Energy Policy 52 (2013) 439–452

Contents lists available at SciVerse ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Relating R&D and investment policies to CCS market diffusion through two-factor learning

Richard Lohwasser*, Reinhard Madlener

Institute for Future Energy Consumer Needs and Behavior (FCN), School of Business and Economics/E.ON Energy Research Center, RWTH Aachen University, Mathieustrasse 10, 52074 Aachen, Germany

HIGHLIGHTS

- ▸ Identified two-factor learning rates for CCS through empirical data from flue gas desulphurization.
- ▸ Evaluated effectiveness of CCS stimulation policies addressing learning-by-doing and learning-by-researching.
- ▸ Both policy types are about equally effective with small policy budgets.
- ▸ Policies addressing learning-by-doing, e.g., subsidies to CCS projects, are more effective with large policy budgets.
- ▸ Analysis deployed HECTOR power market model that simulates 19 European countries on hourly granularity until 2040.

ARTICLE INFO

Article history:
Received 1 May 2011
Accepted 23 September 2012
Available online 31 October 2012

Keywords:
Policy effectiveness
CCS
Two-factor-learning

ABSTRACT

Carbon capture and storage (CCS) has the potential to play a major role in the stabilization of anthropogenic greenhouse gases. To develop the capture technology from its current demonstration phase towards commercial maturity, significant funding is directed to CCS, such as the EU's €4.5 bn NER300 fund. However, we know little about how this funding relates to market diffusion of CCS. This paper addresses that question. We initially review past learning effects from both capacity installations and R&D efforts for a similar technology using the concept of two-factor learning. We apply the obtained learning-by-doing and learning-by-searching rates to CCS in the electricity market model HECTOR, which simulates 19 European countries hourly until 2040, to understand the impact of learning and associated policies on CCS market diffusion. We evaluate the effectiveness of policies addressing learning-by-doing and learning-by-searching by relating the policy budget to the realized CCS capacity and find that, at lower policy cost, both methods are about equally effective. At higher spending levels, policies promoting learning-by-doing are more effective. Overall, policy effectiveness increases in low CO_2 price scenarios, but the CO_2 price still remains the key prerequisite for the economic competitiveness, even with major policy support.

1. Introduction and motivation

A prime challenge for the 21st century is the limiting of global warming to 2 °C through the reduction of anthropogenic greenhouse gas emissions, formulated as a central result in the joint Accord of the Copenhagen Conference on Climate Change (2009) and the Cancun (2010). There are several CO_2 emission reduction targets addressing this challenge, such as the EU's commitment to a 20–30% target by 2020 (EU Commission, 2008).

As the main contributor to these emissions, the energy sector is especially impacted by this development and significant efforts are made to address this challenge. Besides renewable energy sources, energy efficiency increases, nuclear power generation and others, Carbon capture and storage (CCS) is widely seen as a major opportunity to contribute to CO_2 abatement, but at the same time also continue fossil-fuel-based generation. In a context of increasing demand of energy, the measures of improvement of the energy efficiency and the development of the renewable energies are indispensable. However, they are not sufficient to give up fossil energies, which remain the main source of energy in 2030 (IEA, 2010a). The IEA's World Energy Outlook (WEO) 2010 in its 450 ppm CO_2e scenario predicts that 581 GW of CCS capacity will be in operation by 2035 worldwide (IEA, 2010a), and CCS has now been accepted as Clean Development Mechanism by the UN

* Corresponding author. Tel.: +49 89 5594 3190; fax: +49 89 5594 3191.
E-mail addresses: richard.lohwasser@rwth-aachen.de (R. Lohwasser), RMadlener@eonerc.rwth-aachen.de (R. Madlener).

0301-4215/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.enpol.2012.09.061

(IEA, 2010b). Whereas the expectations placed on CCS are very high, the capture technology has still not been widely proven at full scale and technological progress has been limited in recent years, with only a few CCS pilot power plants being operational.[1] This presents a key obstacle to the anticipated large-scale CCS deployment. The solution lies in technological and managerial learning through extended R&D efforts as well as in the physical construction of an increasing number of (demonstration) CCS power plants.

Given the relatively high profile of CCS, we observe the need for additional CCS pilot plants and therefore investments, as foreseen for example in the EU's plan to have 12 plants operational by 2015 and to provide approx. €4.5 billion (300 m EU ETS certificates) of co-funding for CCS pilot plants in the NER300 fund (EU Commission, 2009a). The United Kingdom (UK),[2] Canada,[3] and the State of Illinois, USA,[4] have similar policies in place. This support is also needed, as stand-alone CCS power plant projects are only commercially viable in specific situations, such as in combination with enhanced oil recovery. Without this support, CCS runs the risk of being trapped in the "Valley of Death", the gap between public and private funding, especially due to the high up-front investment costs (Murphy and Edwards, 2003). A variety of support methods are available, such as R&D grants, subsidies for investment costs and others (Woerdman and Couwenberg, 2009). However, whereas the need to support CCS is accepted and continuously growing, we know little about the dynamics of how to optimally support this technology. This paper addresses these questions concerning R&D effectiveness, funding distribution, and funding level.

One method to estimate the relationship between R&D funding and technological improvement is "two-factor learning curves" (2FLC). This approach is based on "technological learning", the phenomenon that the cost of a specific technology decreases along with its cumulative deployment (initially Wright, 1936, and Arrow, 1962), but is extended by the additional consideration of cumulative R&D efforts (Kouvaritakis et al. (2000a, 2000b); Jamasb, 2007). From a policy-analysis perspective, traditional learning-by-doing approaches only consider capacity deployment as the driving factor, thereby limiting any policy research to procurement policies that support investments in new capacity. However, policies supporting R&D, although a very popular method, cannot be analyzed with this approach, especially if the technology is at an early development stage.

In this paper, we estimate a 2FLC for CCS power plants through analogies, as no empirical data are available because CCS deployment has not yet started. We therefore empirically derive the 2FLC for the SO_2 scrubber technology, which is similar to the CO_2 scrubber technology used for CCS power plants,[5] using cost, patents, and deployment data for the years 1970–2000. To validate the results, we compare them to already-published 2FLC estimates across the energy-generation industry as well as existing one-factor learning estimates for CCS, derived through the same SO_2 scrubber analogy (Riahi et al., 2004) or through expert panels (McKinsey, 2008).

Based on the 2FLC, we address the question of R&D and investment policy effectiveness for CCS power plants using a modified version of the HECTOR simulation model (Lohwasser and Madlener, 2009, 2012). We provide an outlook for the European electricity market, including the diffusion of CCS technology under different policy scenarios until 2040 to explicitly consider the long-term effects of technological learning. The long time horizon is required due to the initial development stage of CCS, as early learning has a strong impact on the future. The analysis explicitly analyzes potential CCS policies considering the two effects mentioned: learning-by-doing (stimulation of deployment through investment cost subsidies) and learning-by-searching (promotion of R&D through grants).

The remainder of this paper is structured as follows. In Section 2, we discuss the concept of technological learning which, in Section 3, we then apply to CCS, using our own empirical analysis and comparisons to preexisting one- and two-factor learning curves. Section 4 focuses on the implementation of two-factor learning to the model used to simulate market diffusion as well as the description of the Base Case. In Section 5, we analyze the impact of learning-by-doing and learning-by-searching and, in Section 6, the impact of R&D and investment subsidy policies. Finally, Section 7 concludes with key takeaways and policy recommendations from our analysis.

2. Technological learning

The concept of technological learning is not new. Initially, flight pioneer Wright (1936) noticed the phenomenon that the labor hours required to construct an airframe (i.e., the plane without the engine) decreases with production experience for airplane manufacturing. Later, Arrow (1962) introduced the concept of learning-by-doing in his design of endogenous growth and related it to product manufacturing. Since then, a variety of studies have found empirical evidence for this relationship, known as the "learning curve", across different industries (BCG, 1968; Dutton and Thomas, 1984; Argote and Epple, 1990) and also specifically for power-generation technologies (McDonald and Schrattenholzer, 2001; Junginger et al., 2010). Within power generation, learning curves are frequently used for economic and policy analysis; Kahouli-Brahmi (2008), for example, provides a survey with 14 examples. The most common definition of a learning curve is:

$$C = C_0 \times Cap^{-\alpha} \tag{1}$$

$$LR = 1-2^{-\alpha}. \tag{2}$$

with C as the specific costs of a technology per unit, in our case of electricity (€/MW or €/MW h), C_0 the initial investment cost at zero learning and α the learning elasticity. The learning elasticity can then be converted into a learning rate (LR) with Eq. (2). This rate expresses the constant percentage of cost decline for every doubling of capacity. In the electricity supply industry, we observe a large range between about 2% for hydropower or supercritical coal plants and up to about 30% for wind and solar power plants (McDonald and Schrattenholzer, 2001; Köhler et al., 2006; Junginger et al., 2010). Technologies hereby often achieve a faster learning rate in their early deployment, such as coal power plants with a learning rate of 25% between 1948 and 1969 (Fisher, 1974), compared to the low value of supercritical coal plants mentioned earlier.

The concept of technological learning, especially its widely-used application for modeling energy-technology diffusion and policies

[1] A complete overview of announced and operational CCS projects is available at Global CCS Institute (2011).

[2] The UK in its 2010 Energy Act announced a CCS levy on households to subsidize up to four CCS demonstration plants (UK Parliament, 2010). However, these plans were postponed in the 2011 UK national budget.

[3] Canadian CCEMA Act in Alberta, with the objective of a 50% reduction in greenhouse gas emissions intensity by 2020 (Canada, 2007). With this act, the Alberta Government alone plans to invest €2 billion into CCS (Deutsche Bank, 2009).

[4] Illinois Clean Coal Portfolio Standard Act, requiring that all new plants put into operation after 2017 must capture and store 90% of CO_2 (Illinois, 2009).

[5] Specifically, post-combustion hard-coal-fired CCS power plants, the CCS plant technology closest to commercial readiness and the focus of this paper.