and Statistics*, Vol. 34, No. 2.

Ibenholt, K. (2002). Explaining learning curves for wind power, *Energy Policy*, Vol. 30, 1181-1189.

IEA (2000). *Experience Curves for Energy Technology Policy*, International Energy Agency, Paris.

Jensen, S. G. (2004). Reducing costs of emerging renewable energy technologies: An analysis of the dynamic development with wind power as case study, *International Journal of Energy Technology and Policy*, Vol. 2, Nos. 1-2, 179-202.

Klassen, G., Miketa, A., Larsen, K., and Sundqvist, T. (2002). The impact of R&D on innovation for wind energy in Denmark, Germany, and the United Kingdom, paper presented at the International Energy Workshop, Stanford University, Stanford, CA, 18-20 June.

Kouvariatakis, N., Soria, A. Isoard, S. (2000). Modeling energy technology dynamics: methodology for adaptive expectations models with learning by doing and learning by searching, *International Journal of Global Energy Issues,* Vol. 14, Nos. 1-4, 104-115.

Lieberman, M. B. (1987). The learning curve, diffusion, and competitive strategy, *Strategic Management Journal*, Vol. 8, No. 5.

McDonald, A. and Schrattenholzer, L. (2001). Learning rates for energy technologies, *Energy Policy*, Vol. 29, Issue 4, 255-261.

Miketa, A. and Schrattenholzer, L. (2004). Experiments with a methodology to model the role of R&D expenditures in energy technology learning processes: first results, *Energy Policy* 32, 1679-1692.

Papineau, M. (2006). An economic perspective on experience curves and dynamic economies in renewable energy technologies, *Energy Policy*, Vol. 34, Issue 4, March, 422-432.

Schumpeter, J. A. (1942). *Capitalism, Socialism, and Democracy*, Harper and Row, New York.

Schumpeter, J. A. (1934). *The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle*, Harvard University Press: Cambridge, Mass.

Skytte, K., Jensen, S. G., Morthorst, P. E., Olsen, O. J. (2004). *Støtte til Vedvarende Energi* (in Danish), Jurist- og Økonomforbundets Forlag, Copenhagen.

Spence, M. (1986). Cost reduction, competition, and industry performance, In Stiglitz, J. (Ed.), *New Developments in the Theory of Market Structure*.

Stoneman, P., ed. (1995). *Handbook of the Economics of Innovation and Technological Change*, Blackwell: Oxford, UK.

Söderholm, P. and Klassen, G. (2003). Wind power in Europe: A simultaneous innovation-diffusion model, paper presented at the 12th Annual Conference of the European Association of Environmental and Resource Economists, Bilbao, Spain, June 28-30.

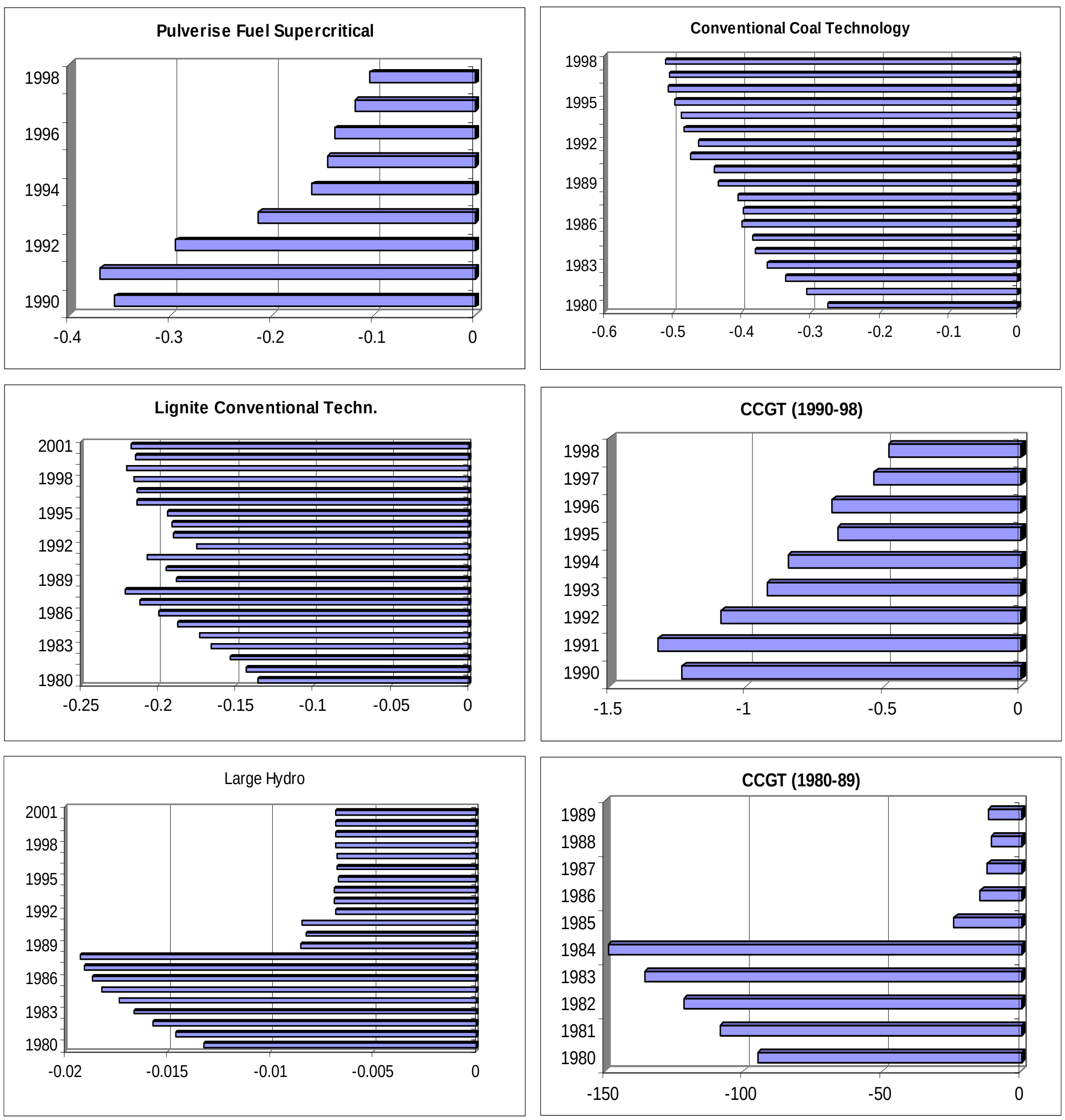
Söderholm, P. and Sundqvist, T. (2003). Learning curve analysis for energy technologies: Theoretical and econometric issues, paper presented at the International Energy Workshop (IEW), Laxenburg, Austria, June 24-26.

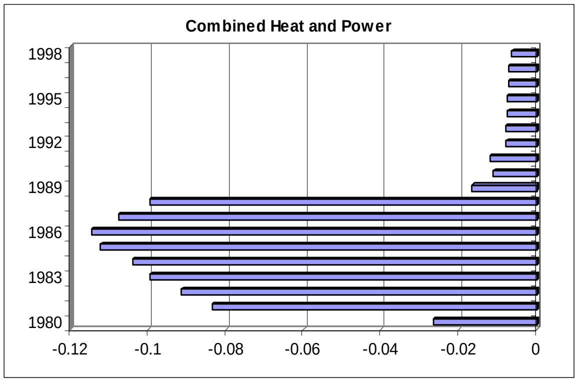
Thirtle, C. G. and V. W. Ruttan (1987). *The Role of Demand and Supply in the Generation and Diffusion of Technical Change*, Harwood Academic Publishers: London.

Wright, T. P. (1936). Factors affecting the cost of airplanes, *Journal of Aeronautical Sciences*, Vol. 3, No. 4.

Appendix A: Elasticity of substitution between technology R&D and capacity expansion - development over time

Figure A1: Elasticity of substitution for energy technologies over time.




Combined Heat and Power
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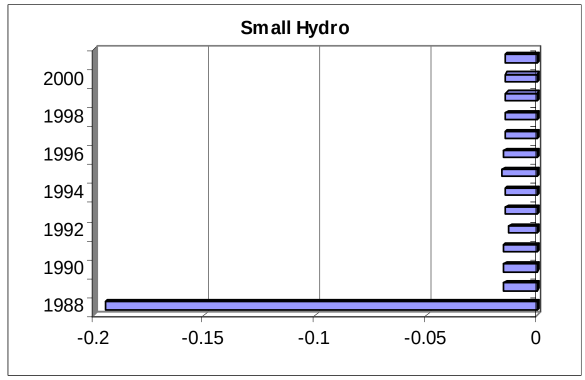
1992
1989
1986
1983
1980
-0.12
-0.1
-0.08
-0.06
-0.04
-0.02
0


Small Hydro
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1998
1996
1994
1992
1990
1988
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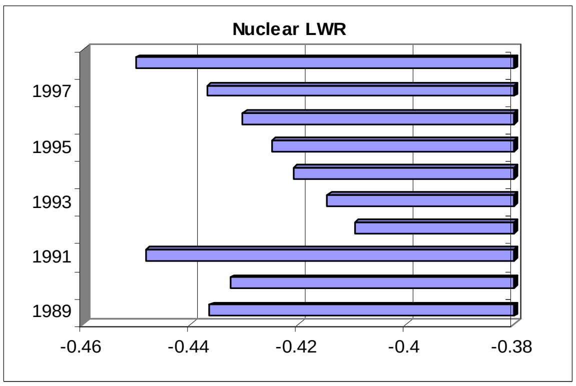
-0.15
-0.1
-0.05
0


Nuclear LWR
1997
1995
1993
1991
1989
-0.46
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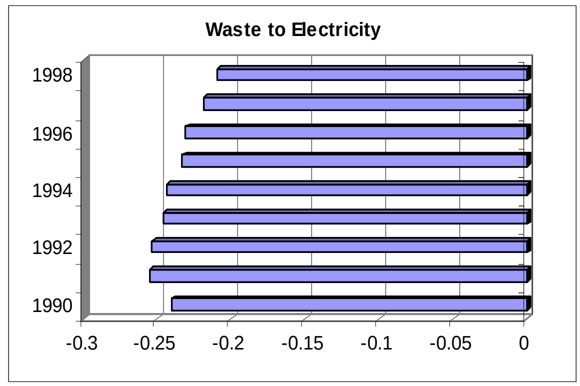
-0.4
-0.38


Waste to Electricity
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1996
1994
1992
1990
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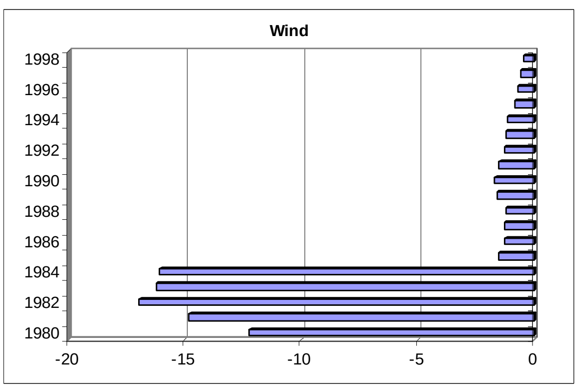
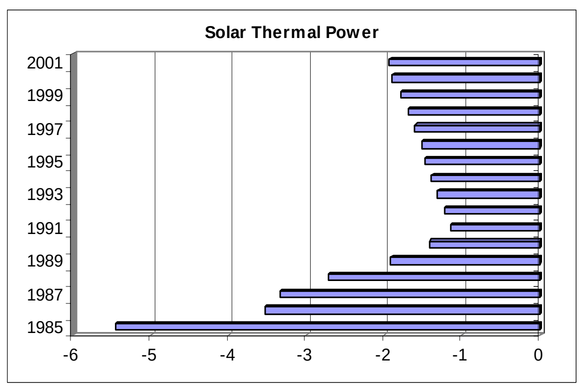
-0.25
-0.2
-0.15
-0.1
-0.05
0


Wind
1998
1996
1994
1992
1990
1988
1986
1984
1982
1980
-20
-15
-10
-5
0


Solar Thermal Power
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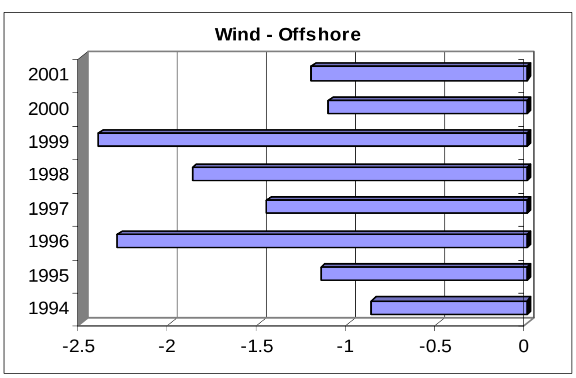
1999
1997
1995
1993
1991
1989
1987
1985
-6
-5
-4
-3
-2
-1
0


Wind - Offshore
2001
2000
1999
1998
1997
1996
1995
1994
-2.5
-2
-1.5
-1
-0.5
0