A review of uncertainties in technology experience curves

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Article Info

Article history:
Received 25 January 2011
Received in revised form 31 July 2011
Accepted 11 November 2011
Available online 19 November 2011

JEL Classifications:
Q52
Q55
Q58
Q4
P2
C60

Keywords:
Experience curve
Learning curve
Learning-by-doing
Uncertainties
Endogenous technological change
Energy-economic models.

Abstract

The use of log-linear experience curves (or learning curves) relating reductions in the unit cost of technologies to their cumulative production or installed capacity has become a common method of representing endogenous technical change in energy-economic models used for policy analysis. Yet, there are significant uncertainties in such formulations whose impact on key model results has been insufficiently examined or considered. This paper reviews the major types of uncertainty in log-linear experience curves and their effect on projected rates of cost reduction. Uncertainties are found not only in the learning rate parameter of a log-linear model, but also in the functional form that determines the shape of an experience curve. Evidence for alternative forms such as an S-shaped curve is reviewed along with case studies that demonstrate the uncertainties associated with cost increases during early commercialization of a technology—a phenomena that is widely recognized but rarely quantified or incorporated in learning models. Additional factors discussed include the effects of learning discontinuities, institutional forgetting, and the influence of social, economic and political factors. We then review other models of causality, which aim to improve modelers’ ability to explain and predict the influence of other underlying processes that contribute to technology cost reductions in addition to learning. Ignoring other types of underlying mechanisms can create a false sense of precision and overestimate the true contribution of learning. Currently, however, uncertainties in such multi-factor models remain large due to the difficulties of estimating key parameters (such as private-sector R&D investments) and extending models of a specific technology to a broader suite of technologies and cost projections. Pending the development and validation of more robust models of technological change, we suggest ways to significantly improve the characterization and reporting of current learning model uncertainties and their impacts on the results of energy-economic models to help reduce the potential for drawing inappropriate or erroneous policy conclusions.

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1. Introduction

Assumptions concerning the nature and rates of technological change are arguably among the most critical assumptions for assessments of long-term energy and environmental issues such as global climate change. In the past, large-scale modeling efforts commonly treated technological change as an autonomous process in which factors like the efficiency of energy production and utilization improved with the passage of time at a specified rate, independent of other factors (Kyperos, 1992; Manne and Richels, 1992; Nordhaus, 1994; Prinn et al., 1999). However, increasing numbers of long-term integrated assessment models for energy and climate policy analysis have incorporated some mechanism of endogenous technological learning in which the rate of technological improvement and/or cost reduction depends on other parameters in the model. The influences of experience from learning-by-doing, knowledge spillovers from other industries and the level of research and development (R&D) expenditures are among the factors that have been most often modeled (Azar and Dowlatabadi, 1999; Clarke et al., 2006; Gillingham et al., 2008; van der Zwaan et al., 2002).

Models of learning-by-doing are most often presented in the form of a learning curve or experience curve (EC) using the log-linear specification of a cost function derived from a Cobb-Douglas production function (Berndt, 1991). Technology experience curves relate changes in specific investment cost (or other cost measure) to the cumulative installed capacity of the technology. While this is regarded as an important step toward more realistically representing the dependency of cost reductions on other variables, experience curves remain an imperfect representation of technical change. It is argued, for example, that the statistical correlations between a reduction in unit cost and the cumulative installed capacity of an energy technology offers little explanation for the underlying process of technological change and the causality between these two variables (Clarke et al., 2006; Ferioli and van der Zwaan, 2009; Gillingham et al., 2008; Nordhaus, 2009).

Aside from the issue of causality, the use of experience curves for forecasting or modeling future cost trends in energy-related technologies is beset by a number of other uncertainties. For example, for the models currently in use, what is the “correct” learning rate for a new