NATIONAL ENERGY TECHNOLOGY LABORATORY

Evaluating the Impact of R&D and Learning-by-Doing on Fossil Energy Technology Cost Reductions: There Can be No Learning if There is No Doing

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1 Executive Summary

Cost reductions from first of a kind to mature technology can be attributed to a combination of research and development (R&D) and learning-by-doing. The learning-by-doing effect was first observed in airplane manufacturing assembly lines, where increased worker experience led to decreased labor time and, as a result, cost reductions. Similar cost reductions and trends have since been studied and applied to capital projects, including energy technologies. This analysis explores the contributions of R&D prior to deployment and learning-by-doing on fossil energy technology cost reductions.

Numerous sources have used learning-by-doing curves to project future capital cost trajectories. However, caution should be taken when using this approach due to the following issues: wide variation in learning rates; learning curve analysis was designed to retrospectively determine learning effects, not predict cost reductions; it is difficult to separate impacts from R&D and learning-by-doing.

A learning curve analysis tool and cash flow model were constructed for carbon capture, utilization, and storage (CCUS) capital costs to quantify these effects. The results of this analysis show that without CCUS R&D prior to deployment, the opportunity to learn-by-doing does not occur because commercial entry costs are prohibitive.

2 Overview of Learning Curve Analyses

In the 1930s, aeronautical engineer Theodore Wright concluded that learning from experience was a factor affecting the cost of airplane manufacturing. He observed that the labor hours required for completing a given operation, such as constructing the airframe, declined when the operation was repeated and the workers' level of experience increased (Wright, 1939). In the early 1960s, Kenneth Arrow published a study that sought to formulate the effects of learning-by-doing more precisely and draw from it a number of economic implications (Arrow, 1962). Over time, the effect of learning-by-doing became known as the "learning curve effect"[1] and a variety of mathematical formulas have been developed over the years to estimate the cost decline that occurs as a new capital good is produced in greater numbers.

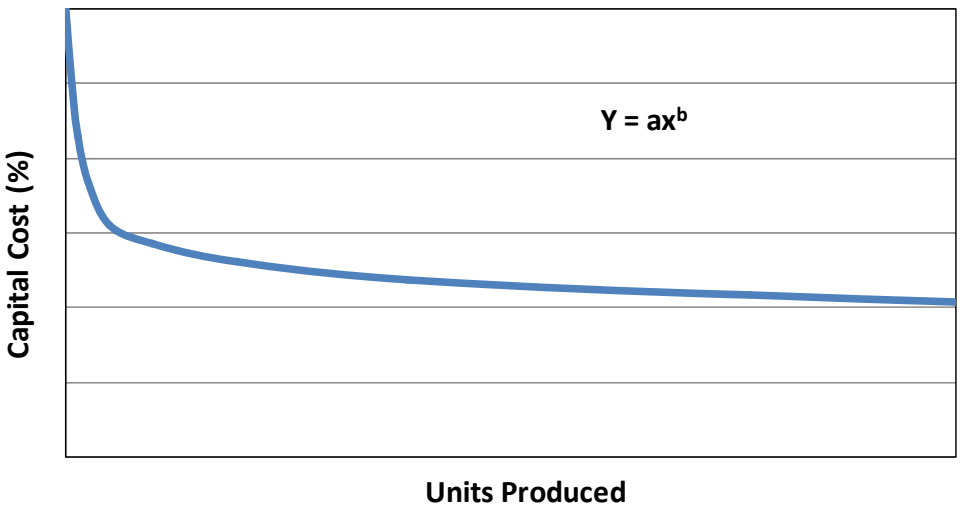
Exhibit 2-1 depicts a conceptual example of a learning curve that is often found in manufacturing or capital projects. Low values on the horizontal axis (units produced) represent a first of a kind process or technology that experiences significant reductions in capital costs during the early adoption phase. As more and more units are produced, the process is slowly perfected and additional decreases in capital costs are marginal. At this point, the process or technology is considered mature.

Such models are increasingly being used to analyze the deployment of energy technologies, including CCUS, and to predict reductions in costs associated with energy projects. Due to the learning curve effect, price forecasts for advanced energy technologies generally assume that the price will decline once the innovation is mass produced. For example, a recent study of large-

[1] This phenomenon is also referred to as the "experience curve effect" and the two terms will be used interchangeably in this paper.

scale offshore wind power in the United States included the learning curve effect in its price forecast (National Renewable Energy Laboratory, 2010). In another example, the Brazilian Energy Initiative sought to increase the commercial use of ethanol by setting mandatory targets that were expected to help bring the cost of ethanol down through the learning curve effect, thereby enabling ethanol to be a cost competitive option in the liquid fuels market when the regulation was no longer in effect (Goldemberg et al, 2003).

Exhibit 2-1. Conceptual Example of a Learning Curve.



Y = Capital Cost, as a percentage of initial capital cost
a = Cost of the first unit produced
x = Number of units produced
b = Learning rate exponent
$1\text{-}2^{-b}$ = Learning Rate; reduction in capital costs for doubling of units produced

However, while learning curves have become a common tool for forecasting the costs of new energy technologies as they penetrate the marketplace, concerns have been raised that there are significant uncertainties involved in the use of learning curves for cost trajectory predictions. One source of debate is the behavioral assumptions associated with learning curve behavior for analyses associated with energy technologies, i.e., the use of the classic log-log linear model (shown in Exhibit 2-1) versus an exponential model, and even the promotion of an S-shaped learning curve (Yeh and Rubin, 2012).

Another issue for learning curve analyses associated with cost reduction predictions is the choice of learning rate that is used within the model. These rates are typically chosen based on learning rates calculated using models of historical learning curves of similar projects from the past. This issue is especially pertinent for learning curve analyses of new energy technologies as large variations in learning rates associated with past projects exist for most energy technologies.

A study by McDonald and Schrattenholzer (2001) that focused on learning rates for energy technologies found large variations in estimated learning rates, even for the same energy technology, examples are shown in Exhibit 2-2. They found that some of the factors that accounted for the variability in the estimated learning rates included experience depreciation, short-term pricing behavior, varying intensities of R&D, economies of scale, differences in performance measures, definitional differences, and cost variability for factors such as land, wages, and interest payments. In their conclusion, McDonald and Schrattenholzer emphasized that "[m]ore work is necessary, however, to properly address [these] factors, particularly experience depreciation and the impact of R&D investments." (p. 260).

Exhibit 2-2. Varying Learning Rates of Energy Technologies.

Technology	Region of Study	Time Period of Study	Estimated Learning Rate	Reference
Coal Power Plants	USA	1960 – 1980	1.0 – 6.4	Joskow & Rose (1985)
Coal for Electric Utilities	USA	1948 – 1969	25	Fisher (1974)
Crude Oil at the Well	USA	1869 – 1971	5	Fisher (1974)
Solar PV Modules	World	1976 – 1992	18	IEA (2000)
Wind Power	USA	1985 - 1994	32	IEA (2000)
Wind Power	EU	1980 – 1995	18	IEA (2000)

Data Source: McDonald and Schrattenholzer, 2001

This highlights an important aspect of learning curves and the learning rates that are based on historical information; they include the effect of continued R&D. As pointed out by Rubin et al (2004): "[T]he observed cost decreases … reflect not only the benefits of learning by doing, but also those derived from financial investments in research and development to improve the technology and its production." (p. 60). Thus, it is difficult to determine what the true learning rate (i.e., in the absence of R&D effects) would be. Applying learning-by-doing directly likely overstates predicted cost reductions.

When undertaking a learning curve analysis, it is important to keep in mind that learning curves were developed as an empirical measurement of learning-by-doing in manufacturing, not as a predictive tool for estimating future costs (Jamasb and Kohler, 2008). As a result of the issues

discussed in this section, namely the debate over learning curve behavior and the many uncertainties associated with estimating learning rates, learning curve models alone do a poor job of accurately forecasting cost trends of new technologies and differentiating between the impacts of R&D and learning-by-doing.

3 CCUS Cost Reduction Analysis

The National Energy Technology Laboratory (NETL) manages a portfolio of laboratory and field R&D focused on capturing carbon dioxide from large stationary sources such as power plants, and sequestering it using geologic or terrestrial approaches. One goal of CCUS R&D is to decrease the capital costs associated with retrofitting existing coal plants with CCUS equipment. NETL intends to achieve this goal prior to commercial deployment of CCUS technologies so that it is cost effective. Once the first CCUS installation takes place, the costs of subsequent installations are expected to decrease as manufacturers and operators learn new and more efficient methods of design and operation.

However, in the absence of R&D, power plant operators will have to begin deployment of CCUS technologies at the current high cost of commercially available CCUS technologies. If these costs are prohibitively expensive, CCUS technologies might have limited or no deployment, in which case cost reductions from learning-by-doing would be minimal or non-existent. This suggests that if there is no cost reduction provided through R&D, then there might be no "doing"; and in turn, no cost reductions from learning effects.

The following analyses explore the contributions of R&D and learning-by-doing to future costs reductions in CCUS capital costs and assess the implications for CCUS deployment within the coal-fired power plant fleet.

3.1 Learning Curve Analysis

To model learning-by-doing for CCUS, a learning curve analysis tool was constructed. The tool uses the classic log-log linear learning curve equation, defined as:

$$\mathbf{Y = ax^b}$$

where:

Y = CCUS capital cost after installation on x plants, as a percentage of the initial cost

a = CCUS capital cost for CCUS installation on the first plant (100%)

x = Number of plants that have installed CCUS

b = Learning rate exponent

$(1 - 2^{-b})$ = Learning Rate, expressed as a percentage

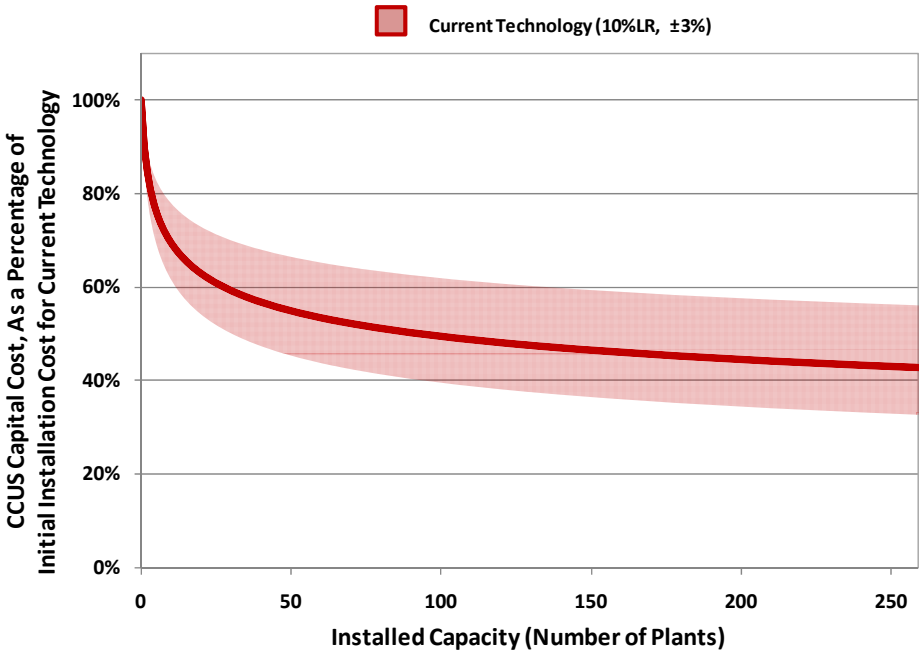
The behavioral assumptions of this particular learning curve model are associated with the fastest cost reductions over time as large decreases occur for the first few installations. As shown below in Exhibit 3-1, even under these assumptions, it still takes a substantial amount of capital investment (installed capacity of about 90 plants) for a 50% reduction in CCUS capital costs to

be realized through learning effects. Other formulations of the learning curve that are mentioned above would be even more conservative with regard to cost reductions and necessitate an even larger capital investment to achieve 50% cost reductions.

As noted in Section 2, the choice of the learning rate is critically important in constructing the learning curve. Historic learning rates for power plant technologies were 5% for pulverized coal units, 10% for gas turbine-combined cycle units, 11% for flue gas desulfurization systems, and 12% for selective catalytic reduction of NOx (Rubin et al, 2007). Citing similarities with flue gas desulfurization technologies, Riahi et al (2004) estimate a 13% learning rate for CCUS technologies. For the purpose of this analysis, a learning rate of 10% ($b = -0.152$) is assumed representing the average of the aforementioned learning rates; an error band representing a learning rate range of 7% to 13% is also assumed to reflect the inherent uncertainty in this assumption.

The learning curve tool was used to construct learning curves for CCUS without R&D at current technology costs and with R&D, assuming that Federal R&D is able to reduce costs by 50% prior to deployment. Exhibit 3-1 shows the influence of learning-by-doing assuming no R&D and current CCUS technology costs.

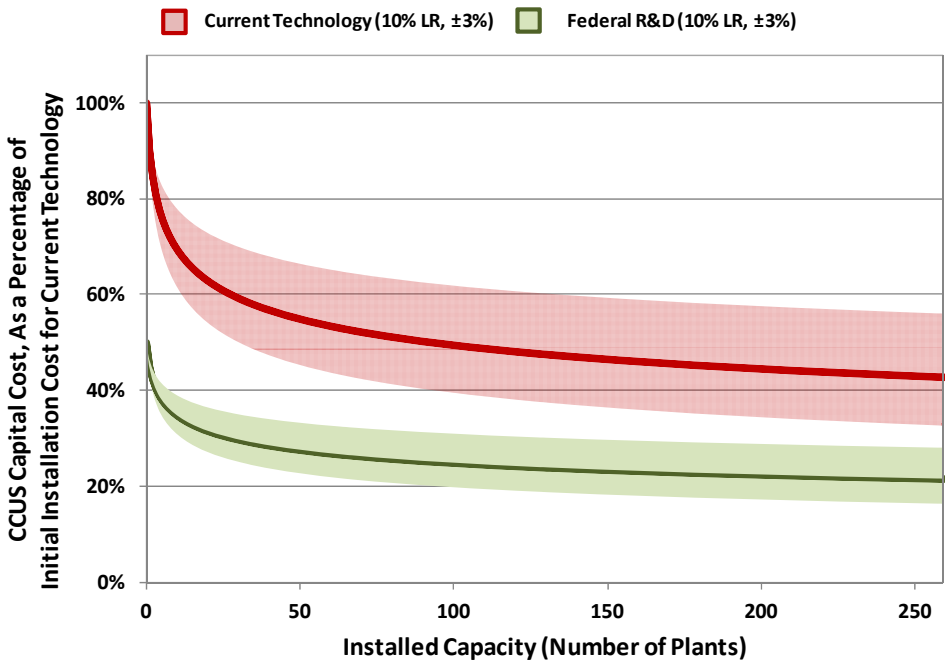
Exhibit 3-1. Learning Curve for CCUS, Current Technology Costs.



At a 10% learning rate, learning-by-doing achieves a 50% capital cost reduction after installation on 90 plants (approximately 77 GW capacity), at an estimated capital cost of $44.5 billion. At a 13% learning rate, 50% capital cost reduction is achieved after installation on 30 plants (approximately 26 GW capacity), at an estimated capital cost of $15.5 billion. If the learning rate were only 7%, learning-by-doing alone might never achieve a 50% capital cost reduction. Thus, an exorbitantly large amount of capital would have to be spent before achieving a 50% cost reduction without any Federal R&D prior to deployment.

A comparison of these results with the results for the case with Federal R&D (50% capital cost reduction before the first commercial installation) is shown in Exhibit 3-2. The green line starts at 50% to represent the cost reduction resulting from pre-commercial R&D. If a 13% learning rate is applied to the Current Technology costs and only a 7% learning rate is applied to Federal R&D costs, the two curves never intersect. This implies that at current costs, learning-by-doing effects alone never achieve the cost reductions that the Federal R&D in combination with learning-by-doing can achieve, even at the higher learning rate.

Exhibit 3-2. Learning Curve for CCUS, 50% Capital Cost Reduction.



3.2 Net Present Value Analysis

Cost reductions from learning-by-doing require the installation of CCUS on one or a few "pioneer" plants, or else learning cannot occur. However, if a technology is too expensive, the first installation will never occur. Thus, to validate the results of the learning curve analysis, it is necessary to determine if power plants would install CCUS technology in the scenarios presented, or make a different choice.

A spreadsheet-based cash flow tool was used to make this determination. The tool, described in an earlier report (Zelek, 2011), performs plant-level economic analyses of new technologies for capturing and storing CO_2 produced by existing coal-fired power plants. The model calculates the 30-year net present value (NPV) of cash flows for four options (retire the plant; continue to operate business-as-usual (BAU); retrofit with CCUS technology (amine scrubbers) for CO_2 capture; or build a new coal-fired plant with CCUS technology integrated into the plant design) at 381 individual coal-fired power plants in the U.S. In exercising the model, each plant "chooses" which option provides the best return, and the aggregate results are presented in tables and figures.

The tool only looks at current coal-fired capacity, and does not consider added capacity. In addition, the model is not a dispatch model (i.e., the plants are not "gamed" against each other, the electricity price is not affected by plant closings, and coal is not compared to other fuels). This model does not incorporate learning effects. It is simply used to determine how many coal-fired power plants would find a CCUS option to be the most economical choice in various CO_2 price ranges.

The following three cases are used to determine the implications of Federal R&D on CCUS deployment (all cases use NEMS forecast electricity prices under the proposed Kerry Graham Lieberman (KGL) bill and 2009 average delivered coal prices):

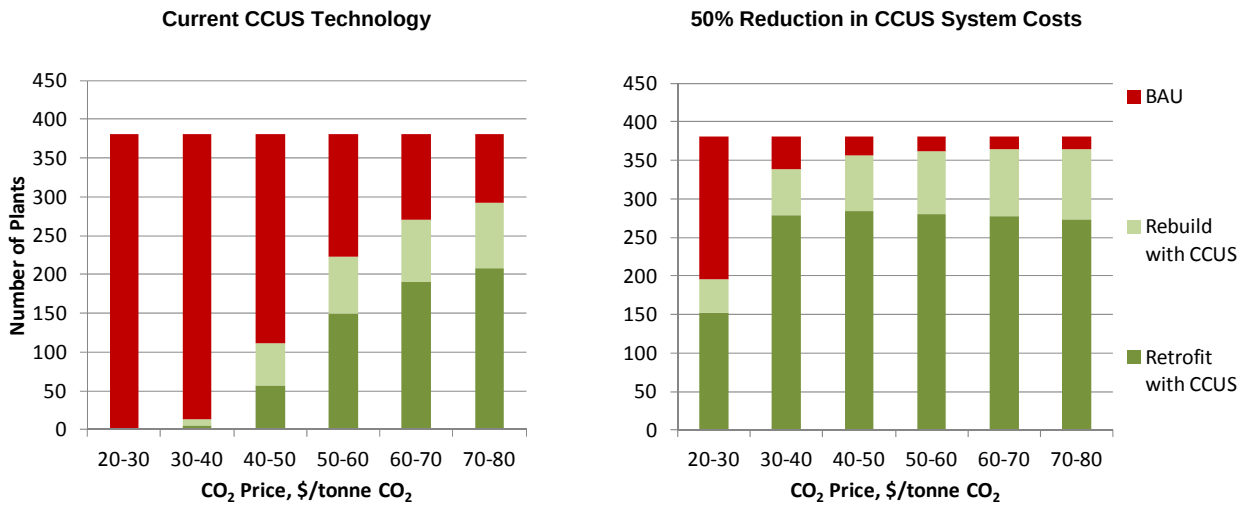
- **Current CCUS Technology case**, which uses current performance values and CCUS system costs from DOE/NETL reports and studies.
- **50% Reduction in CCUS System Costs**, which assumes that Federal R&D is able to reduce CCUS system capital costs by 50% and uses lower capital cost, fixed cost, variable cost and heat rate penalty assumptions.
- **25% Reduction in CCUS System Costs**, which assumes that Federal R&D is able to reduce CCUS system capital costs by 25% and uses lower capital cost, fixed cost, variable cost and heat rate penalty assumptions.

The cases were intended to answer the following questions: 1) Without Federal R&D prior to deployment, how many units would find CCUS to be the best economic choice?; 2) If Federal R&D is able to achieve a 50% reduction in CCUS system costs prior to deployment, how many units would find CCUS to be the best economic choice?; and 3) If the Federal R&D program only results in a 25% reduction in CCUS system costs prior to deployment, how many units would find CCUS to be the best economic choice?. These are not simple questions to answer because the decision to install CCUS depends on the balance between the cost of CCUS and the economic benefit of selling the CO_2 for uses such as enhanced oil recovery. Thus, the decision changes depending on the CO_2 price. This is best illustrated by a figure showing the number of plants that would choose each option under various CO_2 price ranges.

Exhibit 3-3 displays the results of the NPV tool for the Current CCUS Technology Case and the 50% Reduction in CCUS System Costs Case. In the Current Technology Case, at CO_2 prices below $30/tonne, no plants would find CCUS to be the best economic choice and therefore no learning-by-doing would occur. At higher CO_2 prices, the installation of CCUS becomes a good option for some plants. Learning-by-doing cost reductions could start to occur once CCUS retrofits and rebuilds become an economic option in the range of $30-$40/tonne; however, a vast

majority of the coal-fired fleet is still operating under a BAU option at this price and learning-by-doing costs reductions would be minimal. Without further cost reductions or CO_2 price increases, few additional plants would adopt CCUS. To reach the 90-plant installation level that would achieve the 50% reduction in CCUS system costs through learning-by-doing, the CO_2 price would have to be above $40/tonne.

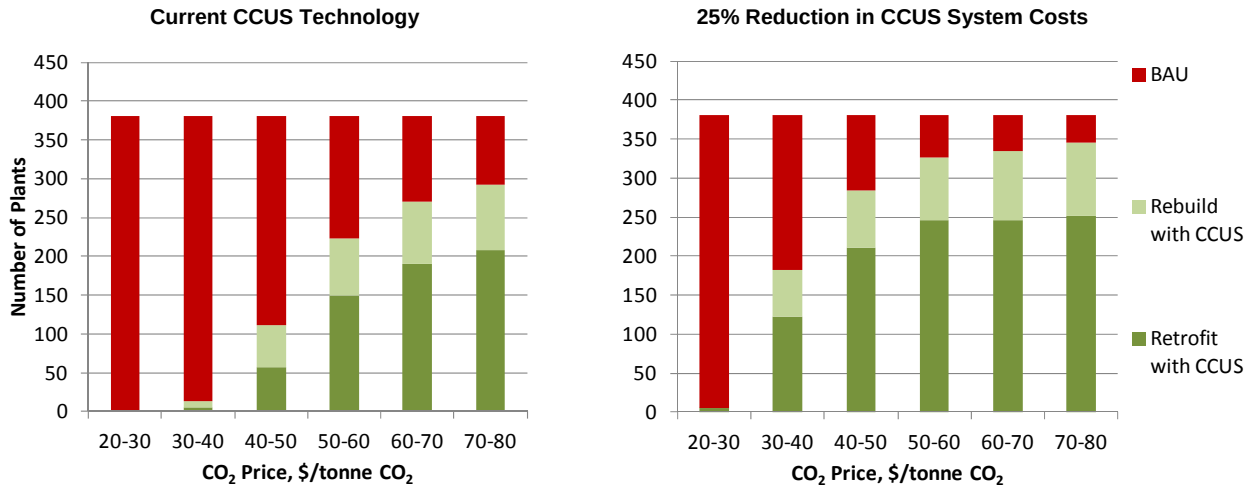
Exhibit 3-3. Coal-Fired Power Plant Choices as a Function of CO_2 Price: Current CCUS Technology vs. 50% Reduction in CCUS System Costs.



The effect of achieving the 50% cost reduction through Federal R&D on these decisions is substantial. At low CO_2 prices ($20-$30/tonne), less than half of the coal fleet would find operating under the BAU option to be the most economical choice and a substantial number of plants would find the best option to be CCUS (approximately 150 retrofits and 50 rebuilds). At CO_2 prices in the $40-$50/tonne range, there are fewer than 30 plants operating under the BAU option, and a large majority of plants find that CCUS is the best choice. At these higher levels of deployment, learning-by-doing will take place and promote further CCUS cost reductions.

The final case explores the effect of achieving only a 25% CCUS system cost reduction through Federal R&D. These results, shown in comparison with the Current Technology Case in Exhibit 3-4, show that very few plants adopt CCUS at CO_2 prices in the $20-$30/tonne range. However, at higher CO_2 prices, there are substantially more new builds with CCUS technology and CCUS retrofits than in the Current Technology Case. These results suggest that even if the Federal R&D is only able to reduce CCUS system costs by 25%, there is still value in the form of increased deployment and the earlier promotion of learning-by-doing.

Exhibit 3-4. Coal-Fired Power Plant Choices as a Function of CO_2 Price: Current CCUS Technology vs. 25% Reduction in CCUS System Costs.



4 Conclusions

Cost reductions in new energy technology can be expected to occur through some combination of R&D and learning-by-doing. This analysis has provided a deeper understanding of the complications that arise when attempting to use learning curves to predict the future cost trajectories of new energy technologies. Also, a cautious application of a learning curve tool in combination with NPV analysis for CCUS is presented as one way to overcome some of these complications and to explore the possible contributions of both R&D prior to deployment and learning-by-doing.

The learning curve analysis suggested that learning-by-doing could lead to substantial cost reductions in CCUS technologies; it suggested that learning-by-doing alone could achieve a 50% CCUS system cost reduction after installation on 90 plants. However, the NPV analysis suggests that the current costs of CCUS technologies are prohibitive and that there would be no deployment of CCUS at a CO_2 price less than $30/tonne and very little deployment at a CO_2 price less than $40/tonne. With zero or only a few initial installations, there would be little learning-by-doing, if any at all.

If Federal R&D prior to deployment is able to achieve a 50% reduction in CCUS system costs, substantial benefits result. At CO_2 as low as $20/tonne, enough plants choose CCUS to enable significant learning-by-doing. At higher rates, most plants find CCUS to be their most economical choice and a substantial amount of CO_2 is captured and stored. Similar, though less substantial, results occur even when Federal R&D is able to achieve a CCUS system cost reduction of 25%. Thus, the most significant CCUS system cost reductions and greatest chance of market penetration result from a mid range price for CO_2, Federal R&D prior to commercial deployment and learning-by-doing.

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