ELSEVIER

Energy Policy 34 (2006) 422–432

ENERGY POLICY

www.elsevier.com/locate/enpol

An economic perspective on experience curves and dynamic economies in renewable energy technologies ☆

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Available online 29 July 2004

Abstract

This paper analyzes dynamic economies in renewable energy technologies. The paper has two contributions. The first is to test the robustness of experience in solar photovoltaic, solar thermal and wind energy to the addition of an explicit time trend, which has been done in experience studies for other industries, but not for renewable energy technologies. Estimation is carried out on the assumption that cumulative capacity, industry production, average firm production, and electricity generation affect experience and thus the fall in price. The second contribution is to test the impact of R&D on price reduction. In general cumulative experience is found to be highly statistically significant when estimated alone, and highly statistically insignificant when time is added to the model. The effect of R&D is small and statistically significant in solar photovoltaic technology and statistically insignificant in solar thermal and wind technologies.

JEL classification: Q4

Keywords: Experience curves; R&D; Renewable energy

1. Overview

The success of the renewable energy industry's expansion can be measured both by the level of cost reduction and the extent of market penetration of renewable technologies. In the past twenty years, cost reduction has been more than expected, whereas market penetration has been markedly lower than expected (Darmstadter, 2000). Accordingly, many researchers have focused on evaluating the process of cost reduction over time, which has led to the application of 'experience' or 'learning' curve analysis to renewable energy technologies. Governments have supported renewable energy through policies such as R&D funding and price subsidisation. However, questions have surfaced in recent years concerning how much support a technology needs to become competitive.[1] Experience curves, named after the inverse relationship observed between cost and cumulative output, have been adopted as a tool to help answer such questions because they provide a simple quantitative relationship between cost and the cumulative production of a technology. Recent work analyzing the long-run cost potential of renewable energy technologies using experience curves includes Matsson and Wene (1997), Neij (1997, 1999), IEA (2000), Neij et al. (2003), and Moor et al. (2003).

The notion of experience as a driver of cost reduction is an attractive one. It refers to the process whereby people become better at doing what they do over time, leading to efficiency increases—and thus permanent cost

☆This paper is based on my MSc thesis in Environmental and Resource Economics at University College London. I would like to thank Costas Meghir, David Pearce, an anonymous referee, and especially Joseph Swierzbinski for helpful comments and suggestions. Any errors are my own.

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[1]The International Energy Agency's IEA (2000) report focused on this issue.

0301-4215/$ - see front matter
doi:10.1016/j.enpol.2004.06.008

reductions—at the firm level. The simplicity and universality of the experience, or learning, framework has led researchers to apply it to everything from airplane manufacturing to chemical processing, textiles production, and nuclear plant operation.[2] Coined by the Boston Consulting Group in the 1960s as a tool to advise clients on competitive strategy, the experience curve concept was adapted from the 'learning-by-doing' literature in economics (Wright, 1936; Hirsch, 1952; Arrow, 1962; Alchian, 1963). The popularity of the experience curve reached a peak in the mid-1970s, and firms were advised to expand output in order to deter entry and gain a long-term cost advantage over rivals. Unfortunately many of these strategies failed because firms did not consider the effect of knowledge diffusion, and the concept lost its favour (Lieberman, 1987). Newfound interest in experience curves has arisen in recent years as governments search for policies to address climate change. Unlike the previous generation of experience curves, when the focus was on production planning or strategic management, the focus in current energy technology applications has shifted to endogenous technical change and the use of reliable estimates of technological learning rates as inputs in energy forecasting models (McDonald and Schrattenholzer, 2001).

The effect of R&D on an industry's capacity to decrease cost is analogous experience, in that it brings about dynamic economies, or downward shifts in the cost curve (see Spence, 1981, 1986). R&D effects can also interact with experience curve effects to increase the pace of dynamic savings. It is thus desirable to test the impact of R&D on cost reduction in renewable energy technologies.

This paper analyzes dynamic economies in renewable energy technologies. The paper has two contributions. The first is to test the robustness of experience curves to the addition of an explicit time trend, as has been done in other industry studies such as has been done by Sheshinski (1967), and Lieberman (1984), both of whom found time to be minor or insignificant factors in comparison to learning. A more detailed explanation for the addition of time is presented in Section 2. The second contribution is to test the impact of R&D. Results are presented for solar photovoltaic (PV), solar thermal, and wind technologies.

The results obtained in the current study indicate that experience is not robust to the addition of a time trend, and that R&D has in general performed poorly in solar and wind technologies. More specifically, (a) experience estimates in the solar industry in the US and Europe are either substantially reduced or statistically insignificant, depending on the experience index; (b) experience estimates in the wind industry in Europe are statistically insignificant for all indices, however, when the effect of better wind capture is incorporated in prices, the estimate is borderline significant at the 10% level; (c) a panel of both solar and wind data yields insignificant experience estimates; and (d) the effect of R&D is small and statistically significant in solar PV but statistically insignificant in solar thermal and wind technologies.

The rest of the paper is organized as follows. Section 2 presents the empirical framework for estimation, the empirical results, and the results discussion. Section 3 concludes.

2. Dynamic learning economies

2.1. Data

Time series data on wind energy prices, turbine installation and turbine sales in Denmark and Germany are from the Extool Project, a research initiative funded by the European Commission. The wind data are the same as that used to estimate experience in Neij et al. (2003). Solar data series on prices, sales and total manufacturers in the industry in the Unites States (US) are from the Department of Energy's Energy Information Administration. Solar photovoltaic (PV) cost data in the US from 1992 to 2000 has been obtained from the National Renewable Energy Laboratory in the US. Solar price data for Germany, Japan, and Switzerland and cumulative installed PV capacity data from Germany, Switzerland and the US are from the IEA's PV Power Systems (PVPS) Programme. Cumulative generated electricity data on both solar and wind energy, and cumulative capacity on wind are from the IEA's renewables database. R&D data are from the IEA. Price series in the panel estimation were converted to real 2000 prices using the exchange rate and GDP deflator series used by the IEA. All data are annual.

2.2. Experience

Learning or experience curve applications can be traced back to Wright (1936), who estimated the relationship between total labour hours and cumulated airplane production. His methodology lead to many other industry studies, such as Hirsch (1952) and Alchian (1963). The curve they estimated is

$$\log N_t = \alpha + \beta \log X_t, \quad (2.1)$$

where N_t is total direct labour input per unit of output in each period t, α is a constant parameter, and X_t is cumulated output in constant units, for all periods up to and including t. The parameter β measures the responsiveness of labour hours to cumulated production. This

[2] Contemporary studies often use the terms 'experience' and 'learning' interchangeably, though strictly speaking a learning curve uses total labour hours as a dependent variable whereas an experience curve uses total cost.