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The determinants of photovoltaic system costs: an evaluation using a hierarchical learning curve model

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ABSTRACT

The uptake of solar power globally as an important alternative energy source to fossil fuels, together with a rapid fall in the cost of photovoltaic (PV) systems, has been phenomenal during the past decade. This trend is widely anticipated to continue for the years to come. The decline in PV installation costs, like many other new technologies through history, has been largely driven by the learning curve effect. However, it is suggested that other factors, such as costs of key production inputs and prices of competing technologies, also impact the costs of PV systems. In this study, we construct a hierarchical learning curve model to quantify the effects that various factors have on installation costs of PV systems based on empirical data from Taiwan. The results show that, in addition to the learning curve effect as underpinned by an increase of cumulative PV capacity, reductions to silicon price have significantly contributed to the decline of the final installation costs of PV systems in Taiwan. By quantifying the effects of critical cost factors, the learning curve effects on PV installation costs in Taiwan are defined which enable a more accurate projection of PV installation costs for governments, PV producers, operators and users.

1. Introduction

During the past decade, solar power has emerged as one of the most promising renewable energy sources to replace fossil fuels in meeting the world's future energy needs. The global solar PV market, in particular, has grown at a phenomenal rate. The total global PV capacity has experienced a 100-fold increase since 2000, from 1.25 GW in 2000 to 139 GW in 2013 (BP, 2014). Among all renewable energy technologies, solar power has attracted the largest investment in the world, accounting for USD 113.7 billion in 2013 (REN21, 2014). Ninety percent of the 2013 investment, or USD 102.3 billion, was committed to increasing worldwide solar PV capacity (REN21, 2014).

Accompanying the rapid uptake of solar PV systems in the world is a drastic reduction to their costs (Mathews and Tan, 2014). According to an estimate by Bloomberg New Energy Finance (BNEF, 2014), the PV price, in terms of a stabilized cost of electricity (LCOE),[1] has declined from around USD 80 (in 2013 $) per watt in 1976 to less than USD 1 (in 2013$) per watt in 2013. Many regard the success of solar PV technology in terms of a greater scale of deployment of the technology in the world as a serious solution to combat climate change lies in further decline of costs of solar PV products.

Many studies have attributed this rapid fall in installation costs of PV systems to the learning curve effect (Bhandari and Stadler,

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[1] According to the definition of BNEF (2014, p.5), LCOE refers to "the long-term offtake price required to achieve a required equity hurdle rate for the project".

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2009). Learning curves show a type of well-recognized non-linear relationship where the performance improves with practices (Ritter and Schooler, 2002). Such learning curve effects are common across industries and are regarded as one of the most important factors in driving diffusion of clean technologies (Kemp and Volpi, 2008). In cases of technology learning, the trajectories of cost reduction and efficiency improvement of many new technologies have been found to follow learning curves as a function of their accumulated production (Junginger et al., 2010). For example, Ibenholt (2002) used learning curve models to estimate trends in the cost reduction of wind power production in Denmark, Germany, and the United Kingdom. Further, McDonald and Schrattenholzer (2001) found the learning rates of different energy technologies vary based on the notion of learning curves and suggested that those of conventional fossil fuels were significantly lower than renewable energies.

While learning curve effects are seen as a major driver of cost reduction in new technologies, including the solar PV technology, other scholars have questioned the use of learning curve effects as a single factor to explain the cost reduction trajectories of PV technologies (Yu et al., 2011; Nemet, 2006). This is especially true given the production of PV systems involves multiple inputs and complex process, as indicated by Fu et al. (2015) in their life-cycle assessment of multi-crystalline PV systems. For example, Nemet (2006) incorporated a set of observable technical factors in his PV cost model, including module efficiency, plant size, yield, polycrystalline share, silicon cost, silicon consumption, and wafer size. The model was found to accurately predict the cost change after 1980, but with a large residual for the period before 1980. Several explanations were proposed to explain the residual, including a shift to low quality products, decreased margins for producers, increasing competition, and standardization (Nemet, 2006). Based on the observation that the price of PV modules stabilized when cumulative capacities increased for certain periods, Yu et al. (2011) argue that a single factor learning curve is not sufficient and recommend that other factors such as scale effects and input prices should play a role in PV cost models.

For several reasons, a more robust model is needed to take into account factors affecting the installation costs of PV systems beyond the learning curve. First, such a model better identifies significant cost-reduction factors for PV installations and quantify their relative contributions and helps governments and industry to develop more effective management and research policies. Second, as observed by Zhang et al. (2011) in their research of the Japanese market, the PV installation cost is the most significant negative effect influencing PV system adoption. A better projection of PV installation costs in the future based on such a model better explains the adoption of solar PV technologies in the market. Finally, to stimulate the development and use of renewable and sustainable energy, many governments have introduced promotional policies and incentive schemes, such as feed-in tariffs (FIT) and renewable portfolio standards (RPS). A key success factor for these policies is to properly determine the FIT prices, providing sufficient incentives to investors while reducing the burden placed on electric power grid operators. An improved PV cost model helps determine a satisficing price, not only in the current market but also for the future.

In this paper, an improved hierarchical learning curve model is introduced that combines the one-factor basic learning curve and the hierarchical linear model to account for factors that impact the relationship between installation costs and cumulative installation capacities. The results, based on empirical data from Taiwan, show that in addition to the learning curve effects from increases in cumulative PV capacities, the reduction in silicon prices significantly reduce the final installation costs of PV systems.

2. Literature review

In this section, the definitions and applications of basic learning curve models are reviewed. Based on generally accepted applications, a hierarchical linear model (HLM) is introduced and applied to model and analyze the historical costs of Taiwan PV systems.

2.1. The basic learning curve model

The concept of the learning curve was first introduced by Wright (1936). By observing the production processes of aircraft manufacture, Wright (1936) showed that when production quantity doubles, the cost of producing a plane decreases at a constant rate. Applying this concept, a learning curve model offers a means to project the future costs based on the historical cost data (Neij, 2008). In general, a learning curve model is described as follows (Wand and Leuthold, 2011):

$$C_x = C_1 X^{\gamma}, \tag{1}$$

where C_x is the predicted costs of producing the xth unit and C_1 represents the initial unit cost of producing the first unit. X represents the cumulative production quantity up to the xth unit and γ denotes the learning index or the experience parameter which is used to estimate the progression rate. The progression rate (PR) measures the rate at which costs decline when cumulated production is doubled. The PR is defined as:

$$\mathrm{PR} = 2^{\gamma} \tag{2}$$

where γ refers to the leaning index. Models based on learning curves have been applied in studies across a wide range of industries. Jaber and El Saadany (2011) report that as the total production quantity (in units) doubles, the cost per unit declines by a constant percentage. Cheng and Wang (2000) have developed models to estimate learning effects in the context of machine scheduling. Learning curve models have also been employed in renewable energy-related studies. Applying the learning curve, Cong (2013) developed the Renewable Energy Optimization Model (REOM) to analyze the benefits of applying wind power, solar power, and biomass power in China from 2009 to 2020. Qiu and Anadon (2012) utilize a learning curve to estimate price variations of wind power in China based on the bidding prices of national wind project concession programs from 2003 to 2007. Their study shows that factors such as new technology adoption, experience accumulated in building wind farm projects, wind turbine manufacturing localization, and wind farm economies of scale greatly affect the costs of wind power generation. Further, Wang et al. (2011) proposed a model based on a logistic learning curve to predict wind power development trends (but not cost trends) in China. The study indicates that the estimated annual growth rate of wind power capacity in China will exceed 30%, if existing policies remain unchanged before 2015.

Learning curve models have also been applied to the photovoltaic (PV) industry, including cost analyses of PV systems, PV modules, and PV electricity. Poponi (2003) uses learning curves to predict the different levels of cumulative world PV shipments required to reach the calculated break-even prices of these systems. Using PV cost data from Europe, Moor et al. (2003) constructed cost learning curves of PV modules and the balance of system (BOS). Their study reports that even though the PV module cost is higher than the BOS cost in a PV power generation system, the learning rates of modules and BOS are almost the same. Bhandari and Stadler (2009) used learning curve analysis to extrapolate PV module price data and study the grid parity analysis of PV systems