Modeling Technology Learning for Electricity Supply Technologies

Phase I Report

to

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May 2013

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Table of Contents

List of Figures

List of Tables

Executive Summary

The phenomenon of unit cost reduction associated with increased production (learning-by-doing) has long been documented for manufactured products. In recent decades this has been extended to energy. The most common approach for characterizing this relationship is the use of a log-linear experience curves (or learning curve) relating reductions in the unit cost of a technology to its cumulative production or installed capacity. This model formulation also has become a common method of representing endogenous technical change in energy-economic models used for policy analysis.

Yet, there are significant uncertainties in the underlying drivers of technological change, and the "proper" formulation of an experience curve (e.g., the appropriate equation, shape, and parameters of an experience curve). Thus, there is uncertainty in how best to use learning curves for making projections and analyzing policy scenarios.

In this report, we review theory of technological change and the underlying drivers for cost reduction reported in the literature. We conducted a comprehensive literature review for eleven power generation technologies including fossil-based power plants and renewable electric technologies. The results are summarized in Table ES-1 below.

Table ES-1: Summary of studies characterizing historical learning rates for electric power generation technologies.

Technology	Number of studies reviewed	Number of studies with one factor	Number of studies with two factors	Range of learning rates for "learning by doing" (LBD)	Range of rates for "learning by researching" (LBR)	Years covered across all studies
Coal*						
PC	2	2	0	5.6% to 12%		1902-2006
IGCC	1	1	0	2.5% to 7.6%		Projections
Natural Gas*	8	6	2	-11% to 34%	2.38% to 17.7%	1980-1998
Nuclear	4	4	0	<0 to 6%		1975-1993
Wind (on-shore)	35	29	6	-3% to 32%	10% to 26.8%	1980-2010
Solar PV	24	22	2	10% to 53%	10% to 18%	1959-2001
BioPower						
Biomass production	4	4	0	12% to 45%		1971-2006
*Power generation***	7	7	0	0% to 24%		1976-2005
Geothermal power	3	0	0			1980-2005
Hydropower	3	0	2	0.48% to 11.4%	2.63% to 20.6%	1980-2001

*Does not include plants with CCS. **Includes combined heat and power (CHP) and biodigesters.

1 Introduction

The Electric Power Research Institute (EPRI) has developed the US Regional Economy, Greenhouse Gas and Energy (US-REGEN) model to assess the effects of various climate, energy and environmental policies on the electric power sector, the overall energy system, and the overall economy of the United States. Understanding how the performance and cost of energy supply technologies change over time is of key importance for analysts and decision-makers concerned with the future evolution of the U.S. energy system. Studies over the past several decades have documented how the costs of various energy technologies have evolved in the past. Based on historical data, various types of "learning curves" (or experience curves) have been proposed to relate the cost of a technology to key parameters such as cumulative installed capacity, R&D spending levels, as well as factors such as economies of scale, market structure, among others.

1.1 Scope and Objectives of This Study

In the context of the preceding discussion, the objectives of this study are to: (1) conduct a comprehensive literature review of technology learning models applicable to electric power generation technologies; (2) characterize the state of the art and key findings stemming from that literature review; (3) review and characterize other large-scale computer models that incorporate technology learning; and (4) from that review, draw lessons and insights potentially applicable to the development and use of EPRI's REGEN model. In particular, the focus of this study is on learning curves applicable to the following power generation technologies:

- Pulverized coal (PC) plants with and without carbon capture and sequestration (CCS)
- Integrated gasification combined cycle (IGCC) plants with and without CCS
- Natural gas combined cycle (NGCC) plants with and without CCS
- Natural gas-fired combustion turbines
- Dedicated biomass plants
- Nuclear plants (third-generation)
- Conventional hydroelectric plants
- Geothermal plants
- On-shore and off-shore wind turbines
- Solar photovoltaic (PV) and concentrating solar thermal plants (CSP).

1.2 Organization of Report

Section 2 of the report next reviews the theory of technological change and some of the model forms that are suggested. Then, Section 3 presents the results of our literature review of learning curves applicable to the electricity supply technologies listed in Section 1.1. In Section 4 we discuss the ways in which learning curves of some type have been incorporated into other large-scale energy-economic models, and their influence on key results. Finally, Section 6 summarizes our overall conclusions and recommendations.

2 Theory of Technological Change

In macroeconomic growth theory, neoclassical growth models such as Solow's (Solow 1956) originally treated technical change exogenously, that is, independent of other factors or variables. However, this assumption leaves a large component of observed growth unexplained. An alternative formulation proposed by Romer (Romer 1986), and since followed by much of the technological change literature, suggests that technological change needs to be modeled endogenously, namely as a function of public and policy choices.

A parallel discussion emerged in recent years in the energy modeling literature. Technological change, i.e., the adoption of new more efficient technologies to provide (energy) services, is key for the world to move toward sustainable, low carbon, energy systems. Policy makers around the world have been using different policy instruments, such as R&D funding and other deployment incentives (such as feed-in tariffs, green certificates, and other mechanisms) in order to promote such sustainability transitions. However, there is still large uncertainty on the degree to which different policies induce technological change. Historically, many of the energy technologies we use today have evolved over time: improvements in manufacturing and in efficiency led to a decline in production costs. As consumers and producers gain experience with technologies, their technical and economic performance increases (Yeh & Rubin 2012; Junginger et al. 2010).

Grubb and Kohler (Grubb & Köhler 2002), suggest that "exogenous technological change" occurs when "technical change is incorporated as an exogenous variable: it is reflected through specific assumptions entered as data about improved efficiency and declining costs of certain kinds of technologies through time." For energy modeling this is a key assumption. Thus, "exogenous technological change" suggests that technical change is mainly an autonomous process: that it just happens in ways that do not depend upon other policy or economic variables." Modeling technological change in this form can be interpreted as meaning that the technological change will arise from sources that are largely unresponsive to policies (Cohen 1995; Clarke et al. 2006; Klepper & Simons 2000).

However, as also mentioned by Grubb and Kohler (Grubb & Köhler 2002), "in the wider literature on technical change, it is acknowledged that [technological change] is not an autonomous process: it occurs as a result of identifiable processes, such as government research and development, corporate technology investment, and economy-of-scale effects. In reality, a great deal of technical change is led by the private sector and is induced in response to government policies, market conditions, investment, and expectations. In modeling terms, therefore, technical change really should be endogenous, i.e., dependent upon other parameters reflected within the model."

The key goal of modeling endogenous technological change is to understand how technology changes as a function of policies promoting technology diffusion and cost reductions, or providing R&D funding (Clarke et al. 2006). Endogenous technological change models also seek to understand the importance of cost reductions or technology components in one sector as function of the cost reductions of that same component in other sectors, that is, understanding "spillover" effects.

Some authors in the environmental policy and innovation area take the approach of categorizing environmental policy instruments as being either “technology-push” or “demand-pull”. Technology-push policy instruments are those that “influence the supply of new knowledge” while “demand-pull” instruments “affect the size of the market for a new technology” (Taylor 2008). This taxonomy was used in the innovation literature in the past and, according to Taylor (Taylor 2008), has gained popularity in recent years in both academia and professional policy circles, although it may not provide the best and most useful characterization of the diversity of policies affecting environmental systems.

Figure 1 illustrates pathways for technological changes that affect cost reductions for a specific technology. The figure also shows how changes in other technologies and components may contribute to changes in the technology under study. The next section describes in detail various types models that have been used to examine the effects of these drivers on technology cost reductions.

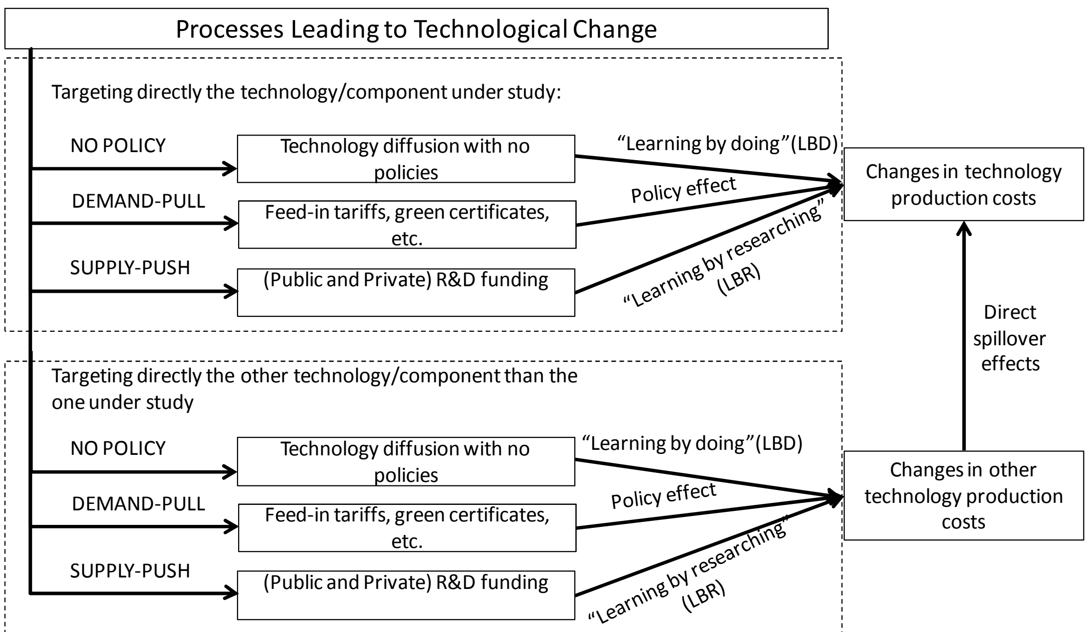


Figure 1: Pathways for technological change.

2.1 One Factor Experience Curves: Learning-by-Doing

There is a large literature that has empirically observed a relationship between unit costs of production and cumulative production across numerous technologies and products. The relationship has been referred to as an “experience curve” or “learning curve” and has been shown to generally take the following generic form (Arrow 1962):

Y = axb **Equation 1**

where:

Y = unit cost of production;
x = cumulative experience (which in the energy innovation literature is typically represented by cumulative installed capacity or cumulative energy production);
a = unit production cost of the first unit; and
b = a constant capturing the rate of cost reduction.

The initial cost of production, Y_0 , can then be expressed as $Y_0 = a(x_0)^b$. The production costs when the cumulative production is doubled is given by $Y = a(2x_0)^b$. This means that the cost reduction associated with a doubling of production is given by:

$$\frac{Y_0 - Y}{Y_0} = \frac{a(x_0)^b - a(2x_0)^b}{a(x_0)^b} = 1 - 2^b = Learning\ Rate \qquad \text{Equation 2}$$

The *learning rate* is defined as the rate at which the per-unit cost of a technology is expected to decline with every doubling of cumulative production. The factor 2^b is called the *progress ratio*, a parameter also commonly reported in the literature. Numerically it is simply equal to (*1 –LR*).

The original derivation of this model form reflected the phenomenon called "learning by doing" (LBD). However, it is often argued that the statistical correlations between a reduction in unit cost and the cumulative installed capacity of an energy technology offers little explanation for the underlying factors and processes of technological change. There is also no inference in the causality between these two variables (Clarke et al. 2006; Ferioli et al. 2009; Gillingham et al. 2008; Nordhaus 2009). Despite several decades of research, our understanding of the factors that contribute to technological change and cost reductions is still rather limited. Various theories have been proposed to explain observed reductions in unit cost as cumulative output increases. Generally, they fall into three categories: (1) costs fall due to changes in production that include process innovations, worker familiarity in the use of tooling, improved management, and economies of scale; (2) costs fall due to changes in the product itself including product innovations, re-design and standardization; and (3) costs fall due to changes in input prices (Yeh & Rubin 2012). While intuitively satisfying, most of these explanations are only qualitatively descriptive and provide little quantification of the direct relationships or contributions of each factor to overall learning or cost reductions.

Some researchers suggest that the overall learning rates derived from empirical experience curves many over-estimate the actual contribution of true learning-by-doing (Jamasb 2007; Clarke et al. 2006; Nordhaus 2009), as these models do not account for R&D spending (Cohen & Klepper 1996; Jamasb 2007; Clarke et al. 2006), knowledge spillovers (Clarke et al. 2006), increased capital investments (Cohen 1995; Klepper & Simons 2000) economies-of-scale (Sinclair et al. 2000; G. Nemet 2006; Yeh & Rubin 2007), the effect of other public policies (Söderholm & Sundqvist 2007; Söderholm & Klaassen 2007), and the effect of changes in input prices. A particular concern is that models that "miss critical pathways or ascribe influence inappropriately could potentially arrive at erroneous, incomplete, or misleading policy conclusions" (Nordhaus 2009). These concerns have led to the development of other learning models that incorporate multiple parameters.

2.2 Two-Factor Experience Curves: Learning-by-Doing and Learning-by-Researching

To take into account additional factors that contribute to changes in technology production costs, alternative models have been developed. “Two-factor learning curve” models describe a relationship in which cumulative R&D expenditures as well as cumulative production or capacity are assumed to be the main drivers of technology cost reductions (Jamasb 2007). While it is widely accepted that both public and private R&D can contribute to such cost reductions, this area of research often includes only public R&D spending, as private R&D data is generally not available publicly.

R&D contributes to an expanded knowledge base, which in turn can stimulate further technological innovation, cost reductions, and technology diffusion. The relative importance of these two factors may vary, depending on the stage of product development: R&D and learning-by-researching (also called learning-by-searching) may play a larger role at early stages of development, while learning-by-doing may dominate as the product or technology matures. The model of Equation 1 can be expanded to include the effect of R&D, as shown in Equation 2:

$$Y = a(x_0)^{b_{lbd}} + b(R\&D)^{b_{lbr}} \qquad \text{Equation 3}$$

Using a logarithmic transformation this can be simplified to:

$$\log(Y) = b_{lbd}\log(x) + b_{lbr}\log(R\&D) + \alpha \qquad \text{Equation 4}$$

where:

b_{lbd} = learning-by-doing parameter
b_{lbr} = learning-by-researching (R&D) parameter
R&D = cumulative R&D investment or knowledge stock
α = specific cost at unit cumulative capacity and unit knowledge stock.

Several researchers have performed empirical work testing this formulation (Söderholm & Sundqvist 2007; Jamasb 2007; Klaassen et al. 2005; Söderholm & Klaassen 2007). Jamasb (Jamasb 2007) examined the impact of R&D spending on technology cost reductions using estimates of the combined government and private R&D expenditures in the UK. This model was coupled with cumulative installed capacity data (representing learning-by-doing) for twelve power generation technologies for the period 1980–2001. The study included mature technologies (e.g., pulverized coal plants, natural gas combined cycle gas plants, large hydropower), reviving technologies (e.g., new combined cycle plants, combined heat and power, small hydropower), evolving technologies (e.g., nuclear power and wind power) and emerging technologies (e.g., solar thermal power and offshore wind turbines). R&D expenditures were estimated from a broad survey of sources including government R&D databases, R&D expenditure estimates for specialized companies, plus several indirect methods of estimating private R&D investments. The results show that the importance of R&D versus learning-by-doing varied across the different categories of technology; but in general, R&D contributed more to cost reductions than learning-by-doing in all stages of technological development. In addition, the study found very little elasticity of substitution between the two factors, i.e., R&D expenditure and capacity expansion were distinctly different and non-interchangeable. However, other studies also found significant correlations between time-lagged cost reductions and cumulative R&D expenses and/or R&D-based knowledge stock (Söderholm & Sundqvist 2007; Jamasb 2007; Klaassen et al. 2005; Söderholm & Klaassen 2007).

2.3 Three-Factor or Multi-Factor Learning Curves

Several studies have used regression analysis or decomposition techniques to estimate unit cost reductions for a technology as a function of several explanatory variables beyond capacity installed and R&D. Such studies include factors such as economies-of-scale (Söderholm & Sundqvist 2007; G. Nemet 2006; Joskow & Rose 1985), input prices for materials (Söderholm & Sundqvist 2007; G. Nemet 2006; Joskow & Rose 1985), labor costs (Joskow & Rose 1985), efficiency improvement (G. Nemet 2006; Joskow & Rose 1985), among others. Not surprisingly, these studies typically find smaller learning rate impacts for cumulative installed capacity compared with studies using the one-factor learning curve. Multi-factor models of this type offer improved explanations of the processes that contribute to cost reductions for the technology under study. Thus, they provide greater precision in projecting the effect of a given factor change on the future cost of that technology.

2.4 Component-Based Learning Curves

Component-based learning curves are essentially an extension of the one-factor model, in which the overall cost of a technology at any given point is given by the sum of the costs of individual components or sub-systems of the technology. Thus:

$$Y = \sum_{i=1}^{n} a_n x^{b_n} \qquad \text{Equation 5}$$

where:

n = a given technology component
a_n = specific cost at unit cumulative capacity for cost component n
b_n = learning parameter characterizing cost component n.

In this model, the capacity or experience base, x, is usually a projected future value rather than an observed historical value. This method of estimating the future cost of a technology has been applied to cost projections for several types of power plants with carbon capture systems (Rubin et al. 2007), as well as to micro-cogeneration of heat and power (Weiss et al. 2010). In each case, the overall plant is disaggregated into a number of sub-sections (such as boilers, gasifiers, and air pollution control systems for power plants). The cost of each sub-section is then projected based on the historical learning rate for the same or similar technology components. The future cost of each component (after some specified increment of cumulative capacity) is then summed to obtain the future cost of the overall plant. The rationale for this approach is that for complex technologies like a coal-fired power plant, different components are currently at different levels of maturity. Thus, the cost of newer components like a carbon capture system may fall more rapidly than the cost of mature component like boilers or steam turbines.

Another type of component-level learning model (Ferioli et al. 2009) projects the cost of technology based on learning *versus* non-learning for different types of costs. Here, some cost components such as raw materials and labor may experience no learning or even become more expensive over time.

2.5 Models with Exogenous Technological Change and Other Factors

Other recent approaches to modeling technological change incorporate time in the experience curve formulation so as to explicitly separate the effect of true learning from that of progress that may occur exogenously over time (Ferioli et al. 2009; Papineau 2006; Jamasb 2007; Nordhaus 2009). Such an approach argues that there is a constant rate of exogenous technological change that is independent of learning-by-doing, such as *inter alia* spillovers from outside the industry, returns to research and development, economies of scale or scope and exogenous fundamental inventions, and changes in the price of materials or labor. The incorporation of these factors implies a much smaller rate of true learning for a technology (Nordhaus 2009). To date, this model has been tested only at a high level of technological aggregation (economic sectors). As with other multi-variate formulations, empirical data to develop and test such models for specific technologies (or classes of technology) is currently limited or unavailable.

2.6 Endogenous Learning-Diffusion Models

A recent direction of the learning literature has been the integration of diffusion and learning model, the so-called endogenous learning-diffusion model (Barreto & Kypreos 2004; Ferioli & van der Zwaan 2009; Jamasb 2007; Söderholm & Klaassen 2007). This approach accounts for the fact that reductions in unit cost can increase the diffusion and adoption of a technology in the marketplace (Jamasb 2007), thus capturing the causality effects that the simple learning curve models do not capture. In turn, faster adoption of the technology may stimulate higher learning rates. This approach provides a greater ability to explain changes in the learning rate over time (or with cumulative production), controlled by the rates of growth and cost reduction.

For example, Jamasb (2007) attempted to endogenize the two-factor learning equation (cumulative R&D and cumulative capacity) by allowing cumulative capacity to be a function of two variables: cost of technology and time. Statistical analysis on a wide range of electric technologies ranging from mature to evolving showed that unit cost reductions for some technologies increased their market diffusion and adoption. Similarly, Soderholm and Klaassen (2007) examined wind power in Europe from 1986-2000 and found that "reductions in investment costs have been important determinants of increased diffusion of wind power, and these cost reductions can in turn be explained by learning activities and public R&D support." The study suggests that innovation and cost reductions are a necessary condition for the diffusion of wind power, and vice versa. However, there are many more important factors that contribute to diffusion than cost reduction alone. For example, policies such as price subsidies and fixed feed-in tariffs were observed to be more effective in promoting diffusion than cost reduction alone. However, a major obstacle to the use of this type of model, as pointed out by Soderholm and Klaassen (2007), is the difficulty (and potential error) that can be introduced by using an estimated econometric model found suitable for one time period and using it to make predictions for another period.

2.7 Spillover Effects

Spillover effects in the learning literature refer to the direct and indirect benefits of technology deployment, R&D expenditures, and other factors on reducing the cost of a technology (or in a particular region) other than the one that was targeted. Direct spillovers occur when deployment and/or R&D in other geographic locations drive cost reductions for a given technology in a different region of interest. Direct spillover also can occur in the form of "knowledge spillover" when deployment and/or R&D in technology *Y* affect the cost of technology *Z* (Clarke et al. 2006; G. Nemet 2011). Indirect spillovers result when R&D spending or technology *Y* occurs as a response to R&D spending on technology *Z* (Clarke et al. 2006).

There is a large literature documenting the evidence for knowledge spillover between industries and sectors, including semiconductors, manufacturing, and the food industry. In the power sector, Yeh et al. (Yeh et al. 2005) examined technology innovation and experience curves for NO_x emission control technologies in coal-fired power plants and found clear evidence of knowledge spillover between countries that resulted in global cost reductions for these technologies of interest. Using a patent analysis, Yeh et al. also found that the United States was able to meet more stringent environmental regulations by acquiring or licensing patents on mature high-efficiency selective catalytic reduction (SCR) technologies developed in Japan and Germany—countries that adopted stringent NO_x emission restrictions 10-20 years earlier than the United States (Yeh et al. 2005). That study did not examine the potential contribution to SCR cost reductions from applications in other settings, such as non-utility oil-fired and gas-fired facilities. This was due in part to data limitations, but also because many of the designs and technical problems associated with coal-fired plants (such as high-fly-ash loadings and trace contaminants that can poison SCR catalysts) do not apply in these other facilities. To the extent that any spillover effects from these other SCR markets also benefited coal-fired plants, the learning rates derived in the 2005 study would decline slightly as the experience base (cumulative capacity) was expanded.

2.8 Cluster Effects

In the context of this report, cluster learning refers to the case where several power generation options share a major component technology, which is itself subject to learning. For example, Seebregts et al. (Seebregts et al. 1999) identifies some eleven technologies that all share a gas turbine component, including integrated coal gasification power plants, combined cycle fuel cell power plants, and combined heat and power (CHP, also known as co-generation) plants. Thus, technological learning in any of these applications is assumed to benefit all other applications that utilize the same component. Seebregts et al. conclude that this type of "cluster feature" improves the internal consistency of models and incorporates some of the mechanisms identified in technology dynamics studies. A number of studies and models have used the cluster concept in studies of technological learning. The National Energy Modeling System (NEMS), used by the U.S. Department of Energy's Energy Information Administration, has twenty-one technology components for which learning rates vary as a technology component goes through different stages: revolutionary, evolutionary, and mature. More detailed reviews of the treatment of clustered learning in these models are included in Section 4 of this report.

2.9 When Does Learning Start?

Most empirical learning curve studies for power generation technologies employ a functional form that yields a decreasing cost trend with cumulative installed capacity or cumulative electricity generation. However, in some studies, it has been found that the cost of a technology initially *increases* as a function of cumulative capacity. Several possible explanations are offered. One is that costs may rise initially due to a lack of competition or other market factors. Another is that the technology in question is not yet able to meet its design criteria and thus requires modifications that increase costs. For example, Yeh and Rubin (Yeh & Rubin 2012), argue that:

> "… for many large-scale technologies such as power plants and their environmental control systems, initial cost estimates for new technologies based on experience from smaller-scale projects or pilot plants are typically lower than the costs subsequently realized for the initial set of full-scale commercial plants. Thus, costs often increase rather than decrease in the early phase of commercial deployment. The reasons for such increases are typically linked to shortfalls in performance and/or reliability resulting from insufficient data for scale-up and detailed design, or from new problems that arise during full-scale construction and operation."

There are a few empirical studies demonstrating initial cost increases. For example, Colpier and Cornland (Colpier & Cornland 2002) show that for natural gas combined cycle (NGCC) systems, the costs increased as function of cumulative capacity from 1981 to 1991, followed by a more traditional decline. Similarly, Ibenholt (Ibenholt 2002) also found initial negative learning rates (i.e., progress ratios higher than 100%) in the case of the first German wind power units. More recently, Yeh and Rubin (Yeh & Rubin 2012) found a similar pattern when assessing the early changes in capital cost and annualized operating and maintenance (O&M) costs of wet limestone flue gas desulfurization (FGD) systems for a standardized new coal power-plant. The authors also identified an initial increase in the capital cost and total levelized cost of selective catalytic reduction (SCR) systems for standardized new coal plants.

Thus, the question of when "learning" (i.e., cost reductions) begins is a critical issue, which is handled in different ways by different analysts and modeling groups. Most importantly, the discussion above indicates that the common assumption that costs always decline with experience (or technology deployment) is not always correct, and can lead to erroneous projections.

2.10 Limitations of Current Learning Models

The use of single-factor experience curves for forecasting or modeling future cost trends in energy-related technologies is beset by a number of other uncertainties. While learning curves explain how a technology has evolved in the past, they provide very limited insight concerning how the technology is likely to evolve in the future. The application of historical learning curves for certain technologies to new or different technologies being developed is arguably even more uncertain. Finally, the question arises of whether there is a "best" functional form of an experience curve for a selected technology. That is, does the learning rate remain constant over time, or does it change over the modeling period? Do costs always decline, or might they also increase and if so, why, when or how? Because there are still no definitive answers to such questions, it is important to recognize that these are sources of uncertainty that can significantly influence the results of energy-economic models.

Similar uncertainties affect multi-factor learning models. For example, uncertainties at the component level lead to system-level uncertainties. Thus, the same set of issues and limitations arise as when using the one-factor learning curve, i.e.: when does learning begin (and end)? What is the appropriate learning rate or progress ratio? What other factors will lead to cost changes besides installed capacity, and what are the implications of not including those factors explicitly in these models? What is the appropriate measure of capacity or experience? The latter question, in turn, raises the additional issue of "spillover" effects, e.g., to what extent is learning shared across a range of technologies or applications? For example, experience with carbon capture systems in the oil and gas industries may directly benefit similar applications in the electric utility industry. To what extent does this occur? Thus, while the concept of "clustered learning" has been used in some integrated assessment models, such as in Seebregts et al. (Seebregts et al. 2000), the basis for such applications remains largely in the realm of technical and professional judgments—another source of uncertainty in current models.

3 Review of Learning Curves for Power Generation Technologies

In this section of the report we summarize our findings from the literature review with regard to learning rates for specific power generation technologies. We focus on the technologies listed in Section 1.1 that are represented in the EPRI REGEN model.

3.1 Coal-Based Power Plants with and without CCS

Power generation technology combusting pulverized coal (PC) is one of the few major energy technologies in use for over a century that is still re-inventing itself. Energy forecasting studies project that coal with or without carbon capture and sequestration (CCS) will remain the largest energy source for electricity generation in the U.S. and globally throughout the first half of this century (EIA 2013; International Energy Agency 2012).

Over the course of the last century, technology improvements in PC boilers and in other plant components have yielded significant economies of scale – and thus cost reductions – along with improvements in efficiency, reliability, and environmental performance of the overall power plant. One recent study found that the cost of coal-fired electricity in the United States between 1882 and 2006 was determined largely by the price of coal and plant construction costs (McNerney et al. 2011). The experience curve derived for plant construction cost implies a learning rate of 12% between 1902 and 2006.

Nonetheless, despite this apparent long-term learning, after the 1980s construction and generation costs generally increased due to a variety of factors. Joskow and Rose (Joskow & Rose 1985) found that real cost increases were primarily due to new regulatory requirements such as environmental, health, and safety standards; changes in work rules; and improved design standards. These findings held while controlling for scale effects, technological differences, input price changes, major environmental control technologies, and other cross-sectional differences in real construction costs. The trend of increased costs for coal-based power plants may likely continue as a result of the growing (and changing) complexity of environmental regulations (such as the mercury and air toxic standards). Similarly, if CCS installations become required under New Source Performance Standards (or other) regulations, plant system costs will increase (Zhai & Rubin 2013).

Increased labor costs, increased construction time, and a decline in construction productivity also contributed to higher costs over the last few decades. Similar findings were observed by Wang and Yu (Wang & Yu 1988). Nonetheless, Joskow and Rose (Joskow & Rose 1985) found significant learning effects for architect–engineering firms and utility companies (albeit at different rates) involved in constructing both subcritical and supercritical plants.

To better analyze the effects of technology learning, some authors have decomposed complex coal-based plants into major components or sub-systems so as to disentangle the cost increases due to changing design requirements, such as the need for new pollution control systems. In this way, selected plant components can be combined to study the effects of learning for plants of a fixed design. As part of this framework, Yeh and Rubin (Yeh & Rubin 2007) fitted historical construction costs of PC subcritical boilers (the basic building block of a power plant) and found the overall learning rate for boiler construction cost from 1942-1999 was 6%. During this period, the size of PC plant boilers increased by nearly 70%, while the average efficiency of the overall PC power plant increased from 30% to 38%. The same study found the learning rate of non-fuel O&M costs from 1929 to 1997 to be 8%, after adjusting for changes in GDP (using the GDP price deflator), real wages (wage and salary for electric and gas employees), and plant utilization.

The future cost of power plants with CCS also is of significant interest, though there is no direct historical experience to call on at this time as the basis for a learning curve. To derive a best estimate, Rubin, et al. (Rubin et al. 2007) argue that current commercial systems for post-combustion capture of CO_2 are technically analogous to post-combustion systems for SO_2 capture (known as flue gas desulfurization systems, or FGD). On this basis a learning rate of about 12% was estimated for capital cost reductions for CCS. For an overall power plant with CCS a smaller learning rate was estimated, on the order of 2–3% for capital cost and 3–4% for cost of electricity, because most of the total plant components are already fairly mature. Table 1 summarizes the sensitivity analysis yielding the learning rate results from that study.

There are only a few commercial integrated coal-gasification combined cycle (IGCC) plants in operation worldwide (two in the U.S.), and none with commercial-scale CCS. Thus, existing studies have used a "bottom-up" approach to estimate the future learning rates of IGCC and coal plants with CCS using the component modeling approach outlined above and discussed earlier in Section 2.4. Table 1 shows results for IGCC with CCS based on the study by Rubin, et al. (Rubin et al. 2007) and van den Broek *et al.*. Similarly, Li *et al.* (Li et al. 2012) used a bottom-up approach to estimate future learning rates of capital and O&M cost for future components of PC and IGCC plants with CCS, as shown in Table 2. The learning rates and other details of previous literature on coal-fired power plants are shown in Appendix A, Table A1.

Table 1: Projected learning rates for pulverized coal (PC) and integrated gasification combined cycle (IGCC) power plants with CCS. (Source: Rubin et al. 2007).

PC Sensitivity Case	Capital Cost ($/kW)				COE ($/MWh)			
	Learning Rate	Initial Value	Final Value	% Change	Learning Rate	Initial Value	Final Value	% Change
Nominal base case assumptions	0.021	1,962	1,783	9.1%	0.035	73.4	62.8	14.4%
Learning starts with first plant	0.013	1,962	1,764	10.1%	0.024	73.4	60.8	17.2%
Learning up to 50 GW	0.018	1,962	1,846	5.9%	0.031	73.4	66.0	10.1%
Current capture capacity = 0 GW	0.026	1,962	1,744	11.1%	0.042	73.4	60.9	17.1%
Non-CSS exp. Multipliers = 2.0	0.029	1,962	1,723	12.2%	0.044	73.4	60.4	17.8%
Coal price = $ 1.5/GJ	0.021	1,965	1,786	9.1%	0.035	79.6	68.2	14.3%
FCF = 11%, CF = 85%	0.021	1,963	1,785	9.1%	0.039	57.2	48.2	15.7%

IGCC Sensitivity Case	Capital Cost ($/kW)				COE ($/MWh)			
	Learning Rate	Initial Value	Final Value	% Change	Learning Rate	Initial Value	Final Value	% Change
Nominal base case assumptions	0.050	1,831	1,505	17.8%	0.049	62.6	51.5	17.7%
Learning starts with first plant	0.029	1,831	1,448	20.9%	0.032	62.6	48.6	22.4%
Learning up to 50 GW	0.044	1,831	1,610	12.1%	0.045	62.6	54.9	12.2%
Current gasifier capacity = 1 GW	0.057	1,831	1,460	20.3%	0.055	62.6	50.2	19.8%
Above + H2-GTCC = 0 GW	0.088	1,831	1,285	29.8%	0.078	62.6	45.9	26.6%
Non-CSS exp. Multipliers = 2.0	0.062	1,831	1,432	21.8%	0.059	62.6	49.5	20.8%
Coal price = $ 1.5/GJ	0.050	1,834	1,507	17.8%	0.048	68.4	56.6	17.3%
FCF = 11%, CF = 85%	0.048	1,832	1,516	17.2%	0.047	47.2	39.2	16.9%

Table 2: Estimated learning rates for future components of PC and IGCC plants with CCS (Source: Li et al. 2012).

Plant Component	Capital Cost	O&M Costs
Air separation unit	5% – 15%	0% – 10%
Coal gasification unit	7% – 21%	5% – 20%
Syngas shift unit	6% – 18%	10% – 30%
Syngas purification unit	6% – 17%	10% – 30%
CO_2 capture unit	10% – 30%	10% – 30%
CO_2 compression unit	0% – 10%	0% – 10%
Combined cycle	5% – 15%	0% – 10%
BOP (Balance of Plant)	0% – 10%	0% – 10%
PC plant	3% – 9%	7% – 30%

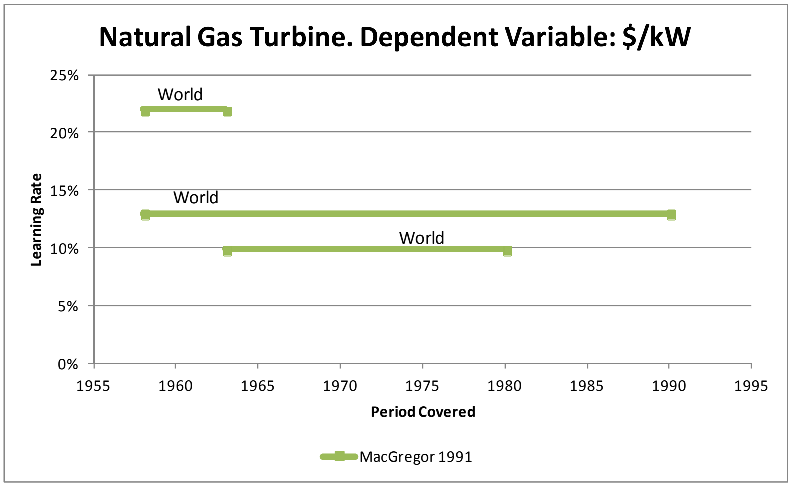
3.2 Natural Gas-Fired Power Plants with and without CCS

Natural gas has been used for power generation since the 1940s. The first gas combined cycle plants were built in the 1970s, but growth was held back as a result of the oil embargo and high natural gas prices at the time, which led to a prohibition on natural gas use for power generation that was subsequently repealed by the U.S. Congress. Construction of natural gas-fired power plants then boomed in the late 1990s and early 2000s when gas prices were low and efficient combined cycle power plant costs fell.

Most studies on learning for natural gas power plants used single factor curves as reported in (McDonald & Schrattenholzer 2001; Colpier & Cornland 2002; Priddle 2000). While most of the studies on learning curves of gas-powered technologies used specific capital cost as the dependent variable, IEA, Colpier and Cornland, and Kouvaritakis et al. (Priddle 2000; Colpier & Cornland 2002; and Kouvaritakis et al. 2000) also report values in which the dependent variable is specific investment price. Investment prices, however, may distort learning rates based on actual cost. Kouvaretakis et al (Kouvaritakis et al. 2000) found a negative learning rate for gas turbine combined cycle plants using world price data for the 1981-1991 period. This result may have been caused by oligopolistic price behavior, so these values have to be used with caution.

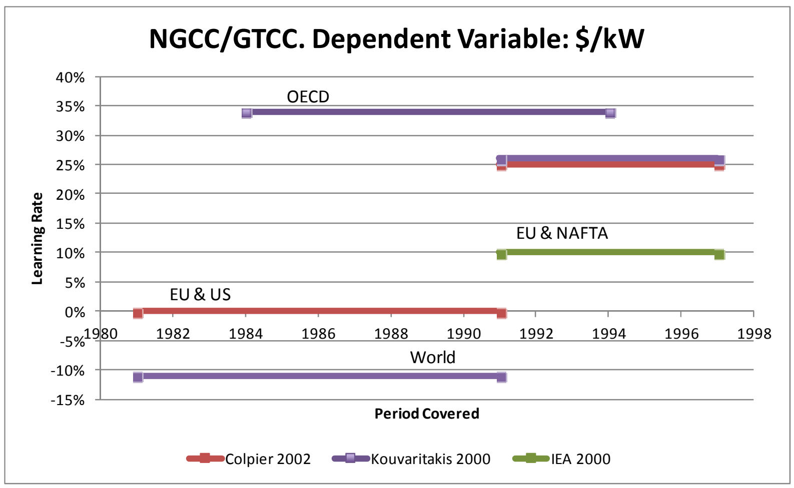
Figure 2 provides a summary of the learning rates available in the literature for natural gas technologies. For each study, the graph shows the time period and geographic region used to derive the learning rate. Figure 2(a) and 2(b) show results for simple natural gas-fired combustion turbines and combined cycle plants, respectively, based on NGCC capital cost. Colpier and Cornland (Colpier & Cornland 2002) also report values in which the dependent variable is electricity production cost ($/kWh) rather than capital cost. Electricity production costs for gas power plants are highly dependent on the price of natural gas. Thus, Colpier and Cornland report two values: one in which the actual natural gas price for each of the years covered is used, and one in which natural gas price is assumed to be constant. The difference in the resulting learning rates (15% vs. 6%) can be observed in Figure 2(c). Figure 3 provides a histogram showing the range of values reported in Figure 2, along with summary statistics for the mean (14%), median (13%), and standard deviation (13%). Appendix A, Table A2, summarizes all the learning rates for natural gas power plants reviewed for this study.

Carbon capture and storage (CCS) technology also can be used at NGCC power plants. However, since CCS has not yet been deployed at power plants at a commercial scale, there is no experience on actual learning rates for natural gas plants with CCS. In the absence of such data, van den Broek et al. (van den Broek et al. 2009) built upon a previous study by Rubin, et al. (Rubin et al. 2007) to estimate learning rates for NGCC plants with CCS using the component-based modeling approach discussed earlier in Section 2.4. The result was a range of learning rates of approximate 2% to 7%, with a nominal value of 5%. Those estimates notwithstanding, the true effect of learning-by-doing for power plants with CCS cannot be thoroughly evaluated until commercial deployment of such systems takes place.



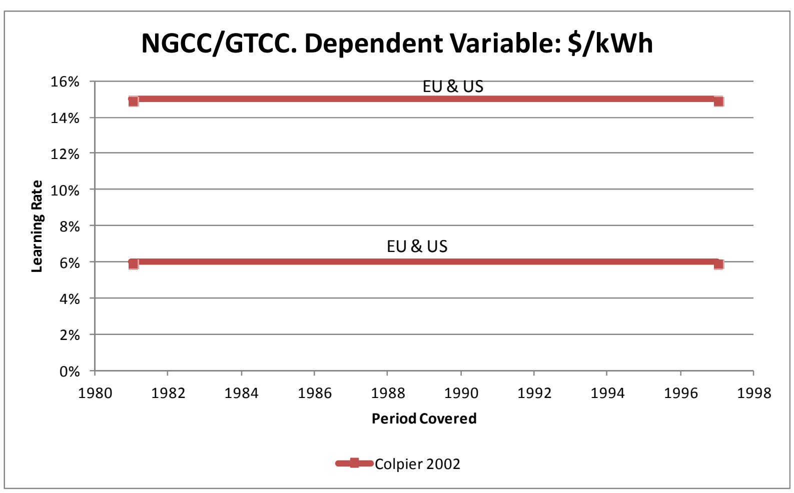
Natural Gas Turbine. Dependent Variable: $/kW
World
World
World
Learning Rate
Period Covered
MacGregor 1991

(a)



NGCC/GTCC. Dependent Variable: $/kW
OECD
EU & NAFTA
EU & US
World
Learning Rate
Period Covered
Colpier 2002
Kouvaritakis 2000
IEA 2000

(b)



NGCC/GTCC. Dependent Variable: $/kWh
EU & US
EU & US
Learning Rate
Period Covered
Colpier 2002

(c)

Figure 2: Summary of learning rates for natural gas-fired power plants reported in the literature: (a) simple gas turbines, (b) NGCC/GTCC based on $/kW, (c) NGCC/GTCC based on $/kWh,

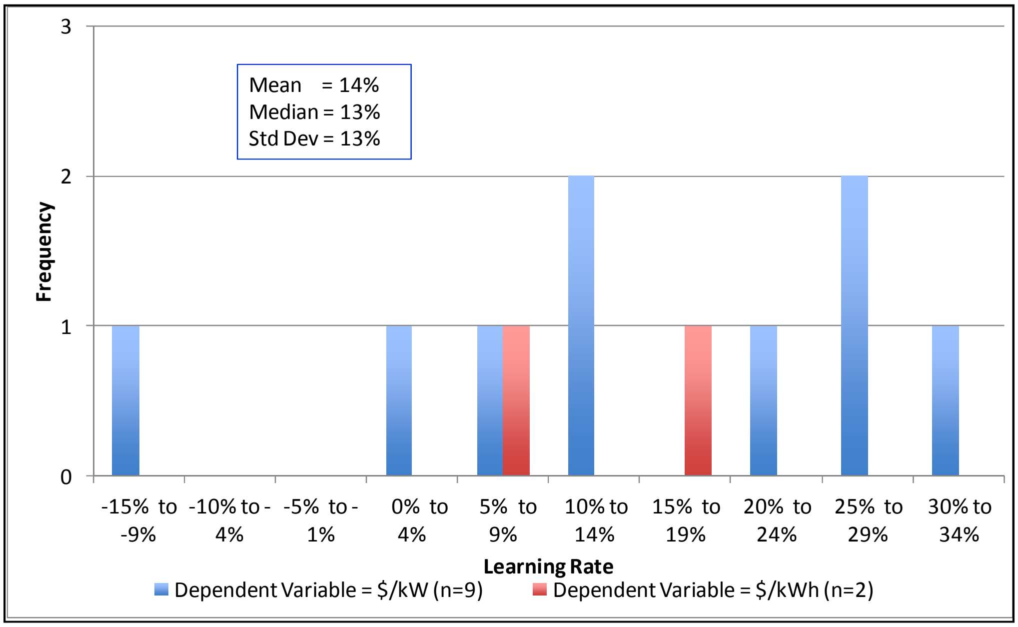


Figure 3: Histogram of learning rates reported in the literature for natural gas-fired power plants. Blue bars are studies based on cost per unit of capacity installed ($/kW). Red bars are studies where the dependent variable is the cost per unit of electricity generation ($/kWh).

R&D expenditures also may influence investment costs for natural gas power plants. However, only one paper reviewed for this project incorporated a learning-by-researching model. Jamasb and Kohler (Jamasb & Köhler 2007) evaluated global data for combined cycle gas turbines built in two periods. For the period between 1980 and 1998, he found a learning-by-doing (LBD) rate and a learning-by-researching (LBR) rate of 0.65% and 17.7% respectively. For the period between 1990 and 1998, he found a LBD rate of 2.2% and a LBR rate of 2.4%.

3.3 Wind Power

3.3.1 Land-based Wind Power

Large-scale deployment of wind turbines occurred in the 1970s and early 1980s, but slowed in the late 1980s and 1990s. In the last decade, wind power has observed the largest growth in installed capacity among all generating technologies in the U.S. During this period, wind technology has evolved: while in the 1980s the most popular turbine size was 55 kW (McDonald &

Schrattenholzer 2001), current land-based wind turbines can be as large as 2 MW, and are expected to continue growing.

Several studies, some performed as early as the 1990s, have estimated the learning rates of land-based wind energy technologies. Learning rates reported in the literature span a very large range between -3% and 35% (McDonald & Schrattenholzer 2001; Ibenholt 2002; Junginger et al. 2005; Neij et al. 2003; Priddle 2000; Neij 2008; Weiss et al. 2010; G. F. Nemet 2009; Lindman & Söderholm 2012; Edenhofer et al. 2011; Kahouli-Brahmi 2008). Most studies focus on Europe and North America. However, the scope of different studies varies widely. Some studies identify the learning rate of individual wind turbines, while others look at learning for entire wind farms (Neij et al. 2003; Junginger et al. 2005; Wiser 2012). Areas of study and years included in the analysis also vary. Appendix A, Table A3, shows the detailed data sources and date ranges for studies that reported values for learning rates.

Most of the studies analyzed have identified single-parameter learning curves based only on cumulative experience (either cumulative installed capacity, or cumulative electricity generation). Some of these studies, however, acknowledge that multiple factors can influence cost reductions. Junginger et al. (Junginger et al. 2005), for example, includes a detailed description of historical factors that have impacted the cost of wind turbines, including increased labor specialization and efficiency, innovations resulting from R&D, product standardization, and product redesign. They suggest that increased turbine size (product redesign) has primarily driven recent cost reductions.

Some studies have attempted to include multiple parameters in the analysis. For example, Ibenholt (Ibenholt 2002) used least square regression to estimate a parameter, α, which was then used to estimate the technology progress rate as $PR = 2^{\alpha}$. In that paper, α is a function of R&D expenditures, input prices, technology-pushing policies, competition, and economies of scale. Similarly, Miketa and Schrattenholzer (Miketa & Schrattenholzer 2004) explored multiple factors affecting cost reductions and developed a learning-by-doing rate (based on cumulative installed capacity), and a learning-by-researching rate (based on R&D investments). The study then developed a linear program that was used to endogenously estimate the optimum R&D levels needed to minimize the sum of discounted costs (energy costs plus R&D costs) during a given period. Finally, Klaassen et al. (Klaassen et al. 2005), Jamsab (Jamasb 2007), Ek and Soderholm (Ek & Söderholm 2010), and Soderholm and Klaassen (Söderholm & Klaassen 2007) also developed two equation-based learning-diffusion models that incorporated a learning-by-doing rate and a learning-by-researching rate.

Appendix A, Table A3, summarizes details of the learning rate values in the studies reviewed. While some studies assumed a constant learning rate throughout the period explored, others divided the curve into separate stages. For example, Ibenholt (Ibenholt 2002) developed a two-stage learning curve. Using data from Denmark, the progress ratio for the first stage (1984-1988) was found to be 88% (corresponding to a learning rate of 12%), while the second stage (1988-1999) was found to have a lower progress ratio of 93% (learning rate of 7%). Recall that Ibenholt (Ibenholt 2002) also developed a learning curve that included multiple parameters.

Our literature review also revealed that different dependent variables are used in different studies. Most learning curves are for the investment (capital) cost of a technology. However, several of the studies reviewed used production cost or price of electricity (in $/kWh of electricity generated) as the dependent variable. Production cost for wind power, however, is highly influenced by capacity factors during operation of the wind farm, which vary from place to place and from year to year. However, most studies that used this measure of cost did not acknowledge the importance or variability of capacity factor. Ibenholt (Ibenholt 2002) did include a discussion of capacity factors. However, it is unclear whether the capacity factor was included in the learning rates reported in the paper. Finally, while some papers used specific investment cost as the dependent variable, some used prices obtained in industry reports and catalogues. Commodity prices, transportation costs and other factors can influence the price of wind equipment, even if the manufacturing costs decrease. Using price data may thus mask reductions in technology manufacturing cost.

Figure 4 to Figure 6 group the different learning rates in the literature by region and by the dependent variable used. Figure 7 shows the same data in the form of a histogram of all rates reported in the literature. These figures do not include one data point from China, which reported a progress ratio of 96% for combined learning-by-doing and learning-by-researching (Qiu & Anadon 2012).

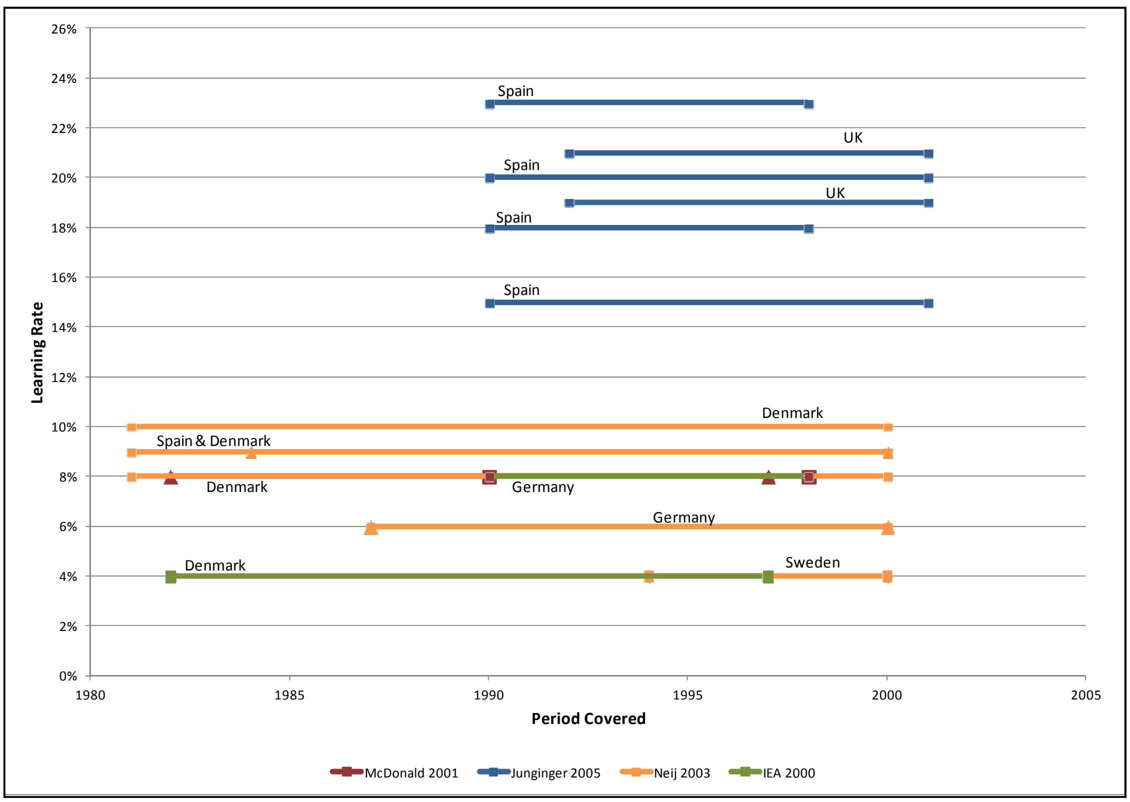


Figure 4: Learning rates for on-shore wind from European studies. The dependent variable is investment cost per unit of installed capacity ($/kW). There are multiple lines per study where authors used different model specifications. For example, Junginger et al used two different time periods for the Spanish and UK data, and two different GDP deflator rates for each data set.

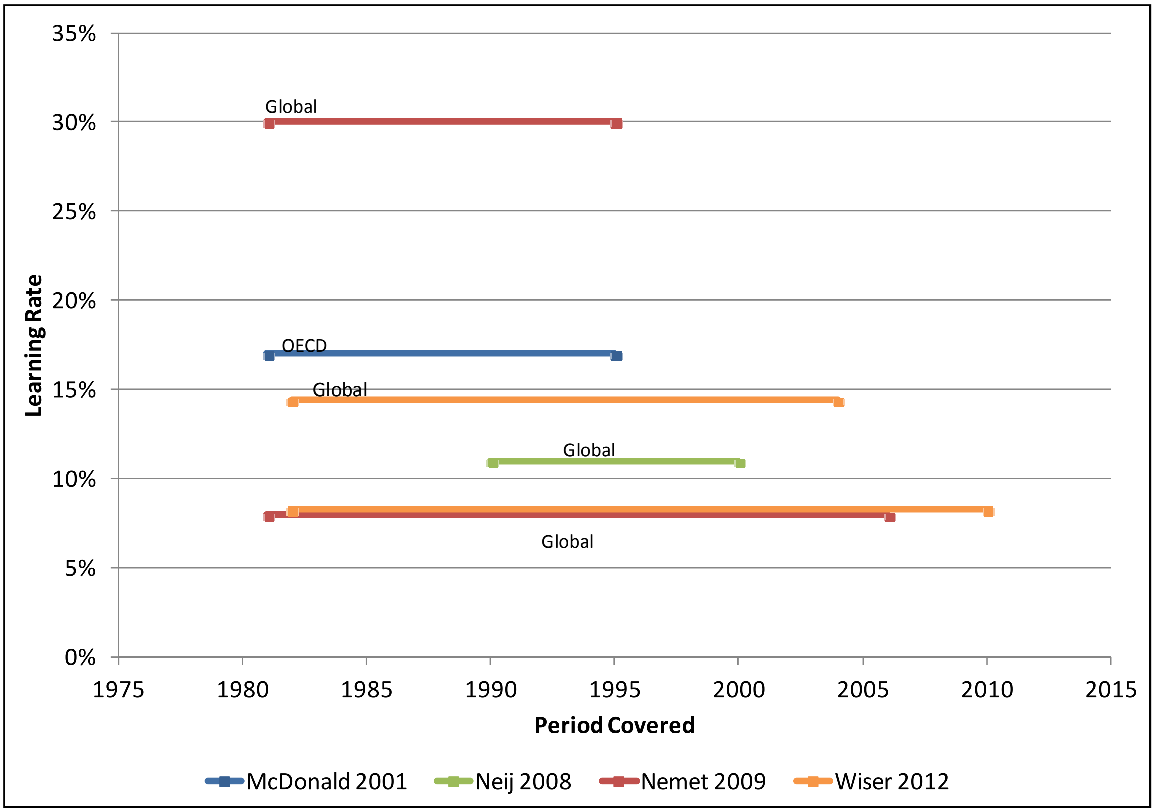
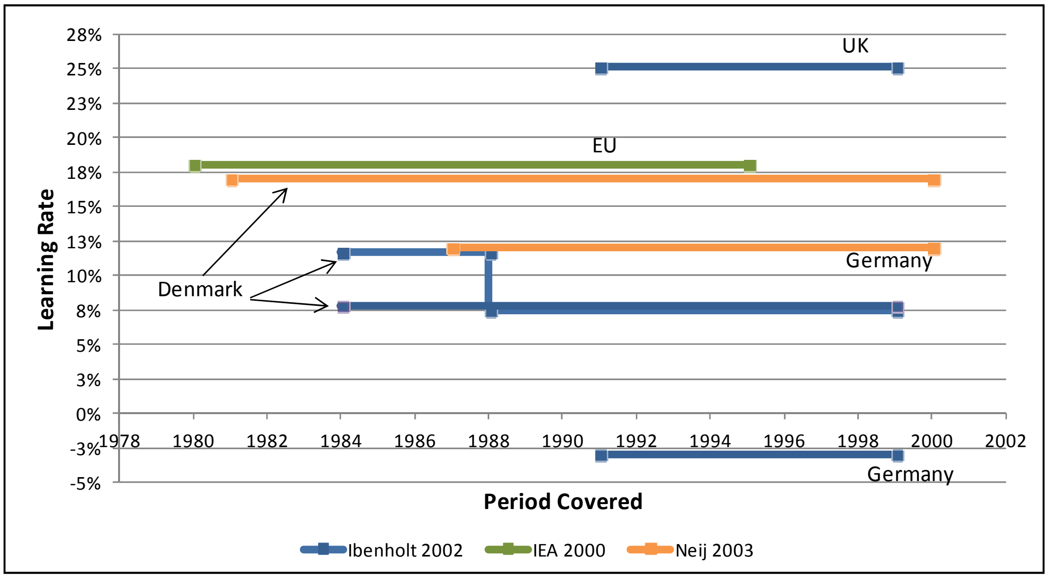


Figure 5: Learning rates for on-shore wind from global and OECD studies. The dependent variable is investment cost per unit of installed capacity ($/kW). There are multiple lines per study where the authors used different model specifications.

(a)



(b)

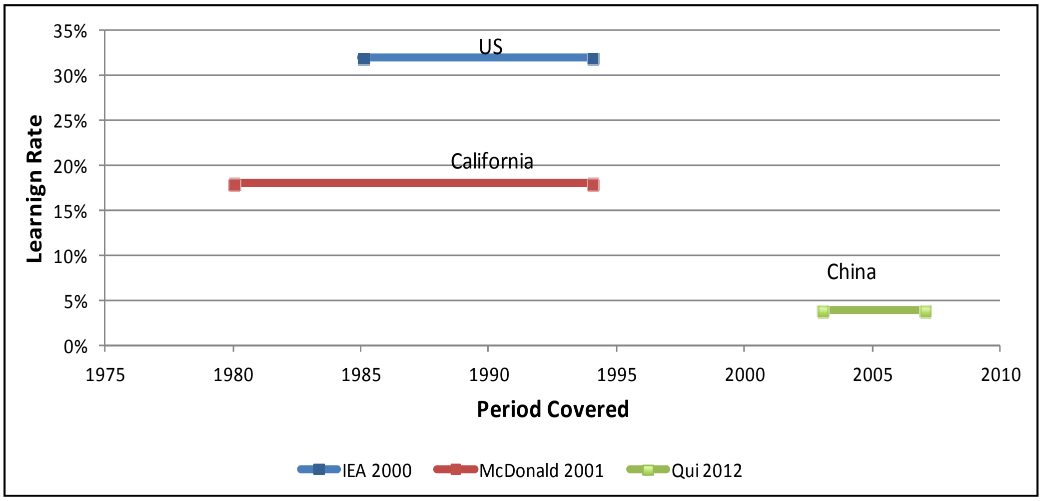


Figure 6: Learning rates for on-shore wind where the dependent variable is investment cost per unit of electricity generated ($/kWh). Top graph (a) show studies for Europe, lower graph (b) shows other world regions. There are multiple lines per study where the authors used different model specifications.

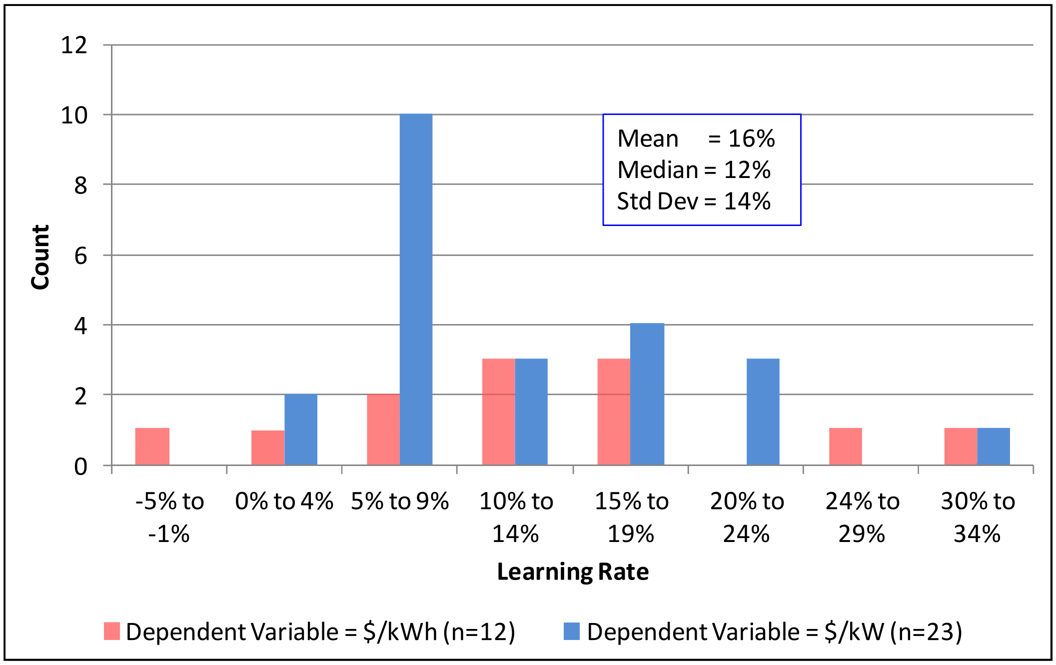


Figure 7: Histogram of learning rates reported in the literature for unit capital cost (blue bars) and cost of electricity (red bars) for on-shore wind systems.

In some cases, the studies shown in **Figure 4** to Figure 6 used different model specifications, which resulted in different values of the learning rate. For example, Neij (Neij et al. 2004) evaluated turbines *produced* by Danish manufacturers between 1981 and 2000. She used the price of the wind turbines as the dependent variable and found a learning rate of 8%. In the same study, she also evaluated turbines *installed* in Denmark in the same time period (1981-2000). Using the price of wind turbines as the dependent variable, she found a learning rate of 9%. The difference in the learning rate results from the difference in the data used. In particular, the values of cumulative capacity, used as the explanatory variables, differed since one analysis looked at manufacturing and the other looked at installations. In general, Figures 4 and 5 indicate that learning rates over longer periods of time tend to be smaller than rates over shorter time periods in most (but not all) studies. More pronounced, however, is the roughly six-fold range of learning rates reported for European capital costs (Fig 4), the three-fold range for global capital costs (Fig 5), and the nearly four-fold range of COE rates over the past two to three decades. Unfortunately, it is not possible to explain the reasons behind these large variations across studies based on the limited information reported in the literature. Pending further investigation we therefore simply show all results that were reported. It is clear, however, that there can be significant variations in the learning rates of wind turbines. Using the different learning rates in energy models that include endogenous learning could significantly affect the results of these models. Since it is not clear that any one rate is more realistic or more accurate than others, caution must be taken in interpreting the results. Doing sensitivity analysis by using the range of learning rates is thus advisable.

3.3.2 Offshore Wind Power

Though there are currently no offshore wind farms operating in the U.S., significant experience with this technology has been obtained in Europe, particularly in the Scandinavian countries. Several of the papers described in the previous section included an analysis of costs of wind turbines manufactured and/or installed in Germany, Sweden, and Denmark. These papers did not specify whether offshore wind turbines were included in the analysis. The periods covered, however, ended in 2000 before the beginning of the offshore wind boom, when global offshore wind capacity grew from roughly 14 GW in 1999 to 197 GW in 2010 (Jamasb 2007; Moccia & Arapogianni 2011; Clarke et al. 2006; Nordhaus 2009).

More recently, two papers have reviewed cost trends for offshore wind power. Lemming *et al.* studied the potential for development of offshore wind power through the year 2050. They assumed the learning rate observed between 1985 and 2000 (10%) would remain valid until 2030, after which the learning rate will decrease to 5% (Nordhaus 2009; Lemming et al. 2009).

Junginer *et al.* (Jamasb 2007; Junginger et al. 2009) produced a more detailed analysis looking at specific components of the cost of an offshore wind farm. They suggest that the learning rate of offshore wind turbines will be similar to the learning rates that have been observed for land-based wind turbines (between 8% an 19%) (Söderholm & Sundqvist 2007; Junginger et al. 2009; Jamasb 2007; Klaassen et al. 2005; Söderholm & Klaassen 2007). The authors further explore the learning rates for the balance-of-plant cost. Looking at data on submarine high voltage direct current (HVDC) cables between 1988 and 2000, they estimate a 38% learning rate for the installation of the interconnection cables. Similarly, they estimated a 29% learning rate for HVDC converter stations. Finally, they evaluated individual turbine installation time for the offshore wind turbines in two projects built in 2000 and 2003. Using these data as a proxy for cost, they suggest a learning rate of 23% for the erection of offshore wind turbines (Jamasb 2007; Junginger et al. 2009). A summary of these results is presented in Appendix A, Table A4.

3.4 Solar Photovoltaics

Solar photovoltaic (PV) systems convert sunlight directly into electricity. The PV module consists of a number of solar cells, which can be categorized in two types: wafer-type (single or multi-crystalline) and thin film. Wafer-type cells are made from wafer cut from a silicon ingot while thin-film PV cells are deposited directly onto a substrate like glass, plastic or steel (Capros et al. 2005; van der Zwaan & Rabl 2004). Today, wafer type technologies still achieve higher efficiencies (12%-15%), than thin film (6%-11%), but there is a consensus that thin film technologies offer the best long term perspective for low production costs (Söderholm & Sundqvist 2007; van der Zwaan & Rabl 2004; Jamasb 2007; Klaassen et al. 2005; Söderholm & Klaassen 2007)

PV technologies can also be grouped in terms of applications, i.e., central station PV versus rooftop PV. If stated by the authors, we identify in our review which of these applications the learning rates refers to.

PV system capital costs include the PV module cost, for which recent prices are in the neighborhood of \$4.5 per peak watt (W_p), plus balance of system (BOS) costs, which include electrical installation, inverters, wiring and power electronics. The latter roughly double the overall cost of a PV system (Söderholm & Sundqvist 2007; Curtright et al. 2008; G. Nemet 2006). Van der Zwaan (van der Zwaan & Rabl 2004) highlights that "PV system prices" (on commercial markets) are generally 20% to 40% higher than PV system costs (of fabrication), since the latter also reflect design and installation costs, as well as profit margin. In many of the reviewed studies, however, it is unclear whether the authors are using cost data or price data.

Most studies reviewed use $\$/W_p$ as a measure of solar PV costs. An exception is Schilling and Esmundo (Schilling & Esmundo 2009), where the authors compare the cost and performance of several energy technologies and use the cost of electricity in \$/kWh, where the costs include capital, maintenance, and operation costs. However, contrary to other studies, Schilling and Esmundo (Schilling & Esmundo 2009) only assess the relationship between technology costs and public R&D spending, ignoring learning-by-doing effects.

Two studies reviewed address effects of both learning by doing and learning by searching (i.e., a two-factor learning curve which includes R&D as one of the explanatory variables). Miketa and Schrattenholzer (Miketa & Schrattenholzer 2004) found a learning-by-researching rate of 10%, and a learning-by-doing rate of 17%. Another paper, from Kobos, Erickson and Drennen (Kobos et al. 2006), also assessed both learning by doing and learning by searching using worldwide data from IEA. The authors highlight the fact that there is a time lag that needs to be considered between when R&D investments are pursued and when associated technology cost declines may occur. Thus, they tested several time lags. The authors also included a depreciation factor to account for the rate of technology obsolescence. Using data for solar PV between 1975 and 2000, they found that the most robust learning-by-doing and learning by search rates are about 18.4% and 14.3%, respectively. The results from Miketa and Schrattenholzer (Miketa & Schrattenholzer 2004) and from Kobos, Erickson and Drennen (Kobos et al. 2006) are consistent with what one would expect: as more explanatory variables are added to the model, the estimate for the learning rate decreases.

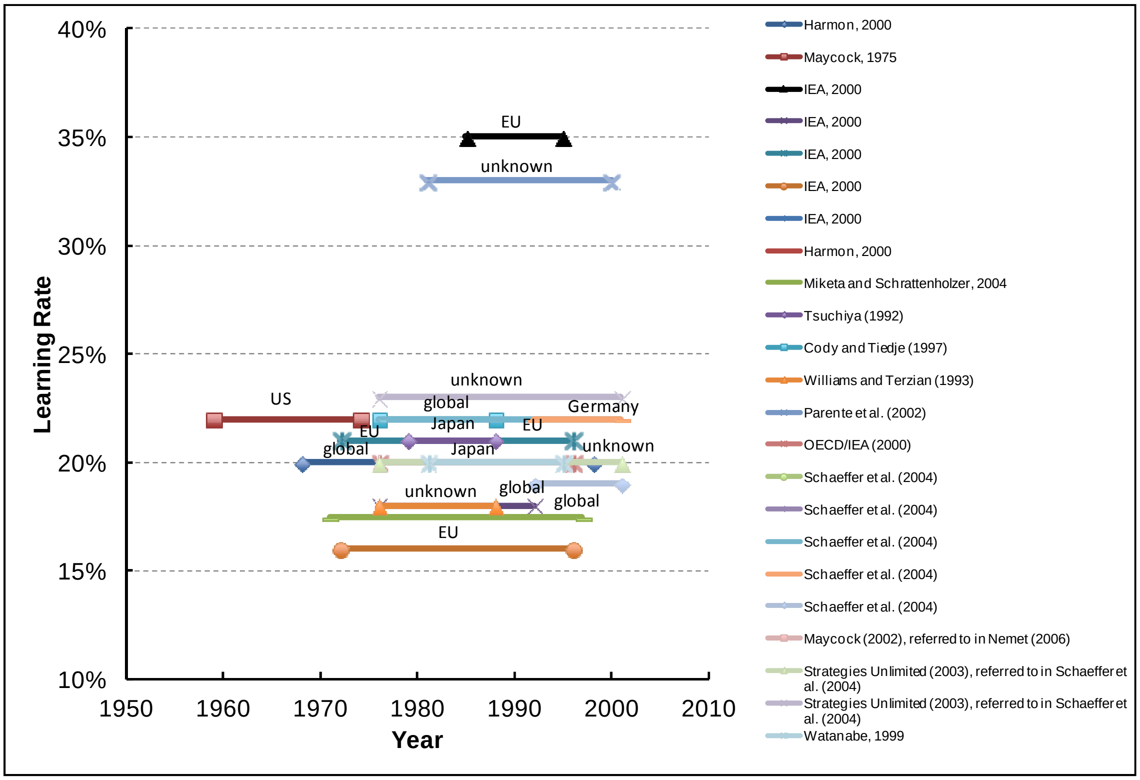


Figure 8: Learning rates for solar PV capital cost ($/Wp) reported in the literature. The x-axis represents the range of years used in the cited papers. The plot also shows the corresponding region included in each study, author and year of publication.

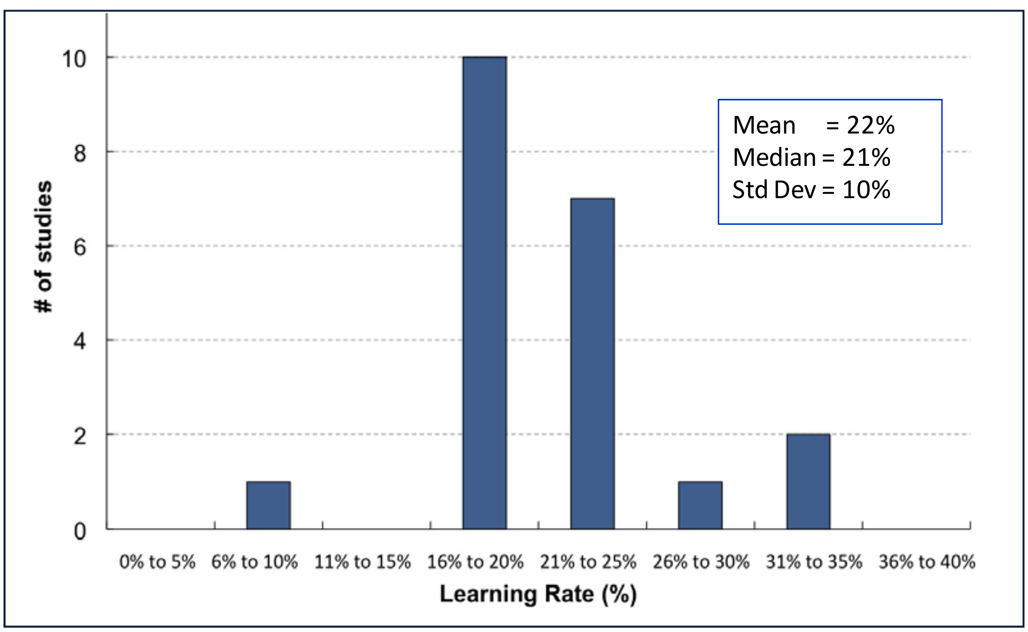


Figure 9: Histogram of capital cost ($/Wp) learning rates for PV reported in the literature. The 10% value does not appear in Fig. 8 as the years used was not reported in that study.

3.5 BioPower

3.5.1 Biomass Production

A review of the studies examining crop-based feedstock production costs, including sugarcane (Brazil), corn (US), and rapeseed (Germany), suggests that feedstock production costs have declined over time. These studies show that the learning rates associated with feedstock costs were in the range of 20% to 45%, as discussed below.

Van Den Wall Bake *et al.* (van den Wall Bake et al. 2009) found a learning rate of 32% for Brazilian sugarcane considering production costs between 1975 and 1998, and sale prices between 1999 and 2004. Sugarcane production during this period expanded from roughly 1 million to 8 billion tonnes of cane (TC), and feedstock costs/prices decreased from US$$_{2005}$ 35/TC to US$$_{2005}$ 13/TC. Van Den Wall Bake *et al.* (van den Wall Bake et al. 2009) explain that cost reductions for rent, soil preparation, and crop maintenance were highly influenced by the increasing length of the ratoon system (the length the same plant can be cut many times on a yearly basis after the first cut) and the rising agricultural yields. Transportation costs declined mainly because of up-scaling, introduction of automated logistic systems, and improved infrastructure. Similarly, Hettinga *et al.* (Hettinga et al. 2009) examined the costs of U.S. corn between 1985 and 2000 when cumulative corn production increased from 2.5 to 8 billion tonnes, and costs decreased from US$$_{2005}$ 250/tonne to US$$_{2005}$ 100/tonne, implying a learning rate of 45%. The authors suggest that higher corn yields and increasing farm sizes were partly responsible for decreased costs.

The study on German rapeseed by Berghout (Berghout 2008) used data from 1971 to 2006, when cumulative production of rapeseed increased from 2 to 64 million tonnes; and production costs decreased from €$_{2007}$800/tonne to €$_{2007}$220/tonne, resulting in a learning rate of 19.6%. Costs reductions resulted from a decline in fertilizer costs, increasing yields, lower fertilizer usage, and improved rapeseed varieties. Finally, a study on forest residue in Sweden and Finland (1975-2003) found that fuel wood price decreased from €$_{2002}$12/GJ to €$_{2002}$35/GJ (Junginger et al. 2006). This yields a learning rate ranging between 12% and 15%. Experience in chipping and forwarding (the transport of logs from the stump to the forest road) explained most of the cost reduction. Although no further reductions are expected in these costs, transportation and logistics costs have potential to decrease in future.

3.5.2 BioPower Generation

Most work on biopower generation has focused on fluidized bed combustion for combined heat and power (CHP), and production of biogas. Koornneef (Koornneef et al. 2007) evaluated the global investment costs of fluidized bed combustion between 1976 and 2005, and found a learning rate ranging between 7% and 10% as a result of learning-by-doing. Similarly, Junginger (Junginger et al. 2006) found that between 1990 and 2002 cumulative installed electrical capacity of fluidized based CHP in Sweden increased from 100 MW to 600 MW, while investment costs decreased from up to €$_{2002}$5,000/kW to €$_{2002}$1,000/kW. Thus this study found a learning rate of

23%. Junginger also assessed the impacts of these costs on the marginal production cost of electricity and found that the learning rate was roughly 8% (Junginger et al. 2006). Finally, they also evaluated decreases in the investment costs of bio digesters used to produce biogas in Denmark between 1988-1998 and found that while cumulative digester capacity increased from 50 m^3/day to 4,000 m^3/day, investment cost decreased from $€_{2002}$40,000/day to 15,000/day (Yeh et al. 2005; Junginger et al. 2006). This resulted in a learning rate of 12%. Looking at the biogas production costs in Denmark between 1984 and 1991, they also found that cumulative biogas production increased from 100,000 Nm^3/day to roughly 5 billion Nm^3/day and production costs decreased from $€_{2002}$1-5/ Nm^3 to roughly $€_{2002}$0.3/Nm^3 (Seebregts et al. 1999; Junginger et al. 2006). For these data, they reported three learning rates: 24% for 1984-1997; 15% for1984-1991; and 0% for 1991-2001.

3.6 Geothermal Power

We found no literature on historical learning rate for geothermal electricity, neither for power plant technology (binary, flash, flash-binary) or geothermal well drilling and resource extraction. One reason could be that geothermal power plants vary considerably and levelized costs are very sensitive to resource temperature, geothermal fluid chemistry, geothermal fluid flow rates, and ambient temperature. This sensitivity to variations makes it extremely difficult to characterize learning rates for this technology.

In examining the influence of R&D spending, however, Schilling *et al.* (Schilling & Esmundo 2009) showed that the performance of geothermal increased with cumulative R&D spending from 7 kWh/R&D dollar to 27 kWh/R&D dollar as R&D spending increased from $1.5 to $4 billion between 1985 and 2000. They report the cost of electricity was 11.3-13.8 cents per kWh in 1980, decreasing to 3.1-4.3 cents per kWh in 2005 (Wang & Yu 1988; Schilling & Esmundo 2009).

3.7 Nuclear Power

While researchers have attempted for decades to estimate learning rates in the nuclear industry, these efforts continues to be punctuated by various industry-specific caveats that render the exercise especially difficult. The picture becomes even murkier when one examines recent efforts to determine the benefits of learning in proposed evolutionary and advanced nuclear technologies, such as small modular reactors (SMRs), where the more traditional technical progress economies are joined by factory fabrication economies, modular construction economies, and various other promised benefits that may never materialize (see, for instance, van den Broek et al. 2009; Carelli et al. 2010).

Grubler (Grubler 2010) studied the French and American nuclear experience, as shown in Figure 10. He finds an “observed real cost escalation [that] is quite robust against the data and model uncertainties that can be explored” (Grubler 2010), i.e., in the case of nuclear there is a “negative learning” effect, in which specific costs increase rather than decrease with accumulated experience. Grubler notes many caveats associated with these data, ranging from institutional changes (such as safety regulations) to cross-generational variations among nuclear reactor designs that make such comparisons questionable (Grubler 2010).

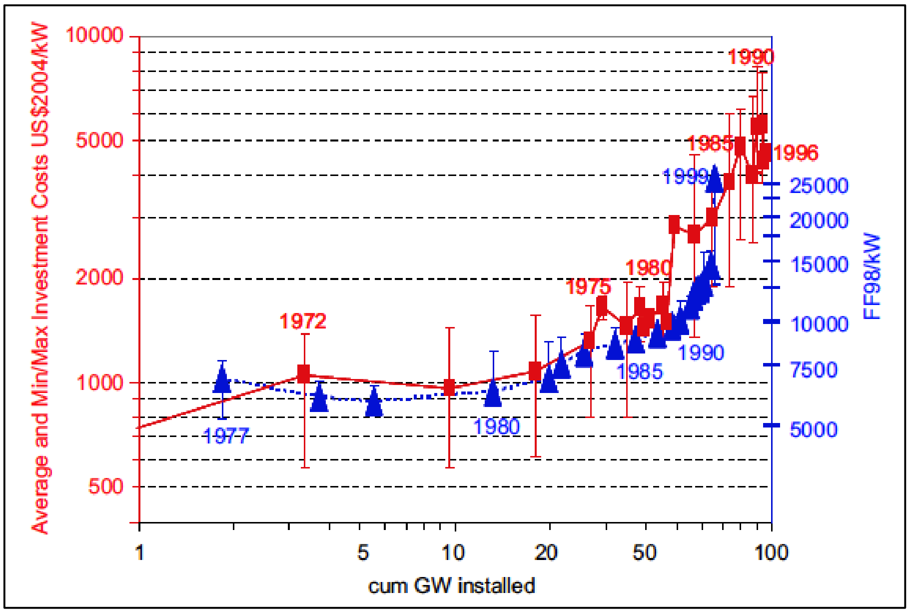


Figure 10: Reactor construction costs per kW as a function of cumulative installed capacity for both the French (blue) and U.S. (red) cases and currency. Source: (Grubler 2010).

McDonald and Schrattenholzer (McDonald & Schrattenholzer 2001) report learning rates for a wide range of energy technologies, including nuclear. Their estimate for the learning rate of nuclear in OECD countries from 1975 to 1993 is about 6%. Cooper (Cooper 2010) constructs a learning curve for U.S. nuclear power plants from his own database. Like Grubler (Grubler 2010), he finds an increasing cost trend as function of the cumulative capacity installed. Finally, Sturm (Sturm 1994) compared learning by operating nuclear reactors in OECD countries with Eastern European countries, using two proxies: the availability and unplanned losses. He noted that there was positive learning in OECD countries but negative learning in Eastern European countries. He also reports significant negative learning in some countries as a result of exogenous shocks, such as the break-up of the Soviet Union.

3.8 Hydropower

Hydropower provides 7% of U.S. power generation and is also a key source of electricity in some European countries. In the U.S. the build-up of large hydroelectric projects took place in the post-World War II period. No additional large-scale hydroelectric projects have been constructed in the U.S. in at least 35 years. Most hydroelectric development is taking place in developing countries. China has put significant resources into building hydro projects, with the Three Gorges Dam being the largest in the world. Brazil is also planning on expanding its hydro capacity, particularly in the

Amazon. Several papers have recently reviewed learning for hydroelectric projects. Kouvaritakis (Kouvaritakis et al. 2000) is the only paper found that reports a single factor learning curve for hydroelectric projects. His numbers are later reported by McDonald *et al.* (McDonald & Schrattenholzer 2001) and Kahouli-Brahmi (Kahouli-Brahmi 2008). Kouvaritakis (Kouvaritakis et al. 2000) used data for OECD countries from 1975-1990 and found a learning rate of 1.4%.

One study also looked at two-factor learning rates for large and small hydroelectric plants. Using global data from 1980 to 2001, Jamasb (Jamasb 2007) reported a learning-by-doing rate of 1.96% and a learning-by-researching rate of 2.63% for large hydropower projects. He also reported LBD and LBR rates of 0.48% and 20.6%, respectively, for small hydropower projects using global data from 1988 to 2001. A summary of the reviewed studies for hydropower is provided in Appendix A, Table A9.

4 Endogenous Technological Learning in Energy Models

This section of the report provides an overview of several energy-economic models that incorporate endogenous technological change. Several of these models assess the effects of incorporating endogenous technological change on the rate of technology adoption and the costs of climate change mitigation. Most efforts to incorporate endogenous modeling of technological change in energy-economy models took place in the early 2000s. A comprehensive review of these efforts was included in the Fourth Assessment Report from Working Group III of the IPCC (Rubin et al. 2004; IPCC 2007). In this section, we review a few selected global energy models, including MESSAGE, ReMIND-R and WITCH, plus two U.S. models, NEMS and MARKAL-EPA. We complement this discussion provided in this section with brief descriptions of each of these models, which are presented in Appendix B, and with summary tables of endogenous learning used in "top-down" energy-economic models (Appendix C) and in "bottom-up" models (Appendix D).

4.1 Global Energy Models

4.1.1 MESSAGE

MESSAGE is an optimal growth model of the global energy system (McDonald & Schrattenholzer 2001; Rao et al. 2006). It can be linked iteratively to MACRO, which is a top-down macroeconomic equilibrium model that captures capital stock, available labor, and energy inputs. In turn, MESSAGE determines the total output of an economy according to a nested constant-elasticity-of-substitution production function. Using a bottom-up technology-rich model, plus a top-down macroeconomic model, results in a fully consistent evolution of energy demand quantities, prices, and macroeconomic indicators (such as GDP, investments and savings).

This model typically runs with an assumption of *exogenous* technical change, i.e., the unit cost and efficiency of technologies improve by constant rates over time and are independent of each other.

The assumed exogenous rates of improvement ranged from 0% to 15% for each doubling of cumulative installed capacity for eighteen energy technologies in the model.

Researchers also have used versions of MESSAGE to implement *endogenous* technical learning. For example, Riahi et al. (Riahi, Rubin & Schrattenholzer 2004a) applied an endogenous learning rate of 12% to three carbon capture and sequestration (CCS) technology clusters (conventional single steam cycle coal plants, conventional single steam cycle gas and NGCC plants, and high-temperature fuel cells). In addition, the model allowed for spillovers among technologies within a cluster (but not from outside the cluster), and also for spillovers across regions by assuming that technology improvements occur at a global scale. Overall, the study found that incorporating endogenous learning for CCS led to higher deployment of CCS technologies, particularly in the electricity sector, relative to an exogenous specification of no learning over time. Other key insights from this model regarding the effects of endogenous learning include:

- The existence of technological learning reduces overall energy system costs and becomes particularly important in the context of a long-term climate policy.
- Alternative parameterizations of technological change have significant implications for the technology portfolio as well as associated costs.
- Spillovers across technologies and regions due to learning result in increased upfront investments and lower overall costs for carbon-free technologies. This results in greater technology deployment and emissions reductions, especially in developing countries.
- Learning and spillover effects can lead to more technologically advanced, cost-effective global energy transition pathways.

4.1.2 ReMIND-R

ReMIND-R is a global welfare maximization model with a top-down macroeconomic model and a bottom-up energy system model (Luderer et al. 2010). Energy system costs (investments, fuel costs, operation and maintenance) are included in a macroeconomic budget constraint so that the energy system and macro-economy are optimized jointly. This model includes a detailed representation of more than thirty energy conversion technologies, including thirteen electricity generation technologies. The model includes one-factor endogenous learning rates for three electricity generation technologies: wind, solar PV, and concentration solar power (CSP) that have a 12%, 20%, and 9% learning rate, respectively. It also assumes learning rates of 10% for energy storage technologies, which are deployed in conjunction with renewable resources. The learning model defines the learning rates as well as a floor of investment costs (in $/kW). Learning-by-doing spillovers are internalized and the learning process is assumed to take place at a global scale. No comparisons were presented, however, between endogenous vs. exogenous learning effects.

4.1.3 WITCH

Similarly to what is found in ReMIND-R's structure, WITCH is a hybrid of top-down (macroeconomic) and bottom-up (technology) assessment models. The top-down component consists of an inter-temporal optimal macroeconomic growth model. The bottom-up component includes detailed treatment of investment and operating costs, performance, and learning curves for major clusters of energy technologies (Bosetti et al. 2009; Bosetti et al. 2011). WITCH includes a two-factor endogenous learning representation: a uniform learning-by-doing rate of 13% and a uniform learning-by-researching rate of 10% are assumed for wind, solar, and two portfolios of backstop technologies producing electricity and non-electricity fuels. As with previous global models we reviewed, costs decline with global installed capacity (perfect learning-by-doing spillovers).

In WITCH, endogenous technical change through investments in energy R&D are modeled for energy efficiency improvements and costs of advanced biofuels. Efficiency improvement can be obtained from the stock of knowledge derived from energy R&D investments in each region (modeled by an innovation possibility frontier characterized by diminishing returns to research). A uniform learning-by-doing rate of 13% and a learning-by-researching rate of 10% are assumed for wind solar and two portfolios of backstop technologies producing electricity and non-electricity fuels. Global spillover effects are allowed within the model. The return on energy R&D investments is assumed to be four times higher than the return on physical capital. At the same time, the opportunity cost of crowding out other forms of R&D and physical investments is also taken into account in a budget constraint. A decreasing function of investment in dedicated R&D is also used to lower the costs of advanced biofuels.

Relative to exogenous learning specifications, key insights from implementing endogenous learning-by-researching and learning-by-doing in the WITCH model include ((Bosetti et al. 2009; Bosetti et al. 2011)):

- R&D investments reduce the investment costs for renewable and backstop technologies. They also increase the efficiency of overall energy production by "... contributing to accumulation of knowledge capital that substitutes for energy demand.”

- Technology change alone (without any explicit climate policy) is unlikely to effectively control climate change. Even with large increases in global climate-related R&D spending, emissions can at best be stabilized above current levels, and CO_2 concentration can be reduced by only a small amount (about 50 ppm) relative to 2100 baseline levels (of over 700 ppm). Carbon pricing is important to achieve this goal.

4.2 U.S. Models

There are a few integrated energy-economic models for the United States. Here we review two such models and their modeling of endogenous technological change.

4.2.1 The National Energy Modeling System (NEMS)

NEMS is an energy-economic model of U.S. developed by the Energy Information Administration (EIA) of the U.S. Department of Energy (DOE). It includes technological learning for overnight costs of new electricity generating facilities. The most recent version of NEMS has a total of 54 electricity generating technologies: 34 represent existing power plants and the remaining 24 are technologies that can be selected for new construction, and to which learning factors are applied. Each power plant type is sub-divided into several components (there are 26 technology components in total across all generating types). NEMS applies technological learning factors at the technology component level (e.g., a gasifier, boiler, or other sub-system), using a traditional one-factor learning curve. It aggregates the capacity of all plant types having a particular component to derive the total learning-related capacity of that component. Different plant types thus share learning if they have the same technology component. The initial learning capacity of a component is its "base year capacity" or its typical unit size, whichever is bigger (Riahi, Rubin, Taylor, et al. 2004b; Gumerman & Marnay 2004). EIA updates base year overnight costs and learning factors for each component annually as part of the Annual Energy Outlook development.

NEMS further identifies each of the technology components as being either "revolutionary," "evolutionary" or "mature". Different learning rates are assumed for each stage of development. For example, a "revolutionary" component becomes an "evolutionary component" after three doublings of the initial capacity. Typical learning rates are 20% for the revolutionary stage, 10% for the evolutionary stage, and 1% for the mature stage (Kypreos & Bahn 2003; EIA 2012). Additionally, each component is set to have a certain annual minimum learning, even if no new capacity additions are made. Once all the learning factors at the component level are applied, the components are aggregated based on their "cost weights," i.e, the fractional contribution of that component to overall plant costs. The results are then used to calculate learning factors at the power plant type level.

NEMS uses several other factors to estimate future overnight costs, such as the technological *optimism factor* (a multiplier of 1.0 or more, applied to the first four units of a new, unproven design to compensate for the tendency to underestimate the actual cost of a first-of-a-kind technology); the *project contingency factor* (a factor to account for unforeseeable cost elements); and the *metals and metal products producer price index* (a macroeconomic variable linking construction costs with commodity prices). NEMS also includes regional cost factors reflecting differences in terrain, weather, and labor wages. In the end, all of these multipliers, together with learning factors, are applied to the base year overnight cost to estimate the overnight cost of a power plant type for each projected year (Barreto & Kypreos 2004; Gumerman & Marnay 2004; EIA 2012).

The NEMS learning model also allows U.S. plants to benefit from technological experience outside the country. Foreign units of new technologies are assumed to contribute to reductions in capital costs for units that are installed in the United States if they meet the following criteria: (1) the technology characteristics are similar to those used in U.S. markets, (2) the design and construction firms and key personnel compete in the U.S. market, (3) the owning and operating firm competes actively in the U.S. market, and (4) there exists relatively complete information about the status of the associated facility. If the new foreign units do not satisfy one or more of these requirements, they are given a reduced weight or not included in the domestic learning effects calculation (Fischer & Newell 2008; EIA 2012). For example, in the 2010 Annual Energy Outlook, international learning experience contributed to cost reductions for U.S. technologies based on capacity built outside the United States from 2000 to 2003 (the most recent data available at that time) (EIA 2011b). This non-U.S. capacity included 5,000 MW of advanced coal gasification combined-cycle plants, 5,244 MW of advanced combined-cycle natural gas plants, 11 MW of biomass capacity, 47 MW each for on-shore and offshore wind farms, and 7,200 MW of advanced nuclear plants. Table 3 shows the learning rate parameters for new generating technology components assumed in the NEMS model.

Table 3: Learning parameters for new generating technology components in NEMS. Source: (EIA 2012)

Technology Component	Period 1 Learning Rate	Period 2 Learning Rate	Period 3 Learning Rate	Period 1 Doublings	Period 2 Doublings	Minimum Total Learning by 2025
Pulverized Coal	-	-	1%	-	-	5%
Combustion Turbine - conventional	-	-	1%	-	-	5%
Combustion Turbine - advanced	-	10%	1%	-	5	10%
HRSG[1]	-	-	1%	-	-	5%
Gasifier	-	10%	1%	-	5	10%
Carbon Capture/Sequestration	20%	10%	1%	3	5	20%
Balance of Plant - IGCC	-	-	1%	-	-	5%
Balance of Plant - Turbine	-	-	1%	-	-	5%
Balance of Plant - Combined Cycle	-	-	1%	-	-	5%
Fuel Cell	20%	10%	1%	3	5	20%
Advanced Nuclear	5%	3%	1%	3	5	10%
Fuel prep - Biomass IGCC	20%	10%	1%	3	5	20%
Distributed Generation - Base	-	5%	1%	-	5	10%
Distributed Generation - Peak	-	5%	1%	-	5	10%
Geothermal	-	8%	1%	-	5	10%
Municipal Solid Waste	-	-	1%	-	-	5%
Hydropower	-	-	1%	-	-	5%
Wind	-	-	1%	-	-	1%
Wind Offshore	20%	10%	1%	3	5	20%
Solar Thermal	20%	10%	1%	3	5	20%
Solar PV	15%	8%	1%	3	5	20%

[1]HRSG = Heat Recovery Steam Generator

4.2.2 The EPA-MARKAL Model

The EPA-MARKAL model is a partial equilibrium bottom-up model of a one-region U.S. economy operated by the U.S. Environmental Protection Agency (EPA) (Shay et al. 2006). The standard version of the model does not include endogenous learning but the effect of endogenous technological change was explored in one version of the hydrogen scenario by Yeh et al.(Yeh et al. 2006). That work included a one-factor experience curve, where endogenous cost reduction was a function of installed capacity.

Other than the EPA-MARKAL model, endogenous learning across technology groups (i.e., clustered learning among gasification, gas turbine, and fuel cell technologies) and across regions (e.g., wind turbines and solar PV in different regions) have been implemented in other MARKAL models (Barreto & Kypreos 2002; Seebregts et al. 2000). For example, MARKAL-Western Europe model (Seebregts et al. 2000) uses clustered learning and divides generation technologies into five clusters: wind turbines (WT), solar PV modules (PV), fuel cells (FC), gasifiers (GF), and gas turbines (GT). Key insights obtained from MARKAL-Western Europe include:

- The overall costs for CO_2 reductions are lower with endogenous learning than without.
- The 'cluster feature' improves internal consistency and allows for assessment of certain spillover effects

4.3 Insights from Modeling Using One-Factor Learning Curves

In general, bottom-up models tend to be partial equilibrium models that include only the energy sector, and they often adopt one-factor learning curves when exploring the effects of endogenous learning on model results. On the other hand, general equilibrium models include all sectors of the economy. Therefore they are able to explore the relationship between investments in energy technologies (to stimulate learning) versus the opportunity costs of the R&D investment. Here, we briefly summarize the insights from modeling using one-factor learning curves. The following section discusses two-factor learning curves.

Energy models that assume autonomous energy efficiency improvements and cost reductions in both business-as-usual and climate policy scenarios typically defer investment decisions until the technology has become cheap enough to be competitive. In the case of greenhouse gas reduction scenarios, even though the absolute emissions abatement requirement increases with later action, it is still better to wait as abatement becomes cheaper in the future.

In contrast, studies with endogenous technological learning based on one-factor experience curves find benefits from the early adoption of a technology, which stimulates cost reduction over the longer term (Nordhaus 2009; Goulder & Mathai 2000; van der Zwaan et al. 2002; Manne & Richels 2004). Thus, the costs of delay may be several times higher with induced (endogenous) technological change than without it (Bosetti et al. 2011; Grubb et al. 1995). For example, Riahi and Rubin *et al*. (Riahi, Rubin, Taylor, et al. 2004b) compared modeling with and without learning for carbon capture and sequestration technology with the MESSAGE-MACRO model. They found that scenarios with endogenous learning lowered the overall cost of CCS, resulting in higher abatement levels using CCS technology (as opposed to other abatement methods), with lower shadow prices of abatement compared to no endogenous learning (see Figure 11).

(a)

(b)

(c)

(d)

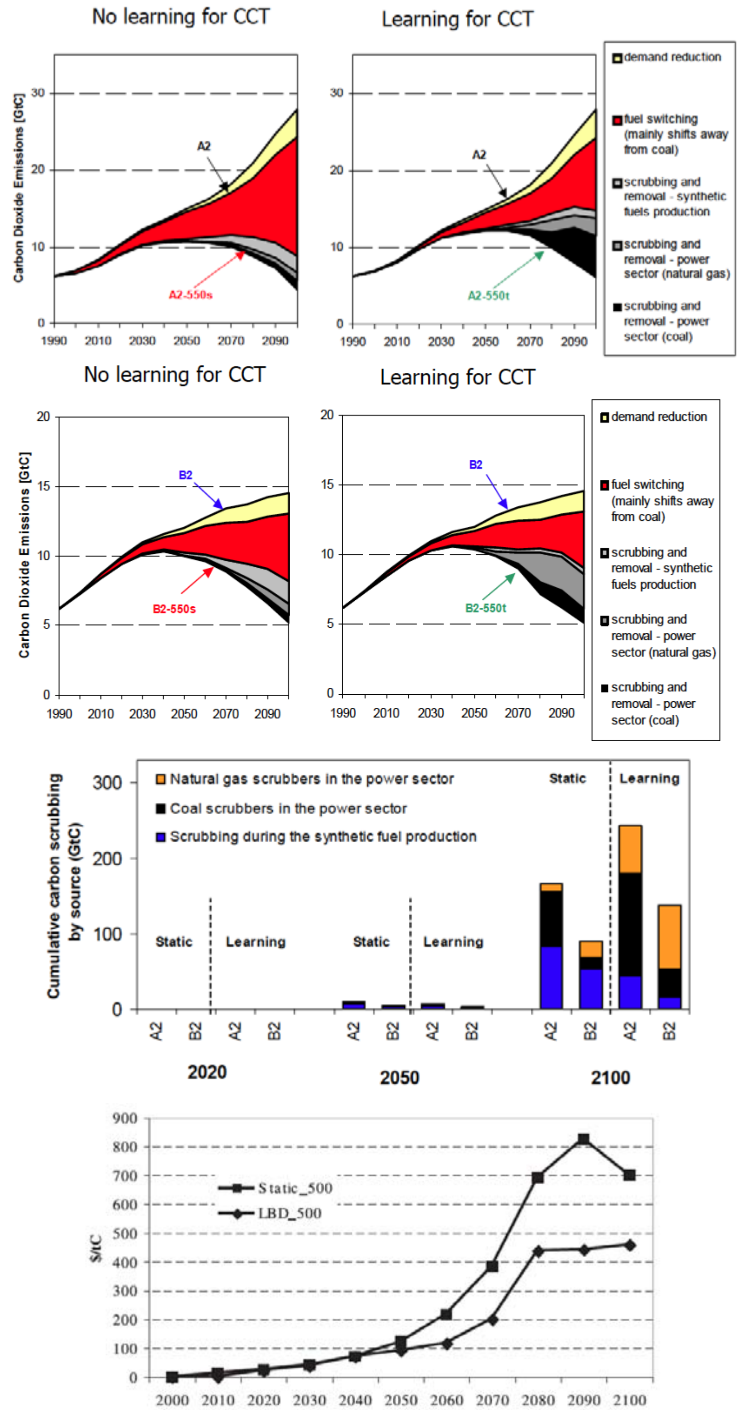


Figure 11: Sources of mitigation in (a) A2 and (b) B2 scenarios; (c) cumulative carbon sequestration by technology; (d) shadow prices of CO2 abatement in the B2 world. The A2 world represents relative slow end-use and supply-side energy efficiency improvements with slow convergence between regions. The B2 case is a world of slower population growth, higher GDP, higher end-use and supply efficiency improvements,

and lower primary energy use and GHG emissions. Sources: (Söderholm & Klaassen 2007; Riahi, Rubin, Taylor, et al. 2004b; Barreto & Kypreos 2004; Rao et al. 2006).

As discussed earlier in Section 3 of this report, the use of one-factor learning curves carry many caveats that modelers should be aware of when drawing conclusions and making recommendations. The key point here, however, is that the use of endogenous models can give results that are very different from exogenous specification of cost reduction trajectories.

4.4 Insights from Modeling Using Two-Factor Learning Curves

Two-factor experience curves of the type discussed in Section 3.2 have been used in large-scale models including MERGE (Wene 2008; Kypreos & Bahn 2003), ERIS (Barreto & Kypreos 2004) and other simulation-based tools (Fischer & Newell 2008). In general, studies find that incorporating two-factor models endogenously tends to lower the long-term costs of environmental policies and achieve higher emission abatement levels than achieved with no learning or only one-factor models (Watanabe et al. 2000; Watanabe et al. 2003; Barreto & Kypreos 2004; Fischer & Newell 2008).

Studies also found that the explicit incorporation of R&D expenses may lead to less aggressive near-term actions to abate greenhouse gas emissions due to the increase in near-term societal costs (Barreto & Kypreos 2004). Similarly, Goulder and Mathai (Goulder & Mathai 2000) found that with R&D, some abatement is shifted from the present to the future. This is because induced innovation not only reduces marginal abatement costs, but also reduces the shadow cost of emissions today (because of lower future abatement costs). The optimal level of abatement is therefore lower in early years and higher later. Learning by doing acts to accelerate the effects of initial R&D efforts (Kouvaritakis & Argiri 2005). Researchers also found that both LBD and R&D create "lock-in" effects: massive R&D funding on some options may lock out other options that fail to benefit from R&D-induced learning. Thus, models are sensitive to initial conditions that lead to results that are path-dependent.

Goulder and Schneider (Goulder & Mathai 2000) claim that with induced technological change, the opportunity cost of redirecting limited R&D resources to the energy sector steepens the decline in GDP associated with the introduction of a carbon tax. Thus, a given tax leads to larger gross costs (25% higher GDP loss in their study). The reason for this is that in equilibrium, the rate of return on R&D is equalized across sectors at the rate of return to other investments. An increase in R&D expenses on renewables with induced technological change thus leads to reduced R&D elsewhere, hence, reduced productivity in other sectors. Nordhaus (Nordhaus 2009) also concludes that omitting the opportunity cost of R&D (and LBD) incorrectly estimates the total marginal cost of output and will therefore "bias optimization models to tilt toward technologies that are incorrectly specified as having high learning coefficients." This is a severe limitation to the effects of induced technological change in his opinion.

Bosetti, Carraro *et al.*(Bosetti et al. 2011) examined the economic efficiency and mitigation cost implications of climate-related R&D and LBD. They used a two-factor learning curve with decreasing marginal returns, so that investment costs for renewable power generation and breakthrough low-carbon technologies was reduced by investments in targetted R&D and technology deployment. The study, implemented using the WITCH model, found that R&D and the subsequent innovation not only reduced the capital cost of technology, but also lowered the overall mitigation cost and reduced CO_2 emissions in the absence of a climate policy. The study also found that R&D expenditures consistent with the peak historical rate at 0.2% of Global World Product (GWP) can achieve similar emission reductions by the end of the century compared with a large R&D program at 2% GWP, though it achieved lower emission reductions in the medium term. This was due to a shift of consumption from earlier to later time periods, plus the diminishing returns of the R&D investment. Finally, the study found that despite small economic costs in the early decades, by internalizing international technological externalities and forcing higher innovation investments in earlier periods, innovation policies delivered some net welfare gains during the second half of the century, at the expense of initial losses.

While the concept of a two-factor learning curve is theoretically appealing, others have pointed to at least two significant problems with this approach, as noted earlier in Section 3. The first is data availability. Reliable data on public and (especially) private-sector R&D spending is often hard to come by, and the quality of available data is often an issue (Capros et al. 2005). The second major shortcoming is the high degree of co-linearity between the two variables. That is, both R&D investments and cumulative production or capacity may respond to the same drivers and/or directly influence one another (Söderholm & Klaassen 2007; Barreto & Kypreos 2004). An increase in product sales, for example, may stimulate R&D spending to further improve the product. In addition, from a policy perspective, there is a distinct difference between government-funded and private sector R&D. Since these funding sources can have very different effects on the cost and performance of a specific technology (Wene 2008), R&D policy conclusions based on a single (combined public/private) R&D indicator can be quite misleading. Nonetheless, for purposes of projecting technology cost trajectories, a two-factor model—if available—can, in principle, provide a better estimate that the more prevalent one-factor model.

5 Summary and Conclusions

The phenomenon of unit cost reduction associated with increased production (learning-by-doing) has long been documented for manufactured products. In recent decades this has been extended to model the cost of various energy supply technologies. The most common approach to characterize this relationship is the use of a log-linear experience curves (or learning curve) relating a reduction in the unit cost of a technology to its cumulative production or installed capacity. This model formulation also has become a common method of representing endogenous technical change in energy-economic models used for policy analysis.

Yet, there are significant uncertainties in the underlying drivers of technological change; in our understanding of the major factors that contribute to learning; and in the “proper” formulation of an experience curve (including the appropriate shape and parameters of an

experience-based model). Thus, there is uncertainty in how best to use learning curves for making projections and analyzing policy scenarios.

In this report, we reviewed the theory of technological change and the underlying drivers for cost reduction reported in the literature. We conducted a comprehensive literature review for eleven power generation technologies including fossil-based power plants, nuclear plants, and a variety of renewable electric technologies. The results are summarized in **Table 4** below.

Table 4: Range of reported one-factor and two-factor learning rates for electric power generation technologies.

Technology	Number of studies reviewed	Number of studies with one factor	Number of studies with two factors	Range of learning rates for "learning by doing" (LBD)	Range of rates for "learning by researching" (LBR)	Years covered across all studies
Coal*						
PC	2	2	0	5.6% to 12%		1902-2006
IGCC	1	1	0	2.5% to 7.6%		Projections
Natural Gas*	8	6	2	-11% to 34%	2.38% to 17.7%	1980-1998
Nuclear	4	4	0	<0 to 6%		1975-1993
Wind (on-shore)	35	29	6	-3% to 32%	10% to 26.8%	1980-2010
Solar PV	24	22	2	10% to 53%	10%	1959-2001
BioPower						
Biomass production	4	4	0	12% to 45%		1971-2006
*Power generation**	7	7	0	0% to 24%		1976-2005
Geothermal power	3	0	0			1980-2005
Hydropower	3	0	2	0.48% to 11.4%	2.63% to 20.6%	1980-2001

*Does not include plants with CCS. **Includes combined heat and power (CHP) and biodigesters.

We found that there is a wide variation in reported learning rates. Some studies include both learning-by-doing and learning-by-researching (reflecting R&D spending), and report both values. In general, there are wide variations even within the same technologies, and no clear trend of learning rates associated with a certain type of technologies, time periods, or regions. Though we also found a narrower range of smaller learning rates associated with fossil power plants, whereas renewable technologies (wind, solar, biopower) have a wide range of learning rates including values as high as 45% to 53%. With the exception of nuclear power, all the studies we reviewed report cost reductions with increased installed capacity.

Some energy models have experimented with incorporating learning curves and explored the impacts on model results. In general, when one-factor learning curves are adopted, models with endogenous technological learning (ETL) (via learning curves) tend to project higher penetrations of advanced technologies and have lower overall costs compare to models that do not take ETL into account. The conclusions are much more complicated when both learning-by-doing and learning-by-researching (R&D) are included in the model. In general, R&D investments also lead to cost reduction. However, when R&D costs are included in the model, there are opportunity costs associated with R&D investments in energy technologies, which add costs to the system.

There are two key categories of uncertainties associated with the application of experience curves. One is the learning curve itself; the other concerns the conclusions drawn from the use of learning curves. Despite a rich literature in learning-by-doing and extensive documentation of historical learning for energy technologies, there remains a large degree of uncertainty as to how reliably historical learning curves can be used to estimate the future cost of the same or similar technology. Thus, the judgment of technology experts and modelers is still required and used to address a host of questions, such as: What is the appropriate learning rate? When does learning begin (and end)? What is the appropriate shape of a learning curve? What is the appropriate measure of experience? Do costs always decrease over time?

The second key uncertainty, regarding the integrity of policy-related conclusions drawn from the use of learning curves, is similarly a topic of discussion and debate. Thus, it is argued, for example, that without a better understanding and ability to model the underlying drivers of technology cost reductions, model projections based on learning rates obtained from one-factor learning curves may inappropriately lend support to policies that favor certain technologies or investment strategies.

So what are energy modelers to do in the face of these uncertainties and our limited understanding of the processes underlying technological change? For one, an expanded and more systematic use of sensitivity studies, especially the testing of alternative model formulations, should be pursued to better and more fully characterize their implications for projected cost reductions and rates of technological change. This also will have implications for the portfolio of technologies that models select in any given scenario. Relatively simple computer experiments can be used to begin exploring these implications.

Over the longer term, continued research into the underlying factors that govern or influence technological innovations and diffusion may yield improved models that can more reliably forecast the implications of proposed energy and environmental policy measures. In the meanwhile, more concerted efforts are needed to explore, understand and display the consequences of uncertainties in current formulations of technology experience curves used to project the future cost of energy technologies.

6 Acknowledgements

We acknowledge the assistance of Carnegie Mellon Ph.D. students Ahmed Abdulla (for the section on nuclear power) and Jinhyok Heo (for the section on the NEMS model), and UC Davis research assistants Gouri Shankar Mishra (for the review of energy models utilizing learning curves) and the section ons BioPower and Geothermal production).

7 References

Arrow, K.J., 1962. The economic implications of learning by doing. *The review of economic studies*, pp.155–173.

Barreto, L. & Kypreos, S., 2004. Endogenizing R&D and market experience in the "bottom-up" energy-systems ERIS model. *Technovation*, 24(8), pp.615–629.

Barreto, L. & Kypreos, S., 2002. Multi-regional technological learning in the energysystems MARKAL model. *International Journal of Global Energy Issues*, 17(3), pp.189–213.

Berghout, N.A., 2008. *Technological learning in the German biodiesel industry: An experience curve approach to quantify reductions in production costs, energy use and greenhouse gas emissions*. Ultrech, The Netherlands: Utrecht University.

Bosetti, V. et al., 2009. *The 2008 WITCH model: New model features and baseline*, Milano: Fondazione Eni Enrico Mattei.

Bosetti, V. et al., 2011. What should we expect from innovation? A model-based assessment of the environmental and mitigation cost implications of climate-related R&D. *Energy Economics*, 33(6), pp.1313–1320.

Capros, P. et al., 2005. *System analysis for progress and innovation in energy technologies for integrated assessment*, Institute Of Communication And Computer Systems Of National Technical University Of Athens.

Carelli, M.D. et al., 2010. Economic features of integral, modular, small-to-medium size reactors. *Progress in Nuclear Energy*, 52(4), pp.403–414.

Clarke, L., Weyant, J. & Birky, A., 2006. On the sources of technological change: Assessing the evidence. *Energy Economics*, 28(5-6), pp.579–595.

Clarke, L., Weyant, J. & Edmonds, J., 2008. On the sources of technological change: What do the models assume? *Energy Economics*, 30(2), pp.409–424.

Cohen, W.M., 1995. Empirical Studies of Innovative Activity. In P. Stoneman, ed. *Handbook of the Economics of Innovation and Technological Change*. Oxford: Blakwell, pp. 182–264.

Cohen, W.M. & Klepper, S., 1996. Firm size and the nature of innovation within industries: the case of process and product R&D. *The Review of Economics and Statistics*, pp.232–243.

Colpier, U.C. & Cornland, D., 2002. The economics of the combined cycle gas turbine—an experience curve analysis. *Energy Policy*, 30(4), pp.309–316.

Cooper, M., 2010. Policy Challenges of Nuclear Reactor Construction: Cost Escalation and Crowding Out Alternatives. *Institute for Energy and the Environment, Vermont Law School, September*.

Curtright, A., Morgan, M. & Keith, D., 2008. Expert assessments of future photovoltaic technologies. *Environmental Science and Technology*, 42(24), pp.9031–9038.

Edenhofer, O. et al., 2011. Renewable Energy Sources and Climate Change Mitigation: Special Report of the Intergovernmental Panel on Climate Change.

Edenhofer, O., Knopf, B. & Barker, T., 2010. The economics of low stabilization: Model comparison of mitigation strategies and costs. *The Energy Journal*, 31(11-48).

EIA, 2012. *Annual Energy Outlook 2012*, Washington, DC: Energy Information Administration. U.S. Department of Energy. Available at: http://www.eia.gov/forecasts/aeo/pdf/0383(2012).pdf.

EIA, 2013. *Annual Energy Outlook 2013 - Early Release*, Energy Information Administration.

Ek, K. & Söderholm, P., 2010. Technology learning in the presence of public R&D: The case of European wind power. *Ecological Economics*, 69(12), pp.2356–2362. Available at: http://www.sciencedirect.com/science/article/pii/S0921800910002685.

Ferioli, F. & van der Zwaan, B.C.C., 2009. Learning in Times of Change: A Dynamic Explanation for Technological Progress. *Environmental Science and Technology*, 43(11), pp.4002–4008.

Ferioli, F., Schoots, K. & van der Zwaan, B.C.C., 2009. Use and limitations of learning curves for energy technology policy: A component-learning hypothesis. *Energy Policy*, 37(7), pp.2525–2535.

Fischer, C. & Newell, R.G., 2008. Environmental and technology policies for climate mitigation. *Energy Policy*, 55(2), pp.142–162.

Gillingham, K., Newell, R.G. & Pizer, W.A., 2008. Modeling endogenous technological change for climate policy analysis. *Energy Economics*, 30(6), pp.2734–2753.

Goulder, L.H. & Mathai, K., 2000. Optimal CO2 Abatement in the Presence of Induced Technological Change. *Journal of Environmental Economics and Management,* 39, pp.1–38.

Grubb, M. & Köhler, J., 2002. INDUCED TECHNICAL CHANGE IN ENERGY AND ENVIRONMENTAL MODELING: Analytic Approaches and Policy Implications - Annual Review of Energy and the Environment, 27(1):271. *Annual Review of Energy and …*.

Grubb, M., Chapuis, T. & Duong, M.H., 1995. The economics of changing course. *Energy Policy*, 23(4-5), pp.417–431.

Grubler, A., 2010. The costs of the French nuclear scale-up: A case of negative learning by doing. *Energy Policy*, 38(9), pp.5174–5188.

Gumerman, E. & Marnay, C., 2004. *Learning and cost reductions for generating technologies in the national energy modeling system (NEMS)*, Lawrence Berkeley National Laboratory.

Hettinga, W.G. et al., 2009. Understanding the reductions in US corn ethanol production costs: An experience curve approach. *Energy Policy*, 37(1), pp.190–203.

Ibenholt, K., 2002. Explaining learning curves for wind power. *Energy Policy*, 30(13), pp.1181–1189.

International Energy Agency, 2012. *World energy outlook 2012*, OECD Publishing.

IPCC, 2007. *Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, 2007* B. Metz et al., eds., IPCC Fourth Assessment Report: Climate Change 2007.

Jamasb, T., 2007. Technical change theory and learning curves: Patterns of progress in electricity generation technologies. *The Energy Journal*, 28(3), pp.51–72.

Jamasb, T. & Köhler, J., 2007. Learning curves for energy technology: a critical assessment. In M. Grubb, T. Jamasb, & M. G. Pollitt, eds. *Delivering a Low Carbon Electricity System: Technologies, Economics and Policy*. Cambridge University Press.

Joskow, P.L. & Rose, N.L., 1985. The effects of technological change, experience, and environmental regulation on the construction cost of coal-burning generating units. *The RAND Journal of Economics*, pp.1–27.

Junginger, M. et al., 2006. Technological learning in bioenergy systems. *Energy Policy*, 34(18), pp.4024–4041.

Junginger, M., Faaij, A. & Turkenburg, W.C., 2009. Cost Reduction Prospects for Offshore Wind Farms. *Wind Engineering*, 28(1), pp.97–118.

Junginger, M., Faaij, A. & Turkenburg, W.C., 2005. Global experience curves for wind farms. *Energy Policy*, 33(2), pp.133–150.

Junginger, M., Van Sark, W. & Andre P.C. Faaij, 2010. *Technological Learning in the Energy Sector: Lessons for Policy, Industry and Science*, Northampton, MA: Edward Elgar Publishing Limited.

Kahouli-Brahmi, S., 2008. Technological learning in energy-environment-economy modelling: A survey. *Energy Policy*, 36(1), pp.138–162.

Klaassen, G. et al., 2005. The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom. *Ecological Economics*, 54(2), pp.227–240.

Klepper, S. & Simons, K.L., 2000. The Making of an Oligopoly: Firm Survival and Technological Change in the Evolution of the U.S. Tire Industry. *Journal of Political Economy*, 108(4), pp.728–760.

Kobos, P.H., Erickson, J.D. & Drennen, T.E., 2006. Technological learning and renewable energy costs: implications for US renewable energy policy. *Energy Policy*, 34(13), pp.1645–1658.

Koornneef, J., Junginger, M. & Faaij, A., 2007. Development of fluidized bed combustion—An overview of trends, performance and cost. *Energy Policy*, 33(1), pp.19–55.

Kouvaritakis, N. & Argiri, E., 2005. *Systems analysis for progress and innovation in energy technologies for integrated assessment*, Athens: ICCS-NTUA.

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

Kypreos, S. & Bahn, O., 2003. A MERGE Model with Endogenous Technological Progress. *Environmental Modeling and Assessment*, 8(3), pp.249–259.

Lemming, J.K., Morthorst, P.E. & Clausen, N.E., 2009. *Offshore wind power experiences, potential and key issues for deployment*, Forskningscenter Risø Roskilde.

Li, S. et al., 2012. Learning rates and future cost curves for fossil fuel energy systems with CO2 capture: Methodology and case studies. *Energy Policy*, 93, pp.348–356.

Lindman, Å. & Söderholm, P., 2012. Wind power learning rates: A conceptual review and meta-analysis. *Energy Economics*, 34(3), pp.754–761.

Luderer, G. et al., 2010. *Description of the ReMIND□R model*, Postdam Institute for Climate Impcat Research.

Manne, A. & Richels, R., 2004. The impact of learning-by-doing on the timing and costs of CO2 abatement. *Energy Economics*, 26(4), pp.603–619.

McDonald, A. & Schrattenholzer, L., 2001. Learning rates for energy technologies. *Energy Policy*, 29(4), pp.255–261.

McNerney, J., Doyne Farmer, J. & Trancik, J.E., 2011. Historical costs of coal-fired electricity and implications for the future. *Energy Policy*, 39(6), pp.3042–3054.

Miketa, A. & 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(15), pp.1679–1692.

Moccia, J. & Arapogianni, A., 2011. *Pure Power-wind energy targets for 2020 and 2030*, European Wind Energy Association.

Nakicenovic, N. & Riahi, K., 2001. *An assessment of technological change across selected energy scenarios*, International Institute for Applied Systems Analysis.

Neij, L., 2008. Cost development of future technologies for power generation—A study based on experience curves and complementary bottom-up assessments. *Energy Policy*, 36(6), pp.2200–2211. Available at: http://www.sciencedirect.com/science/article/pii/S0301421508001237.

Neij, L. et al., 2003. *Experience curves: A tool for energy policy assessment*, Environmental and Energy Systems Studies, Univ.

Neij, L., Andersen, P.D. & Durstewitz, M., 2004. Experience curves for wind power. *International journal of energy technology and policy*, 2(1), pp.15–32.

Nemet, G., 2006. Beyond the learning curve: factors influencing cost reductions in photovoltaics. *Energy Policy*, 34(17), pp.3218–3232.

Nemet, G., 2011. Knowledge spillovers from learning by doing in wind power. *cepe.ethz.ch*.

Nemet, G.F., 2009. Interim monitoring of cost dynamics for publicly supported energy technologies. *Energy Policy*, 37(3), pp.825–835.

Nordhaus, W.D., 2009. *The perils of the learning model for modeling endogenous technological change*, National Bureau of Economic Research.

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

Priddle, R., 2000. *Experience curves for energy technology policy*, International Energy Agency.

Qiu, Y. & Anadon, L.D., 2012. The price of wind power in China during its expansion: Technology adoption, learning-by-doing, economies of scale, and manufacturing localization. *Energy Economics*, 34(3), pp.772–785.

Rafaj, P. & Kypreos, S., 2007. Internalisation of external cost in the power generation sector: Analysis with Global Multi-regional MARKAL model. *Energy Policy*, 35(2), pp.828–843.

Rafaj, P., Kypreos, S. & Barreto, L., 2005. Flexible Carbon Mitigation Policies: Analysis with a Global Multi-Regional MARKAL Model. In *link.springer.com*. Advances in Global Change Research. Berlin/Heidelberg: Springer-Verlag, pp. 237–266.

Rao, S., Keppo, I. & Riahi, K., 2006. Importance of technological change and spillovers in long-term climate policy. *The Energy Journal*, 1, pp.123–140.

Riahi, K. et al., 2005. Towards fossil-based electricity systems with integrated CO2 capture: Implications of an illustrative long-term technology policy. In 7th International Conference on Greenhouse Gas Control Technologies (GHGT-7). Vancouver.

Riahi, K., Rubin, E.S. & Schrattenholzer, L., 2004a. Prospects for carbon capture and sequestration technologies assuming their technological learning. *Energy*, 29(9-10), pp.1309–1318.

Riahi, K., Rubin, E.S., Taylor, M.R., et al., 2004b. Technological learning for carbon capture and sequestration technologies. *Energy Economics*, 26(4), pp.539–564.

Roehrl, R.A. & Riahi, K., 2000. Technology Dynamics and Greenhouse Gas Emissions Mitigation. *Technological Forecasting and Social Change*, 63(2-3), pp.231–261.

Romer, P.M., 1986. Increasing returns and long-run growth. *The Journal of Political Economy*, pp.1002–1037.

Rubin, E.S. et al., 2004. Learning curves for environmental technology and their importance for climate policy analysis. *Energy*, 29(9), pp.1551–1559.

Rubin, E.S. et al., 2007. Use of experience curves to estimate the future cost of power plants with CO2 capture. *International Journal of Greenhouse Gas Control*, 1(2), pp.188–197.

Schilling, M.A. & Esmundo, M., 2009. Technology S-curves in renewable energy alternatives: Analysis and implications for industry and government. *Energy Policy*, 37(5), pp.1767–1781.

Seebregts, A., Kram, T. & Schaeffer, G.J., 2000. Endogenous learning and technology clustering: analysis with MARKAL model of the Western European energy system. *International Journal of Global Energy Issues*, 14(1-4), pp.289–319.

Seebregts, A.J. et al., 1999. Modelling technological progress in a MARKAL model for Western Europe including clusters of technologies. In European IAEE/AEE Conference 'Technological Progress and the Energy Challenge'. Paris, France: Netherlands Energy Research Foundation ECN.

Shay, C. et al., 2006. US EPA National MARKAL Database: Database Documentation.

Sinclair, G., Klepper, S. & Cohen, W., 2000. What's Experience Got to Do With It? Sources of Cost Reduction in a Large Specialty Chemicals Producer. *Management Science*, 46(1), pp.28–45.

Solow, R.M., 1956. A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, 70(1), p.65.

Söderholm, P. & Klaassen, G., 2007. Wind Power in Europe: A Simultaneous Innovation–Diffusion Model. *Environmental and Resource Economics*, 36(2), pp.163–190.

Söderholm, P. & Sundqvist, T., 2007. Empirical challenges in the use of learning curves for assessing the economic prospects of renewable energy technologies. *Renewable Energy*, 32(15), pp.2559–2578.

Sturm, R., 1994. *Stochastic process analysis for nuclear power plant operations*, Santa Monica, CA: RAND Corporation.

Taylor, M., 2008. Beyond technology-push and demand-pull: Lessons from California's solar policy. *Energy Economics*, 30(6), pp.2829–2854.

van den Broek, M. et al., 2009. Effects of technological learning on future cost and performance of power plants with CO2 capture. *Progress in Energy and Combustion Science*, pp.1–24.

van den Wall Bake, J.D. et al., 2009. Explaining the experience curve: Cost reductions of Brazilian ethanol from sugarcane. *Biomass and Bioenergy*, 33(4), pp.644–658.

van der Zwaan, B. & Rabl, A., 2004. The learning potential of photovoltaics: implications for energy policy. *Energy Policy*, 32(13), pp.1545–1554.

van der Zwaan, B.C.C. et al., 2002. Endogenous technological change in climate change modelling. *Energy Economics*, 24(1), pp.1–19.

Wang, J.L. & Yu, O.P.I., 1988. The price of power. *Potentials, IEEE*, 7(2), pp.28–30.

Watanabe, C., Nagamatsu, A. & Griffy-Brown, C., 2003. Behavior of technology in reducing prices of innovative goods—an analysis of the governing factors of variance of PV module prices. *Technovation*, 23(5), pp.423–436.

Watanabe, C., Wakabayashi, K. & Miyazawa, T., 2000. Industrial dynamism and the creation of a "virtuous cycle" between R&D, market growth and price reduction. *Technovation*, 20(6), pp.299–312.

Weiss, M. et al., 2010. A review of experience curve analyses for energy demand technologies. *Technological Forecasting and Social Change*, 77(3), pp.411–428.

Wene, C.-O., 2008. Energy Technology Learning Through Deployment in Competitive Markets. *The Engineering Economist*, 53(4), pp.340–364.

Wiser, R., 2012. *2010 Wind Technologies Market Report*, US Department of Energy.

Yeh, S. & Rubin, E.S., 2007. A centurial history of technological change and learning curves for pulverized coal-fired utility boilers. *Energy*, 32(10), pp.1996–2005.

Yeh, S. & Rubin, E.S., 2012. A review of uncertainties in technology experience curves. *Energy Economics*, 34(3), pp.762–771.

Yeh, S. et al., 2006. An Integrated Assessment of the Impacts of Hydrogen Economy on Transportation, Energy Use, and Air Emissions. *Proceedings of the IEEE*, 94(10), pp.1838–1851.

Yeh, S. et al., 2005. Technology Innovations and Experience Curves for Nitrogen Oxides Control Technologies. *Journal of the Air & Waste Management Association*, 55(12), pp.1827–1838.

Zhai, H. & Rubin, E.S., 2013. Comparative Performance and Cost Assessments of Coal- and Natural-Gas-Fired Power Plants under a CO 2Emission Performance Standard Regulation. *Energy Fuels*, p.130214084607001.

Appendix A: Learning Curves from Previous Studies

Table A1: Single factor learning rates for pulverized coal-fired power plants reported in the literature.

Study	Time period	Region	Scope	Learning Rate	R^2	Dependent variable	Explanatory variable
McNerney et al (2011)	1902-2006	US	Pulverized coal plant	12%	NA	Capital cost ($/kW)	Cumulative Installed Capacity (MW)(US)
Yeh and Rubin (2007)	1942-1999	US	Pulverized coal plant	5.6%	0.94	Construction Cost ($/kW)	Cumulative Installed Capacity (MW)(World)

Table A2: Single factor learning rates for natural gas power plants reported in the literature.

Study	Time period	Region	Scope	Learning Rate	R^2	Dependent variable	Explanatory variable
Van den Broek 2009[1]	n/a	Global	GTCC	10%	n/a	Capital Cost ($/kW)	n/a
Van den Broek 2009	n/a	Global	NGCC w/ amine capture	11%	n/a	n/a	n/a
Van den Broek 2009	n/a	Global	Compression of CO2 at NGCC-CCS Plant	0%	n/a	n/a	n/a
Colpier 2002		US & EU	GTCC Plant	0%	n/a	Specific Investment Price ($/kW)	Cumulative Installed Capacity (MW)
Colpier 2002	1991-1997	US & EU	GTCC Plant	25%	n/a	Specific Investment Price ($/kW)	Cumulative Installed Capacity (MW)
Colpier 2002	1981-1997	US & EU	GTCC Plant	25%[2]	n/a	Electricity Production Cost ($/kWh)	Cumulative Production (TWh)
Colpier 2002	1981-1997	US & EU	GTCC Plant	6%[3]	n/a	Electricity Production Cost ($/kWh)	Cumulative Production (TWh)
IEA 2000	1981-1997	Europe and NAFTA	NGCC Plant	10%	n/a	Price ($/kW)	Cumulative Installed Capacity (GW)
MacGregor 1991 via McDonald 2001	1963-1980	World	Gas Turbine	10%	n/a	Specific Investment Cost ($/kW)	Cumulative Installed Capacity (MW)
MacGregor 1991 via McDonald 2001	1958-1990	World	Gas Turbine	13%	0.94	Specific Investment Cost ($/kW)	Cumulative Installed Capacity (MW)

[1]Data used in this analysis was obtained from the IECM model at Carnegie Mellon University
[2]Natural gas prices vary by year
[3]Natural gas prices are assumed to be constant throughout the period

Table A3: Single-factor learning rates for wind power reported in the literature.

Study	Time period	Region	Scope	Learning Rate	R^2	Dependent variable	Explanatory variable(s)
Wiser 2012	1982-2004	Global	Land-based wind farm	14%	n/a	Capital cost ($/kW)	Cumulative capacity (MW)
Wiser 2012	1982-2010	Global	Land-based wind farm	8%	n/a	Capital cost ($/kW)	Cumulative capacity (MW)
Qui 2012	2003-2007	China	Land-based wind farm	4%	n/a	Price of electricity ($/kWh)	Cumulative capacity (MW), R&D spending ($)
Lemming 2009	1985-2000	n/a	Offshore wind farm	10%	n/a	n/a	n/a
Junginger 2009	1988-2000	Global	HVDC cable for offshore wind farm	38%	0.966	HVDC Cable Costs ($/MW-km)	Cumulative submarine HVDC installation (GW-km)
Junginger 2009	1970-2000	Global	HVDC converter stations for offshore wind farm	29%	0.581	Price per converter station ($/kW/station)	Cumulative converter station installed (GW)
Junginger 2009	2000; 2003	Two offshore wind farms	Offshore turbine installation	77%	n/a	Installation time (days)	Cumulative number of offshore turbines installed.
Nemet 2009	1981-1995	Global	Land-based turbines	30%	n/a	Capital cost ($/kW)	Cumulative capacity (MW)
Nemet 2009	1981-2006	Global	Land-based turbines	8%	n/a	Capital cost ($/kW)	Cumulative capacity (MW)
Neij 2008	1990-2000	Global	Land-based turbines	11%	n/a	Turbine list price ($/kW)	Cumulative installed capacity (MW)
Junginger 2005[1]	1992-2001	UK	Land-based wind farm	19%	0.978	Turnkey investment cost ($/MW)	Global cumulative installed wind capacity
Junginger 2005	1992-2001	UK	Land-based wind farm	21%	0.98	Turnkey investment cost ($/MW)	Global cumulative installed wind capacity
Junginger 2005	1990-2001	Spain	Land-based wind farm	15%	0.887	Turnkey investment cost ($/MW)	Global cumulative installed wind capacity
Junginger 2005	1990-2001	Spain	Land-based wind farm	20%	0.907	Turnkey investment cost ($/MW)	Global cumulative installed wind capacity
Junginger 2005	1990-1998	Spain	Land-based wind farm	18%	0.875	Turnkey investment cost ($/MW)	Global cumulative installed wind capacity
Junginger 2005	1990-1998	Spain	Land-based wind farm	23%	0.905	Turnkey investment cost ($/MW)	Global cumulative installed wind capacity
Neij 2004	1981-2000	Denmark	Turbines produced by Danish Manufacturers	8%	0.84	Price of wind turbines ($/kW)	Cumulative capacity produced (MW)
Neij 2004	1987-2000	Germany	Turbines produced by German manufacturers	6%	0.74	Price of wind turbines ($/kW)	Cumulative capacity produced (MW)
Neij 2004	1981-2000	Denmark	Turbines produced by Danish Manufacturers	14%	0.97	Specific production cost ($/kWh)	Cumulative capacity produced (MW)
Neij 2004	1987-2000	Germany	Turbines produced by German manufacturers	12%	0.87	Specific production cost ($/kWh)	Cumulative capacity produced (MW)
Neij 2004	1981-2000	Denmark	Turbines produced by	17%	0.97	Levelized production cost ($/kWh)[4]	Cumulative capacity produced (MW)

			Danish Manufacturers				
Neij 2004	1987-2000	Germany	Turbines installed in Germany	6%	0.88	Price of wind turbines ($/kW)	Cumulative capacity installed (MW)
Neij 2004	1981-2000	Denmark	Turbines installed in Denmark	9%	0.94	Price of wind turbines ($/kW)	Cumulative capacity installed (MW)
Neij 2004	1981-2000	Denmark	Wind farms built in Denmark	10%	0.92	Total installation cost ($/kW)	Cumulative installed capacity (MW)
Neij 2004	1984-2000	Spain	Wind farms built in Spain	9%	0.85	Total installation cost ($/kW)	Cumulative installed capacity (MW)
Neij 2004	1994-2000	Sweden	Wind farms built in Sweden	4%	0.32	Total installation cost ($/kW)	Cumulative installed capacity (MW)
Ibenholt 2002	1991-1999	Germany	Land-based turbine	-3%	n/a	Price of electricity ($/kWh) & Cumulative installed capacity (MW)	R&D, input prices, technology-pushing policies, competition, economies of scale
Ibenholt 2002	1991-1999	UK	Land-based turbine	25.1%	n/a	Price of electricity ($/kWh) & Cumulative installed capacity (MW)	R&D, input prices, technology-pushing policies, competition, and economies of scale
Ibenholt 2002	1984-1999	Denmark	Land-based turbine	7.8%	n/a	Price of electricity ($/kWh) & Cumulative installed capacity (MW)	R&D, input prices, technology-pushing policies, competition, and economies of scale
Ibenholt 2002	1984-1988	Denmark	Land-based turbine	11.7%	n/a	Price of electricity ($/kWh) & Cumulative installed capacity (MW)	R&D, input prices, technology-pushing policies, competition, and economies of scale
Ibenholt 2002	1988-1999	Denmark	Land-based turbine	7.5%	n/a	Price of electricity ($/kWh) & Cumulative installed capacity (MW)	R&D, input prices, technology-pushing policies, competition, and economies of scale
IEA 2000	1985-1994	US	Land-based wind farm	32%	n/a	Cost of Electricity ($/kWh)	Cumulative production (TWh)
IEA 2000	1980-1995	EU	Land-based wind farm	18%	n/a	Cost of Electricity ($/kWh)	Cumulative production (TWh)
IEA 2000	1990-1998	Germany	Wind turbines sold in Germany	8%	n/a	Specific investment price ($/kW)	Cumulative capacity (MW)
IEA 2000	1982-1997	Denmark	Turbines produced by Danish Manufacturers	4%	n/a	Price ($/kW)	Cumulative Sales (MW)
Kouvaritakis 2000 via McDonald 2001	1981-1995	OECD	Land-based wind farm	17%	0.94	Specific investment cost ($/kW)	Cumulative capacity (MW)
Durstewitx 1999 via McDonald 2001	1990-1998	Germany	Land-based wind farm	8%	0.95	Specific investment price ($/kW)	Cumulative capacity (MW)
Neij 1999 via McDonald 2001	1982-1997	Denmark	Land-based wind farm	8%	n/a	Specific investment price ($/kW)	Cumulative capacity (MW)
CEC 1997 & Loiter 1999 via McDonald 2001	1980-1994	California	Land-based wind farm	18%	0.85	Specific production cost ($/kWh)[3]	Cumulative production (TWh)

[1]Junginger 2005 reports two different values for each country for each period based on two different GDP deflator values.

Table A4: Multi-factor learning-diffusion models for wind power

Study	Time period	Region	Scope	Learning Rate	R^2	Dependent Variable	Explanatory Variable(s)
Ek 2010	1986-2002	Global	Land-based wind farm	LBD= 17%, LBR= 20%	0.88	Investment Price ($/kW)	R&D ($) and cumulative capacity (MW)
Jamasb 2007	1980-1998	Global	Land-based wind farm	LBD = 13.1%, LBR = 23.8%	n/a	Unit cost of generation ($/kW) and cumulative installed generation capacity (MW)	Cumulative private and public R&D spending (million $), cumulative number of technology patents, time variable (years)
Soderholm 2006	Varies by country	Global based on data from Denmark (1986-1999), Germany (1990-1999), Spain (1990-1999), Sweden (1991-2002), and UK (1991-2000)	Wind farm	LBD= 3.1%, LBR= 13.2%	0.81	Investment Price ($/kW)	R&D ($) and cumulative capacity (MW)
Klaassen 2005	1986-2000	Denmark, UK, & Germany	Land-based wind farm	LBD = 5.4%, LBR = 12.6%	0.72	Specific investment cost ($/kW)	R&D ($) and cumulative capacity (MW)
Miketa 2004	1979-1997	Global	Land-based turbine	LBD= 9.73%, LBR= 10%	0.8	Investment cost ($/kW)	Cumulative Capacity (GW) and knowledge stock (cumulative R&D minus depreciation)

Table A5: Single factor learning rates for solar PV reported in the literature.

Study	Time period	Region	Scope	Learning Rate	R^2	Dependent variable	Explanatory variable
Schaeffer 2004 via Neij 2008	1992-2001	Germany	PV modules	16%, 47%, 21%	n/a	n/a	n/a
Schaeffer 2004 via Neij 2008	1976-2001	Netherlands	PV modules	10%	n/a	n/a	n/a
Schaeffer 2004 via Neij 2008	1976-2001	Global	PV modules	12%	n/a	n/a	n/a
Schaeffer 2004 via Neij 2008	1992-2001	Germany	PV BOP[1]	12%	n/a	n/a	n/a
Schaeffer 2004 via Neij 2008	1992-2001	Netherlands	PV BOP	19%	n/a	n/a	n/a
Strategies United 2003 via Neij 2008	1976-2001		PV modules	20%	n/a	n/a	n/a
Strategies United 2003 via Neij 2008	1976-2001		PV modules	23%	n/a	n/a	n/a
Maycock 2002 and Nemet 2006 via Neij 2008			PV BOS	26%	n/a	n/a	n/a
Parente 2002 via Neij 2008	1981-2000		PV modules	23%	n/a	n/a	n/a
OECD/IEA 2000 via Neij 2008	1976-1996		Crystalline silicone PV modules	20%	n/a	n/a	n/a
Harmon 2000 via McDonald 2001	1968-1998	World OECD	Panel or Plant	20%	0.99	Specific Investment Price ($/kW Peak)	Cumulative Installed Capacity (MW)
IEA 2000 via McDonald 2001	1985-1995	EU		35%	n/a	Production Cost ($/kWh)	Cumulative Production (TWh)
IEA 2000 via McDonald 2001	1976-1992	World		18%	n/a	Sale Price ($/W Peak)	Cumulative Sales (MW)
IEA 2000 via McDonald 2001	1976-1992	EU		21%	n/a	Sale Price ($/W Peak)	Cumulative Sales (MW)
IEA 2000 via McDonald 2001	1976-1992	EU		16%	n/a	Sale Price ($/W Peak)	Cumulative Sales (MW)
IEA 2000 via McDonald 2001	1976-1992	EU		53%	n/a	Sale Price ($/W Peak)	Cumulative Sales (MW)
Harmon 2000 via Ferioli 2009			PV modules	20%	0.99	Price ($/W)	Cumulative Capacity (GW)
Watanabe 1999	1981-1995	Japan	PV modules	22%	n/a	n/a	n/a
Cody 1997 via Neij 2008	1976-1988	US	PV modules	22%	n/a	n/a	n/a
Williams 1993 via Neij 2008	1976-1988	Global	PV modules	18%	n/a	n/a	n/a
Tsuchiya 1992 via Neij 2008	1979-1988	Japan	Crystalline silicon PV modules	21%	n/a	n/a	n/a
Maycock 1975, via McDoanld 2001	1959-1974	US		22%	0.94	Specific Sale Price ($/kW Peak)	Cumulative Installed Capacity (MW)

1BOP = Balance of plant

Table A6: Multi-factor learning-diffusion models for solar PV

Study	Time period	Region	Scope	Learning Rate	R^2	Dependent Variable	Explanatory Variable(s)
Kobos et al, 2006	1981-1997	Global	n/a	LBD = 18.4%, LBR = 14.3%	0.99 (adj. R^2)	n/a	Cumulative Capacity (GW) and knowledge stock (cumulative R&D minus depreciation)
Miketa 2004	1971-1997	Global	PV	LBD = 17.46%,	0.94	Price ($/W)	Cumulative Capacity (GW) and

			modules	LBR = 10%			knowledge stock (cumulative R&D minus depreciation)

Table A7: Single factor learning rates for biomass feedstock and biomass energy reported in the literature.

Study	**Time period**	**Region**	**Scope**	**Learning rate**	R^2	**Dependent variable**	**Explanatory variable**
Van den Wall Bake 2009	1975-2004	Brazil	Sugarcane production	32%	0.85	Sugarcane cost ($/TC[1])	Cumulative sugarcane production (million TC)
Hettinga 2009	1980-2005	US	Corn	45%	0.87	Corn cost ($/tonne)	Cumulative corn production (million tonnes)
Berghout 2008	1971-2006	Germany	Rapeseed	19.6%	0.97	Rapeseed production cost ($/tonne)	Cumulative rapeseed production (million tonnes)
Koornneef 2006	1976-2005	Global	Fluidized bed CHP plant	7-10%	n/a	Price ($/kWe net)	Cumulative FBC capacity (MWe net)
Junginger 2006	1990-2002	Sweden	Fluidized bed CHP plant	13%	0.21	Specific investment cost ($/kW)	Cumulative installed capacity (MWe)
Junginger 2006	1990-2002	Sweden	Fluidized bed CHP plant	8-9%	n/a	Electricity production cost ($/kWh)	Cumulative electricity production (MWh)
Junginger 2006	1988-1998	Denmark	Bio digester	12%	n/a	Investment cost ($/day)	Cumulative digester capacity (m^3/day)
Junginger 2006	1984-1997	Denmark	Bio digester	24%	0.98	Production cost ($/$Nm^3$)	Cumulative biogas production (Nm^3/day)
Junginger 2006	1984-1991	Denmark	Bio digester	15%	0.98	Production cost ($/$Nm^3$)	Cumulative biogas production (Nm^3/day)
Junginger 2006	1991-2001	Denmark	Bio digester	0%	n/a	Production cost ($/$Nm^3$)	Cumulative biogas production (Nm^3/day)
Juginger 2005	1975-2003	Sweden and Finland	Forest residue	12-15%	n/a	Fuel wood prices ($/GJ)	Cumulative PFF[2] production (PJ)

[1]Tonne of cane

[2]PFF: primary forest fuel.

Table A8: Single factor progress rates for hydroelectric projects reported in the literature.

Study	Time period	Region	Scope	Learning Rate	R^2	Dependent Variable	Explanatory Variable(s)
Kouva-ritakis 2000	1975-1990	OECD	Hydro	1.4%	n/a	Investment Cost ($/MW)	Cumulative Capacity (MW)

Table A9: Multi-factor learning-diffusion models for hydroelectric power

Study	Time period	Region	Scope	Learning Rate	R^2	Dependent Variable	Explanatory Variable(s)
Jamasb 2007	1980-2001	Global	Large Hydro	LBD = 1.93%, LBR = 2.63%	n/a	Unit cost of generation ($/kW) and cumulative installed generation capacity (MW)	Cumulative private and public R&D spending (million $), cumulative number of technology patents, time variable (years)
Jamasb 2007	1988-2001	Global	Small Hydro	LBD = 0.48%, LBR = 20.6%	n/a	Unit cost of generation ($/kW) and cumulative installed generation capacity (MW)	Cumulative private and public R&D spending (million $), cumulative number of technology patents, time variable (years)

Appendix B: Characteristics of Energy Models with Learning

Table B1. Message Model

Model	MESSAGE
Modeling Type	Optimization
Geographic Scope	Global
Data Sources	Rao, Keppo, and Riahi (Rao et al. 2006)
Type of learning	Default is exogenous (AEEI). Endogenous learning - single factor and constant learning rate is applied in some studies
Technology representation/details	A total of 18 technologies are assumed to have ETL. Learning rates range from 0-15%. Exogenous learning rates of 3-5% are assumed according to the B2 scenario for the other technologies.
Cluster learning	Spillover across tech. 'technology clusters' has been applied in several modeling approaches (Seebregts et al. (Seebregts et al. 2000); Riahi et al. (Riahi et al. 2005)). Technological spillovers can occur within a cluster (for example: carbon capture technologies, centralized and decentralized solar PV) but not from outside the cluster (for example: improvements in the semi-conductor industry).
Spillover	Spillover across regions. The learning process for technology improvements is assumed to take place on a global scale. Although this might not necessarily be consistent with the existence of trade barriers, regional economic blocks or the importance of localized learning
MACRO	MESSAGE and MACRO are linked iteratively to include the impact of policies on energy costs, GDP and on energy demand. MACRO, a top-down macroeconomic equilibrium model captures capital stock, available labor, and energy inputs determine the total output of an economy according to a nested constant elasticity of substitution (CES) production function. The linking of a bottom-up technology-rich model and a top-down macroeconomic model results in a fully consistent evolution of energy demand quantities, prices, and macroeconomic indicators (such as GDP, investments and savings).
Key insights	1. The existence of technological learning while reducing overall energy system costs becomes particularly important in the context of a long-term climate policy. 2. Spillovers across technologies and regions due to learning results in increased upfront investments and hence lower costs of carbon free technologies, thus resulting in technology deployment and emissions reductions, especially in developing countries.3. Learning and spillover effects can lead to technologically advanced cost-effective global energy transition pathways. 4. Earlier studies using the MESSAGE model (Roehrl and Riahi (Roehrl & Riahi 2000); Nakicenovic and Riahi (Nakicenovic & Riahi 2001)) have shown that alternative parameterizations of technological change have significant implications for the technology portfolio as well as associated costs.

Table B2. ReMIND-R Model

Model	ReMIND-R
Modeling Type	Optimization (Welfare Maximization)
Geographic Scope	Global
Data Sources	Luderer, Liembach, et al. (Luderer et al. 2010)
Type of learning	Endogenous - single factor
Technology representation/details	A detailed representation of technology - around 30+ energy conversion technologies including 13 electricity generation technologies. Learning is assumed for only two technologies - Solar PV, Solar CSP and Wind. Learning rates and floor investment costs are defined. Learning is also assumed for energy storage technologies which are used in conjunction with renewable electricity
Spillover	Spillover across regions. The learning process for technology improvements is assumed to take place at a global scale
Notes	Learning rate for storage technologies is assumed to be 10%

Table B3. WITCH08 Model

Model	WITCH08
Modeling Type	Optimization (Welfare Maximization)
Geographic Scope	Global
Data Sources	Bosetti et al. (Bosetti et al. 2009); Bosetti et al. (Bosetti et al. 2011)
Type of learning	Endogenous - Two Factors
Technology representation/details	Learning-by-Doing and Learning-by-Researching is assumed for Wind, Solar, two portfolios of Backstop technologies producing electricity and non-electricity fuels (primarily H2). A uniform LbD of 13% and LbR of 10% is assumed
Cluster learning	A portfolio of backstop technologies is considered - this may be considered a cluster
Spillover	Spillover across regions. The learning process for technology improvements is assumed to take place at a global scale - global knowledge stock and global capacity buildup
Key insights	(1) Innovation alone unlikely to effectively control climate change. Even under large increases in global climate- related R&D spending, emissions can be at best stabilised above current levels and CO2 concentration be reduced by about 50 ppm relative to baseline by 2100 (from over 700 ppm to about 650 ppm, or over 750 ppm CO2eq). Carbon pricing is important.
Notes	1. R&D investments reduce the investment costs of renewable and backstop technologies. They also increase the energy efficiency of overall production function by"... contributing to accumulation of knowledge capital that substitutes for energy demand.

Table B4. POLES Model

Model	POLES
Modeling Type	Partial equilibrium optimization
Geographic Scope	Global
Data Sources	Edenhofer et al. (Edenhofer et al. 2010)
Type of learning	Endogenous - Two Factors
Technology representation/details	Learning rates for wind and solar only. Learning rate evolves with the distance to floor costs. PV: 20% in 2010, 4% in 2050; large scale solar: 30% in 2010, 3% in 2050; wind: 14% in 2010, 5% in 2050
Spillover	Spillover across regions. The learning process for technology improvements is assumed to take place at a global scale

Table B5. GCAM Model

Model	GCAM
Modeling Type	Dynamic-recursive model (partial equilibrium)
Geographic Scope	Global coverage with 14 regions
Data Sources	Clarke et al. (Clarke et al. 2008)
Type of learning	Exogenous (AEEI)
Technology representation/details	Technology-detailed bottom-up modeling
Note	Comparison of technology change assumptions in GCAM with other large scale models can be found in Clarke et al. (Clarke et al. 2006) and Clarke et al. (Clarke et al. 2008).

Table B6. MARKAL-TIMES Model- Europe

Model	MARKAL-TIMES
Modeling Type	Partial equilibrium optimization
Geographic Scope	Western Europe
Data Sources	Seebregts et al. (Seebregts et al. 2000)
Type of learning	Default is exogenous (AEEI). Some studies experimented endogenous - single factor and constant learning rate.
Technology representation/details	Technology-detailed bottom-up modeling
Cluster learning	Five clusters: wind turbines (WT), solar PV modules (PV), fuel cells (FC), gasifiers (GF), and gas turbines (GT).
Key insights	1.the overall costs for CO_2 reduction are lower with learning (ETL) than without (NETL). 2. 'cluster feature' improves the internal consistency and allows for assessment of spill-over and cross-over effects

Table B7. MARKAL-TIMES Model- Global

Model	MARKAL-TIMES
Modeling Type	Partial equilibrium optimization
Geographic Scope	Global five world regions
Type of learning	Endogenous - single factor and constant learning rate
Technology representation/details	Technology-detailed bottom-up modeling
Spillover	The multi-regional model allows simulation of bi-lateral and global trade of selected energy or environmental commodities (e.g., fuels, electricity, emission permits. In addition, the marginal cost of emission reduction are equalized across the regions. Based on the two above conditions, regional spillover are implicitly modeled.
Data Sources	Rafaj et al.(Rafaj et al. 2005)
Key insights	endogenized technology learning substantially reduces the overall cost of CO2 mitigation

Appendix C: IPCC Review of Endogenous Learning in Global Top-Down Models

Table C1: IPCC Review of Endogenous Learning in Global Top-Down Models (IPCC 2007).

Study	Model	ETC channel	Number of production sectors	Number of regions	Major results (impact of ETC)	Comments	Focus of analysis
Bosetti *et al.*, 2006	FEEM-RICE	LBD	1	8	An index of energy technological change increases elasticity of substitution. Learning-by-doing in abatement and R&D investments raise the index. Energy technological change explicitly decreases carbon intensity.		Experimental model exploring high inertia.
Crassous *et al.*, 2006	IMACLIM-R GCE	R&D and LBD	1	5	Cumulative investments drive energy efficiency. Fuel prices drive energy efficiency in transportation and residential sector. Learning curves for energy technologies (electricity generation).	Endogenous labour productivity, capital deepening.	
Edenhofer *et al.*, 2006	MIND Optimal growth	LBD	1	1	R&D investments improve energy efficiency. Factor substitution in a constant-elasticity-of-substitution (CES) production function. Carbon-free energy from backstop technologies (renewables) and CCS. Learning-by-doing for renewable energy. R&D investments in labour productivity. Learning-by-doing in resource extraction		
Gerlagh, 2006	DEMETER-1 CCS	LBD	1	1	Factor substitution in CES production. Carbon-free energy from renewables and CCS. Learning-by-doing for both and for fossil fuels.		
Masui *et al.*, 2006	AIM/Dynamic - Global	R&D	9	6	Factor substitution in CES production. Investments in energy conservation capital increase energy efficiency for coal, oil, gas and electricity. Carbon-free energy from backstop technology (nuclear/renewables).		Focus on energy efficiency with limited supply-side substitution.
Popp, 2006	ENTICE-BR	R&D	1	1	Factor substitution in Cobb-Douglas production. R&D investments in energy efficiency knowledge stock. Carbon-free energy from generic backstop technology	R&D investments lower price of energy from backstop technology.	

Rao et al., 2006	MESSAGE/MACRO CGE	LBD	1	11	Carbon-free energy from backstop technologies (renewables, carbon scrubbing & sequestration). Learning curves for electricity generation and renewable hydrogen production	Factor substitution in CES production in MACRO.	
Barker *et al*., 2006	E3MG, econometric	LBD and R&D	41	20	Cumulative investments and R&D spending determine energy demand via a technology index. Learning curves for energy technologies (electricity generation). Cumulative investments and R&D spending determine exports via a technology index.	Econometric model. Investments beyond baseline levels trigger a Keynesian multiplier effect. Sectoral R&D intensities stay constant overtime	Long-term costs of stabilization Income and production losses
Bollen, 2004	WorldScan CGE	R&D (and occasionally LBD)	12	12	ETC magnifies income losses.	Includes international spillovers. No crowding-out effect	Compliance costs of Kyoto protocol
Kverndokk *et al*., 2004	CGE model for a small open economy	LBD	1	1	Innovation subsidy is more important in the short term than a carbon tax. Innovation subsidy may lead to 'picking a winner' and 'lock in'	Numerical illustrative model	Optimal timing and mixture of policy instruments Welfare effects of technology subsidies
Popp, 2004	ENTICE, optimal growth	R&D	1	1	Impact on cost is significant. Impact on emissions and global temperature is small	Partial crowding-out effect	Welfare costs Sensitivity analysis of R&D parameters
Rosendahl, 2004	Builds on Goulder and Mathai (2000)	LBD	1	2	Restrictions on emissions trading are cost-effective. Optimal carbon tax in Annex I region is increased with external spillovers	Outcomes are sensitive to learning rate, discount rate and slope of abatement curve	Optimal carbon tax (or permit price) over time in two regions Optimal emissions trading +restrictions
Buonanno *et al*., 2003	FEEM-RICE optimal growth	R&D and LBD	1	8	Direct abatement costs are lower, but total costs are higher. ET ceilings have adverse effects on equity and efficiency.	Factor substitution in Cobb-Douglas production.	Impact of emissions trading (+ restrictions)

Gerlagh and Van der Zwaan, 2003	DEMETER Optimal growth	LBD	1	1	Costs are significantly lower. Transition to carbon-free energy. Lower tax profile. Early abatement	Results are sensitive to elasticity of substitution between technologies as well as to the learning rate for non-carbon energy	Optimal tax profile Optimal abatement profile Abatement costs
Nordhaus, 2002	R&DICE optimal growth	R&D	1	8	ETC impact is lower than substitution impact and quite modest in early decades.	Deterministic Full 'crowding-out' of R&D High aggregation	Factor substitution versus ETC Carbon intensity Optimal carbon tax
Goulder and Mathai, 2000	Partial cost-function model with central planner	R&D LBD	1	1	Lower time profile of optimal carbon taxes. Impact on optimal abatement varies depending on ETC channel. Impact on overall costs and cumulative abatement varies, but may be quite large	Deterministic One instrument High aggregation Weak database	Optimal carbon tax profile Optimal abatement profile
Goulder and Schneider, 1999	CGE multisectoral model	R&D	7	1	Gross costs increase due to R&D crowding-out effect. Net benefits decrease.	Lack of empirical calibration Focus on U.S. Full 'crowding-out' effect	Abatement costs and benefits

Appendix D: Review of Learning Rates for Electricity Generation Technologies in Bottom-up Energy System Models

Table D1: Review of learning rates for electricity generation technologies using one- and two-factor learning curves in selected bottom-up energy system models.

	(a) One-factor learning curves				(b) Two-factor learning curves			
Technology	**ERIS**	**MARKAL**	**MERGE-ETL**	**MESSAGE**	**ERIS**		**MERGE-ETL**	
Learning					**LBD**	**LBR**	**LBD**	**LBR**
Adv. coal	5%	6%	6%	7%	11%	5%	6%	4%
NGCC	10%	11%	11%	15%	24%	2%	11%	1%
New nuclear	5 %	4%	4%	7%	4%	2%	4%	2%
Fuel cell	18%	13%	19%	-	19%	11%	19%	11%
Wind power	8%	11%	12%	15%	16%	7%	12%	6%
Solar PV	18%	19%	19%	28%	25%	10%	19%	10%

Source: (IPCC 2007).

Table D2: Review of learning rates for electricity generation technologies using one-factor learning curves in selected bottom-up energy system models.

Technology Type	MESSAGE(a)	MESSAGE(b)	MARKAL(c)
Subcritical coal power plants	0%	0%	
Supercritical coal power plants	5%	3%	6%
IGCC	10%	10%	
Single cycle gas PPL	0%	0%	
NGCC	8%	7%	10%
Solar photovoltaics	15%		19%
Solar thermal PPL	7%		
Wind power	7%		10%
Conventional biomass PPL	4%		
Advanced biomass PPL	5%		
Renewable H2	10%		
Fossil H2	Exogenous (3-5%)		
Ethanol	10%		
Methonol	Exogenous (3-5%)		
Carbon capture and storage	13%		
High temperature fuel cell (coal)		10%	
High temperature fuel cell (gas)		10%	18%
CCS_coal		12%	7%
CCS_gas		12%	10%
CCS_IGFC		12%	
Hydrogen fuel cell CHP (Industrial sector)			18%
Hydrogen fuel cell CHP (Res. & Com. sectors)			18%
Advanced new nuclear			4%

(a) (Rao et al. 2006); (b) (Riahi et al. 2005); (c) (Rafaj & Kypreos 2007)