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Estimating the learning rate of a technology with multiple variants: The case of carbon storage

Garrett Upstill*, Peter Hall

School of Business, UNSW Canberra, Northcott Drive, ACT, Australia

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ABSTRACT

Learning rates enable the generation of first-order estimates of the cost of a technology as cumulative production grows, and play an important role in energy-economic modelling. This paper extends the component-based approach to estimating future learning rates to the case of a technology with multiple variants. It sets out a bottom-up method for estimating the composite learning rate including the situation where the proportional contribution of the different variants changes as cumulative production increases. The method is demonstrated for carbon storage using representative cost and distribution data from recent studies of storage in the European region.

Carbon storage comprises four technology variants defined by the nature of the storage reservoir – (onshore or offshore) depleted oil & gas reservoirs and (onshore or offshore) saline aquifers – and each variant has a different learning rate reflecting its different cost structure. Moreover, the proportional contribution of each variant to total storage is likely to change with the growth of global storage capacity. The composite learning rate for carbon storage is estimated for scenarios in which the relative contributions change: a negative learning rate is determined in one scenario.

1. Introduction

Carbon capture and storage (CCS) is one of a limited number of competing low-carbon energy technologies able to reduce carbon dioxide emissions and contribute to the containment of global warming (Global CCS Institute, 2015).

Determining the future cost of these technologies is a challenging issue. One approach is to estimate future learning rates (the learning rate being defined as the relative reduction in unit production costs for each doubling of cumulative production). Such learning rates are important inputs to energy-economic modelling and the development of energy and climate policy.

In this paper we apply a component-based approach to estimating learning rates to the general case of a technology with multiple variants. We derive the composite learning rate and model situations where the proportional contributions of the different variants – the distribution – may change as cumulative production grows.

This approach is illustrated for the case of carbon storage. Because this technology comprises four technology variants distinguished by the nature of the storage reservoir – (onshore or offshore) depleted oil and gas reservoirs and (onshore or offshore) saline aquifers.

The remainder of the paper is organised as follows. Section 2 backgrounds the literature on technology learning and the component-based approach to estimating learning rates. The technological activities in carbon storage are analysed and two cost components which are common to each of the four technology variants are identified. Section 3 presents data from recent modelling studies of carbon storage for the European region, including cost and future distribution data.

Section 4 sets out a bottom-up component- based method for determining the learning rate of an emerging technology with multiple variants and the method is illustrated for the case of carbon storage. In Section 5 the method is summarised and the results discussed. The concluding section considers the wider implications of this study.

2. Background

2.1. Technology learning

The role of technology learning in the reduction of the unit costs of production with accumulating production has been the subject of considerable study. The concept has its origins in observations at the plant level for aero-manufacturing where a uniform decrease in labour inputs accompanied each doubling of cumulative production (Wright, 1936). The systematic link between decreasing unit production costs

* Corresponding author.
E-mail addresses: g.upstill@adfa.edu.au (G. Upstill), p.hall@adfa.edu.au (P. Hall).

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and cumulative volume has since found empirical support in a wide range of products and has been extended to industry sectors and technologies. A total of 47 of the 48 energy technologies analysed by McDonald and Schrattenholzer (2001) followed this pattern. Recent studies of technology learning in power generation have included consideration of CCS with a principal focus on carbon capture (Rubin et al., 2007; van den Broek et al., 2009; Azevedo et al., 2013; Rubin et al., 2015).

Technology learning is commonly modelled as a *learning curve* which plots unit costs against cumulative volume of production. This single factor relationship may be expressed as:

$$C(Q_t) = C(Q_0).\ [Q_t/Q_0]^{-b} \tag{1}$$

where Q_t is the cumulative production,

b is the positive learning parameter,
$C(Q_t)$ is the unit cost of production at Q_t,
$C(Q_0)$ and Q_0 are respectively the cost and cumulative production at an arbitrary starting point.

The relationship may be plotted as a learning curve or alternatively as a linear function on a log-log scale. The associated *learning rate* (LR) is defined as the relative cost reduction in unit production costs for each doubling of cumulative production:

$$LR = 1-2^{-b} \tag{1a}$$

or $100 \times (1-2^{-b})$ when the learning rate is expressed as a percentage.

The underlying mechanics of technology learning are not well defined. Early formulations of the process of "learning by doing" at a plant level linked falling unit labour costs to productivity improvements from repetitious manufacturing through increased labour efficiency, work specialisation and improved production methods (Arrow, 1962). With the extension of the concept to industry wide technologies has come the need to expand this explanation. Other complementary and, in varying degrees, overlapping mechanisms include "learning by searching" which focuses on technology improvements enabled by RD&D investment (Cohen and Levinthal, 1989); "learning by using" (Rosenberg, 1982); "learning by diversity" (Newbery et al., 2009); "learning by scaling" (Sahal, 1985); "learning by copying" – taking advantage of knowledge spillovers from other industries (Sagar and van der Zwaan, 2006); and "learning-by-interacting" within the innovation system (Kamp et al., 2004; Lundvall, 2010).

Two-factor and multifactor modelling approaches to technology learning have been developed but the single factor model is commonly used to represent endogenous technical change in energy-economic modelling (Wiesenthal et al., 2012). Learning rates relate technology improvement or cost reduction to other parameters in the model and play an important role in energy-environment modelling, notably long-term integrated assessment models (Kahouli-Brahmi, 2008; Hayward and Graham, 2013).

2.1.1. Component learning

The *component learning* approach (Ferioli et al., 2009) extends the single factor model by treating the cost of a technology as a sum of the costs of its individual components. It allows technology improvement to occur at different rates for different components. Assuming that the cost of each component decreases over time according to a power law relation as a result of learning, then the technology learning relationship may be expressed as follows (where the index i represents a given cost component):

$$\begin{aligned} C(Q_t) &= \sum C_{0i}(Q_{ti}/Q_{0i})^{-b(i)} \\ &= C_{01}(Q_{t1}/Q_{01})^{-b(1)} + C_{01}(Q_{t2}/Q_{02})^{-b(2)} + \ldots + \quad C_{0n}(Q_{tn}/Q_{0n})^{-b(n)} \end{aligned} \tag{2}$$

where $b(i)$ is positive learning parameter for component i,

$C(Q_t)$ is the unit cost of production at cumulative production Q_t,
Q_0 is the cumulative production at an arbitrary starting point,
C_{0i} is the cost and Q_{0i} is the cumulative production of component i at an arbitrary starting point.

Component learning is a way of disaggregating the technology learning process into separate parts (e.g. plant and equipment, operating costs, etc.) and building a composite learning rate based on analysis of the separate components (Ferioli et al., 2009). This approach opens the way to improved rate estimation for new technologies by drawing on historical learning rates for directly comparable technologies, and then combining them into a single rate. Different components may well be at different states of maturity: newer components may, for example, have higher learning rates than mature components, and there may be components for which zero rates are appropriate.

A caveat in this approach is that writing the function additively implicitly assumes that the components are separable and non-interactive in their effects. Ferioli et al. (2009) comment in relation to carbon capture and storage, for example, that "the overall learning rate for total CCS application will probably depend on the interaction between its individual constituents in a non-trivial way" (p. 2533).

2.2. Carbon storage

2.2.1. Technology variants

CCS is widely seen as an essential element in a least cost technology package to reduce CO_2 emissions from the energy sector. But it is a technology in early deployment and will need to expand dramatically to play its full part (Herzog, 2011). Just over 20 million tonnes of CO_2 are currently stored geologically each year. By contrast the IEA's 450 scenario pathway to achieving the two degree climate goal entails permanent storage of CO_2 rising to 5.1 Gt per year by 2040 and 52 Gt of cumulative storage by that time (IEA, 2015). Indeed, the integrated assessment models reviewed at the 27th round of the Energy Modelling Forum (Kriegler et al., 2014) projected the cumulative storage of CO_2 for the 2010–2100 period to be from 600 Gt to 3050 Gt. The implied expansion from the present base is massive, and would imply a carbon storage industry by 2050 of a size on a par with the current oil and gas industry (Bellona Europa, 2014).

There is scope for a massive increase in carbon storage underground. The IPCC (2005) has estimated the global capacity of depleted fields to be 675–900 Gt and that of aquifers to be up to 10,000 Gt. These estimates are consistent with recent national data (Consoli and Wildgust, 2017) and figures for total storage capacity in the United States of 2600 Gt including 230 Gt in depleted fields (NETL, 2015). Moreover, numerous areas of high prospectivity have been identified (IEA, 2011, Appendix 1). Information on depleted fields is available due to the past operations of the oil and gas industry, but less is known about the behaviour and the long-term trapping mechanisms of aquifers.

In this study we consider the four technology variants of carbon storage, as defined by their storage reservoirs. These are (onshore or offshore) depleted oil and gas fields and (onshore or offshore) deep saline aquifers (henceforth referred to, respectively, as depleted fields and aquifers). We do not include enhanced oil recovery (EOR) as a technology variant in this report. In EOR, the focus is on maximising oil recovery and sites are traditionally not selected, operated nor monitored to achieve permanent storage. While it may be a useful bridging technology, it is unlikely to play an important part in the large scale storage of CO_2 needed to achieve global warming targets.

2.2.2. Cost components

Fig. 1 sets out the technological activities involved in the life cycle of carbon storage at a particular reservoir which typically span several decades. The **selection and characterisation** of a suitable site is the key to effective geological storage. A suitable geological formation must