Learning and cost curves: Historical experiences

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Policy options to support future fuels deployment

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IMPORTANT DISCLAIMER

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PROJECT INFORMATION	
Project number	RP 2.2-04
Project title	Policy options to support future fuels deployment
Research Program	Research Programs 1 and 2
Milestone Report Number	Draft report reviewing cost curve shifts
Description	This project is designed to allow stakeholders to better assess the implications of policy options for a national Renewable Gas Target (RGT) and their implications for the broader adoption of future fuels. It considers alternative approaches to the design and implementation of a national RGT, their implications for Australia's future fuels mix and their implications for economic outcomes in the Australian States and Territories. Furthermore, this project will enhance stakeholder confidence with respect to potential policy and regulatory frameworks and their impacts on the sequence of events and investments necessary to ensure success and manage risks. This project will develop a broader understanding of the implications of RGT mechanisms for future fuels. It will explore a number of aspects of the design of an RGT to inform stakeholders on the likely outcomes of alternative RGT policies for the future fuels sector and the broader economy. The details of the policy scenarios will be discussed and agreed with the reference group, as will an appropriate baseline scenario which may relate to a policy "do nothing" scenario or a more concerted economywide intervention such as a carbon price.
Research Provider	The University of Adelaide
Project Leader and Team	Lead: Associate Professor Jim Hancock, University of Adelaide Ms Suraya Abdul Halim, University of Adelaide Dr John Kandulu, University of Adelaide Mr Anthony Kosturjak, University of Adelaide Dr Laurence Lester, University of Adelaide Dr Virginie Masson, University of Adelaide Associate Professor Liam Wagner, University of Adelaide
Industry Proponent and Advisor Team	Lead: Dr Dennis Van Puyvelde (ENA) Jordan McCollum (APGA) Rachel Cameron (Australian Gas Infrastructure Group) Jenny Thai (Australian Gas Infrastructure Group) Tania Coltman (Jemena) Hugh Smith (ATCO) Kiran Ranbir (ATCO) Eliza Cochrane (AusNet Services) Michael Probert (Department of Planning and Environment - NSW) Sophie Gove (Department of Environment, Land, Water and Planning - Victoria) Damien Moyse (Department of Environment, Land, Water and Planning - Victoria)
Related Commonwealth Schedule	RP1.1.3 Report on future fuels for decarbonisation of industrial, residential (heat), electricity, and other sectors delivered. RP2.2.2 Report on best practice policy solution to support successful adoption of future fuels delivered to industry, community and government stakeholders. RP2.2.3 Situation analysis and policy briefing documents for policy-makers and other key future fuels stakeholders delivered.
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Executive Summary

Australia’s renewable gas industry is at an early stage of its development. The two most prospective renewable gases, green hydrogen and biomethane, are presently produced only on a very small scale. The production activity at present comprises pilot tests and is a miniscule fraction of domestic natural gas consumption.

However, there is widespread interest in expanding renewable gases’ role in the energy system. There are several developments in planning which will, when completed, be much larger than the existing production facilities. It is clear that the renewable gas sector has substantial potential for growth.

The costs of renewable gases, relative to established energy types such as natural gas and electricity, are high at present, and consequently they are generally not cost competitive with those other forms of energy. But there are good prospects for reductions in costs if the markets for these renewable gases scale up. If that happens, producers can operate at greater scale and, simultaneously, they will accumulate knowledge that enables them to produce more efficiently.

As products move through their lifecycles from infancy to maturity, it is typical to see improvements in the efficiency of their production processes. Productivity improvements have been observed over many decades across many industries, products and countries. The reasons for these cost reductions include causes such as:

- the realisation of scale economies;
- learning-by-doing;
- learning-by-(re)search; and
- other forms of learning such as learning-by-interaction.

Given that there is scope for a very substantial growth of renewable gas use in Australia, there is also a potential for substantial cost reductions as a result of scale growth and learning effects. This report summarises the findings from a review of the literature on scale and learning effects as products progress from infancy to maturity and draws out lessons for the future of renewable gas in Australia.

Retrospective studies are not available for the renewable gases that are in prospect. This is inevitable, given the early stage of their development. Instead, we consider the evolution of costs for numerous other energy sources, drawing on a substantial body of existing research.

There are significant challenges in identifying the impacts of scale and learning. In principle, the two can be estimated in a straightforward way, but this relies on having suitable data. In practice, most datasets are inadequate in some ways, and this makes it difficult to separate the roles of scale and the different types of learning.

We focused in particular on findings from studies of solar PV and wind generation. These two technologies have had very large scale expansions over an extended period, both in an energy system context, and Australian energy market participants and policy makers have a degree of familiarity with them. Many of these studies do not separate the different roles of scale, learning-by-doing and learning-by research.

In the case of solar PV, there are numerous studies that estimate double-digit learning rates, and some in excess of 20 per cent. Many of these studies do not separate scale and learning effects. Moreover, a number of them relate to the early years of solar PV, prior to 2000. A recent study by Castrejon-Campos, Aye and Hui (2022), covering 2009 to 2016 in the US, reports a learning-by-doing rate of 7 per cent.

Estimates of learning rates for wind vary considerable across studies, but generally are lower than for solar PV. Schauf and Schwenen (2021) estimate learning-by-doing rates of 2 to 3 per cent and learning-by-search rates of 7 to 9 per cent, in terms of levelised cost of electricity, in a study of onshore wind in Europe over 1998 to 2018. Anderson, Leslie and Wolak (2019) consider the cost of installing wind projects in the U.S. from 2001-2015. Their results suggest that scale effects are quite small, with point estimates around 1 per cent. They also estimate parameters for learning from own experience and learning from others’ experience. Their results are quite imprecise; but suggest a learning-by-doing from own experience effect of 0 to 4 per cent and are too imprecise to say much about effects from others’ experience (conventional confidence interval selections suggest learning rates in the range 0 to 40 per cent, which is a huge spread).

It is apparent from the studies reviewed that there is large variation in learning rates (and technology cost reductions) across different technologies. When we seek to predict a learning rate for a new technology we do not know which mature technologies are a good basis for comparison. For example, we do not know whether solar or wind technologies provide a more useful guide to renewable gas cost curves.

We then simulate what might happen to renewable gas costs as a result of learning and scale effects, taking scenarios for green hydrogen and for biomethane. In both cases we consider a range of learning and scale effects, taking a 4 per cent learning effect and a 5 per cent scale effect as central scenarios. These scenarios are chosen on the basis that they sit in the middle of the range of high quality estimates that we identified for other technologies in the literature.

We present an illustrative scenario in which green hydrogen consumption grows from a starting point 25TJ in 2024 to 100PJ in 2035, a 4,000-times increase in size. To estimate scale and learning effects we must select assumptions about scale effects and learning-by-doing rates. Assuming a 4 per cent learning effect and a 5 per cent scale effect, the unit cost in 2035 is 68 per cent lower, other things held constant. We regard these assumptions as plausible based on past histories of learning, but materially different alternative assumptions are also plausible. Sensitivity tests show how the productivity gain varies with other plausible scale effect and learning rate assumptions. None of these scenarios should be interpreted as forecasts.

We present an illustrative scenario in which biomethane consumption grows from a starting point 100TJ in 2024 to 100PJ in 2035, a 1,000-times increase in size. We assume a 4 per cent learning effect and a 5 per cent scale effect, and this leads to a unit cost 60 per cent lower in 2035, other things held constant. We regard these assumptions as plausible based on past histories of learning, but materially different alternative assumptions are also plausible. We also present sensitivity tests. None of these scenarios should be interpreted as forecasts. While these scale and learning effects are plausible for biomethane, there is a risk that biomethane faces adverse productivity pressures in connection with rising infrastructure costs as the pursuit of biogas feedstocks pushes developers to more remote or difficult to extract sources.

The overall conclusion of this study is that there is a strong likelihood that the scale and learning effects that will emerge with industry development will bring substantial cost reductions for both green hydrogen and biomethane. However, the extent of these cost reductions remains highly uncertain.

If it were the case that cost reductions were entirely captured by firms whose decisions give rise to them, then one might conclude that firms have all the incentives that they need to develop new products and supply chains. However, this is unlikely to be the case, especially in respect of learning.

Cost reductions from learning are rarely captured entirely with a firm, and it is likely that at least some of the learning benefits will spill over to other firms in the renewable gas industry and ultimately to gas consumers. Markets can under-deliver on innovation effort when there are “spillovers” (of benefits from innovation). The problem is that there may be some innovations for which society-wide gains justify development costs, but for which the developer’s share of those society-wide gains is insufficient to cover costs. In such a situation the developer will not proceed with the innovation activity, even though it would be socially beneficial for it to proceed. Innovation effort is inefficiently low.

In cases where spillovers are likely to lead to inefficiently low innovation activity, there is a case on efficiency grounds for government intervention to support the innovation. This intervention might be in the form of a subsidy for the innovation activity. In the case of renewable gases, a renewable gas target mechanism seeks to provide that subsidy to renewable gas producers with the aim of promoting innovation in the supply chain.

1. Introduction

There are essentially two paths to decarbonise Australia's gas supply, these being electrification and renewable gases.[1] Of these two decarbonisation pathways, the renewable gas sector is still very much in its infancy. Costs of renewable gases are relatively high at present, but there are good prospects for reductions in costs albeit to an unknown extent.

The two most prospective renewable gases for stationary uses are green hydrogen and biomethane. It is possible that other renewable gases will over time emerge as contenders, but at this stage green hydrogen and biomethane seem the most likely to play a transformative role in the domestic energy supply.[2] The uptake of these gases will require, to varying degrees, innovations all the way down energy supply chains, from equipment inputs and skilled labour, through production processes, into transport, storage and distribution, and on to end user processes and appliances.

As industries move from infancy to maturity, there is a tendency for them to achieve cost reductions. This phenomenon occurs widely and has been observed over many decades across many industries, products and countries. The reasons for these cost reductions may include:

- the realisation of scale economies;
- learning-by-doing;
- learning-by-(re)search; and
- other forms of learning such as learning-by-interaction.

In most activities renewable gases are at present not cost-competitive with natural gas or the electrification alternative. But given that renewable gas supply chains are at an early stage of development, there are good prospects for reductions in costs if they are introduced into the energy mix. Just how far they will fall, and how widely renewable gas will be adopted, remains unknown.

The purpose of this study is to consider the potential for cost reductions in the renewable gas supply chain as its scale grows and producers and users become more experienced with renewable gas. Because there is no significant history of producing green hydrogen and limited experience with biomethane, we turn instead to indirect evidence. We review the historical experience for solar panels, wind generators and, based on very limited material, biogas.

Section 2 discusses theoretical issues around the measurement of scale effects and learning rates. Section 3 summarises the findings of a number of studies of learning rates in the energy supply system. Section 4 discusses the implications of different scale effect and learning rate scenarios for the future costs of renewable gases. Section 5 discusses implications for policy.

[1] The electrification pathway relies on replacing natural gas with renewable electricity, not coal or gas generation. A third possibility is that natural gas continues in use with offsets used to counter its emissions.
[2] Blue hydrogen with full carbon capture and storage (CCS) would constitute a net-zero emissions energy supply and could in principle contribute to decarbonisation alongside green hydrogen and biomethane. But at present CCS technology falls far short of achieving full capture, with no identified technology to get there. Synthetic methane, manufactured by extracting CO2 from the atmosphere then burning to release CO2 would also be net-zero, and could also in principle contribute to decarbonisation, but it remains well short of viability even on a prospective basis.

2. Theoretical perspectives on cost curves

"The cost of new technologies falls with increasing deployment, both for energy technologies and other industry sectors" (Neuhoff (2008)).

Economists have long had a keen interest in technological change, including its determinants, the pathways by which it takes effect, and its consequences. One of the important determinants of output growth is growth in inputs to the production process—inputs such as labour, capital and natural resources. But at least as far back as Abramovitz (1956), it has been recognised that, over the long run, changes in productivity are as important for output growth as changes in the quantity of available inputs.

Broad measures of productivity generally show an upward trend over the long term. But if we simply accept rising productivity as a long-run time trend, we learn nothing about what might drive productivity growth and what policies might influence it. In the words of Arrow (1962), "trend projections, however necessary they may be in practice, are basically a confession of ignorance, and, what is worse from a practical viewpoint, are not policy variables" [p. 155]. Arrow proposes that productivity depends on the amount of knowledge that is available to producers, and that the acquisition of knowledge occurs by processes of learning. Thus learning is a fundamentally important driver of technological change. Arrow focuses on a particular type of learning, the learning that comes with experience in production, known as "learning-by-doing"; later work acknowledges the importance of other forms of learning, such as R&D activity—"learning-by-search"—and the learning that arises when people associate and mix in workplaces and elsewhere—"learning-by-interacting".[3]

In essence, productivity growth means producing more with the same inputs (or producing the same with less inputs). Thus it requires changes in the ways in which inputs are combined and processed to produce outputs. Productivity growth may arise from a number of sources, including:

- the realisation of scale economies;
- learning-by-doing;
- learning-by-(re)search; and
- other forms of learning such as learning-by-interaction.

Changes in regulation may also affect productivity, insomuch as they cause changes in the way that production is carried out (either imposing constraints on the production process or removing constraints).

Scale economies arise because there are scale-invariant costs which fall in per-unit-output terms as output increases. These scale economies may come in many forms. For example, the costs of developing safety procedures for staff is unlikely to arise linearly as the number of staff increases. Another example is that the cost of providing security services to a facility is unlikely to increase in line with its output. In these cases, the cost per unit of developing safety procedures and providing security therefore falls as output increases.

Learning-by-doing is the process whereby the repeated act of producing a good or service enables producers to learn how to better allocate and manage resources to produce the product. Typically a producer will be able to use its resources more efficiently with each subsequent year of production which will, other things equal, reduce production costs. For example, a pipeline operator might learn that a particular valve configuration leads to problems transporting hydrogen gas, and would in subsequent years adopt a better configuration, resulting in cost savings.

Scale effects and learning effects are quite distinct in concept. If the scale of production of a good were held constant through its product lifecycle, there probably would still be productivity improvements from the learning process through that product lifecycle. But while scale and learning effects are conceptually distinct, they will often exist simultaneously. (If output of a product is growing year-by-year, the scale of production grows and simultaneously a learning process occurs as more and more experience is accumulated.) This presents a challenge for measurement, making it difficult to differentiate the impacts of scale and learning. The problem is

[3] Arrow says that "Learning is the product of experience. Learning can only take place through the attempt to solve a problem and therefore only takes place during activity" [p. 155].

not necessarily insoluble, but good data sources are needed to deal with it effectively. Often the data sources available for modelling fall short of ideal.

2.1 MEASURING THE IMPACT OF LEARNING

There is a vast body of work that seeks to identify the impact of learning on productivity. Here, we refer to productivity in its technical sense: quantity of output per unit input or its flipside quantity of input per unit output.[4] We measure this impact by calculating the *learning effect,* which in principle is defined as:

$$learning\ effect = -\frac{\%\ change\ in\ composite\ input\ requirement\ per\ unit\ of\ output|_{scale,regulation\ controlled}}{\%\ change\ in\ knowledge} \times 100.$$

The learning effect thus is an elasticity concept: it shows the per cent reduction in inputs per unit of output if the knowledge base is doubled (i.e. increased by 100 per cent).

While the intent of the learning effect measure is straightforward, there are several issues that arise in estimating it, relating to both the numerator and the denominator.

Measuring productivity change

The change in input requirement per unit of output is a measure of productivity, and specifically of production efficiency: if input requirement goes down, the production process has become more productive.

There are a number of factors that may affect productivity. When there are economies of scale in a production process, the input requirement will fall as output increases. And when regulations that affect the production process change, input requirements may go up or down, with consequences for production efficiency. For instance, tougher environmental regulations might increase the inputs required for a unit of output. These scale and regulation impacts are separate from knowledge, so to abstract from their influence we seek a measure which controls for them. The measure that is produced by controlling for them will then capture the changes in productive efficiency that are brought about by learning. We may also consider different learning channels—different ways of augmenting knowledge—as discussed below.

Sometimes the measurement of output is straightforward. For example, if we consider 91-octane petroleum, the product is highly standardised over time, and comparability issues over time are likely to be quite limited. In general, output measurement is straightforward for commodities, but more difficult for goods which have changing characteristics and attributes over time. Many products do have changing characteristics over time, for instance laptops, mobile phones, random access memory sticks, etc.

Measuring input requirement per unit of output is made more difficult when there are changes in the attributes of output. As products evolve over time, they may have new features added to them (or removed) which mean that they are not identical one year to another. For example, in the case of computers, a mainstream laptop today will have a significantly different specification to a widely purchased laptop a decade ago (which may not even be available on the market today). The laptop today will likely be more powerful (can run more processes in parallel), able to run more memory- and space-intensive applications, have a better battery, have a higher screen resolution, etc. A measure of productivity needs to take into account that the laptop today is different—better—than the one produced a decade ago. The standard approach is to use a notional quantity index, so that if the computer produced a decade ago is regarded as 1.0 units of computer then the computer produced today might be regarded as 1.5 units of computer. The quantity indexes could be calculated in a variety of ways, but a typical approach is to look at value differences in the beginning period; if the standard laptop a decade ago cost $1,000 and today's standard laptop cost $1,500 a decade ago, then today's standard laptop is counted as a 50 per cent greater quantity of laptop than the one produced a decade ago (see Australian Bureau of Statistics (2021)). Similar issues arise when there are changes in the attributes of inputs (e.g. when computers are part of the production process).

[4] The technical efficiency perspective is distinct from an allocative efficiency perspective, which is concerned with ensuring that the right output mix is produced, in the sense of being the most socially valuable output mix.

It is important as well to be clear on what the output is. Contrast, for example, the following:

- the manufacture of solar panels, in which case the main inputs will be labour and capital in the production process plus silicone solar cells, glass, metal for frames and electrical wiring;
- the construction and commissioning of solar PV installations, in which case the main inputs will be solar panels, building materials and electrical materials, and design, approval and construction services;
- the production of electricity from solar PV installations, in which case the main inputs will be solar PV installations and maintenance services.

The types of learning that affect productivity in each of these activities may be very different. In addition, an improvement in the productivity of solar panel manufacturing that is passed into prices will not be a productivity improvement for the construction of solar installations, but rather will be a reduction in the cost of inputs.

Measuring the change in knowledge

Turning now to the denominator in the learning effect calculation, we require an estimate of the proportional change in knowledge, which in principle is given by.

$$\%\ change\ in\ knowledge = \frac{learning}{knowledge} \times 100.$$

This measure is likely to be most meaningful if the numerator is construed as net learning (i.e. new knowledge less knowledge that becomes obsolete) and the denominator as net knowledge (i.e. accumulated learning net of obsolete knowledge).

In fact it is not practical to quantify knowledge, in net or gross terms, nor the changes in it in the form of learning and obsolescence. There is no established metric for knowledge, let alone data for it.[5] Therefore it is necessary to turn to proxies for the *change in knowledge*, which helps to sidestep the practical difficulties that would arise with knowledge accounting. But it is useful to keep in mind the changing stock of knowledge as the motivation for choosing the indicators to serve as proxies for changes in knowledge.

When we turn to proxies for the change in knowledge, it is desirable that the chosen proxies be truly representative of changes in knowledge. The selection of a proxy must be guided by both data availability and a judgement about relevance of the proxy.

Types of learning and proxies

The learning impact can be calculated separately for different types of learning, or simultaneously, with different indicators for each. A number of different types of learning may be relevant, including:

- learning-by-doing (learning from experience);
- learning-by-search (sometimes described as learning-by-research); and
- and learning-by-interacting—Samadi (2018).

The indicators that capture each of these types of learning will be different.

In the case of learning-by-doing, one approach to estimating learning has been to calculate the ratio of the current period output quantity to cumulative production over a run of several years—possibly going back to the introduction of the product. The logic is that knowledge moves in line with the number of units produced. An alternative to this is to measure learning as the ratio of current investment to accumulated investment. The logic for this approach is that learning has its effect through improvements in the configuration of production facilities as new facilities are built. Sheshinski (1967) notes that "If "learning" is a true phenomenon, the decision as to which description is more appropriate has, of course, to depend on the empirical evidence" [p. 569]. His results,

[5] The knowledge stock is akin to a capital stock. It is standard to measure the size of the capital stock in terms of its value, defined as equal to accumulated investment less an allowance for depreciation and obsolescence. But this approach is not available for the stock of knowledge.

which are now very dated, suggest that measures based on investment perform better than measures based on output.

The relative appropriateness of production versus investment indicators of learning will in fact vary from case to case. Arrow cites a study of the Horndal steel works in Sweden by Lundberg (1961). Lundberg found that, over a 15-year period in which there was no investment, output per man hour (a productivity measure) rose by 2 per cent. In this case the learning would appear to relate to what was learnt as more and more output was produced.

In the case of learning-by-search, a possible approach is to calculate the ratio of current year R&D spending to accumulated R&D expenditures. This cost-based approach is less than ideal as it makes no allowance for whether or not R&D spending was successful. An alternative formulation uses indicators of patent activity to proxy research output. A drawback of this approach is that many useful learning outcomes are not patented and, in addition, patents vary hugely in their usefulness.

It is also relevant to distinguish learning within firms and learning within industries. The most obvious source of learning-by-doing gains is gains within the firm. But it is possible that gains travel beyond the firm, for instance when employees and suppliers interact at network events, when employees and suppliers move from one firm to another, etc. Some studies have sought to identify separately the in-firm and across-firm impacts of learning-by-doing, but because of data limitations this is often difficult to investigate.

Estimation

Estimates of learning-by-doing effects can be distorted if they do not comprehensively control for all the factors that affect productivity. The problem is substantial when the omitted factors that affect productivity are correlated with the learning measure. When that is the case, an indicator of learning may pick up the influence of those other omitted factors, rather than the impact of learning itself. For example, suppose that an industry is growing, and has economies of scale but no learning effects. Because there are economies of scale, productivity will be increasing over time. If we estimate the impact of learning without allowing for scale, then we will find that productivity improves with learning, but this correlation is not causal. The risk is that we wrongly conclude that learning effects are present. Berndt (1990) discusses robust estimation with allowance for simultaneous learning and scale effects.

It is common to see studies that take a two-factor or multi-factor approach. For example, in the two-factor case, they may control simultaneously for learning-by-doing and learning-by-search. Two-factor and multi-factor specifications reduce the risks of biased estimates of learning impacts. A multi-factor approach is best practice, but it requires data that may not always be available.

Elia et al. (2021) review the state of learning assessments and note the inadequacy of one-factor learning models when there are multiple drivers of technology cost reductions (e.g. R&D, learning-by-deploying, input costs etc). Failure to allow adequately for the full range of cost drivers can lead to spurious results. One manifestation of this is that some studies produce negative estimates of learning rates. It is hard to rationalise a negative learning rate because it implies that the activity causes the stock of knowledge to shrink. While a loss of knowledge is possible under some circumstances as a result of atrophy—for example, ancient languages—it is hard to see how “doing” could cause this to happen. It is very likely that negative learning rates have more to do with inadequate model specifications, such as poor controls for other key cost drivers like economies of scale effects, market dynamics, and quality changes associated with the implementation of enhanced design standards.

An example provided by Elia et al. is the case of one-factor studies of nuclear pressurized water reactors (PWRs) in the US from mid 1950s to 1978. They refer to previous work that estimated the learning-by-doing rate based on unit capital costs ($ per W) for construction of PWRs was 18 per cent before 1970, but turned negative thereafter. They argue that the underlying cost data are affected by the challenges with operating new, more reliable reactors to adhere to more stringent safety regulations implemented after the Three Mile Island incident, and challenges with ramping up plant size with large-scale reactors (greater technical complexity), and associated impact on construction lead times, and that these factors were not adequately allowed for in the one-factor analysis.

In addition, the models used to estimate learning rates sometimes have a specification that imposes a constant learning rate.[6] But this may not be realistic. In reality, learning rates may, and probably will, change over time as the technology progresses through different stages of development (e.g. R&D, demonstration, rollout and full commercialisation). Some studies use specifications that allow for changes in the learning rate, but these are the exception.

Elia et al. conclude that the "development of multi-factor learning curve models and bottom-up cost models are still in their infancy." Learning-by-doing and learning-by-researching drivers are generally well studied, but other learning drivers such as market dynamics and learning-by-interacting across stakeholders and regions are less developed. They also consider the changing importance of different types of learning through the product cycle. They conclude that that "learning-by-doing, learning-by-researching and learning-by-interacting are important drivers at the earlier stage of development, while during commercialization stages, the pre-eminent drivers are market demand, supply-chain dynamics, and economies of scale".

Similar themes are developed by Söderholm and Sundqvist (2007). They note four important aspects that the analyst should take into account:

- it is important to perform a sensitivity analysis, for instance considering different time periods and variable definitions;
- omitted variable bias needs to be seriously considered—for example, failing to account for scale effects leads to a positive bias of the learning rate;
- "the issue of simultaneity in the technology learning rate estimations addresses the fact that diffusion and innovation are not independent variables"; and
- a time trend should be used to test the robustness of the estimates in terms of whether cumulative capacity actually captures the impact of learning-by-doing activities versus exogenous technical progress that occurs over time.

Learning curves

It is very common to see learning effects discussed in terms of a "learning curve", this curve being a graph of unit costs and some indicator of knowledge. It is also common to see discussion of "experience curves", a term which originates with Henderson (1968), and relates to learning-by-doing. Henderson, whose focus was on usable insights for corporate strategy, made a distinction between learning and experience curves. He argued that learning curves take into account only the production costs of the good in question. In contrast, he argued, it was important to take into account as well "R&D, sales expense, advertising, overhead, and everything else" [p. 1]. In practice, the terms "learning curve", in respect of learning-by-doing, and "experience curve" appear to be almost interchangeable, and the distinction between them is not necessarily maintained in empirical studies. See Castrejon-Campos, Aye and Hui (2022).

Experience was typically defined as the cumulative installed capacity of the technology, although other metrics such as the number of plants built and number of products made or shipped (e.g. PV modules) have also been used.

Two-factor learning curves were eventually developed to give a richer depiction of technological development. These added a measure of learning-by-search, for instance public R&D expenditure, to the experience measure in order to capture technological change more fully.

Multi-factor learning curve models have extended this approach by broadening the range of factors that have an impact on technology costs beyond cumulative production. They may include economies of scale effects, efficiency improvements for technological inputs, changes in input prices, change in technology mix, import penetration etc. This approach is advantageous because of its potential to minimise omitted variable bias. However, the scope to implement a comprehensive multi-factor assessment will often be constrained by data

[6] A conventional specification involves a linear relationship between logs of unit costs and logs of learning (conditional on other influences). This linear specification constrains the learning rate not to change.

limitations. Studies using multi-factor estimation approaches typically find smaller learning-by-doing effects than studies using one-factor estimation Yeh and Rubin (2012).

Joskow and Rose (1985) provide a good example of a comprehensive multi-factor assessment of a cost function for the building of coal-burning steam-electric generating units in the United States. They fit a model that estimates the impacts of numerous factors on the real cost per kw of construction of a generating unit. These are:

- the capacity of the generating unit to capture economies of scale in construction;
- the type of generating technology in terms of design steam pressures which affects thermal efficiency;
- regional average wages for construction workers to control for regional differences in construction costs;
- whether the unit was built with a scrubber and/or cooling tower to capture higher environmental performance;
- a time variable (i.e. dummy variable) to recognise units built during the period pf more stringent environmental regulations to capture any residual costs of meeting environmental restrictions not captured by the presence scrubbers or cooling towers;
- a measure of experience for the architect-engineer based on the number of cumulative “like” units;
- a measure of utility experience with coal units; and
- a measure of industry experience to capture learning affects that accrue to the industry as a whole.

Their results pointed to substantial economies of scale effects associated with the construction of generating units and also learning effects for utilities and architect-engineers.

2.2 RELATED APPROACHES

In addition to multi-factor experience curves, bottom-up cost models are being increasingly used to understand the influence of multiple drivers on technology cost developments. Bottom-up cost models are a method of cost estimation derived from the bottom-up engineering approach to cost assessment for technologies. They involve breaking down a technology into its component parts or tasks, estimating the costs of each individual element, and then summing up these costs to arrive at a total cost. Modern bottom up cost models extend beyond considering pure unit input costs to account for changes in input efficiencies, performance, scale effects and input mix. For example, a bottom up approach to quantifying the causes of photovoltaic cost decline may consider factors such as changes in production yields for wafers, cells and modules, module efficiency in terms of converting solar energy into electricity, silicon costs, PV manufacturing plant size, and area of wafers used to manufacture solar cells (Kavlak, McNerney and Trancik, 2018). While a bottom up approach provides insight into the relative drivers of cost improvement, they do not provide explicit learning rates. Instead, expert judgement is used to understand the extent to which outcomes for particular drivers are the result of learning versus non-learning factors.

Learning curve models seek to explain how the unit costs of a technology decline in response to accumulated learning. However, cost data are sometimes not readily available due to commercial considerations or because of accounting issues such as decisions about how to allocate overheads. In the absence of comprehensive cost data some studies resort to using prices as a proxy for costs. Such studies implicitly assume that margins are constant over time. If that assumption holds, then product prices and costs will move together.

But margins will not always be constant. One reason for this is that firms may have a changing degree of market power, which changes their ability to inflate margins. Another reason is that firms may, for strategic reasons, decide to “loss lead” at certain stages of the product cycle. Changes in production taxes and subsidies may also have an impact. In summary, margins may vary as a result of various market dynamics and industry structure effects (e.g. takeovers). For example, Thomassen, Van Passel and Dewulf (2020) observe that prices may not closely follow costs at the early stages of technology development. Margins may be maintained at a high level in the early stage of technology development in order to ensure a return on investment, and then decline over time as the technology becomes more dispersed and competitive pressures within the industry become more prominent. Some industries, such as energy production, are characterised by market power, and this may undermine price movements as an accurate measure of cost movements. As a consequence of these factors, extra care needs to be exercised when using and interpreting models based on prices.

2.3 KNOWLEDGE SPILLOVERS

When a firm engages in activities that produce knowledge, that knowledge is often useful to other parties, such as firms in the same industry. We say that knowledge “spillovers” exist when knowledge disseminates beyond the entity that creates it, especially when this happens in an uncontrolled or unplanned way. For example, knowledge that one pipeline operator creates about how to configure valves might be valuable to other firms who also reap cost savings by adopting it. The knowledge could be disseminated by the movement of employees, publications, presentations at industry fora, etc.

Knowledge spillovers are of special economic significance because markets tend to underinvest in them. Insomuch as firms reap benefits internally from knowledge-generating activities, they have incentives to engage in activities that generate knowledge them. But they have little incentive to carry out activities that benefit others, even though those activities are also socially valuable.[7] If the incentives are not present to “internalise” the benefits to other firms into the knowledge-creator’s decision, there is a case for a government intervention, such as a subsidy to the activity set at a level consistent with the value of spillovers.[8] The support could seek to boost production and investment, with a view to stimulate learning-by-doing, or it could seek to boost research activity, etc.

Learning-by doing spillovers are one of the main planks of the so-called “infant industry argument”: the argument that newly emerging industries should be supported to accelerate their growth with the goal of unlocking benefits down the track from learning-by-doing (or scale). When putting forward infant industry arguments, it is important to focus support on activities that genuinely can expect to achieve cost reductions, and to avoid those which are permanently dependent on support.

[7] For example, suppose that production at an early stage by Firm A incurs a loss of $1 million. Suppose also that if the production activity is carried out, Firm A can expect to earn profits of $600,000 and it will generate knowledge spillovers that create profits of $800,000 for other firms. In this case the social benefit from the activity is $1.4 million, which exceeds the $1 million cost, so it is efficient for the activity to proceed. It might be possible for the firms that benefit to make side payments of $400,000 or more to convince Firm A to carry out the activity but sometimes this will not be practical.

[8] While a firm that creates knowledge might be able to claw back the benefits going to other firms by means of intellectual property arrangements, not all knowledge can be or is captured in this way.

3. Case studies of learning and cost curve shifts

In this sub-section we report on selected studies which estimate learning rates in several energy sectors. These studies are drawn from the academic and grey literature relating to the impacts of scale expansions and experience and learning on costs across a range of energy technologies.

There is a vast literature investigating these issues for many different technologies/processes, and a selective approach is required. The approach that we have taken is:

- to review studies of the cost curves for solar electricity and wind energy and identify those that are of high quality and relevant to the questions of how scale and learning affect costs
- to identify high quality studies of the arrival and maturation of other technologies that identify the experience with a broader range of technologies/production processes

The "quality" criteria to guide selection place a premium on highly-ranked economics journals and grey research published by government agencies. We also consider materials published in other highly ranked journals and grey publications from consultants with relevant expertise. We have favoured studies that appear to deal simultaneously with scale and learning impacts (and we prefer those that treat "doing" and "research" separately). Among those studies, we priorities learning rate estimates which control simultaneously for learning-by-doing, learning-by-search and scale.

The key research question is: What is the experience across different industries and technologies with regard to scale- and learning-related cost reductions? Subsidiary questions are: To what extent are cost reductions localised versus universal? To what extent do cost savings spill over beyond the firms that carry out activities that create cost reductions.

3.1 GENERAL

Choi and Kim (2023) estimate one-factor and two-factor experience curves for lumpy (e.g. coal, nuclear) and granular (e.g. solar, wind) energy technologies to estimate local and global learning experiences in relation to energy technology deployment in Korea.

They conduct a literature review and report learning rates from the literature. The reported learning rates need to be interpreted with some caution as there is variation across studies in the factors that are controlled for and the learning measures that are used. They find that learning rates for solar PV are generally reported in the range 15 to 25 per cent, i.e. a doubling of installed capacity reduces input requirements per unit output by 15 to 25 per cent—see Table 1. Learning rates for wind power plants are generally found to be lower, ranging from 3 to 17 per cent for onshore plants.

Choi and Kim also make estimates of their own using one- and two-factor models.[9] They find a large learning-by-research impact for solar panels (+45 per cent for 2005-21). For wind generation, over 2004-21 they find a large learning-by-doing effect (17 per cent) and a large negative effect for learning-by-research (-25 per cent). Many of their estimated coefficients are not statistically significant.

Negative learning rates are difficult to justify on theoretical grounds and they probably arise from measurement error. Large negative rates for lumpy technologies may reflect that they have reached a mature stage of development and have incurred additional costs due to adoption of advanced technologies, more stringent environment regulation, and more demanding safety standards.

[9] The authors acknowledge the limitations of using one- and two-factor experience curves to project future cost trends given their inability to control for other factors, including institutional policy instruments, economies of scope and changes in prices for inputs.

Table 1: Learning rates for Solar PV and Wind from studies identified by Choi and Kim (2023)

Study	Technology	Geography	Model	Dependent cost variable	Experience metric	Other variables controlled for	Period	Learning rate
Mauleón (2016)	Solar PV modules	Global		Module prices	Installed capacity	In alternative model specifications: silicon prices, fossil fuel energy prices	1981-2013	23-35%
Sampedro and Gonzalez (2016)	Solar PV installation	Spain	1FLC	PV installation cost (€/Wp)	Cumulative installed capacity (kWp)		2001-2008 2009-2012	7.13% 0.16%
Gan and Li (2015)	Solar PV modules	Global	1FLC, MFLC	PV module cost per watt	Cumulative production	Silicon price, supply-demand gap, Chinese share in global PV output	1988-2006	5.2 to 16.2%
Wei et al. (2017)	Fuel cells	US(a) Japan(b)	1FLC 1FLC	Price per kW Price micro-CHP system	Cumulative production (kW) Cumulative units		2001-2015 2005-2015	0-5% 18%
Partridge (2013)	Wind power	India	MFLC (one experience metric only)	Investment cost per MW or LCOE	Cumulative installed capacity (MW)	Project capacity (MW), project capacity factor (%), regional dummy, exchange rate, and steel price and plant cost indices.	2005 - 2011	17.2% (investment cost) 17.7% (LCOE)
Klaassen et al. (2005)	Wind power	Denmark, Germany and UK	2FLC	Investment cost per kW	Cumulative capacity in MW Public R&D expenditure, lagged with knowledge depreciation factor		1986-2000	LBD: 5.4%, LBS: 12.6%
Ek and Söderholm	Wind power	Denmark, Germany, Spain, Sweden and the UK	MFLC (two experience metrics)	Windmill investment costs (US$ per kW)	Cumulative installed capacity of windmills (MW) globally Cumulative public R&D expenses, lagged with knowledge depreciation factor	Average size of wind turbines (kW) (returns to scale factor)	1986-2002	LBD: 17% LBS: 12%(c)
Söderholm and Klaassen (2007)	Wind power	Germany, UK, Demark and Spain	MFLC (two experience metrics)	Investment costs (US$ per kW)	Cumulative installed capacity of windmills (MW) Cumulative public R&D expenses, lagged with knowledge depreciation factor	Turbine scale, feed in tariff level	1986 - 2000	LBD: 3.1% LBS: 13.2%

Legend: 1FLC = one-factor learning curve, 2FLC = two-factor learning curve, MFLC = multi-factor learning curve, LBD = learning-by-doing (based on installed capacity), LBS = learning-by-searching (based on knowledge stock or R&D expenditure), LCOE = levelized cost of energy.

Note: (a) California Self-Generation Incentive Program. (SGIP).
(b) Micro-combined heat and power (CHP) program.
(c) Only statistically significant at the 12 per cent level.

Source: Choi and Kim (2023) and specific studies listed in the table.

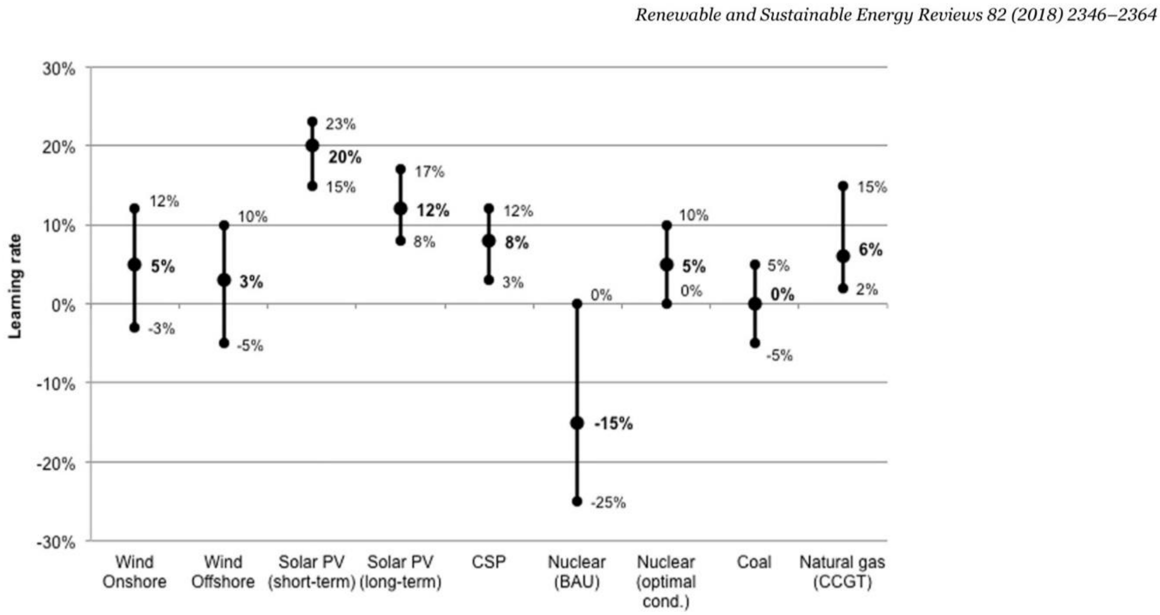
Samadi (2018) reviews the literature on experience curves for electricity generation technologies. A total of 67 studies were identified for eight different types of generation: wind onshore, wind offshore, concentrated solar thermal power (CSP), biomass, nuclear, coal and natural gas. Most studies focused on onshore wind or PV.

Samadi finds that learning rates tend to be higher for small scale generation technologies like solar and onshore wind than for larger scale technologies such as nuclear and offshore wind. This may be attributable to small scale technologies being able to achieve a higher level of standardisation, due to their modular nature, whereas for larger technologies the need for bespoke designs may limit the cost gains from expansion of the stock of generators.

Learning rates for onshore wind turbines, nuclear power plants and coal plants appear to have declined for more recent time periods.

Samadi's estimates of learning rates for the eight electricity generation technologies, including short and long term estimates for solar PV, are shown in Figure 1, which is taken from his study. Learning rates have been highest for solar PV (20 per cent for short-term and 12 per cent for long-term, on the central estimates). Central estimates of learning rates for wind were 5 per cent (onshore) and 3 per cent (offshore). It is important to note that these learning rates relate to the investment cost of the generator, rather than the cost of electricity generated (which depends in part on the load factor, which is an important consideration for technologies such as wind).

Figure 1: Estimates of plausible future learning rates for several important electricity generation technologies.



Source: (Samadi, 2018)

Jamasb (2007) uses simultaneous two-factor learning and diffusion models to estimate the effects of learning-by-doing and learning-by-research for twelve different energy technologies, using aggregate global data.

Traditional learning curve approaches treat unit cost as a function of cumulative experience, which is typically measured by installed capacity or cumulative production. However, the adoption or diffusion of a technology may itself increase in response to a reduction in unit costs. Jamasb allows for this two-way causal relationship by treating cumulative capacity (MW) as a function of unit cost of generation capacity (€/KW) and time (years). The time variable is included to separate out the effect of learning from research and doing from the exogenous progress that occurs over time. Knowledge stock here is measured by cumulative private and public R&D spending.

Jamasb groups energy technologies into four broad categories, based on stage of progress:

- mature (e.g. coal, lignite conventional, large hydropower)

- reviving (e.g. combined heat and power, CC gas turbine)
- evolving (e.g. nuclear, wind, waste to electricity)
- emerging (e.g. solar, offshore wind).

He then estimates two-factor learning-diffusion models (“Model-I”). In those cases that do not produce significant results he estimates traditional two-models (“Model-II”).

Jamasb’s estimates of learning-by-doing and learning-by-research effects are summarised in Table 2 below. On average the learning effects are stronger for learning-by-research than for learning-by-doing. (The average of learning-by-doing rates across these studies is about 10 per cent and the average of learning-by research rates is about 13 per cent.)

Table 2: Learning-by-doing and Researching Rates by Electrical Generation Technology

Technology	Maturing stage	Year	Learning-by-doing rate (per cent)	Learning-by-research rate (per cent)	Method
Pulverized fuel supercritical coal	Mature	1990-1998	4	6	Model-I
Coal conventional technology	Mature	1980-1998	12	1	Model-I
Lignite conventional technology	Mature	1980-2001	6	2	Model-II
Combined cycle gas turbine (1990-98)	Mature	1990-1998	2	2	Model-I
Large hydropower	Mature	1980-2001	2	3	Model-II
Combined cycle gas turbine (1980-89)	Reviving	1980-1989	1	18	Model-I
Combined heat and power	Reviving	1980-1998	0	9	Model-I
Small hydropower	Reviving	1988-2001	0	21	Model-II
Nuclear power (light water reactor)	Reviving	1989-2001	38	24	Model-I
Waste to electricity	Reviving	1990-1998	42	44	Model-I
Wind power – onshore	Reviving	1980-1998	13	27	Model-I
Solar power – thermal	Emerging	1985-2001	2	5	Model-II
Wind power – offshore	Emerging	1994-2001	1	5	Model-II

Source: Jamasb (2007).

The estimated learning-by-doing rates were highest for waste to electricity (42 per cent) and nuclear power (38 per cent), which both also had relatively high learning-by-research rates (44 per cent and 24 per cent respectively). Among the renewable technologies, onshore wind power exhibited a significantly higher learning-by-doing and research rates (13 per cent and 27 per cent) than offshore wind (1 per cent and 5 per cent). Large and small hydropower were both estimated to have low learning-by-doing rates (2 per cent and no effect), but modestly higher learning-by-research rates.

Jamasb produces data that demonstrate the tendency for one-factor models to overestimate learning-by-doing effects for newer technologies. Table 3 compares the learning-by-doing rates that are estimated using single-factor and two-factor models. Estimated learning-by-doing rates are universally higher under the single-factor approach for each of the technologies considered. The differences tend to be particularly pronounced for emerging technologies, such as thermal solar power and offshore wind.

Table 3: Learning-by-doing rates using single and two-factor models

Technology	Learning-by-doing rate, two-factor curves (per cent)	Learning-by-doing rate, single-factor curves (per cent)
Pulverized fuel supercritical coal	4	5
Coal conventional technology	12	15
Lignite conventional technology	6	8
Combined cycle gas turbine (1990-98)[a]	2	3
Large hydropower	2	3
Combined cycle gas turbine (1980-89)[a]	1	3
Combined heat and power	0	2
Small hydropower	0	3
Nuclear power (light water reactor)	38	53
Waste to electricity	42	58
Wind power – onshore	13	16
Solar power – thermal	2	23
Wind power – offshore	1	8

Note: [a] Learning rates for the two combined cycle gas turbine study periods as published by Jamasb (2007) in comparison to the single-factor curves estimates are flipped relative to the estimates published in the earlier tables. The correct assignment is unknown. For presentation purposes the earlier published learning-by-doing rates are assumed in this table.

Source: Jamasb (2007).

Thomassen, Van Passel and Dewulf (2020) review contemporary literature on learning rates to provide guidelines on how learning effects can be applied for prospective technology assessment. The review focused on studies in the period from January 2014 to March 2019. It reported results from 80 prospective studies and 51 retrospective studies.

The retrospective studies were assigned a quality ranking, in one of four categories, based on goodness-of-fit, sample size and the number of doublings of the experience variable (when there are many doublings, the implication is that the study covers a long span of learning). 3 of the studies were in the top category and 13 were in the second category, and the authors suggest that attention be confined to these studies. (Many of the studies in the lower categories were there because there was insufficient information to assess them, so they were not necessarily unsuccessful on statistical/sample criteria.) This quality assessment does not cover all relevant aspects, e.g. whether or not the study used one-factor or two-factor specifications and whether it controlled for scale. There were few studies that simultaneously controlled for learning-by-doing, learning-by-search and scale, and the ones that did had low quality rankings.

A total of 444 learning rates were identified from the reviewed studies. Figure 2, taken from Thomassen et al., shows the distribution of learning rates by technology type and whether the learning rate referred primarily to technological, economic or environmental performance. Technological performance here refers to enhancement of a technology’s capabilities, efficiency, or effectiveness (e.g. greater energy efficiency, reduced materials requirements), economic performance relates to improvements in unit production or capital costs, and environmental performance refers to the environmental impact of a technology, such as emissions potential or waste generation.

The study covered a broad range of energy technologies. Aside from solar and wind, the studies estimated learning rates for batteries, hydrogen production plants, hydrogen storage, compressors for hydrogen production, electrolysers, electrolysis, biofuels, biodiesel, gasification to methanol, gasification to hydrogen, pipeline compression capacity, etc.

The authors also present some rule of thumb estimates of learning rates by operational level (i.e. simple or complex task, and share of manual operations), technology level (i.e. mature, reviving, evolving and emerging), and industry level (aerospace, shipbuilding, repetitive electronics manufacturing etc.). The raw average learning rate across industry classes was about 13 per cent. The calculation base includes numerous studies which do not control for scale.

Figure 2: Learning rates

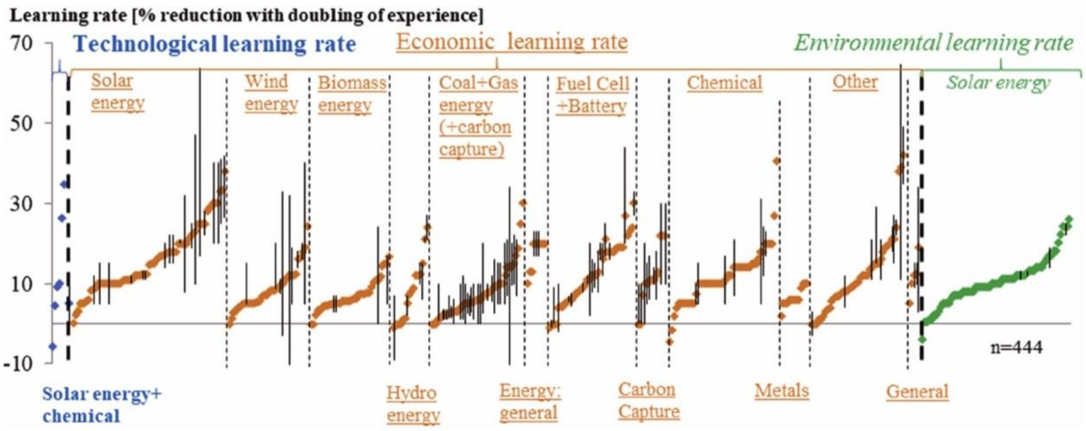


Fig. 3. Overview of the 444 learning rates in the reviewed papers, categorized according to sort of technology and technological (f.e. material requirement) economic (f.e. production cost) or environmental improvement (f.e. Global Warming Potential).

Source: Thomassen, Van Passel and Dewulf (2020).

3.2 SOLAR PHOTOVOLTAIC GENERATION

Elia et al. (2021) consider the role of innovation in driving energy technology cost reductions by reviewing a number of studies estimating multi-factor learning curves that have been constructed for onshore wind and solar

PV technologies. They note the importance of allowing for the full range of factors affecting the modelling of learning curves, including the influence of stage of development.

The studies that they report indicate that learning by doing effects are substantial for solar PV in both early stages (learning effect estimates range from 2 to 28 per cent) and mature stages (6 to 21 per cent) and substantial for onshore wind in early stages (10 to 31 per cent) but relatively small in mature stages (2 to 4 per cent). Scale effects exist in both early and mature stages, but are not particularly large (of the order of 1 per cent).

Nemet (2006) analyses the technical sources of photovoltaic (PV) capital cost reduction over the period 1975 to 2001 in order to understand the role of learning from experience. The analysis is conducted from worldwide data using weighted average cost for PV modules manufactured from mono-crystalline and poly-crystalline silicon wafers. The cost of PV modules fell 95 per cent over the study period.

Nemet al.so reports on the two most comprehensive world surveys of PV prices at the time of writing. A survey by Maycock (2002) produced a learning rate of 26 per cent, while a survey by Strategies-Unlimited (2003) gave a learning rate of 17 per cent. These estimates need to be treated with caution as they are based on simple one-factor learning curves that relate the change in the price of PV modules ($ per watt-peak) to cumulative capacity (MW). They consequently do not control for other non-learning factors, such as reductions in input costs and more efficient inputs due to technological learning occurring outside the solar PV industry, and are therefore probably biased upwards.

Nemet developed a bottom-up cost model which distinguishes seven of the most important factors affecting the cost of PV module manufacturing: module energy efficiency, manufacturing plant size, yield, poly-crystalline share which influences average module cost, silicon cost, silicon consumption per watt of PV module, and wafer size. These seven factors were found to explain about 60 per cent of the decline in cost over the period from 1975 to 2001. The model performed much better explaining the price change over the period 1980 to 2001 (95 per cent) than over the initial period from 1975 to 1979 (41 per cent).

The weakness of the model in explaining prices changes during the late 1970s can be attributed to important market dynamics during this period rather than learning-by-doing mechanisms. The market for PV modules during this period shifted from space to terrestrial applications, which led to a reduction in costs through a lowering of the required quality of modules. This shift in market composition also led to a shift down the demand curve given that customers with terrestrial applications would generally have a lower willingness to pay. Other important market factors that emerged during this period included an increase in competitive pressures due to an increase in suppliers which reduced industry concentration, and the standardisation of PV products with the increase in the number of customers. This suggests that experience curves need to be used with caution when using energy technologies such as fuel cells which are at the early stages of their development (Nemet, 2006).

Nemet found that, for the period from 1980 to 2001, plant size (43 per cent), module efficiency (30 per cent), and to a lesser degree, silicon cost (12 per cent), were the most important factors behind cost reductions. The other factors considered only made minor contributions.

Nemet argues that learning-by-doing played little role in the three main factors that drove the reduction in the cost of PV manufacturing. The size of manufacturing facilities built by new entrants increased quite rapidly, indicating that a lack of experience was not a limiting factor to increasing plant size. Rather, the ability to raise capital and willingness to undertake large scale investment were more important in expanding plant size. In terms of module efficiency, a majority of the major breakthroughs in cell efficiency were accomplished by universities which were not engaged in large scale production, emphasising the importance of fundamental R&D over learning-by-doing in driving efficiency improvements. Meanwhile, reductions in silicon costs were almost exclusively a by-product of manufacturing improvements made by the microprocessor industry. While learning-by-doing experience may have played a larger role in those other factors that contributed to the reduction of manufacturing PV modules, these factors ultimately only explain a small production of the overall reduction in costs (i.e. less than 10 per cent). Hence, Nemet concludes that there was only a weak contribution from learning-by-doing to cost reductions in PV.

Sens, Neuling and Kaltschmitt (2022) project capital expenditures and levelised costs of electricity for solar PV plants and onshore and offshore wind turbines in Germany for 2030 and 2050. They base their projections on one-factor experience curves, drawing on calculations of learning rates for the period 2012 to 2020, based on the unit capital expenditure (€ per kW) and cumulative installed capacity (GW). Learning rates are estimated for various components in each case:

- Solar PV plant: 29 per cent for the module, 11 per cent for inverter, 13 per cent for racks, 23 per cent for other (grid, cable connections etc);
- Onshore wind farm: 7 per cent for turbine, 27 per cent for foundation, 36 per cent for other components; and
- Offshore wind farm: 7 per cent for turbine, 5 per cent for foundation, 28 per cent for grid connection, and 26 per cent for other components (e.g. project planning and installation).

Castrejon-Campos et al. (2022) develop a model to assess the effects of different learning processes, specifically learning-by-deploying and learning-by-researching, on the costs of solar PV and onshore wind in the United States. Learning-by-deploying captures experience gained through learning-by-doing, learning-by-using and learning-by-interacting with different stakeholders. They consider a number of possible model specifications, including distinguishing the relative importance of global and local experience on cost developments.

The authors report recent estimates of learning rates for solar PV deployed in the USA. Of particular note are the two-factor models that they discover, which allow simultaneously for learning-by-doing and learning by research. One of these studies considers the period 1975-2000, and finds a learning-by-doing rate of 18 per cent, while the second covers the period 2009-16 and reports a lower, but still substantial, rate of 7 per cent. (The learning-by-research rates for these two studies were 14 and 75 per cent respectively). They also report the results of one-factor studies which have a median learning-by-doing rate of around 20 per cent, with this result potentially distorted by the omission of learning-by-research and other cost drivers.

Castrejon-Campos et al.'s own modelling work involves five different specifications, these differing in the mix of global and local knowledge leading to learning effects, whether knowledge stock leads to learning effects, and whether international knowledge spillovers occur. They conclude that "technology cost developments are better explained when: (1) experience is defined as a function of global and local experience; (2) knowledge stock is also considered in the model formulation; and (3) technological processes affect only a fraction of the total capital cost" (Castrejon-Campos, Aye and Hui, 2022).

They estimate learning rates for solar PV power generation technology for two periods: 1992-2009 and 2010-2020. The estimated learning rates exhibit large variability across the various model specifications and display significant shifts over time, including from positive to negative. The model that they regard as best-performing (2FLC-D) produces learning-by-deploying rates for solar PV in the USA of 16 per cent for the period 1992-2009 and 33 per cent for the period 2010-2020. (The corresponding estimated learning-by-researching rates were 46 and -60 per cent respectively.)

On a methodological level, the authors note that learning rates—learning-by-doing and learning-by-research—are dependent on context. Applying historical learning rates for one technology in one period to another technology at a different time can provide misleading guidance due to differences in technological and market dynamics, the stage of technology development, etc.

Castrejon-Campos et al. conclude that public investment in R&D is more effective in the early stages of technological development, while market deployment becomes more important in the more advanced stages of technological development.

They also find that the benefits of experience depend in part on a country's relative technical and market position within the global environment. For example, "if the country of interest possesses a strong domestic supply chain (i.e. manufacturing capability) and leads the development of the technology under study (i.e. the country is a technological leader), experience may be better represented by global experience (i.e. global installed capacity in this case). However, if the country's supply chain significantly relies on imports and follows technological trends (i.e. the country is a technological follower), experience may be limited to its domestic capacity." (Castrejon-Campos, Aye and Hui, 2022)

3.3 WIND GENERATION

As noted in the previous section, **Castrejon-Campos et al. (2022)** estimate the rates of learning-by-deploying and learning-by-researching for onshore wind and solar PV in the United States.

The authors identify recent estimates of learning rates for wind in the USA using different model formulations. They report on five two-factor models and one multi-factor model. Estimated learning-by-doing rates vary significantly, ranging from 4 per cent to 18 per cent. (Learning by research rates vary from 9 per cent to 37 per cent.) and display greater variability compared to estimates for solar PV. Excluding one negative result, the estimated learning rates ranged from a low of 4.2 per cent to a high of 40 per cent, with an average learning rate of 13.7 per cent. Although one-factor learning curve approaches are generally considered to lead to estimates of learning rates that are biased upwards, several of the two-factor learning curve models resulted in higher leaning by doing rates compared to the one-factor models.

Castrejon-Campos et al. also make two-factor estimates of their own, but there are questions over the robustness of their results They considered the three periods 1989-2004, 2004-2010 and 2010-2020, and found large negative learning-by doing and learning-by-research results. It appears that their data were affected by other factors that could not be controlled in their study—sharp rises in some input costs and changes to specifications.

Anderson, Leslie and Wolak (2019) investigate the extent of across-firm learning-by-doing and within-firm learning-by-doing in the design and construction of wind power projects in the US. They estimate various cost functions that capture firm-specific and across-firm knowledge, based on cumulative installed MW capacity or cumulative number of installed projects, whilst controlling for other factors that may influence costs, including changing input prices, scale effects, and exogenous technological progress.

The measurement approach makes allowance for various factors that influence knowledge acquisition and retention. These factors include that knowledge depreciates over time due to previous technologies becoming outmoded, that experience can be acquired through joint ventures and acquisitions, and that nearby projects may offer greater experience benefits than more distant projects due to familiarity with the local area (e.g. topographical conditions, local contractors). The model parameters are estimated based on wind power projects completed in the US between 2002 and 2015.

The authors find evidence of small firm-specific learning. Doubling of a firm's own experience is estimated to lead to a 1 to 2 per cent reduction in the cost to install a megawatt of wind generating capacity. Their results are inconclusive as to whether there are economically significant inter-firm spillover effects.[10]

Nemet (2012) assesses the existence of learning-by-doing (LbD) in a panel of onshore wind generation projects in California over the period from 1985 to 2003. California was a major centre of global wind turbine investment during this period, due in large part to a highly supportive policy environment. Wind turbine performance as measured by the capacity factor – i.e. the amount of electricity production in a given period as a proportion of full theoretical maximum electrical output that could be achieved over that period – improved by a factor of 4 from 1985 to 2005.

Learning-by-doing may lead to higher capacity through better decisions about both the installation and operation of wind turbines. The experience gained from installing turbines may lead to better understanding of where it is best to site new installations, taking into account for example about the microscale wind dynamics created by topography and adjacent turbine placement. Similarly, installing different types of wind turbines (in terms of efficiency, reliability, maintenance costs) may provide insight into what models are best suited for specific locations. Experience in the operation of wind turbines may provide knowledge about how to maintain equipment in order to minimise costs and preserve components, and when to schedule maintenance. Timing maintenance periods to coincide with less-windy periods is important to maximising electricity production.

Nemet finds evidence that firms learn from their own experience and the experience of others. However, both types of experience are subject to diminishing returns and also depreciate quite rapidly. The existence of diminishing returns suggests that learning from experience may perform best in terms of bringing about incremental improvements to existing technologies rather than radical transformations. Knowledge depreciates because of the loss of employees and because technological innovations sometimes make existing technologies obsolete. In the case of California, the nascent wind turbine industry was characterised by frequent bankruptcies and high employee attrition, which would lead to knowledge loss.

[10] Standard errors on coefficients for other firms' learning are large. While they generally cannot reject the null hypothesis "there are no inter-firm knowledge spillovers" they also would generally not reject the null hypothesis "the learning effect from other firms is 10 per cent" (which would be an economically significant learning effect).

Nemet finds that the benefits of experience were found to be stronger within projects than across projects within firms. He speculates that this may be due to knowledge gains being highly project specific and/or a lack of vectors to transfer the knowledge (e.g. experienced personnel moving from one firm to another).

Söderholm and Sundqvist (2007) develop a dozen different learning curve model specifications using panel data for wind power installations in four European countries: Denmark (1986-1999), Germany (1990-1999), Spain (1990-1999), and the UK (1991-2000). They find that learning rates differ significantly across different model specifications and econometric approaches. Their estimates of learning-by-doing rates range from 0 to 8 per cent depending on the model specification.

Qiu and Anadon (2012) estimate joint learning arising from learning-by-doing and learning-by-searching using bidding prices for the construction of wind farm projects greater than 50MW under China's national wind project concession program from 2003 to 2007. Their study uses a novel knowledge stock metric based on technology adoption by domestic technology development and international technology transfer, in contrast to the conventional measure of R&D investment.

The joint learning rate, which captures learning-by-doing of both manufacturers of wind turbines and developers as well as learning-by-searching (i.e. R&D), was significant and estimated to be about 4 per cent. There was little evidence of intra-firm learning but evidence of learning from the whole industry.

van der Zwaan et al. (2012) investigate drivers of costs for offshore wind power. Costs for offshore wind parks in Europe increased significantly from 2005 to 2008, due in large part to a surge in prices for copper and steel. Other contributing factors include capacity constraints experienced by manufacturers and system installers, the increasing sea depth at which turbines are built and the increasing distance from the shoreline.

The authors estimate a learning rate for offshore wind power construction projects in Denmark, the Netherlands, Sweden and the UK over the period 1991 to 2008. (van der Zwaan et al., 2012). After correcting for price fluctuations for copper and steel, a learning rate of 3 per cent is obtained, although there is limited statistical significance due to limited observations. A higher learning rate of 5 per cent is obtained if one restricts the analysis period to 1991 to 2005 in order to exclude market demand – supply imbalances that emerged post 2005. Distance from shore and depth were not controlled for.

Elia et al. (2021) use a bottom up cost model to understand what drove a decline in the costs of onshore wind turbines between 2005 and 2017, based in part on wind turbine prices for Vestas, a leading Danish manufacturer of wind turbines. The real annual average turbine selling price measured on a per kW basis fell by 31 per cent over this period, from US$1,348 per kW in 2005 to US$925 per kW in 2017[11].

Changes in material costs, legal and financial costs and improvements in labour productivity accounted for 30 per cent of the cost reduction over the period. Learning-by-deployment was the most important innovation driver, accounting for half of the cost reduction. However, these conclusions are partly driven by assumptions around the extent to which learning-by-doing, learning-by-research, supply chain dynamics, market dynamics etc, drives changes for particular cost components, and should consequently be treated with some caution.

The authors emphasise the importance of policies being tailored to the stage of technology development. Given that onshore wind turbines have entered a mature phase, the authors argue that it is more important to have in place a stable support scheme and appropriate regulatory and investment environment than to provide more support for R&D.

Schauf and Schwenen (2021) estimate learning rates for onshore wind in Europe over the period 1998 to 2018. They use country-level data and control for learning-by-doing, learning-by-search and scale. They note the very wide range of estimated learning rates from prior studies, and propose an estimation strategy which they argue is more robust.

They find learning-by-doing rates of 2 to 3 per cent and learning-by-search rates of 7 to 9 per cent in terms of levelised cost of electricity. They find that the learning arises mostly from improved siting decisions and not from

[11] Real prices expressed in 2016 US dollars.

efficiencies in installation costs. They also find economically significant economies of scale, in the range 5 to 16 per cent (per doubling of scale, with scale measured as assets of the turbine manufacturing sector).

3.4 BIOGAS AND BIOMETHANE

Biogas and biomethane—and biomass more generally—are well-established components of many countries' energy systems. However, we were not able to find studies that estimate learning curves for biogas and biomethane production from historic data.

There are a number of studies that consider historic learning rates for generation with biogas, biomethane and biomass. In some case they make assumptions about learning rates for biomass or biogas generation, but those studies will be affected by other factors, such as turbine costs. They may even exclude learning in the gas production component of the supply chain if they are constructed to cover only the downstream component.[12]

Junginger et al. (2006) use a case study approach to investigate whether a cost curve methodology can be used to estimate cost reductions for three types of bioenergy systems: biofuelled heat and power (CHP) plants in Sweden, biogas plants in Denmark, and fluidized bed boilers at a global level. Learning-by-using and learning-by-interacting are considered to be important learning mechanisms for biogas plants as they have a strong local dimension, whereas upscaling is found to be the main driver for cost reductions of CHP plants utilising fluidized bed boilers.

Junginger et al. note that biomass energy systems are more complex than some other technologies, such as wind turbines and solar, as they require fuel, which has an important bearing on the costs of electricity produced. An additional complexity is that biomass power plants are sensitive to local conditions, with plants being custom-designed to meet local conditions in terms of heat and electricity demand, infrastructure, and available biomass fuel types. In addition, biomass energy systems can produce more than one type of output, including a combination of electricity, heat, transportation fuels and polymers.

The estimated learning rates for the biomass energy systems are summarised below. The results need to be treated with caution as Junginger, de Visser et al. focus on one-factor experience curves, so are unable to control for other factors including the contribution of research and development, different plant layouts and scale.

Biofuelled CHP systems used to produce heat and electricity for district heating-networks in Sweden installed between 1980 and 2002. The learning rate for investment costs (i.e. plant construction) was estimated to be 23 per cent, however the correlation coefficient was very low ($R^2 = 0.21$). The learning rate in respect of the average production costs of electricity (€ per kWh) produced from biofueled CHP systems was estimated to be 9 per cent, with a much higher correlation coefficient (R2 = 0.85). The discrepancy in the correlation coefficient for investment versus electricity costs is thought to be explained by several factors, including investment costs falling as a share of total electricity production costs over time, fuel costs remaining stable through time, and average load factors improving significantly over time, which points to learning-from-using benefits.

Since the mid-1980s, twenty centralised biogas plants have been established in Denmark. The plants digest manure and organic waste to produce biogas. The biogas is transported to decentralized CHP plants to generate heat and electricity. These plants have been built by Danish contractors, which suggests that any learning effects in relation to investment have been locally concentrated. Learning rates were calculated based on the investment costs for each plant relative to the maximum daily digester capacity to process biomass (i.e. per normal cubic meter). A learning rate of 12 per cent was estimated with a modest correlation ($R^2 = 0.69$). They consider that investment costs may not be a reliable measure of technological learning because relatively few plants have been built, resulting in few data points, and productivity performance has also improved through the redesign and refurbishment of existing plants.

In response to these limitations, the authors develop an experience curve for the average production costs of centralised biogas, based on investment costs, annual operating and maintenance costs, and annual biogas production. The learning rate was estimated to be 15 per cent from 1984 to 1991, falling to around zero from 1991 to 2001. Junginger et al. suggest several explanations for the lack of learning benefits from 1991 onwards:

[12] For instance, a study of biogas or biomethane generation could take the gas purely as an input to the production process, and adjust out any cost variations. In this case the learning effect in gas production is excluded and the focus is narrowed to the generation activity.

basic plant design had been optimised by this stage following a period of experimentation including some setbacks; a decline in the quality of available industrial organic waste feedstock after the most suitable supplies were secured by the initial plants; and the liberalisation of the energy market discouraging new investments in biogas plants due to heightened uncertainty around future electricity prices.

In his extensive survey of generation learning curve estimates, **Samadi (2018)** reports on three studies relating to biomass generation (it is not clear whether gasification is involved). He notes that these curves are difficult to construct due to the non-standardised nature of the technology, with biomass power plants varying in the type of biomass feedstock used, technological approach, plant layout, and scale. The studies that he covers report learning rates in the range 2 to 15 per cent, relating to early-stage development. It appears that they may not have controlled for scale and learning-by-search effects.

A lack of detailed data has also contributed to the lack of empirical studies of experience curves for investment costs of biomass-fuelled power plants (Junginger et al., 2006).

Lin and He (2016) model the impact of a number of factors on the investment costs and the levelized cost of electricity for biomass power in China over the period 2005 to 2012. They account for learning-by-doing effects, economies of scale, policy environment etc. using detailed firm-level data.

Lin and He's model includes controls for a range of factors including individual project installed capacity, whether the project proponent is state owned, changes in material costs based on steel price and industrial producer price index, year dummies to control for economy wide factors on firm performance, district dummy variables to capture regional differences in regulation and labour costs. In addition to most of these factors, the full model of levelized cost of electricity considered changes in biomass costs and wages. Lin and He also sought to individually capture learning-by-doing and learning-by-search effects using patent data as a measure of knowledge stock. However, there was a high correlation between the experience and knowledge stock, meaning the two learning effects could not be separated.

Lin and He report six alternative learning curve models of investment costs which show learning effects of 6 to 8 pe cent. The learning curve models of levelized cost of electricity also showed a significant learning rate effect, ranging from 2 per cent to 6 per cent depending on model specification. Economies of scale could not be detected in the model of investment costs, but were present in the model of electricity production costs.

One odd aspect of their results was that stronger policy support appears to have had a negative effect on technology improvement. Lin and He suggest that this may occur through mechanism such as artificially encouraging plants to be built in less favourable areas. Measurement issues may also have played a part.

Millinger et al. (2017) simulate the future competitiveness of advanced and conventional biofuels produced from biomass for use in road transport in Germany. Due to a lack of historical data, the authors adopt simplifying assumptions for the learning rates for plant investment varying according to the maturity and complexity of the technologies. For relatively mature biofuels such as biomethane, bioethanol and biodiesel they assume a learning rate of 5 per cent. Emerging biofuel technologies were considered to have greater scope for learning, and higher learning rates were assumed for these technologies, specifically 10 per cent for synthetic natural gas and biomass-to-liquid, and 15 per cent for bioethanol from lignocellulosic biomass. These presumed rates are guided by assumed rates adopted by Neij (2008) and Chen, Khanna and Yeh (2012). Neij suggests a learning rate of 15 per cent for the logistics and production of bioenergy feedstock, and a learning rate of 5 per cent for conversion technologies (i.e. biomass to fuel, electricity).

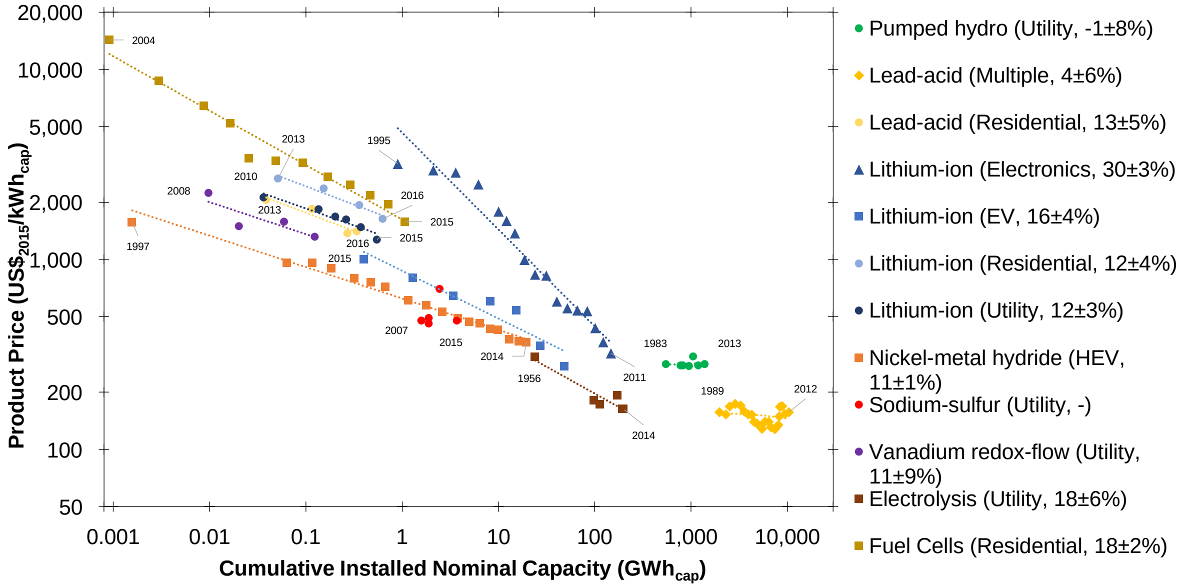
3.5 OTHER

Electricity storages are an increasingly important component of the electricity system. How the costs of electrical energy storage evolves will have a significant bearing not just on the uptake of these technologies, but also on electricity prices and the uptake of intermittent generators such as wind and solar. As part of a cost projection exercise, **Schmidt et al. (2017)** construct experience curves for 11 electrical energy storage technologies using historic product prices (US$ per kWh) and cumulative installed capacities (GWh). Taking a global perspective, they draw on data from existing academic literature, grey literature, energy storage databases and interviews.

Figure 3 shows Schmidt et al.'s estimated experience curves for the various energy storage technologies. Most energy storage technologies have exhibited declining unit product prices with increasing cumulative installed capacities. The main exceptions have been pumped hydro and, to a lesser degree, lead-acid modules for multiple applications (e.g. heavy duty transport, uninterruptible power supplies). The lack of learning for lead-acid modules would largely be explained by the mature state of this technology.

In terms of hydrogen technologies, the learning rate for electrolysis in utility applications is estimated to be 18 per cent, while fuel cells in residential use are also found to have an 18 per cent learning rate. Lithium-ion batteries in electronics are estimated to have the highest learning rate (30 per cent) among storage technologies. Learning rates for lithium-ion storage in other applications were lower, including in electronic vehicles (16 per cent), residential (12 per cent) and utility-scale applications (12 per cent). A lower learning rate for lithium-ion in these other applications would be partly due to the larger scale nature of these applications – such installations occur less frequently and therefore provide less opportunities for learning. However, it would also reflect a combination of different levels of market maturity and associated scale effects that have not been controlled for in the one-factor experience curves used here. Such scale effects reflect that lithium-ion batteries in electronics are a relatively mature technology that has reached widespread deployment, whereas their use in other applications is still at an earlier stage of deployment, with greater scope for realising future economies-of-scale benefits.

Figure 3: Experience curves for electrical energy storage technologies



Source: Schmidt et al. (2017)

Böhm, Goers and Zauner (2019) present a component-based analysis of potential cost reductions for electrolysis and fuel cells. To this end they review the literature and make estimates of learning-by-doing rates for a number of components for alternative electrolysis technologies (polymer electrolyte membrane (PEM), alkaline electrolysis cells (AEC) and solid oxide electrolysis cells (SOEC)). They use component learning rates in the range 5 per cent to 18 per cent. It is difficult to assess the basis for these estimates and, in particular, whether they incorporate effective controls for scale and R&D.

Santhakumar et al. (2021) apply the experience curve approach to three emerging offshore energy technologies: offshore wind, wave and tidal, and biofuel production from seaweed. They summarise studies of learning rates for offshore wind technology which have estimated learning rates of 8 per cent for investment between 1991 and 2001, 3 per cent between 1991 and 1997, and a negative learning rate for investment over the period 1991-2012 (which reflects an increasing cost trend in the 2000s, reflecting commodity price trends, changes in project location such as deeper waters; thus the study fails to control for relevant non-learning factors and is distorted).

The authors also report learning rates from past studies that range from 5 to 15 per cent for tidal stream technology, 3 to 18 per cent for wave energy technology, and 6 to 20 per cent for tidal stream and wave energy technology. Wave and tidal stream technologies are emerging technologies and there is limited empirical evidence to validate past studies. Therefore a disaggregated approach involving component-based experience curves is considered a superior approach for modelling future cost reductions. The authors note that Carbon Trust (2011) uses this approach, combined with engineering analyses, to estimate learning rates for different components for wave and tidal energy technologies. For example, in terms of tidal energy, they estimate learning rates of 12 per cent for structure and prime mover, 13 per cent for power take-off, 12 per cent for station keeping, 2 per cent for connection, 15 per cent for installation, and 18 per cent for O&M.

3.6 OVERVIEW

These studies produce widely varying estimates of learning rates. Even for the mature technologies that have been studied, there is still considerable uncertainty around estimated learning rates. But some generalisations can reasonably be made.

- there are numerous reports of double-digit learning rates in the literature, but frequently they represent a combination of learning-by-doing, learning-by-research and scale effects;
- studies that simultaneously control for doing, research and scale (or just two of them) often have unstable parameter estimates;
- in those studies with stable parameters, the learning-by-doing effects are often smaller than learning-by-research and scale;
- it is sometimes suggested that learning-by-doing effects weaken as the product matures, but there is no consistent support for that conjecture in the studies considered here; and
- for given technologies there is considerable variation across studies in learning rate estimates (which cannot all be correct); and
- there is considerable variation in reported learning rates across different technologies.

The studies reported here suggest that there is considerable variation in learning rates across technologies. Therefore there is no single generic learning rate that could be expected to hold for a new technology.

It appears that an unconditional combined learning rate and scale effect of 9 per cent is likely a reasonable estimate of the average effect across technologies. Strictly speaking learning rates and scale effects are not the same thing and should not be added. But in studies that omit allowance for learning rates, learning-by-doing is likely to be picked up in estimates of scale effects, and vice versa. The unweighted average of midpoint technology learning rates from Samadi's (2018) review was 7 per cent. In the model estimates made by Jamasb (2007) study, the average "learning-by-doing" rate after controlling for learning-by-research, was 9 per cent but this figure appears to conflate both learning-by-doing and scale. But as can be seen in the review of learning curves the range of estimates is large and it is not possible to rigorously identify an estimate of the average.

A learning effect of 4 per cent and a scale effect of 5 per cent would be roughly consistent with a 9 per combined effect.

4. Some scenarios for renewable gas costs

In this section we consider the potential for growth in renewable gas production in Australia and the potential learning effects arising from it.

In 2020/21, Australian domestic consumption of natural gas was 1,570PJ, with 990PJ of this being final consumption (DCEEW 2022). Green hydrogen production and consumption volumes are miniscule, estimated to be less than 1PJ per year at present, but with plans for significant new developments over the next couple of years. Biomethane production volumes are also very small.

4.1 HYDROGEN

As of late 2022, Australia's largest green hydrogen electrolyser was a 1.25MW unit at Hydrogen Park South Australia. The potential output may be of the order of 10 TJ per year. A number of other larger hydrogen electrolysers are under development, for example a 10MW electrolyser at Karratha, WA, with commissioning in 2024, and a 250MW electrolyser planned for South Australia' Upper Spencer Gulf, which is expected to be the largest in the world, with commissioning in 2025.

For the purposes of illustration, we consider a scenario in which Australian green hydrogen production increases from 25TJ in 2024 to 100 PJ in 2035, a 4,000-times increase. We assume scale effects of 5 per cent and a learning-by-doing rate of 4 per cent. In combination these two factors drive cost reductions of about 8 per cent per doubling of scale/experience, which sits in the midst of the range of learning rates reported in the previous section.

We identify changes in scale and learning associated with growth of the green hydrogen industry and apply the scale and learning effects, year by year, to estimate cost reductions year by year.[13] Figure 4 below shows cost trends from 2023 to 2035, under this scenario. With input prices held constant, the production cost of green hydrogen is reduced by 68 per cent over the 12 years to 2035.

The extent of cost reductions is strongly dependent on the assumptions regarding the strength of scale and learning effects. Table 4 shows the ultimate (2035) cost reductions under alternative scale effect/learning rate combinations. With the minimal gains scenario, unit costs of green hydrogen fall by nearly a half. On the most optimistic scenario, they fall by 80 per cent.

The range of cost impacts in Table 4 is wide. But even if we discount the "high" scenarios, and confine attention to the upper two and leftmost two rows, the cost reductions are of the order of one half to two-thirds. The scale and learning rates are consistent with what has been seen for other technologies.

Table 4: Scenarios for reductions in green hydrogen costs in 2035

Scale effect:	3 per cent	5 per cent	7 per cent
Learning rate:			
2 per cent	46	58	68
4 per cent	60	68	75
6 per cent	68	75	81

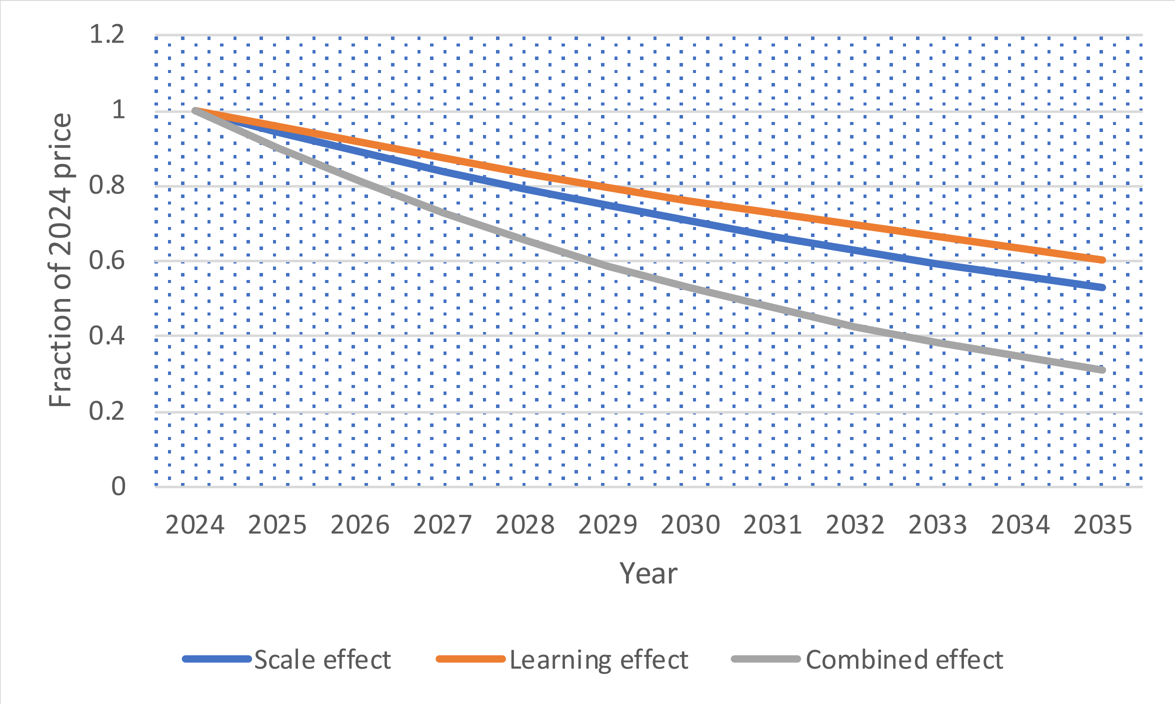
Source: SACES calculations

[13] The formula used is

$$Cost\ index_t = \frac{1}{100}\left(100 - scale\ effect \times \log_2 \frac{scale_t}{scale_0}\right)\left(100 - learning\ rate \times \log_2 \frac{learning_t}{learing_0}\right)$$

where scale effect and learning rate are expressed as percentage reduction in costs per doubling of scale/cumulative output and t indexes the year.

Figure 4: Scenario for green hydrogen scale and learning effects



Source: SACES calculations

4.2 BIOMETHANE

Biomethane production volumes in Australia are also small in the context of gas consumption. Domestic consumption of biogas in 2020/21 was just 18.0PJ, with 13.2PJ of this being landfill gas and 4.8PJ being other biogas. Very little of this is converted to biomethane. As recently as 2021 there was no commercial-scale biogas to biomethane conversion in Australia (Enea and Deloitte for ARENA, 2021). Very recently Jemena has commenced a pilot injecting biomethane into its Sydney distribution network at its Malabar Biomethane Injection Plant. The Plant has an initial capacity of 95 TJ. Renewable gas consumption thus amounts to about 1 per cent of natural gas consumption. Its share of gas delivered over distribution networks is even smaller.

Australia's Bioenergy Roadmap (Enea and Deloitte for ARENA, 2021) reports that that there is significant potential for bioenergy in Australia's gas grid. However, there is presently no commercial-scale biogas to biomethane conversion. The *Roadmap* suggests that under a "Business as Usual" scenario biomethane could account for 39PJ of Australia's pipeline gas by 2030. Under a "Broad Use" scenario it reaches 50 PJ and under "Targeted Deployment" it reaches 105 PJ.

The challenges in bringing biomethane into the energy mix are quite different to those arising with green hydrogen. There is a need to capture biogas at points of emission, and this may limit the potential for large-scale purification facilities. Once biomethane is extracted from biogas it is essentially indistinguishable from natural gas in pipelines. There are significant challenges with biomethane relating to how to capture the biogas and how to transport it to consumers; challenges with purification are in significant degree due to small scale.

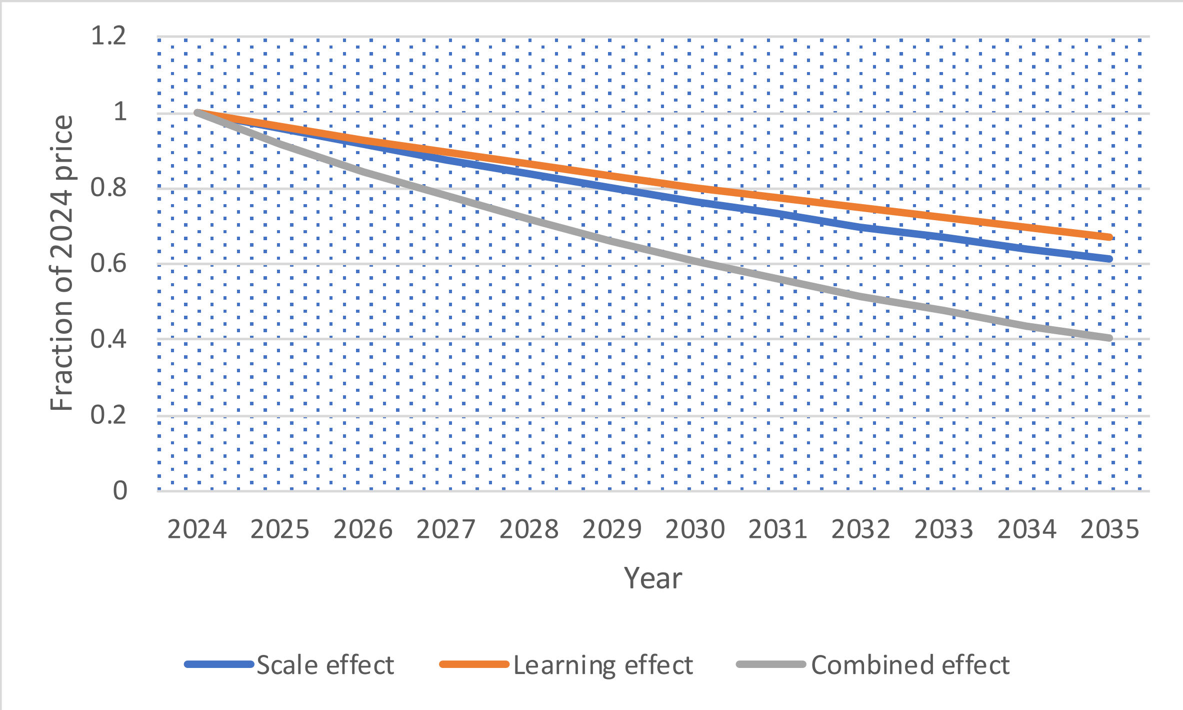
We considered a scenario in which biomethane grows from 100 TJ in 2025 to 100 PJ in 2035, a 1,000-times increase. We maintain the scale and learning assumptions from the green hydrogen scenario – a 5 per cent scale effect and a 4 per cent learning rate. Figure 5 shows the trajectory of costs; with input prices constant they fall by 60 per cent by 2035.

We identify changes in scale and learning associated with growth of the biomethane industry and apply the scale and learning effects, year by year, to estimate cost reductions year by year. Table 5 shows biomethane cost reductions in 2035 under alternative scale effect/learning rate combinations. With the minimal gains scenario, unit costs of biomethane fall by 39 per cent. On the most optimistic scenario, they fall by 74 per cent.

The range of cost impacts in Table 5 is wide. But even if we discount the "high" scenarios, and confine attention to the upper two and leftmost two rows, the cost reductions are of the order of one half to two-thirds. The scale and learning rates are consistent with what has been seen for other technologies.

The challenge for biomethane may lie in the non-uniformity of the biogas feedstocks that it relies on. If development of the sector involves the use of increasingly inaccessible locations then the rising costs of infrastructure may outweigh gains from scale and learning effects.

Figure 5: Scenario for biomethane scale and learning effects



Source: SACES calculations

Table 5: Scenarios for reductions in biomethane costs in 2035

Scale effect:	3 per cent	5 per cent	7 per cent
Learning rate:			
2 per cent	39	50	59
4 per cent	50	60	67
6 per cent	60	67	74

Source: SACES calculations

5. Implications

An understanding of the potential for renewable cost reductions is relevant for policy. In particular, if there are cost reductions available from scale and learning effects, there may be a case for policies to boost the development of the product so that these cost reductions can be delivered.

This argument does not rely on any qualitative difference in scale or learning effects that arise from policy versus those that flow from normal commercial decisions. It simply recognises that policy may boost the quantum of scale and learning beyond what would happen under normal commercial considerations. The questions is whether there is a policy rationale to do this.

It is apparent from the studies reviewed that there is large variation in learning rates (and technology cost reductions) across different technologies. When we seek to predict a learning rate for a renewable gas we do not know which mature technologies are a good basis for comparison. For example, we do not know whether solar or wind technologies provide a more useful guide to renewable gas cost curves.

The overall conclusion of this study is that there is a strong likelihood that the scale and learning effects that will emerge with industry development will bring substantial cost reductions for both green hydrogen and biomethane. However, the extent of these cost reductions remains highly uncertain.

If it were the case that cost reductions from scale and learning were entirely captured by firms whose decisions give rise to them, then one might conclude that firms have all the incentives that they need to develop new products and supply chains, in which case there might be no case for policy intervention. However, this is unlikely to be the case, especially in respect of learning.

Cost reductions from learning are rarely captured entirely with a firm, and it is likely that at least some of the learning benefits will spill over to other firms in the renewable gas industry and ultimately to gas consumers. Markets can under-deliver on innovation effort when there are “spillovers” (of benefits from innovation). The problem is that there may be some innovations for which society-wide gains justify development costs, but for which the developer’s share of those society-wide gains is insufficient to cover costs. In such a situation the developer will not proceed with the innovation activity, even though it would be socially beneficial for it to proceed. Innovation effort is inefficiently low.

In cases where spillovers are likely to lead to inefficiently low innovation activity, there is a case on efficiency grounds for government intervention to support the innovation. This intervention might be in the form of a subsidy for the innovation activity. In the case of renewable gases, a renewable gas target mechanism seeks to provide that subsidy to renewable gas producers with the aim of promoting innovation in the supply chain.

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