LEARNING BY DOING EFFECT FROM SOLAR PHOTOVOLTAIC RD&D

Youah Lee

Department of Energy Systems Engineering

Seoul National University

599 Gwanak-ro, Gwanak-gu

Seoul 151-744, Republic of Korea

Phone: +82-2-880-8705, Fax: +82-2-882-2109

E-mail: youah@snu.ac.kr

Abstract
Cumulative capacity and investment in research and development (R&D) are important factors for cost reduction in solar energy systems. In this research, I examine the effect of learning-by-doing and learning-by-research using recent data (2001–2010) for solar photovoltaic (PV) systems in 12 countries. I use the panel estimation method to control the individual country characteristics. From the analysis, I show that the learning-by-doing and learning-by-research rates have reduced over time. This means that a reduction in the cost of PV systems can only be brought about by adding solar PV capacity and making more R&D investments. From the panel analysis, I also show that the countries share common trends in learning-by-doing and learning-by-research.

1. Introduction

Cumulative capacity and investment in research and development (R&D) have long been considered as important factors for cost reduction in solar energy systems; however, cost reduction also includes many other factors. The learning curve method can be used to measure the effects of learning-by-doing on the one hand and learning-by-research on the other. Learning curves describe how specific investment costs for a given technology are reduced through one or more factors representing the accumulation of knowledge and experience related to R&D expenditures and the production and use of that technology (Kahouli-Brahmi (2008).

Many studies have used the learning curve method to forecast cost reduction relative to the cumulative capacity of a technology and R&D investment made in it(Maya 2006; Söderholm and Sundqvist 2007; Ek and Söderholm 2010; Qiu and Anadon 2011). Renewable energy, in particular, has been used in conjunction with learning curve methods for several reasons, the most significant being the availability of sufficient data allowing for statistical analysis and the continued expectation of technology development. At an initial stage of the analysis, the one-factor model, which considered the cumulative capacity alone, was widely used(Klaassen, Miketa et al. 2005; Söderholm and Sundqvist 2007; Winkler, Hughes et al. 2009; Kim and Chang 2012). However, with an increase in R&D-related investment by the government, the two-factor model is more commonly used now. The two-factor model explains the cost reduction of technology in terms of learning-by-doing and learning-by-research. However, there are some limitations in previous studies, as most of them use data preceding the year 2000. After 2000, the world renewable energy industry developed rapidly. For example, the cumulative capacity of solar energy was 103 MW in 1992 and 678 MW in 2000. In 2010 alone, it increased by 34,953 MW, or about 339 times the level in 1992 and 52 times that in 2000(IEA 2010). Consequently, there is a need to update research using this data. Additionally, while using the R&D variable, most studies employed knowledge stock as the representative data for R&D investment. However, there is lack of understanding concerning R&D variables in the learning curve.

The purpose of this research is to show the effect of learning-by-doing and learning-by-research considering recent data in the solar photovoltaic (PV) energy sub-sector. For my analysis, I use the panel estimation method, using data from 12 countries. I control the characteristics of individual countries in order to gain distinct perspectives for learning-by-doing and learning-by-research. I also develop three kinds of R&D variables; pure R&D, accumulated R&D, and knowledge stock. I then examine the importance of choosing the R&D variables in the two-factor experience curve model.

The paper proceeds as follows. In Section 2, I analyze the methodological aspects of technological learning concepts and previous studies. I also provide the estimation equation. In Section 3, I present the empirical framework for estimation, the empirical results, and the discussion. In Section 4, I discuss the results and draw conclusions.

2. Method

(1) Literature review

In this Section, I introduce the concept of technological learning and the learning curve methodology.

Technological learning—alternatively, the learning effect—is a concept that permits the evaluation of the decrease in unit production costs when the cumulative production increases (Kahouli-Brahmi 2008). Technological learning plays a very important role in cost reduction of newly developed technologies(Kobos, Erickson et al. 2006; Sagar and van der Zwaan 2006). Innovations could result from technological learning. There are many aspects of technological learning (Table 1): learning-by-doing, learning-by-researching, learning-by-using, learning-by-interacting and economies of scale (Grübler and Messner 1998; Junginger, Faaij et al. 2005; Junginger, de Visser et al. 2006). Measuring technological learning requires the quantification of various factors. However, these factors should not be treated as separate entities, as one factor could have a bearing on others, and vice versa. Therefore, studies have primarily concentrated on learning-by-doing as the comprehensive factor. They assume that each idea, after all, produces a learning-by-doing effect, and in turn leads to technological innovation

Additionally, with recent improvement in R&D, attention is now being focused on the need to consider learning-by-doing and learning-by-researching separately (Watanabe, Wakabayashi et al. 2000; Klaassen, Miketa et al. 2005). R&D is unique in that it has a spillover effect. To improve R&D development, the government invests a huge amount of money in R&D. Hence, as suggested by the studies, using the mechanism of separately considering the rate of learning-by-doing and learning-by-research could benefit the technological learning process.

Table 1. Mechanisms of technological learning

	Definition	Researchers
Learning-by-doing	Repetitive manufacturing tasks involve an improvement in the production process, which can also be supported by a number of forces such as labor efficiency increases, new processes, changes in production methods, changes in the administrative structure, etc.	Arrow (1962); Bodde (1976)
Learning-by-researching	The R&D expenditure acts as a learning mechanism that allows the firm to identify and exploit the knowledge propagated in its environment. Learning-by researching thus represents improvements related to the innovation process and the absorptive capacity of the firm.	Cohen and Levinthal (1989)
Learning-by-using	When the product is introduced in the market, the market provides opportunities for learning-by-using. It is crucial for the development of the product since this development cannot be completely achieved inside factories and/or research laboratories. The user's feedback becomes an important source of technological learning for the firm, and over time, lead to cost reductions.	Rosenberg (1986); Criqui et al. (1998)
Learning-by-interacting	Interactions among various actors like research laboratories, industry, end-users and political decision-makers, enhance the diffusion of knowledge. Network relationships play a crucial role in achieving efficient product improvements and increasing the knowledge base, as the firm is able to exchange information about product characteristics and user requirements generated during the learning-by-doing and learning-by-using processes. Learning-by-interacting allows the firm to benefit from external sources of learning and is largely associated with the increasing diffusion of technology.	Lundvall (1988); Habermeier (1990)
Economies of scale	The unit cost curve as the output increases translates into cost advantages a firm obtains due to expansion. Economies of scale are also considered to be a learning mechanism that takes place at the mass production stage. Economies of scale encourage large-scale production that in turn promotes learning effects.	Kahouli-Brahmi (2008)

Note: reorganizing based on Kahouli-Brahmi (2008)

As mentioned previously, the learning curve method has been used to measure learning-by-doing and learning-by-research(van der Zwaan and Rabl 2003; Söderholm and Sundqvist 2007; Smit, Junginger et al. 2007; Qiu and Anadon 2011). Learning curves describe how the specific investment costs of a given technology are reduced through one or more factors representing the accumulation of knowledge and experience related to R&D expenditures, and the production and use of that technology (Kahouli-Brahmi 2008). The learning curve model is of two types: the one-factor model and the two-factor model. The so-called one-factor learning curve considers the cumulative installed capacity or production of a certain technology (Neij 1999; Karin 2002; Schaeffer, Alsema et al. 2004; Wand and Leuthold 2011), while the two-factor model also factors in cumulative R&D expenditures or knowledge stock with regard to that technology. Therefore, it follows that the one-factor model is used to examine learning-by-doing alone, while the two-factor model allows one to study learning-by-doing and learning-by-research together.

Cost reduction in renewable energy has interested many researchers using the learning curve for several reasons (Schaeffer, Alsema et al. 2004). The history of renewable energy stretches back several decades. This means there is sufficient data for statistical analyses. Furthermore, renewable energy technologies consist of many components. Relating learning-by-experience in PV systems, for example, would lead to learning at the component level. This could provide insights into how experience curves work, which could then be used towards a policy analysis. Also, renewable energy is seen as a “promising technology” in the framework of transition to a cleaner energy system in the longer term, and is therefore a subject of active energy policy interventions in many countries (Schaeffer, Alsema et al. 2004).

Table 2 presents some notable studies using learning curve estimation conducted for renewable energy technologies. The studies can be divided based on the type of model used and period of analysis. In the earlier years, researchers used the one-factor model (Neij 1999; Neij, Andersen et al. 2003; Junginger, de Visser et al. 2006; van den Wall Bake, Junginger et al. 2009). However after Watanabe, Wakabayashi et al. (2000) introduced the two-factor model, many researchers employed it in their studies of learning curve estimations for renewable energy technologies (Klaassen, Miketa et al. 2005; Maya 2006; Söderholm and Sundqvist 2007; Ek and Söderholm 2010; Qiu and Anadon 2011). The estimation result of the one-factor model served as a base for economic evaluation while forecasting cost reduction(Zangwill and Kantor 2000; Duke 2002; Weiss, Junginger et al. 2010). However, increasingly, with developments in the learning curve method, researchers have started opting for the two-factor model, as it improves the reliability of estimation methods.

Kahouli-Brahmi (2008) mention that despite little information about the underlying “micro-channels” through which R&D expenditures affect cost, cost reductions that result from R&D are quite distinct from those attributable to capital investment. New R&D expenditures allow the firm to better handle the economic and technological characteristics of the new technology, and in doing so, to construct its own knowledge stock. New R&D expenditure is also bound to increase production levels, and further stimulate the learning-by-doing process. Thus, new R&D investments support the learning-by-researching process, which in turn supports technological innovation in the production process. Moreover, the production process exerts a feedback effect on R&D activities, and by extension, on the learning-by-researching rate (Watanabe et al., 2000).

Knowledge stocks usually serve as representative data for R&D investment. However, researchers have varying opinions about how knowledge stock should be calculated. Klaassen, Miketa et al. (2005) calculated the knowledge stock with lag 1, while Kobos, Erickson et al. (2006) used lag 5. Furthermore, there is a lack of agreement on the depreciation rate to be employed. This prompted me to develop three kinds of R&D variables and use different lag lengths for this study.

The literature review also revealed another interesting issue. While a considerable number of studies have been conducted in this domain, the data period and number of countries analyzed for a particular renewable energy technology are nevertheless limited. Most of the recent studies use data preceding 2000. Data from Japan, Spain and Germany has been used for solar energy technology, while Denmark and England provide data for wind energy studies. With the increase in the cumulative capacity of renewable energy technologies (specifically solar PV) post-2000, I believe it is important to incorporate this data into the two-factor model.

Table 2. Some notable studies using learning curve estimation conducted for renewable energy technologies

Factor	Researchers	Renewable energy technology	Period	Country
One-factor model	van den Wall Bake, Junginger et al. (2009)	Bio (ethanol)	1974–2004	Brazil
	Junginger, de Visser et al. (2006)	Bio	1990–2002 1975–2002	Sweden (CHP) Denmark (biogas plant)
	Junginger, Faaij et al. (2005)	Bio	1981–2003	Sweden
	Goldemberg, Coelho et al. (2004)	Bio	1980–2002	Brazil
	Wand and Leuthold (2011)	Solar	2009–2030	Germany
	Gregory F (2006)	Solar	1975–2001	World
	van der Zwaan and Rabl (2004)	Solar	1976–1996	-
	van der Zwaan and Rabl (2003)	Solar	1976–1999	-
	Neij, Andersen et al. (2003)	Wind	1981–2000	Denmark, Germany, Sweden
	Junginger, Faaij et al. (2005)	Wind	1992–2001 1990–2001	UK Spain
	Karin (2002)	Wind	1983–1999 1991–1999	Denmark Germany, UK
	L (1999)	Wind	1986–1997	Denmark
	Kim and Chang (2012)	Renewable	2001–2010	Korea
	Colpier and Cornland (2002)	CCGT*	1980–1997	North America, Europe
	Winkler, Hughes et al. (2009)	Renewable	2003–2050	South Africa
Two-factor model	Qiu and Anadon (2011)	Wind	2003–2007	China
	Ek and Söderholm (2010)	Wind	1986–2002	Denmark, Germany, Spain, Sweden, UK
	Söderholm and Sundqvist (2007)	Wind	1986–1999 1990–1999 1991–2000	Denmark Germany, Spain UK
	Klaassen, Miketa et al. (2005)	Wind	1986–1999	Denmark, Germany, UK
	Maya (2006)	Solar, wind	1992–2000 1987–2000	USA, Denmark, Germany (wind)
	Kobos, Erickson et al. (2006)	Solar, wind	1975–2000 1981–2000	World
	Watanabe, Wakabayashi et al. (2000)	Solar	1974–1995	Japan

*: Combined Cycle Gas Turbine

(2) Two-factor model

The two-factor learning curve (also known as “progress function”) quantifies the magnitude of cost reduction engendered by the cumulative output and R&D increase (Kahouli-Brahmi 2008). The equation for the two-factor learning curve can be described as:

$$C(CC, RD) = A \cdot CC^{-\alpha} \cdot RD^{-\beta}, \quad (1)$$

where $C(CC, RD)$ is price of a technology per unit (specific cost) in US$ (2010) per kilowatt (KW), CC is the cumulative capacity in MW, RD is the R&D-based knowledge stock in US$ (2010), $-\alpha$ is the learning-by-doing index, $-\beta$ is the learning-by-researching index, A is the specific cost at unit cumulative capacity and unit knowledge stock in US$ (1990).

From Equation (1), we can determine the progress rate (Pr) or the learning rate (Lr).

$$Pr = 2^{-\alpha},\ 2^{-\beta} \tag{2}$$

$$Lr = 1 - Pr = 1 - 2^{-\alpha}, 1 - 2^{-\beta} \tag{3}$$

The progress rate is the rate at which the cost declines each time the cumulative production doubles. For example, a progress rate of 90% means that costs are reduced to 90% of their previous level after doubling cumulative production. It also means that the learning rate is 10%, and that costs decrease by 10%. The learning curve is generally estimated under its logarithmic functional form as seen in Equation (4).

$$log(C) = log(a) - \alpha\, log(Q) - \beta\, log(KS) + \varepsilon \tag{4}$$

Generally, ordinary least squares (OLS) methods are used for learning curve estimation. However, OLS methods suffer from some limitations, for example, spurious regression. Moreover, Kahouli-Brahmi (2008) mentioned that with an estimation based on single country data, country specifications are included in the estimated parameter. Further, there is no way to distinguish them from the learning parameter. With fixed-effect model formulation of panel data, we can eliminate unobserved country-specific variations from the estimation of learning parameters, regardless of the selection of countries. By doing so, we can obtain more robust estimations of learning. Consequently, in this study, I estimate Equation (4) using a panel data set of 12 countries—Australia, Canada, Denmark, Germany, France, United Kingdom, Italy, Japan, Korea, Portugal, Sweden, and Unites States.

I develop three sets of R&D data to examine the differences in the estimation results depending on the choice of the R&D variable and lag lengths. Kobos et al. (2006) conducted sensitivity analysis on time lag assumption ranges between 3 to 5 years. Klaassen et al. (2005) discovered that compared to the industrial scale, shorter time lags (2 years) are more appropriate for the uptake of energy (such as solar) at the smaller scale. I thus chose a time lag range between 1 to 3 years for accumulated R&D and knowledge stock. I set the depreciation factor at 3%, following the observations made by Klaassen et al. (2005) and Kobos (2000).

The fist R&D data is pure R&D investment at time t, $RD1$.

$$RD1_{it} = RD_{it} \tag{5}$$

The second R&D data is cumulative R&D without depreciation, $RD2$.

$$RD2_{it} = \sum_{x=1\ or\ 2\ or\ 3}^{n} RD_{it-x} \tag{6}$$

The third R&D data is knowledge stock with depreciation assumed at 3%, $RD3$.

$$RD3_{it} = (1-\delta)K_{t-(x+1)} + RD_{t-x}\ , \tag{7}$$

where δ is the annual knowledge stock depreciation rate (3%); and x is the time lag in years (1 or 2, or 3).

3. Estimation results

3.1 Data description

Table 3 summarizes the key characteristics of the variables of 12 countries. To select the data, I reviewed previous studies and related references. The period of data spans from 2003 to 2010. The majority of data shows that the standard deviation is larger than the mean. This means that there are large differences in the data for the time period and countries in question.

Table 3. A basic statistical analysis of the selected data (2003-2010)

	Mean	Standard deviation	Country
Cost of PV (US$/W, 2010)	5.71	2.47	Australia (AUS), Canada (CAN), Denmark (DNK), Deutschland (DEU), France (FRA), United Kingdom (GBR), Italy (ITA), Japan (JPN), Korea (KOR), Portugal (PRT), Sweden (SWE), Unites States (USA)
Cumulative capacity (MW)	817.05	2224.05	
RD1 (US$, million)	39.16	59.19	
RD2 (US$, million)	422.13	2244	
RD3 (US$, million)	2459.67	3495.95	

Note: (1) RD2 and RD3 data are corrected from 2001 to allow consideration of lag.
(2) RD2 and RD3 data are for lag 0.

The cost is the dependent variable and the most important element in the learning curve. However, the cost of a PV system depends on many factors, such as the photovoltaic module, inverters, storage batteries, construction, labor and so on. Some factors influence not only the technological development, but also social conditions. Therefore, it is logical to use the module price as a representative cost of a PV system (as done by many studies in this field). The module price is almost half the production cost. I corrected the data using the Photovoltaic Power System Program Annual Report of the International Energy Agency (IEA PVPS), a collaborative research and development agreement established in 1993 within the Agency.

Figure 1 presents the trend in module price from 2003 to 2010. The module price decreased during the analysis period. The weighted average price almost halved in the period under consideration—from US$ 6.59/W in 2003 to US$ 3.91/W in 2010. This implies that the chosen analysis period is acceptable for the estimation of the learning curve.

The cumulative installed capacity in PV was also corrected using the IEA's PVPS Annual Report. As seen from Figure 1, it increased gradually for the period under review—from 1,707 MW in 2003 to 29,635 MW in 2010. This translates to an average increase of 3,989 MW/year. Notably, in the case of Germany, there were massive increases in the cumulative installed capacity owing to the enthusiastic response to its feed-in tariff (FIT) policy. The trend for cumulative installed capacity in PV therefore opposes that seen for cost reduction. This means that the cumulative installed capacity in PV could explain the reduction in PV module price.

I corrected the R&D variables using IEA's Energy R&D Database on PV Systems (code 312). Figure 2 shows the trends in R&D variables. Pure R&D or public R&D expenditure does not show a constant increase. Some countries reduced public expenditure in R&D for PV systems in certain years, such as Canada and the USA. Accumulation of R&D and knowledge stock from R&D expenditures showed similar patterns. However knowledge stock is smothering than accumulation of R&D.

Figure 1. Indicative module price and cumulative installed solar PV capacity (2003–2010)

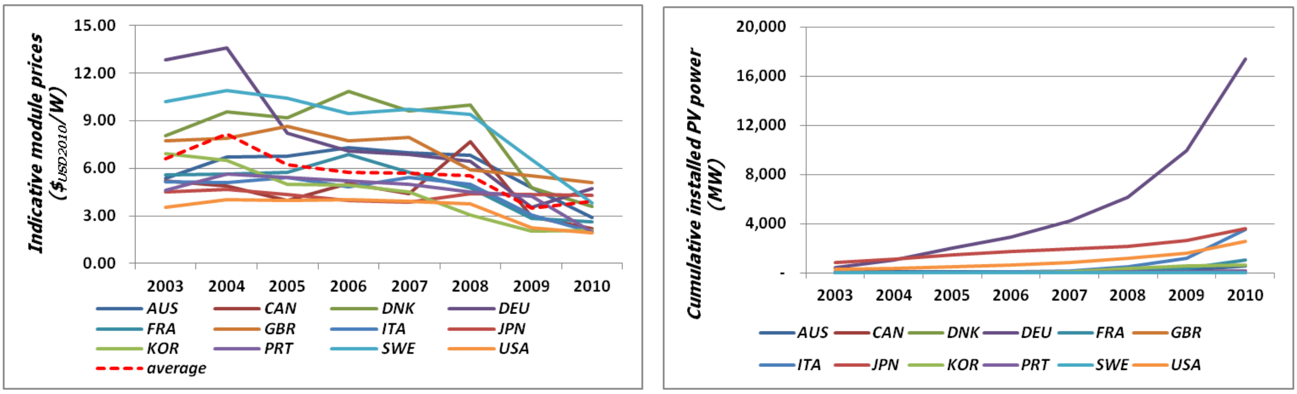
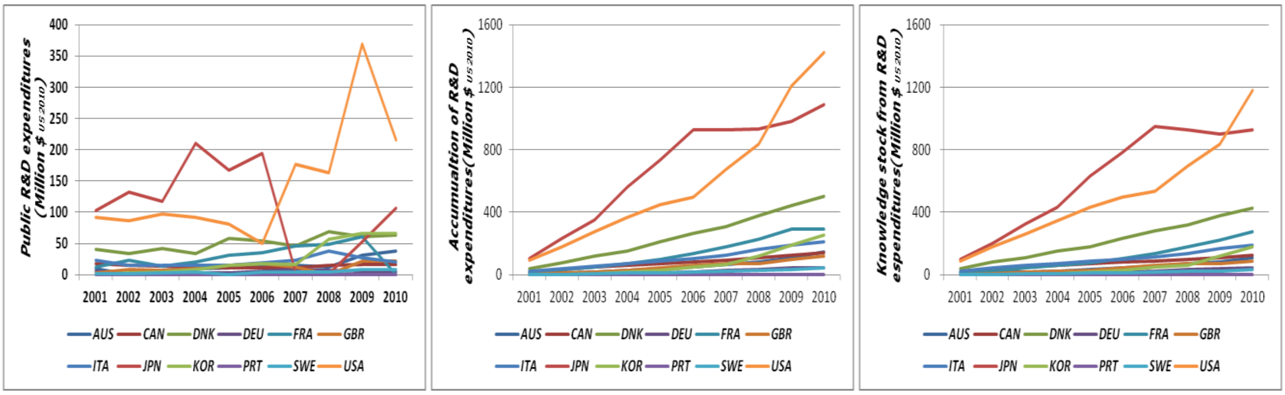


Figure 2. R&D variables (2001–2010)



3.2. Empirical results

There are seven models, depending on the type of R&D variable and lag lengths. Model 1 uses the pure R&D variable (RD1). Models 2, 3, and 4 use accumulated R&D expenditure (RD2) with lags 1, 2, and 3. Models 5, 6 and 7 use the knowledge stock from R&D variable (RD3) with lags 1, 2, and 3.

Table 4 depicts the results of the learning curve using the panel data set of 12 countries for the period 2003–2010. F-statistics provide the significance of the overall estimation result. All models reject the null hypothesis that the three independent variables are equal to zero. This means that all three types of R&D variable models are statistically significant.

The estimators of cumulative PV capacity and R&D variables carry the negative sign for all models. It is an acceptable result, in that it shows that the variables lead to a cost reduction. The R&D variable is not significant within 10% of the significant level in Model 1 alone, which uses the pure R&D variable. Except for Model 1, the R&D variables are statistically significant in the remaining six models.

The estimators of cumulative PV range from -0.145 to -0.159. The ranges are similar with the exception of Model 1, where the R&D variable is not significant and the accumulation estimator of cumulative capacity variable is -0.206. I also compare these results with those of previous studies (analysis period before 2000). The estimator of cumulative capacity is smaller than that found in previous studies that used the one-factor model, and ranged from -0.2 to -0.31. In studies using two-factor models (Maya (2006) and Kobos et al. (2002)), the value ranged from -0.19 to -0.294. This confirms a decreasing trend for cumulative capacity, which may be attributed to the fact that technology development in this case has reached a plateau. In the early days of technology development, it is easy to decrease the cost of production through accumulation of human capital, because there are many inefficient factors. However, in the developed stage, it is not as easy to reduce these inefficient factors, and hence, it becomes increasingly difficult to reduce the cost.

The estimator of R&D variable ranges between -0.133 and -0.227. It shows the extent of elasticity between the R&D variables and lags. Pure R&D is not significant, but RD2 and RD3 are statistically significant. It means that the accumulation of R&D expenditure as well as knowledge stock from R&D expenditures have a long-term effect. Additionally, the estimators for RD2 are larger than that for RD3. This is probably because I consider a depreciation rate for the knowledge stock, and therefore, the effect of cost reduction appears smaller than that of accumulated R&D expenditure. However, it is not possible to discern which variable is more appropriate from the result. For RD2, the greater the lag, the smaller the cost reduction effect. On the other hand, the RD3 models show the opposite trend. Kobos et al. (2006) reported the elasticity of R&D ranging from -0.223 to -0.409, which is larger than that seen in this study. This means that the cost reduction effect has decreased from the viewpoint of accumulation of R&D expenditure as well as the knowledge stock from R&D expenditure.

Sigma_u and sigma_e represent the estimators of standard deviation error terms U_i and e_{it}. The rho depicts the ratio of fraction of variance due to U_i from the total variance.

$$\hat{\rho} = \frac{\widehat{\sigma_u}^2}{\widehat{\sigma_u}^2+\widehat{\sigma_e}^2} \qquad (8)$$

If the value of rho is close to 1, it is important to consider the individual characteristic that is time-invariant. The rho statistic ranges from 0.79 to 0.90. So I the considering with group estimation is acceptable in PV price reduction. It means that the decrease in the solar cost is homogeneous. Therefore, learning-by-doing and learning-by-research display a common trend.

Table 4. Estimation results of the learning curve

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R&D variable	RD1	RD2 (lag 1)	RD2 (lag 2)	RD2 (lag 3)	RD3 (lag 1)	RD3 (lag 2)	RD3 (lag 3)
CC	-0.206*** (-7.36)	-0.145*** (-4.54)	-0.153*** (-4.94)	-0.158*** (-5.03)	-0.159*** (-4.76)	-0.153*** (-4.41)	-0.149*** (-4.25)
R&D	-0.203 (-0.66)	-0.227*** (-2.94)	-0.191*** (-2.78)	-0.183*** (-2.52)	-0.133** (-2.2)	-0.149** (-2.33)	-0.156** (-2.38)
A	2.620** (-23.4)	3.389*** (-11.75)	3.214*** (-13.11)	3.179*** (-12.47)	3.190*** (-10.96)	3.241*** (-10.89)	3.246*** (-10.88)
F-statistics (P-value)	40.62 (0.000)	54.24 (0.000)	53.25 (0.000)	48.43 (0.000)	50.21 (0.000)	47.48 (0.000)	43.66 (0.000)
R^2	0.18	0.14	0.15	0.15	0.17	0.16	0.15
sigma_u	0.48	0.68	0.64	0.64	0.57	0.59	0.61
sigma_e	0.25	0.23	0.23	0.23	0.24	0.24	0.24
rho	0.79	0.90	0.88	0.88	0.86	0.86	0.87

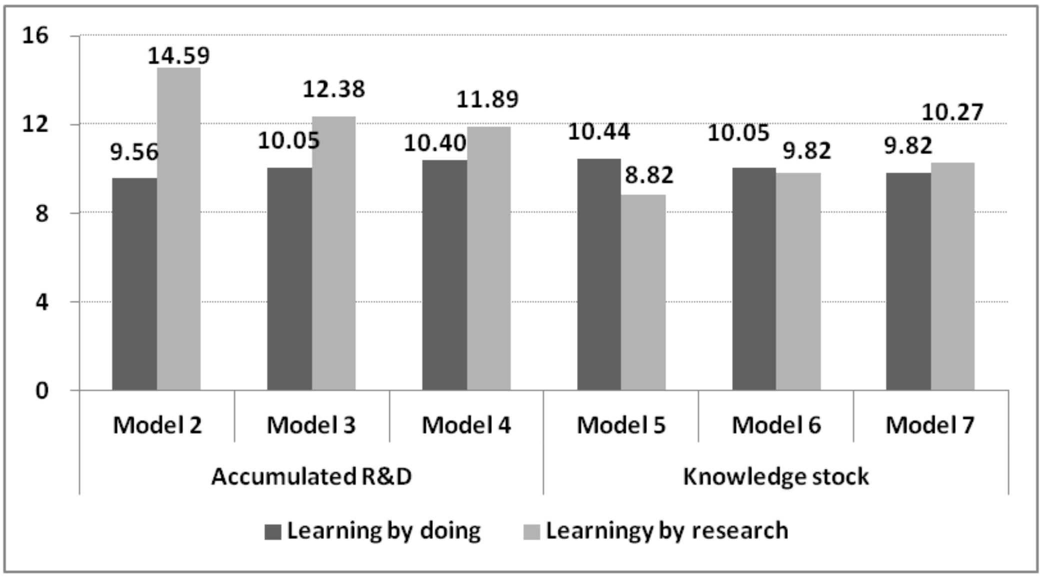
Note: (1) The PV module price is the dependent variable.

(2) *, **, *** represent 10%, 5%, and 1% rejection respectively within the significant level.

(3) Values within "( )" represent t-statistics.

From the estimation result, we can calculate the learning-by-doing rate and the learning-by-research rate (Figure 3). The estimator of R&D is insignificant for pure R&D. Therefore, I calculate the learning rate for accumulated R&D and knowledge stock only. The learning-by-doing rate for accumulated R&D in Model 2 is 9.56. This means that the cost of a PV module decreases by 9.56% when the cumulative installed capacity for solar PV doubles. Similarly, the rate of learning-by-research is 14.59, which means that there would be a cost reduction of 14.59% in the event accumulated R&D expenditure doubles. The models of accumulated R&D show that the learning-by-research rate is higher than the learning-by-doing rate. However, the models of knowledge stock show that the learning-by-doing rate is slightly higher or lower than the learning-by-research rate. This means that the selections of R&D variable and lags have an effect on the learning rates.

Figure 3. Learning rates of learning-by-doing and learning-by-research



4. Discussion and conclusions

In this research, I developed a more recent (post-2000) database for PV module prices, cumulative installed capacity of solar PV, and R&D investment. Using this data, I analyzed the effect of cumulative installed capacity and R&D investments on cost reduction. I applied the panel estimation method using data for 12 countries and different R&D variables.

The results can be summarized as follows. The learning rate for solar PV renewable energy technology has decreased after 2000. The estimator of the cumulative capacity and R&D variables showed a decrease when compared to previous studies that utilized data from before 2000. The reduction is larger for the learning-by-doing rate. The role of cumulative capacity in cost reduction also decreased, and as a result, R&D could be a more effective instrument for enabling cost reduction.

Learning rates also differed depending on the selection of R&D variables. Pure R&D investment turned out to be insignificant, while accumulated R&D and knowledge stock were significant. However, it was not possible to discern which variable of the two was more appropriate for experience curve analysis. Nevertheless, it is possible to conclude that R&D exerts a long-term effect.

From the panel analysis, I also showed that the countries share common trends in learning-by-doing and learning-by-research. The panel analysis controls the individual effect in PV cost reduction, and therefore, employing the panel analysis was a better option as compared to OLS estimation. The result implies that R&D investment and cumulative installed solar PV capacity have spillover effects on the reduction of PV cost globally.

Acknowledgement

This work was supported by the New and Renewable Energy Program of the Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant funded by the Korea government Ministry of Knowledge Economy (No. 20093021020020)

References

Arrow, K. J. (1962). "The economic implications of learning by doing." The Review of Economic Studies **29**(3): 155-173.

Bodde, D. (1976). "Riding the experience curve." Technology Review **79**: 53-58.

Cohen, W. M. and D. A. Levinthal (1989). "Innovation and learning: the two faces of R & D." The Economic Journal **99**(397): 569-596.

Colpier, U. C. and D. Cornland (2002). "The economics of the combined cycle gas turbine—an experience curve analysis." Energy Policy **30**(4): 309-316.

Duke, R. D. (2002). "Clean Energy Technology Buydowns." Economic Theory, Analytic Tools, and the Photovoltaics Case. Ph. D. diss., Princeton University.

Ek, K. and P. Söderholm (2010). "Technology learning in the presence of public R&D: The case of European wind power." Ecological Economics **69**(12): 2356-2362.

Goldemberg, J., S. T. Coelho, et al. (2004). "Ethanol learning curve—the Brazilian experience." Biomass and Bioenergy **26**(3): 301-304.

Grübler, A. and S. Messner (1998). "Technological change and the timing of mitigation measures." Energy Economics **20**(5-6): 495-512.

Gregory F, N. (2006). "Beyond the learning curve: factors influencing cost reductions in photovoltaics." Energy Policy **34**(17): 3218-3232.

IEA (2010). "IEA—PVPS Annual Report 2010." IEA PVPS.

Junginger, M., E. de Visser, et al. (2006). "Technological learning in bioenergy systems." Energy Policy **34**(18): 4024-4041.

Junginger, M., A. Faaij, et al. (2005). "Technological learning and cost reductions in wood fuel supply chains in Sweden." Biomass and Bioenergy **29**(6): 399-418.

Junginger, M., A. Faaij, et al. (2005). "Global experience curves for wind farms." Energy Policy **33**(2): 133-150.

Kahouli-Brahmi, S. (2008). "Technological learning in energy-environment-economy modelling: A survey." Energy Policy **36**(1): 138-162.

Karin, I. (2002). "Explaining learning curves for wind power." Energy Policy **30**(13): 1181-1189.

Kim, D. W. and H. J. Chang (2012). "Experience curve analysis on South Korean nuclear technology and comparative analysis with South Korean renewable technologies." Energy Policy **40**(0): 361-373.

Klaassen, G., A. Miketa, et al. (2005). "The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom." Ecological Economics **54**(2-3): 227-240.

Kobos, P. H., J. D. Erickson, et al. (2006). "Technological learning and renewable energy costs: implications for US renewable energy policy." Energy Policy **34**(13): 1645-1658.

Lundvall, B. A. (1988). "Innovation as an interactive process: from user-producer interaction to the national system of innovation." Technical change and economic theory **369**.

Maya, P. (2006). "An economic perspective on experience curves and dynamic economies in renewable energy technologies." Energy Policy **34**(4): 422-432.

McDonald, A. and L. Schrattenholzer (2001). "Learning rates for energy technologies." Energy Policy **29**(4): 255-261.

Neij, L. (1999). "Cost dynamics of wind power." Energy **24**(5): 375-389.

Neij, L., P. D. Andersen, et al. (2003). Experience curves: A tool for energy policy assessment.

Qiu, Y. and L. D. Anadon (2011). "The price of wind power in China during its expansion: Technology adoption, learning-by-doing, economies of scale, and manufacturing localization." Energy Economics(0).

Rosenberg, N. (1982). Inside the black box: technology and economics, Cambridge Univ Pr.

Söderholm, P. and T. Sundqvist (2007). "Empirical challenges in the use of learning curves for assessing the economic prospects of renewable energy technologies." Renewable Energy **32**(15): 2559-2578.

Sagar, A. D. and B. van der Zwaan (2006). "Technological innovation in the energy sector: R&D, deployment, and learning-by-doing." Energy Policy **34**(17): 2601-2608.

Schaeffer, G. J., E. Alsema, et al. (2004). "Learning from the sun; analysis of the use of experience curves for energy policy purposes: The case of photovoltaic power. final report of the PHOTEX project." Report ECN DEGO: ECN-C–04-035, ECN Renewable Energy in the Built Environment.

Smit, T., M. Junginger, et al. (2007). "Technological learning in offshore wind energy: Different roles of the government." Energy Policy **35**(12): 6431-6444.

van den Wall Bake, J. D., M. Junginger, et al. (2009). "Explaining the experience curve: Cost reductions of Brazilian ethanol from sugarcane." Biomass and Bioenergy **33**(4): 644-658.

van der Zwaan, B. and A. Rabl (2003). "Prospects for PV: a learning curve analysis." Solar Energy **74**(1): 19-31.

van der Zwaan, B. and A. Rabl (2004). "The learning potential of photovoltaics: implications for energy policy." Energy Policy **32**(13): 1545-1554.

Wand, R. and F. Leuthold (2011). "Feed-in tariffs for photovoltaics: Learning by doing in Germany?" Applied Energy **88**(12): 4387-4399.

Watanabe, C., K. Wakabayashi, et al. (2000). "Industrial dynamism and the creation of a “virtuous cycle” between R&D, market growth and price reduction: The case of photovoltaic power generation (PV) development in Japan." Technovation **20**(6): 299-312.

Weiss, M., M. Junginger, et al. (2010). "A review of experience curve analyses for energy demand technologies." Technological Forecasting and Social Change **77**(3): 411-428.

Winkler, H., A. Hughes, et al. (2009). "Technology learning for renewable energy: Implications for South Africa's long-term mitigation scenarios." Energy Policy **37**(11): 4987-4996.

Zangwill, W. I. and P. B. Kantor (2000). "The learning curve: a new perspective." International Transactions in Operational Research **7**(6): 595-607.