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

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Better understanding of the role of learning in technical progress is important for the development of innovation theory and technology policy. This paper presents a comparative analysis of the effect of learning and technical change in electricity generation technologies. We use simultaneous two-factor learning and diffusion models to estimate the effect of learning by doing and learning by research on technical progress for a range of technologies in four stages of development. We find learning patters broadly in line with the perceived view of technical progress. The results generally show higher learning by research than learning by doing rates. Moreover, we do not find any development stage where learning by doing is stronger than learning by research. We show that simple learning by doing curves overstate the effect of learning in particular for newer technologies. Finally, we find little substitution potential between learning by doing and research for most technologies.

1. INTRODUCTION

The importance of technological progress as a major force behind factor productivity and economic growth is well established in the literature. The focus of early literature on science and technology was, however, on the effect and measurement of technical change on output and growth. Technical change was treated as an exogenous phenomenon to the economy a view which posed clear limitations for policy analysis. Since the 1960s, the focus of the literature has shifted to

The Energy Journal, Vol. 28, No. 3.

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The author wishes to extend special thanks to the SAPIENT project (DG Research) at the LEPII-EPE, Grenoble, France for generous help and providing access to data for this work. He would also like to thank Bruce Chen for research assistance and anonymous referees and acknowledge the financial support of the UK Research Councils' (ESRC and EPSRC) Supergen and TSEC projects.

the role of economic factors in technical change (Thirtle and Ruttan, 1987). The new paradigm views technical change as an endogenous factor and that it may be induced. This view is reflected in the increased interest in the use of learning curves in technology analysis. Recently, the notion of induced technical change has been adopted in analysis of energy and environmental technologies (Criqui et al., 2000; Grubb et al., 2002).

Innovation theory and cross-technology analysis using learning curves can shed light on the characteristics and the stages of technical change process. It is also of interest to improve the process of learning and identify those technologies that are likely to achieve most progress during a given period. 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 on capacity promotion policies.

In recent years, learning curves have been applied to analysis of induced technical change in energy technologies. The most commonly used forms are single-factor learning curves that estimate the effect of cumulative capacity or production on reducing the cost of technology (learning by doing). This framework overlooks the effect of R&D as an influential factor and policy tool (learning by research). As a result, not only the effect of R&D on technical progress cannot be determined but the estimates of learning by doing can also be affected. In addition, understanding the relative importance of learning by doing and learning by research on technical progress is important for improving innovation theory and energy technology policy.

This paper presents a comparative analysis of technical change in a range of electricity generation technologies at different stages of development using extended learning curves that reflect the main tenets of innovation theory. We use simultaneous two-factor learning curves and diffusion models to estimate the effect of learning by doing and learning by research on technical progress. We then examine the relative importance of R&D and capacity deployment for different technology categories. The results generally show higher learning by research than learning by doing rates. We do not find any technological development stage where learning by doing is the dominant driver of technical change. We also compare the learning by doing results from our model with those of single factor learning by doing models. Finally, we calculate the elasticity of substitution between R&D and capacity deployment for the technologies examined. The next section reviews the relevant literature and concepts of technical change and technology learning curves. Section 3 describes the methodology and data used for the analysis in the paper. Section 4 presents the results of the analysis. Section 5 summarizes and concludes the paper.

2. INDUCED TECHNICAL CHANGE AND LEARNING CURVES

Technical change is generally conceptualized as a gradual process that involves different stages of progress. The process and its stages have been described in various ways. The most established of these is Schumpeter's invention-innovation-diffusion paradigm (Schumpeter, 1934; 1942). Briefly, 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 but a non-linear process with feedbacks between its components (Stoneman, 1995). However, this process is not well understood and a coherent theory of technical change remains illusive. The concepts and characteristics of the stages and process of technical change also apply to electricity generation technologies as these generally evolve through similar stages of progress (see Jensen, 2004).

R&D and capacity deployment are the main drivers of change in energy technologies (Skytte et al., 2004; Criqui et al., 2000). R&D has a role in all stages of technical progress although the nature of it can change. There is a broad correspondence between the process of technical change and the main R&D activities – i.e. basic research, applied research, and development. Basic research is related to the invention and early stages of conception of technology. As the technology matures, applied research and development are associated with the innovation and diffusion stages of technical progress. In addition, the knowledge and learning by doing gained from manufacturing, scale of production, and utilization is an important source of technical progress.

The perceived view of the process of technical progress is that the relative importance of R&D and capacity deployment varies in different stages of development of a technology. At early stages of development, technical progress is mainly achieved through R&D and, in the absence of commercial viability, growth in capacity is limited. Gradually, diffusion of installed capacity begins to grow as cost reductions and technology support policies improve commercialization of a technology. While capacity deployment is constrained, R&D plays a leading role in achieving technical progress. As the technology matures and is adopted the effect of capacity deployment increases.

It is, therefore, important to study the relative importance of technology push and market pull and, in particular, their role in different stages of technological development (see Grübler et al., 1999). This will enhance our understanding of the process and stages of technical changes and will help in the design of more effective policies and allocation of technology promotion resources between R&D and capacity deployment. However, it takes a long time before a technology evolves from invention to innovation stage and ultimately becomes fully commercialized. The transition from invention and innovation to diffusion stage is crucial for technological progress. Theory informed policies and empirical evidence could improve the process and contribute to better allocation of technology promotion funds between R&D and capacity deployment across technologies.

2.1 R&D and Technology Policy

There is a range of electricity generation technologies at different stages of progress. Meanwhile, the notion of induced technical change implies that the process of innovation can be influenced. The logical extension of this is that policies can be devised to mitigate market failure for new technologies. A typology of such policies, consistent with the invention-innovation-diffusion paradigm, divides these into supply push and demand pull measures.

R&D activities can be subject to three 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 enhance the knowledge base and development of technologies. In turn, market or demand-pull measures promote technical change and learning by creating demand and developing markets for new technologies. Government R&D and promotion schemes are more important at the basic research and development stage. As the technology matures policies supporting demand pull will gradually become 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 learning rates. Learning curves are used to estimate technical change as a result of innovative activities. The concept of learning effect as a distinct source of technical change was presented in Wright (1936) and Arrow (1962) and is often termed as "learning-by doing". Technical change through learning effect is generally derived from learning curves where progress is typically measured in terms of reduction in the unit cost (or price) of a product as a function of experience gained from increase in cumulative capacity or output.

The concept of learning curves has been known for some time. However, early applications of these, between 1930s and 1960s, were related to product manufacturing (Wright 1936; Alchian, 1963; Arrow, 1962; Hirsh, 1952). In 1970s and 1980s, they were applied in 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, the pressing need for economic and policy analysis of energy technologies has been an important source of interest in application of learning curves to this area (Papineau, 2006; McDonald and Schrattenholzer, 2001; Criqui et al., 2000; IEA, 2000).

In the 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 is defined as in Equation (1). The learning effect of capacity increase on the cost of technology is expressed as "learning rate" LR measured in terms of the percentage cost reduction for each doubling of the cumulative capacity or production as in Equation (2).

$$c = \alpha * Cap^{\varepsilon} \tag{1}$$

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

where:

c	unit cost
Cap	cumulative capacity (or production, etc.)
ε	learning elasticity
a	constant
LR	learning rate

Some 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 both push and pull instruments can induce technical progress. Therefore, single-factor learning curves in energy technology analysis pose some 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 only lead to capacity-oriented recommendations while ignoring the role of R&D in technical change. In addition, in the absence of R&D, single-factor curves are likely to produce inaccurate estimates of learning by doing rates.

Moreover, in the context of technology analysis, there can be a degree of endogeneity between cost reduction and capacity expansion - i.e. reduction in the cost of a technology is also likely to increase deployment of that technology. Therefore, within the framework of the invention-innovation-diffusion paradigm, single-factor curves amount to leaving out the main aspect of technology diffusion. By using cumulative capacity only, single-factor learning by doing curves are just a partial model of the diffusion aspect of the technical change process. Consequently, single-factor curves are not appropriate for analysis of evolving and emerging technologies where the innovation stage of the technological process is generally of most interest.

2.3 Two-factor Learning Curves

In some recent studies, the notion of learning effect has been extended to include "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 proxies for stock of knowledge (Kouvariatakis et al., 2000). As a policy analysis tool, two-factor learning curves acknowledge a role for R&D and, thus, in effect, for technology policy in promoting and achieving induced technical progress.

The concept of two-factor learning curves was first proposed in Kouvariatakis et al. (2000) where cumulative R&D and cumulative production are assumed to be the main drivers of technology cost improvement. Despite their relative advantages, however, there are only few examples of application of two-factor technology learning curves. Klassen et al. (2005) and Cory et al. (1999) have applied two-factor learning curves in analysis of innovation in wind power. Also, Miketa and Schrattenholzer (2004) and Barreto and Kypreos (2004) have used two-factor learning curves in large scale bottom-up optimization models of energy technologies.

3. METHOD AND DATA

3.1 Method

All electricity generation technologies produce a homogenous energy output. However, the underlying technical characteristics and knowledge base of these can vary greatly. There are also differences in contextual factors such as in market conditions, policy, and regulatory framework within which the technologies evolve. In addition, technologies can be at different stages of maturity and exhibit differences in their progress. Consequently, it is unlikely that there exists a single learning model and specification for all technologies that produces the best estimates of learning rates.

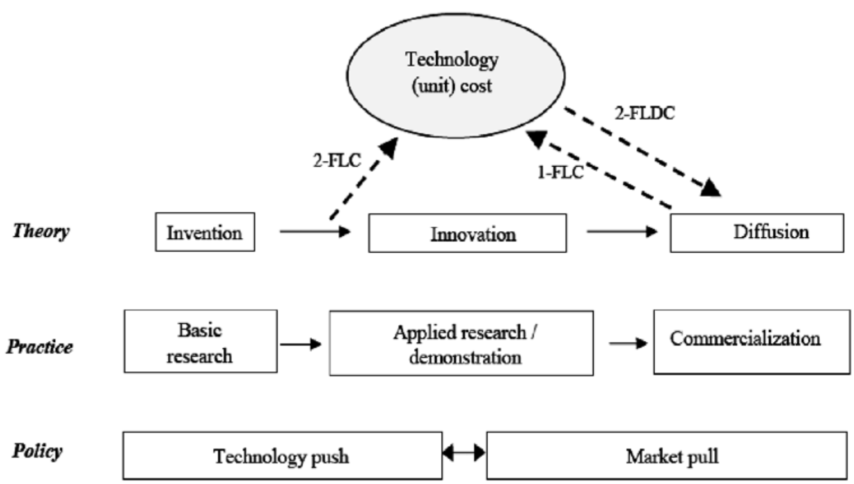
Estimates of learning rates are context-dependent and driven by model specification, variables used, and aggregation level. Indeed, there is considerable variation in the empirical estimates of learning rates for some energy technologies (McDonald and Schrattenholzer, 2001; Ibenholt, 2002). Moreover, estimated learning rates can vary depending on the time period for which they are measured (Claeson Colpier and Cornland, 2002). Therefore, there is not an absolute or unique learning rate for a given technology. Also, due to the underlying differences, estimations of learning rates for different technologies may lend themselves to different models and specifications. This is expected as the characteristics of different technologies can vary.

Models used for estimation of learning rates should take the effect of R&D on reducing the cost of technology into account. As suggested in Söderholm and Sundqvist (2003), inclusion of R&D spending in learning curve models adds a controllable policy variable and reduces the problem of omitted variables bias that would attribute some cost reduction achieved by R&D to cumulative capacity. In addition, models of learning need to take into account the endogeneity of the capacity and cost of technology – i.e. while higher installed capacity can result in unit cost reduction, the cost reduction can stimulate market diffusion and policies favoring capacity deployment.

Figure 1 summarizes the theoretical, practical, and policy conceptualisation of technical change and how these relate to different models of technology learning. As shown, 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. The two-factor learning curve model (2-FLC) incorporates the effects of both R&D (technology push) and capacity deployment (market pull) on technical change. However, the diffusion and installed in installed capacity of a technology can in turn increase as a result of reduction in the cost of that technology and with time. The 2-FLC model can be extended to also include these effects on the uptake of technology. The extended model (2-FLDC) therefore reflects both the causal relationship between cost and diffusion and endogeneity of innovative activities and diffusion as policy instruments. Therefore, the 2-FLDC model depicted in Figure 1 captures the main features of the Schumpeterian paradigm of technical change as depicted in dashed arrows.

A system of simultaneous equations incorporating R&D and endogeneity of capacity on cost, transforms single-factor learning by doing curves from a partial model to a theory-informed learning-innovation-diffusion model 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 (2007) which uses simultaneous learning-diffusion equations to estimate the effect of promotion policies for wind power in the UK, Spain, Denmark, and Germany. The study finds evidence of diffusion i.e. significant positive effect from cost reduction on cumulative capacity as well as effect of policy type and design on cost development of wind power.

Figure 1. Technical Change Concepts and Models of Learning Curves



Based on the conceptual model of technical change and innovation outlined in Figure 1, we estimate the two-factor simultaneous learning-diffusion model (Model-I) as specified in Equations (3) and (4). We use the three-stage least squares (3SLS) method to estimate the model for each technology separately. Equation (3) is a two-factor learning curve estimating the learning effect of cumulative capacity and R&D on the unit capacity – capacity – i.e. the diffusion or uptake of a technology. Equation (4) reflects the effect of cost reduction and time on cumulative capacity i.e. the diffusion of a technology.

The unit cost of technology *c* and the cumulative installed capacity *Cap* are treated as *endogenous variables* – i.e. they are determined within the model. Other variables such as cumulative R&D spending *RD*, time variable *T* (when significant), and cumulative number of patents *Pat* for each technology are used as exogenous variables. The exogenous variables (e.g. number of technology patent) do not need to be part of the structural variables and are used in the first stage of the SLS estimation to regress the endogenous variables on exogenous variables of the system. In addition, the cumulative number of patents *Pat* is, where appropriate, used as instrumental variable.

Two-factor learning equation:

$$Logc_{nt} = \alpha_n + \beta_n * LogRD_{nt} + \kappa_t * LogCap_{nt} \qquad (3)$$

Capacity diffusion equation:

$$LogCap_{nt} = \mu_n + \omega_n * Logc_{nt} + \chi_t * LogT_{nt} \qquad (4)$$

Endogenous variables: $Logc_{nt}$, $LogCap_{nt}$
Exogenous variables: $LogRD_{nt}$, $LogPat_{nt}$, $LogT_{nt}$

where:

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

A general issue in estimation of learning models is to separate the effect of learning on technical change from that of exogenous progress that occurs over time. Therefore, a time variable *T* is included in the Equation (4) in order to separate the effect of time on technical change. Although it s generally preferable to include a time variable in the technology learning models, in cases where inclusion of this results in wrong sign or insignificant coefficient, we drop this variable from the estimation. The main reason for this is that the sign and significance of the learning by doing and learning by research coefficients are important for the reliability of the learning rates and elasticity of substitution that are calculated from these. It is possible that some technologies are less influenced by exogenous technical change or that in the future longer time series may shed more light on the role of time and exogenous effects.

The nature and actual progress path of some technologies can differ from the above general model. The first preference is to apply the more complete Model-I to all technologies. However, for technologies that Model-I does not find correct sign or statistically significant coefficients we use a simpler single-equation two-factor specification (Model-II) as in Equation (2) instead. Model-II uses two-stage least squares (2SLS) estimation method and, where possible, with cumulative number of patents *Pat* or time variable *T* as exogenous variables. Some studies of technology learning rates have used time lags or some measures of knowledge depreciation. Such extensions of learning models are conceptually correct and useful but care should also be taken in the underlying assumptions and application to individual technologies. For the purpose of this study which involves a range of different technologies this could not be handled properly.

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

$$\sigma = \frac{\beta_n}{\kappa_n} * \frac{Cap_{nt}}{RD_{nt}} \tag{5}$$

A substitution elasticity equal to unity represents the case of constant returns to scale. The extent to which the measured elasticity deviates from unity indicates the degree of difficulty with which the main two learning factors and sources of technical change can substitute each other.

3.2 Data

Any attempt to estimate technology learning rates is faced with the choice of proper 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. As this paper aims to examine high-level patterns of technical change, we use aggregate global data in order to obtain a broad view of technological progress. An advantage of using global level data for this analysis is that they capture the effect of unobservable factors such as spillover effects of technical progress which occur at national and regional levels. A potential drawback of using global level data is that the accuracy of some of data may decrease. For example, best available technology or cost improvements can reach developing countries with a

Table 1. Technologies and Data Summary (Mean Values)

	Technology	Year	Unit cost of capacity ($1999/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	5,407
9	Nuclear light water reactor	1989-2001	3,015	334,266	100,729	-
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	-

delay. In addition, some information may be lost in conversion of costs in different currencies into a single monetary unit.

Table 1 summarises the technologies and time periods examined in this study. The data for the technologies used were compiled from the information in the database of the POLES model.[1] The unit cost and R&D spending figures are expressed in constant 1999 US dollars. The R&D data comprise the estimated government and private spending on research and development. The patent data used is the cumulative number of patents for the technology being examined. Margolis and Kammen (1999) have shown that there is a positive and strong correlation between the number of technology patents and R&D spending. The data is based on the count of the electricity technology patents submitted by OECD countries to the European Patent Office. A consistent procedure has been used in order to transform the primary data in the patent office classification coding system into specific electricity generation technologies categories for the model.

The data enables us to estimate the learning effect for a varied set of electricity generation technologies. The choice of technologies studied here has 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 analyzed. For the combined cycle gas turbine technology, the post-1990 period was separated due

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.

to an apparent structural break in the data. This coincides (though it may not fully explain the break) with the start of liberalization of the sector in the UK and later in other countries where gas was the technology of choice in deregulated markets and resulted in significant expansion of the installed capacity.

4. RESULTS

As discussed previously, moving from simple single-factor learning curves to two-factor learning-diffusion models is conceptually preferable. However, in some cases, this may cause practical estimation issues. While the former models always return some significant result, the latter models may not necessarily do so. Technology learning rates often rely on econometric estimations of relatively short time-series data that also exhibit strong trends. The results of regression analysis may, therefore, be spurious and the R-squares can overestimate the relationship between the dependent and independent variables. Moreover, some estimated coefficients can become statistically insignificant or may even show the wrong sign.[2]

There are significant differences in the underlying technical and knowledge properties of the electricity generation technologies. This can result in different models being suitable for estimation of the learning rates for these. We use two model specifications to the set of technologies in the following order of preference. We first estimate simultaneous two-factor learning-diffusion models with exogenous variables (Model-I). Where this approach does not yield significant and reasonable results, we use the simpler single-equation two-factor learning curves (Model-II).

The results are organised by placing the technologies in four categories (mature, reviving, evolving, and emerging) that are broadly in line with their perceived level of development. In addition, we calculate elasticity of substitution between learning by doing and learning by researching in reducing the cost of different technologies.

4.1 Mature Technologies

The first category of technologies consists of the more mature and established generation sources. The technologies in this category have been developed and utilized over a long period of time and have had a major share of the expansion of electricity sectors worldwide (Table 2). Column 1 of Table 2 indicates whether a full two-factor learning-diffusion or a two-factor learning model produced the best results. Columns 2 and 3 show the estimated elasticities of cumulative capacity (and significance level) and the corresponding learning by doing rate for the

2. Cory et al. (1999) estimate two-factor learning curves for wind turbines in the United States between 1981 and 1995 and first obtain positive sign for the coefficient of the number of turbines. They attribute this to large changes in market growth in part of the period of study and find plausible estimates after splitting the data into two separate periods.

Table 2. Learning Elasticities and Rates for "Mature" Technologies

		Learning Equation				Diffusion Equation		Instrumental/ Exogenous variables
	1	2	3	4	5	6	7	8
Technology	Method	Capacity Elasticity	Learning by Doing	Research Elasticity	Learning by Research	Diffusion	Year	Variable
Pulverized fuel supercritical coal	Model-I	-0.055*	3.75%	-0.090	6.03%	-11.05***	0.045***	RD, T, Pat
Coal conventional technology	Model-I	-0.191***	12.39%	-0.018	1.25%	-2.33***	0.15***	RD, T
Lignite conventional technology	Model-II	-0.084***	5.67%	-0.025*	1.72%	–	–	–
Combined cycle gas turbine 1990-98	Model-I	-0.032***	2.20%	-0.035***	2.38%	-16.465	0.601	RD, T, Pat
Large hydropower	Model-II	-0.029***	1.96%	-0.038*	2.63%	–	–	–

Table 3. Learning Elasticities and Rates for "Reviving" Technologies

		Learning Equation				Diffusion Equation		Instrumental/ Exogenous variables
	1	2	3	4	5	6	7	8
Technology	Method	Capacity Elasticity	Learning by Doing	Research Elasticity	Learning by Research	Diffusion	Year	Variable
Combined cycle gas turbine 1980-89	Model-I	-0.009***	0.65%	-0.282***	17.7%	-8.451	0.227	RD, T, Pat
Combined heat and power	Model-I	-0.003***	0.23%	-0.135***	8.9%	-26.23***	–	RD, Pat
Small hydropower	Model-II	-0.007***	0.48%	-0.333***	20.6%	–	–	–

*** 5% significance ** 10% significance * 15% significance "learning equation" respectively. Similarly, columns 4 and 5 show the estimated learning by research elasticities and rates respectively. Columns 6 and 7 show the coefficients of diffusion and time for the "diffusion equation" respectively – i.e. the effect of reduction in the cost of technology and time on cumulative capacity. Column 8 shows the instrumental variables used in the learning-diffusion models.

The estimated elasticities have all the expected signs – i.e. an increase in cumulative capacity or R&D spend reduces the cost of technologies. Likewise, a reduction in the cost of the ttechnologies and an increase in time results in higher uptake and cumulative capacity. The results show that the mature technologies exhibit fairly comparable learning characteristics – i.e. they show low learning by research and learning by doing rates. These technologies, due to their mainstream position and widespread use, have faced little market constraints in terms of commercial and expansion opportunities than other technologies. Mature technologies are also comparatively less capital intensive than the newer technologies owing to a longer process of technological improvement and relatively larger 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, in practice, it should be noted that, given the high levels of existing capacity for established technologies, a doubling of capacity and further cost improvements can only take place over a long period of time.

4.2 Reviving Technologies

The next category of technologies comprises a set of "reviving" generation sources. These technologies have been utilised for a long time and as such are not radical innovations (Table 3). The results show that there are some common learning characteristics among the technologies in this category in the form of low levels of learning by doing while showing a fairly high degree of learning by research.

The low learning by doing rates for these technologies suggest limited scope for future cost reductions through capacity deployment. Moreover, the existing high levels of installed capacity for these technologies suggest that they have limited scope for cost reductions – i.e. in terms of learning rates it takes a longer time for their installed capacity to double. At the same time, the learning by research rates show considerable potential for further cost reductions. Although, the extent to which the high learning by research rates can sustain in the future is uncertain.

During the periods studied here, the reviving technologies have achieved technical progress and due to their environmental advantages, have benefited from favorable policies and market opportunities. As a result, market uptake of these technologies has been unconstrained and these have realized much of their learning by doing potential. Small hydropower benefited from increased research in renewable energy 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 it. Combined cycle gas turbines achieved technical progress mainly by increasing the efficiency and reducing the cost effective size of the turbines.

Another shared characteristic of the reviving technologies is that R&D and technical change has lowered the cost efficient size of generation plants. Moreover, similar to mature technologies, reviving technologies are not comparatively capital intensive. Therefore, the required capital investments in these technologies have decreased which, in liberalised electricity markets, amounts to a comparative advantage.

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 power. These technologies have existed either for a shorter time and/or have experienced more constraints, due to environmental concerns or planning issues, in their capacity expansion than reviving technologies during the period under consideration.

The estimated learning rates for these technologies show high levels of learning by doing as well as learning by research (Table 4). Nuclear power has not been a priority area in energy policy and environmental concerns with accidents and radioactive waste have significantly reduced its market opportunities. Wind power has enjoyed a favorable policy environment in many countries and, as a result of capacity deployment and promotion schemes, has shown considerable growth in recent years. However, due to reliance on public subsidies and lack of full cost competitiveness in relation to established conventional technologies, wind technology faces market constraints in reaching a significant share of generation resource mix. Waste to electricity is in a middle position. Environmental concerns with emissions and siting constraints have meant that this technology has not experienced an expansive market growth. Moreover, liberalisation of the sector in many countries has further limited the market potential for the evolving technologies. Without government support these technologies will not be the obvious choices for private investors operating in competitive markets.

As noted, the evolving technologies have faced some market constraints that have limited their growth potential. It is, therefore, plausible that these technologies still have significant potential for further cost improvement through learning by doing, for example, throught increase in manufacturing scale and design standardisation. Their moderate or low levels of installed capacity also suggest that these technologies still possess scope for significant capacity increases and cost reductions through learning by doing.

Moreover, the estimated learning by research rates show considerable potential for cost reduction. Nuclear and wind power are capital intensive technologies and the initial capital investments required in these technologies are comparatively higher than those of fossil fuel based technologies. As a result, much of

Table 4. Learning Elasticities and Rates for "Evolving" Technologies

	Learning Equation					Diffusion Equation		Instrumental/ Exogenous variables
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Technology	Method	Capacity Elasticity	Learning by Doing	Research Elasticity	Learning by Research	Diffusion	Year	Variable
Nuclear power (light water reactor)	Model-I	-0.680***	37.6%	-0.392***	23.8%	-1.21***	-0.009***	RD, T
Waste to electricity	Model-I	-0.774***	41.5%	-0.829***	43.7%	-0.76***	–	RD, Pat
Wind power	Model-I	-0.202***	13.1%	-0.450**	26.8%	-3.46***	–	RD, Pat

Table 5. Learning Elasticities and Rates for "Emerging" Technologies

	Learning Equation					Diffusion Equation		Instrumental/ Exogenous variables
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Technology	Method	Capacity Elasticity	Learning by Doing	Research Elasticity	Learning by Research	Diffusion	Year	Variable
Solar power – thermal	Model-II	-0.032***	2.2%	-0.078***	5.3%	–	–	–
Wind power – offshore	Model-II	-0.015	1.0%	-0.072***	4.9%	–	–	Cap, T

*** 5% significance ** 10% significance * 15% significance future cost improvements in these technologies can also come from learning by research resulting in lower 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 power. The emerging technologies have existed for a relatively shorter time and show a lesser degree of technical progress during the period under consideration. The estimated learning rates for both technologies indicate low learning by doing and learning by research rates (Table 5).

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

Similar to evolving technologies, electricity sector liberalisation 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, need to come in the form of reductions in investment requirements.

Single-factor learning curves do not reflect the effect of R&D on technical change and overstate the effect of learning by doing. Table 6 compares the learning by doing rates from two-factor learning curves with those of simple single-factor learning curves as specified in Equations (1)-(2). As shown in the table, the learning by doing rates from single-factor learning curves are higher than those estimated by two-factor learning-diffusion curves. Moreover, the overstatement is larger for evolving and emerging technologies, which are of particular interest to the current energy technology policy debate. An implication of devising policies based on overestimated learning by doing rates is that they can shift the scarce resources earmarked for innovation resources from more productive R&D activities to less productive and more costly capacity deployment policies.

The main results and characteristics for the four technology categories are summarized in Table 7. The results indicate that emerging technologies can initially experience a relatively long period during which they respond slowly to R&D efforts and capacity deployment. In the next development stage, as evolving technologies, they exhibit both high learning by doing and learning by research rates.

Table 6. Learning by Doing Rates Using Single-factor Curves

	Technology	Learning by Doing Rate Two-Factor Curves	Learning by Doing Rate Single-Factor Curves
1	Pulverized fuel supercritical coal	3.75%	4.8%
2	Coal conventional technology	13.39%	15.1%
3	Lignite conventional technology	5.67%	7.8%
4	Combined cycle gas turbines (1980-89)	2.20%	2.8%
	Combined cycle gas turbines (1990-98)	0.65%	3.3%
5	Large hydro	1.96%	2.9%
6	Combined heat and power	0.23%	2.1%
7	Small hydro	0.48%	2.8%
8	Waste to electricity	41.5%	57.9%
9	Nuclear light water reactor	37.6%	53.2%
10	Wind - onshore	13.1%	15.7%
11	Solar thermal power	2.2%	22.5%
12	Wind – offshore	1.0%	8.3%

Table 7. Development Stage, Learning Rate, Capital Intensity, and Market Opportunity for the Technology Categories

	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

Moreover, it is noteworthy that reviving technologies show considerable potential for technical improvement through learning by research 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 by research rates. In addition, the reviving and mature technologies are relatively less capital intensive than evolving and emerging technologies. As technical progress is mainly embodied in the stock of capital, emerging and evolving technologies have a significant potential for achieving further cost reductions that need to be realized. Furthermore, mature and reviving technologies have accounted for the bulk of generation capacity offering them large market shares and thus potential for learning by doing effect. On the other hand, evolving and emerging technologies still face market constraints and need public support that limits their potential benefits from learning by doing.

As expected, some of the results show that unit cost reductions tend to increase market 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 slow the pace of progress in emerging and evolving technologies.

4.5 Elasticity of Substitution Between R&D and Capacity

An interesting technology policy question following from the discussion of learning by doing versus learning by research is the extent to which these may substitute each other and whether this may be dependent on the stage of the development of technologies. This knowledge would be particularly useful in allocation of public funds for technology promotion between technology push (learning by research) and market pull and deployment (learning by doing) measures. Table 8 shows the average elasticity of substitution for the technologies during the first and second half of the periods of the study.

As shown in the table, while some technologies have moved closer to unity (full substitution) others have moved further away from this. It is difficult to determine the cause of this from the analysis here. However, it is important to note that the diverse nature of the technologies may partly explain this. For most of the technologies the substitution elasticities deviate from unity thus indicating only weak substitution possibility between learning by doing and learning by research. Notable exceptions are, however, onshore wind, offshore wind, and solar thermal power technologies where we find some evidence of relative ease of substitution between R&D and deployment as the main innovation input factors. In addition, conventional coal and CCGT (1990-98) technologies show some indication of substitution possibility.

Table 8. Elasticity of Substitution – R&D and Capacity

	Technology	First half-period	Second half-period
1	Pulverized fuel supercritical coal	-0.308	-0.127
2	Coal conventional technology	-0.361	-0.481
3	Lignite conventional technology	-0.180	-0.205
4	Combined cycle gas turbines (1980-89)	-121.68	-14.78
	Combined cycle gas turbines (1990-98)	-1.142	-0.644
5	Large hydro	-0.015	-0.007
6	Combined heat and power	-0.093	-0.009
7	Small hydro	-0.040	-0.015
8	Waste to electricity	-0.248	-0.227
9	Nuclear light water reactor	-0.427	-0.320
10	Wind - onshore	-9.044	-1.097
11	Solar thermal power	-2.593	-1.624
12	Wind – offshore	-1.441	-1.648

It should be noted that, as seen from Equation (5), the coefficients for cumulative capacity (β) and R&D (κ) are constant and the time variation in the elasticities is due to changes in values of cumulative capacity *Cap* and R&D spending *RD* over time. Therefore, the changes in the elasticities over time should be interpreted with some care. For example, most of the technologies analyzed here exhibit a decline in substitution elasticity from the first to the second half of the periods. This can be due to relatively higher increase in installed capacity in relation to R&D spending which has been negatively affected by a global decline since the 1980s (see Jamasb and Pollitt, 2005).

5. CONCLUSIONS

A better understanding of the role of learning in technical change and at different stages of technological progress is important for developing better theories of innovation and designing more effective technology policies. This paper presents a comparative empirical analysis of progress and learning in electricity generation technologies towards this aim using the invention-innovation-diffusion paradigm of technical change. We estimate the learning by doing and learning by research rates for a range of generation technologies in different stages of progress using two-factor models of technology learning. The estimated learning rates of the technologies broadly reflect their expected stage of development.

We find that emerging technologies experience a period during which they respond slowly to R&D and capacity deployment. 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. Finally, mature technologies exhibit similar learning characteristics to emerging technologies.

The relative effectiveness and the relationship between R&D and capacity expansion is an important policy related matter and, at the same time, little understood aspect of technical change. The results generally point to the relative importance of R&D in technological progress. We find higher learning by research than learning by doing rates (although not always statistically significant). Moreover, we did not find any stage of technological development where learning by doing alone was the dominant driver of progress.

In addition, the results show that single-factor learning curves overestimate the effect of learning by doing and in particular for emerging and new technologies. At the same time, we generally find little scope for potential substitution between learning by doing and learning by research for most of the technologies. The effects of R&D and capacity deployment on technology cost improvement can thus be regarded as largely independent from each other.

A crucial policy question 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 different technologies. Better data will enable more elaborate models of technology learning. This will in turn enhance the contribution of empirical studies towards improving innovation theory and technology policy.

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