King Abdullah Petroleum Studies and Research Center

Estimating the Learning Curve of Solar PV Balance-of-Systems for Over 20 Countries

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Key Points

The capital cost of a solar photovoltaic (PV) system comprises the module and balance-of-systems (BOS). The latter refers to everything else that is needed to make the solar system functional including cables, mounts, labor, etc. While modules are priced internationally, the BOS is country-specific. Price developments of modules, which have been thoroughly studied in literature, followed an 80 percent learning curve (LC). On the other hand, research on the LC for BOS has not been as extensive. In this paper:

The LC for BOS in residential PV systems is estimated for more than 20 countries via an extensive dataset. We show that the BOS LCs for these countries are typically lower than that of modules, affirming the few single-country studies reported previously.

Our calculations yielded a global LC for the BOS of 89 percent, which corresponds to a progress ratio of 11 percent compared with 20 percent for modules.

The data was then divided into two periods – pre- and post-2008 – to study the effects of the global financial crisis on LC development. It was found that many countries were able to sustain progress in the LC post-2008 despite reduced financial policy support, indicating that there are effective steps that could be taken by policymakers to reduce BOS costs without requiring (significant) financial policy support.

Executive Summary

Capital costs (CAPEX) of any solar photovoltaic (PV) system comprise two main elements: the module, which converts sunlight to electricity, and the balance-of-system or BOS, which is an all-encompassing term and refers to all other components and services needed to make the PV system operational including, and not restricted to, ground mounts, cables, labor costs and the inverter.

Modules are the backbone of the solar PV industry and the energy circle relies on the price of the module as an indicator to assess the competitiveness of the solar technology with respect to other conventional technologies. Dozens of industrial reports and academic journals have analyzed the cost development of the module and concluded that modules have been following an 80 percent learning curve (LC). A LC of X percent for any product means that each time the global cumulative production doubles, the new cost of production is X percent of the previous level.

Research on the BOS has not been as intensive partly because the module has historically been responsible for a significantly larger share of CAPEX than BOS. The situation is now reversed. After almost four decades of technological advancements and market developments, the cost of modules has shrunk significantly and BOS now accounts for more than half of CAPEX. In this paper, we will fill the gap that exists in literature and estimate using econometrics country-specific LC for the BOS segment of residential solar PV systems. With the aid of an extensive data set, the BOS cost for more than 20 countries has been deduced. In aggregate, the countries considered in this study are responsible for over 85 percent of global solar installations.

For most countries, it was found that the BOS LC is slower than modules. Furthermore, it was observed that developed countries were faster learners than developing states. Also, for the first time, a global LC was deduced for the BOS in residential systems and was found to be 89 percent. Comparing this with that of the LC of modules (i.e., 80 percent), we confirm that modules, thus far, have performed better in terms of learning. This finding is in line with the very few previous single-country studies, thereby allowing for wider global generalization.

To extract further insight from the data, we performed a time-specific study where the period of analysis was divided into two: one that precedes 2008 and the other succeeding. After the financial crisis in 2008, the financial policy support allocated to renewables decreased significantly. Our study shows that the LC of BOS continued to progress steadily despite a global policy environment shaped with less funding. This important observation indicates that, contrary to what most would assume as reasonable, many steps could be taken by policymakers to promote cost reductions in the BOS segment without significant financial commitments. Such initiatives include promoting market competition between installing companies, legal process standardization and adopting collective purchasing and installation schemes.

Cost Details of Renewables Versus Conventional Fuels

The success of policies promoting renewable energy sources (RES) in the last two decades has been propelled by the new sociopolitical attitude toward climate change issues. The main goal of controlling emissions by curbing fossil fuel usage calls for the implementation of new policy instruments geared toward improving energy efficiency and deploying RES.

The European Union (EU) has been a central actor on the international scene of RES deployment by setting targets for carbon emission reduction and RES deployment. In 2008, the EU issued the 2020 Climate and Energy Package (EU 2009), and more recently issued the 2030 Climate and Energy Policies Framework (EU 2014). After setting the target to 2020 of 20 percent CO2 reduction and 20 percent of RES as a share of total energy consumption, the EU now proposes ambitious 2030 targets, requiring CO2 emissions at minimum of 40 percent below 1990 levels and to increase the share of RES to at least 27 percent.

In the U.S., federal initiatives aimed at developing and deploying RES technologies are integrated into many legislative actions. There are several incentive policies at both the federal and state level aimed at increasing the long-run competitiveness of RES technologies and efficiently integrating high levels of RES electricity generation into the nation's power system. The National Renewable Energy Laboratory (NREL) estimates that in 2050 renewables could reach 80 percent of total generation, and 50 percent of it would be from wind and PV (Hand et al. 2012).

In China, recent developments (where RES generation capacity increased from 21 percent in 2006 to 32.5 percent in 2015, totaling 490 GW) point toward continuous policy support for RES. China targets are set to reach 740 GW of renewable capacity by 2020 (CCCPC 2016). Deployment of RES in oil-rich countries is also gaining momentum. Saudi Arabia, for example, has set a renewable energy target of 9.5 GW to be installed by 2023. These targets will spur a new round of investments in renewables in the short to medium terms, which raises the question of how the cost structure of these technologies would evolve.

From a cost perspective, power generation technologies, whether conventional or renewable, can generally be compared using two metrics: the capital costs or the levelized cost of energy (LCOE). The capital expenditures, also known as CAPEX, turnkey costs or overnight costs, refer to the upfront costs required to build the generation plant assuming the plant can be built overnight. On the other hand, the levelized cost of energy is fundamentally the ratio of all the costs that are incurred throughout the lifetime of the plant to the total energy that was generated. CAPEX does not entail any operational costs, whereas the LCOE represents an average generation cost per unit of energy.

One of the fundamental differences between conventional and renewable technologies is that conventional generation requires fuel. Renewables on the other hand, boast (near) zero variable costs but are not dispatchable. This difference, among others, results in different cost implications as shown in Figure 1, where the LCOE breakup for solar and a conventional combined cycle (CC) plant is illustrated.

With CC plants, nearly three quarters of the costs are dominated by variable costs, including fuel, and is spread over the lifetime of the plant. Hedging or entering into long-term fuel supply contracts

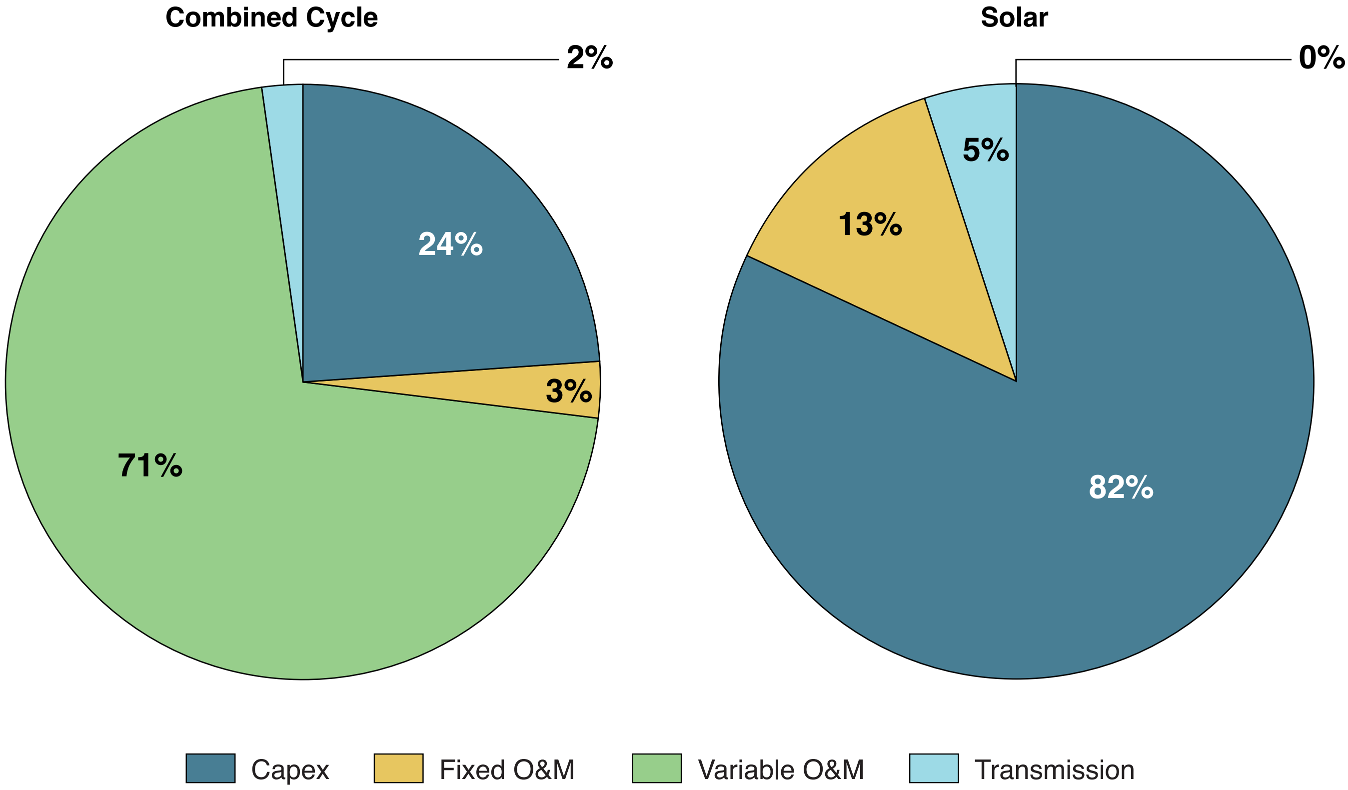

Figure 1. LCOE breakup for solar and combined cycle technologies. In the combined cycle plant, most of the costs are attributed to variable operations and maintenance (O&M) costs, which include fuel, and are incurred through the lifetime of the facility. However, for solar, most of the LCOE is governed by the CAPEX.

Source: KAPSARC based on DOE-EIA data 2015.

is an option to mitigate fuel price risk, while rates are adjusted to changes in fuel price in a given regulatory setting. In contrast, the LCOE of solar generation is dominated by its CAPEX, as amortized over time. Investing in solar PV requires a long-term view on interest rates as its profitability is heavily driven by the spread between the cost of capital and prevailing regulatory environment.

The cost structure of any PV system comprises mainly two components: (1) the module, which converts sunlight to electricity, and (2) the balance of system (BOS) costs, which is an all-encompassing term representing everything else needed for the solar system to be erected and functional including inverter(s), mounts, cables, bolts, labor, permitting, grid connection, etc. Due to economies of scale, the costs, in dollars per watt, vary with the size of the solar facility, which may be residential (2kW – 10kW), commercial (10kW – 500KW) or utility (~1MW and above).

From virtually no installations in 1990, the solar PV industry grew to a formidable 227 GW of installed capacity worldwide by the end of 2015 (REN21 2016). The costs of solar technology have declined in tandem with this expeditious installation rate. Learning and expanding supply chains, buoyed by policy support, allowed for such a drop to occur.

Throughout the literature, demonstrating that the economics of solar PV have been following a downward trajectory was achieved via the average selling price (ASP) of modules, since modules are the cornerstone of the industry. As manufacturing experience accumulates, module manufacturers become more efficient and this enhanced efficiency translates into cost reductions. The latter concept is referred to as the learning curve (LC), and is a concept that can be applied to other industries as well. Plotting the module prices can be done against time (NREL 2016) or manufactured capacity (Ezysolare 2016), though the theoretical definition of LC relates monetary values to manufactured capacity, not time.

Relying on selling prices of modules to be the benchmark for cost trends in the solar PV industry did not happen accidentally. Modules can essentially be treated as a commodity and several organizations worldwide track and publish the spot price of modules regularly – similar to the price of oil. As such, monitoring the module price evolution gives a global picture on how the industry is progressing. The same does not immediately apply to the BOS. Each country has unique industry, policy and energy environments, and because renewable targets vary across countries, it is expected that the BOS costs would also evolve differently between countries (Neij et al 2017). Regional specificities associated with the BOS include tax rates and labor wages for example.

Furthermore, when trying to forecast PV system costs in a certain country, projecting how the cost of modules would develop globally and how the BOS costs would evolve regionally should be carried out simultaneously (Neij et al. 2017). The different CAPEX values prevailing in each country are mainly attributed to the variation in BOS, not in module costs.

Some reports rely on quoting annual LCOE values to illustrate how solar PV costs have declined (IRENA 2012). Although cost declines could be conveyed using the LCOE, this practice should not be confused with the actual LC of the industry. It is the module costs and the BOS costs that are used to arrive at the LCOE – not vice versa.

As the prices of modules have declined at a faster rate compared with BOS, the BOS has grown to form a larger share of CAPEX (Stapersma 2015). The latter observation warrants a detailed study of the evolution of the BOS globally. In this paper, we deduce for the first time the LC of the BOS component for more than 20 countries with the aid of an extensive dataset. Another important aspect of this study is that it uses recent data covering up to 2015 compared with previous studies that are mostly over a decade old. Such an analysis identifies countries that have succeeded in reducing the BOS component more effectively, and will consequently aid in identifying best practices that can potentially be replicated in other countries.

Learning Rates, Prices and Costs in the Solar PV Industry

General definitions and review

One goal of this paper is to deduce country-specific LC for the BOS segment within the solar PV industry – an undertaking that has so far not been carried out. Hence, it is crucial to clearly and explicitly agree on the definitions to avoid confusion or misinterpretation of the terms that will be used.

The LC is a concept that is often utilized to predict how the costs of a product or process may evolve based on historical trends. Manufacturers, through time, become better at producing a good or offering a service; this enhanced efficiency results in cost reductions. The LC can also be referred to as the learning rate, learning curve, experience curve, or Henderson Curve since Bruce Henderson, founder of the Boston Consulting Group, articulated the concept in 1968 (Henderson 1968).

The idea of the LC stems from empirical evidence. Henderson observed that cost reductions are observed with each doubling of cumulative production. In mathematical form, the LC can be expressed as:

$$C_Q = C_1 \bullet Q^{-\beta} \tag{1}$$

where CQ is the marginal cost of producing the Q-th unit, C1 is the cost of producing the first unit, Q is the cumulative quantity produced and β is the learning coefficient. The corresponding LC would be equal to $2^{(-\beta)}$ as derived in Appendix A.

Typical industries possess β values ranging from approximately 0.15 to 0.5, which corresponds to a LC of 90 percent to 70 percent, respectively. If a certain product possesses a LC of 85 percent for example, this means that each time the cumulative manufactured quantity doubles, the new cost of production is 85 percent of the previous level. Alternatively, a LC of 85 percent also means that each time the cumulative produced quantity doubles, the manufacturing costs fall by 15 percent. The progress of 15 percent achieved is often referred to as the progress ratio (PR). Clearly, PR = 1 – LC. For ease of reference, Table 1 summarizes several LC values with their corresponding β and progress ratios. Note that the higher the β, the quicker the learning. There are different variations to Equation (1) as detailed by Wiesenthal et al. (2012), but we restrict our study in this paper to that shown above.

It is important to bear in mind that Equation (1) does not possess a time component; the expression is restricted to quantity only. Whether the doubling in

Table 1. Learning curves and corresponding progress ratios and β. Note that PR = 1 – LC.

Learning Curve (LC)	Corresponding Progress Ratio (PR)	Corresponding β
95%	5%	0.0740
90%	10%	0.1520
85%	15%	0.2345
80%	20%	0.3219
75%	25%	0.4150
70%	30%	0.5146

Cost reductions occur more rapidly

Source: KAPSARC analysis.

quantity occurs in one year or otherwise, the value of the learning coefficient, β, will not be affected.

Given the central role that energy plays in our world, it is not surprising to see that estimating the LC (or equivalently PR) for generation technologies has been attempted in many studies (Jamasb 2007; Ferioli et al. 2009). Rubin et al. (2015) provide a summary of these studies (see Table 2). Although the data are relatively old, one can see that the solar PV technology has been progressing well compared with other generation technologies. The overwhelming majority of these solar PV LC studies discuss and analyze the learning associated with modules, not BOS (Rubin et al. 2015; Neij 2008; McDonald and Schrattenholzer 2001).

Dedicated studies on BOS learning are scarce. Schaeffer et al. (2004) estimate a LC for the BOS component for Germany and Netherlands only with data covering 1992 to 2001; the BOS LC was around 80 percent for both countries for that time period. More recently, Strupeit and Neij (2017) estimated the LC for the BOS in Germany at about 89 percent for 1990–2013.

The LC in the solar industry

Obtaining accurate manufacturing costs of products might not always be possible or easy. Hence, research centers and market reports often resort to applying the LC concept to prices, and the latter has been the case for the solar PV industry. The LC of modules has been determined by the evolution of the average selling price (ASP), or spot prices, as seen in Figure 2. The module industry followed a LC of approximately 80 percent, or a 20 percent progress ratio.

As expected, the LC shown in Figure 2 varies slightly in the literature because it is difficult to get exact data on price and global production. Nonetheless, most of the LC deduced are close to 80 percent (Fraunhofer 2015a). With the aid of Figure 2, it is important to emphasize the following:

> The prices are plotted against global cumulative production. Since the axes are in log-scale, the exponential decay is transformed into a linear decrease. Once again, we emphasize that the LC relates prices to production, not to time. The years superimposed in Figure 2 are included for completeness.

> Learning curves do not continue indefinitely. Typically, in the early years of deploying a technology or manufacturing a product, the learning and advancement occurs at a relatively faster rate.

Table 2. Estimated progress ratios as collected from the literature.

Technology	Progress Ratios (%)	Time period
Coal	5.6–12	1902–2006
Natural gas	-11–34*	1980–1998
Nuclear	0–6	1972–1996
Wind (onshore)	-11 to 32*	1979–2010
Solar PV	10–47	1959–2001
Biomass	0–24	1976–2005
Hydropower	1.4	1980–2001

* A negative progress ratio indicates that costs are increasing. More of this will follow in a later section.
Source: Rubin et al. (2015).

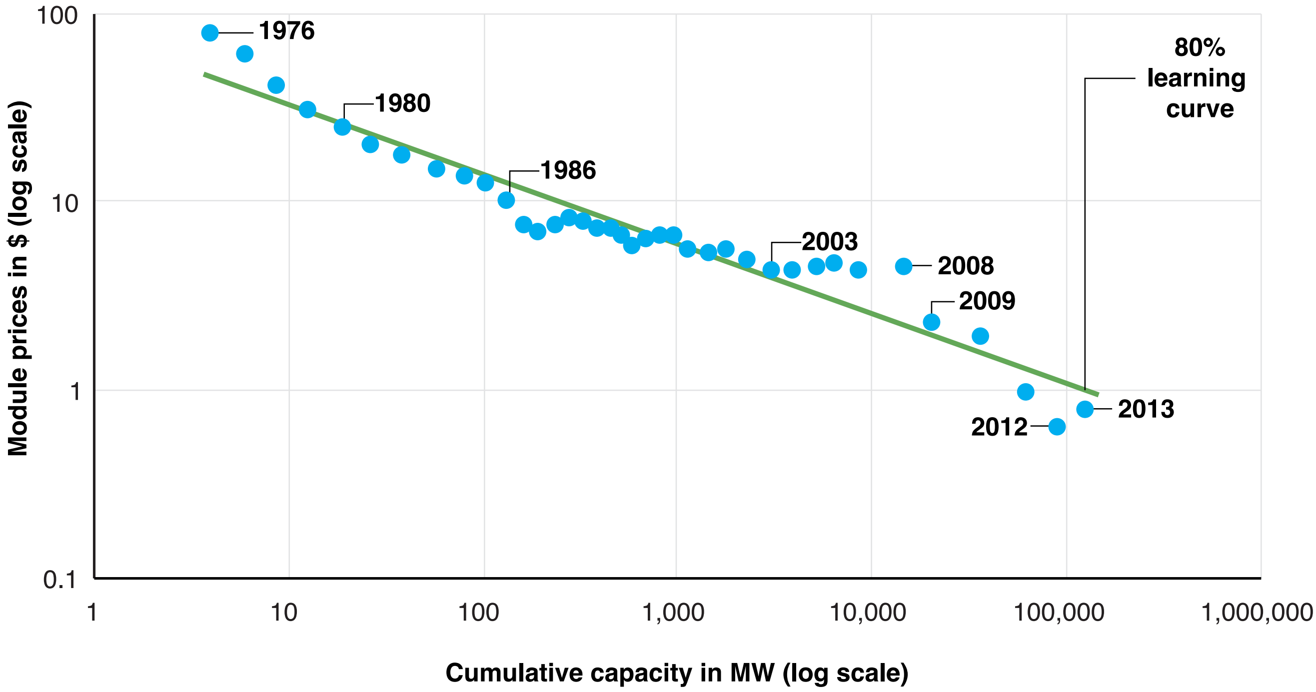

Figure 2. Learning curve of the solar PV module.

Source: Bloomberg New Energy Finance (BNEF).

However, after a reasonable amount of time has passed, achieving additional cost reductions becomes more difficult: a certain level of manufacturing 'maturity' is reached and doubling the production quantity requires a lot more time. It is for this reason that during the early years of adopting a technology, a rather rapid annual rate of cost decline is observed, which slows down thereafter. This 'annual' decline rate is not the same as the learning rate as explained earlier.

Learning curves report cost/price evolution regardless of the drivers. For example, the module manufacturing process includes countless steps: raw material mining, processing, purification, creation of ingots, doping, slicing wafers, etc. Cost reductions may have come from one or more steps. Irrespective of where the cost reductions stem from, the market only sees the final price of the product.

Learning curves do not necessarily reflect price reductions due only to technological advancements. In Figure 2, for example, one can see that a few years before the financial crisis, prices were constant at around $4.5/W but witnessed a sharp fall immediately after 2008. The pre-crisis period was shaped by high demand of solar systems in Europe, which allowed suppliers to keep prices high and enjoy windfall profits. Although technological progress and cost reductions were achieved by manufacturers during this period, these advancements were not reflected in the module price. It was only after the financial crisis that suppliers had to compete in a shrunken market, and did so by slashing their previously inflated prices. Hence, the observer needs to be mindful that market dynamics and global economic conditions can affect the learning rates, and be wary whether the prices are a genuine indication of manufacturing costs.

BOS Deserves Attention

Although the costs of solar cells have fallen precipitously and followed an 80 percent learning curve, BOS costs have not declined at the same rate in all countries. Today, the BOS accounts for the majority of solar PV capital costs. Costs associated with BOS include: land acquisition, site preparation and civil works, mounting structures, inverter, cables, legal costs, permitting, zoning, grid connection, charge control devices, labor, taxes, profits, marketing, etc. Some reports consider the inverter separate from BOS (Fraunhofer 2015a), but we bundle it with BOS in this paper. As such, the BOS is treated as a 'catch-all' term for everything other than the module (Mauleon 2016).

An important component of BOS is the regulatory framework that impacts the cost of PV installations. The EU, for example, has intervened early on to promote RES by setting obligations to streamline and accelerate administrative procedures and arrangements to ensure the removal of existing barriers whether administrative, social, economic or financial (European Commission 2001).

According to industry reports from the U.S., modules were used to represent almost two-thirds of the capital before 2008. By 2012, BOS had the biggest share in capital costs according to Green Tech Media (GTM 2012). Similar trends were also found in Germany as shown in Figure 3.

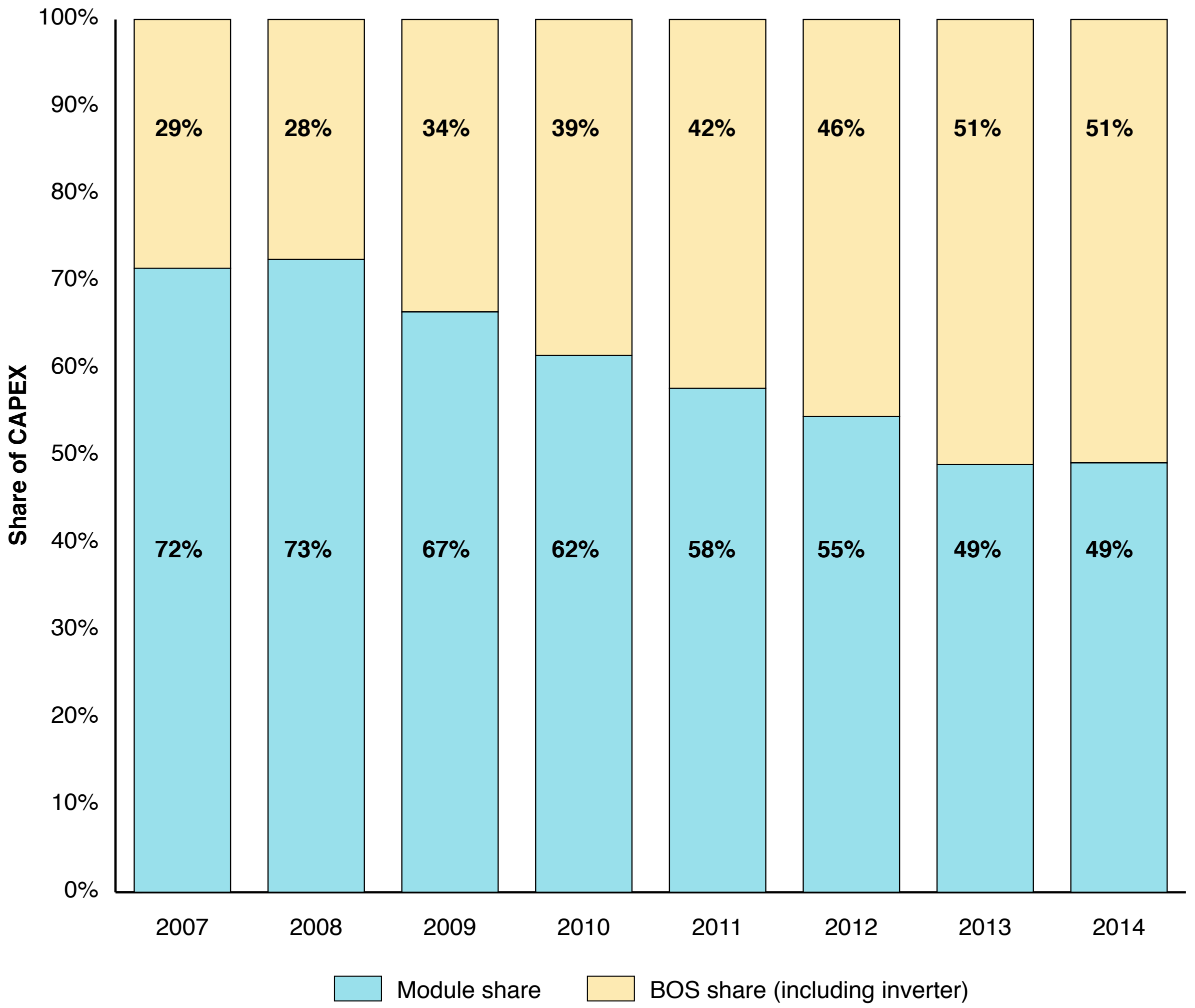

Figure 3. Share of modules and BOS (including inverter) in the average price of rooftop solar systems in Germany. Note how the BOS is increasingly taking up a larger share of capital costs.

Source: KAPSARC analysis based on data from Fraunhofer ISE (2015a).

Although BOS was about 30 percent of CAPEX in 2007, by 2014 it represented a major portion of capital costs. According to Bloomberg New Energy Finance (BNEF), the displacement of solar cell costs with BOS costs as the main driver of this form of renewable energy is common in many regions.

BOS taking a larger share of CAPEX will naturally have implications on the LCOE breakdown. We see in Figure 4 that, using the assumed the parameters, BOS costs now represent about 70 percent of the LCOE for this form of electricity generation. Given the capital intensive nature of renewable energy and of solar PV in particular, reducing BOS costs will now have a greater impact on making solar energy competitive than by reducing module costs.

The growing share of BOS in the total cost of solar PV has direct implications on its competitiveness. The role of BOS, however, did not receive the same research attention compared with modules (Fraunhofer 2015; IRENA 2012; Reichelstein and Yorston 2013) for two main reasons. First, modules were used to account for the bulk of CAPEX and, hence, studying the BOS was not a priority. Secondly, studying the BOS globally requires the compilation of a large dataset of installations and costs to produce meaningful insights. The first reason no longer holds as shown in Figure 3, while the second has been addressed by compiling an extensive dataset for over 20 countries. Studying the available data allows for the BOS learning rates to be computed, and then enables an analysis of countries with the lowest BOS. Ultimately, we may identify the sources of these differences and their scope for replication. Better understanding of the LC for the BOS segment is also crucial in drafting more effective climate change policies (Nachtigall and Rübbelke 2016; Kverndokk and Rosendahl 2007).

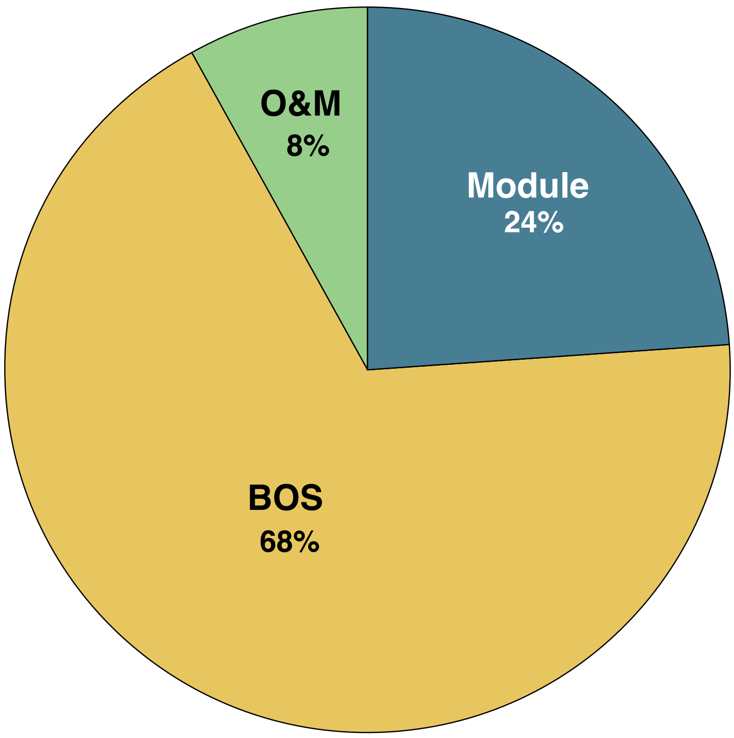

Figure 4. Contribution of the module, BOS and O&M costs to the LCOE of a typical solar system.

Source: KAPSARC analysis using the following assumptions: Module = $0.75/W; BOS = $1.25/W (for a total CAPEX of $2/W); Discount Rate = 2.5%; Operation and Maintenance = $10/kW/year; Solar Irradiation = 1,300 kWh/m2; Annual Module Degradation = 0.5%; De-rating Factor = 85%; Lifetime = 25 years.

Data, Modeling and Results

Overview

As mentioned, module prices are relatively accessible whereas global BOS data are not. In order to quantify the LC for the BOS, two parameters need to be available. Namely: total cumulative system installations and the BOS costs. With respect to installations, we have compiled a detailed dataset for solar PV installations and associated CAPEX for over 20 countries for 1983-2015. In line with the literature, the CAPEX is collected in nominal dollars. Availability of data are different across the countries, i.e., the data are an unbalanced time series of cross sections and not a panel dataset.

Further, the data distinguishes between residential and utility installations. For simplification purposes, we aggregate residential and commercial installations given their similarities, while we treat utility installations as separate. Data was collected from a variety of publically available sources including the International Energy Agency (IEA), ministry websites, national reports and others. The data and its sources are available at [BOS Learning Curves Data](). As for the second parameter, which is the BOS cost, we rely on the CAPEX data available in each country and the global spot price of modules. We assume that BOS = CAPEX – Module Price.

The time pattern of PV costs is crucial to understanding its competitiveness in the future. To this end we developed a model to capture the relationship between cost and scale of installed capacity to deduce the LC of the solar industry and more specifically the BOS component. The forecast of future installed capacity can aid in estimating the future PV cost development.

We analyze the effect of the growth in the PV market on its costs utilizing a cost function possessing the same form as Equation (1):

$$C_{Qi}=C_{1i}\bullet Q_i^{-\beta i} \tag{2}$$

Where

C_{Qi} is the BOS cost of installing the Q-th MW of solar PV in country i.

C_{1i} is the BOS cost of the first installed MW in country i. We can choose to describe C_{1i} as $= f(z_i)$, where z_i is a vector of exogenous factors relevant to country i.

Q_i is the installed capacity of solar systems in MW in country i.

β_i is the learning parameter observed in country i; this is the unknown parameter that will be estimated. We can choose to describe this parameter as $\beta_i = f(Y_i)$, where Y_i represents exogenous variables.

With the aid of Equation 2, we can estimate the learning parameter β and also recover a time path cost of C_{Qi} as a function of the quantity Q. The model can also be used to forecast a time path of C_{Qi} based on an exogenous input time path of C_{Qi}. The same concept in Equation 2 can also be applied to deduce learning rates for CAPEX and modules. We reiterate that the CAPEX is the sum of the module cost and the BOS, with a global spot price for the modules but country-specific BOS component.

There are two main sets of results provided in this paper. In the first, we derive the 'basic' LC and learning coefficient (i.e., β) for the countries relying only on BOS and cumulative installations. We refer to this calculation as the classical model. In the second set of results, however, we redo the regression assuming that β is a function variable that is affected by important inputs including the price of polysilicon (raw material used to make modules), steel (used in mounts) and other indicators that will be detailed shortly. The second method is referred to as the enhanced model.

After quantifying the LC in both models, we go a step further and estimate two LC values by splitting the study into two periods: before and after the financial crisis of 2008. The global environment of policy support toward renewables was very different in those two periods and, thus, distinguishing them is justified and also useful for policymakers.

Country-specific BOS learning curve – the classical model

The results of the analysis are shown in Table 3. We have taken logs of variables in Equation (2), so that the empirical equation is:

$$\log C_{Qi} = (\log C_{1i}) - \beta i \,.\, \log Qi \tag{3}$$

In general, all the different estimation methods presented in Table 3 show significant coefficient estimates for all countries at 1 percent level and that there is no severe error auto-correlation or heteroskedasticity for most countries. The log likelihood values are reported for the simultaneous estimations (Methods 2 and 3).

The first set of results estimates the learning parameter β assuming C_{1i} and β are constants using the ordinary least square (OLS) method for each country. Note that β was not calculated for the Czech Republic, India and Greece due to lack of data. This method is referred to in Table 3 as Method 1. The OLS method is relatively basic and does not take into account possible simultaneous error correlations across countries.

In order to account for a more general error structure in the econometric model, we re-estimate the learning parameter using the seemingly unrelated regression (SUR) method, or Method 2. The SUR method allows for estimating simultaneously a set of equations (time series) belonging to several countries (cross section). In other words, the SUR method allows to estimate efficiently a system of equations taking into account potential correlation across the equations. In our case, where the data are organized as a panel of times series for several countries, the SUR method allows to estimate country-specific parameters, considering that the propagation of some shock can affect contemporaneously each country via correlation of the stochastic component of each equation (i.e., the error term).

Note that in Method 1, some β values were not calculated for certain countries due to lack of data. However, we were able to impute a β to these countries in the SUR method because the simultaneous estimation procedure exploits a larger availability of degree of freedom for the entire sample (the degrees of freedom of the SUR regression is equal to the total number of observations minus twice the number of countries, because there are two parameters per country to be estimated in Method 2).

Given that Germany is considered to be a world leader in residential installations, we find that it possesses a rather high learning parameter of 0.316 as expected. Table 3 also includes the time period associated with each country. The time frame represents the period for which data for CAPEX, installations or both was available. To avoid repetition, the time period is not included again in the rest of the tables.

Country specific BOS learning curve – the enhanced model

In the enhanced model, as shown in the rightmost columns of Table 3, we not only rely on the price and quantity to estimate β, but we also incorporate the oil price (oil), polysilicon spot price (poly), steel index price (steel) and consumer price index (cpi) data in advanced economies. These four parameters were chosen as they can affect solar deployment. For example, a reduction in the cost of polysilicon or steel would reduce the CAPEX of solar systems and hence stimulate installations. This method is referred to as Method 3.

We assume that the learning coefficient is not a constant through time, but is a function of these variables:

$$\beta_{it} = f(Y_{it}) \tag{4}$$

where Y_{it} are exogenous time-varying variables. We have assumed a linear model for equation (4) as follows:

$$\beta_{it} = \beta_0 + (\beta_1.oil_t) + (\beta_2.poly_t) + (\beta_3.steel_t) + (\beta_4.cpi_t) \tag{5}$$

The advantage of this specification in Equation (5) is that we can capture some time variability in the learning coefficient, which can be easily ascertained by testing the joint significance of the coefficients β_1 to β_4. In this way, we can explain the occurrence of a more flexible pattern of the learning process, which may accelerate or decelerate through time, as a function of structural and market variables. Equation (4) can be viewed as a simple version of the general time varying coefficient regression model (Cai 2008). In the interest of brevity, we only focus and report β_{it} rather than the individual betas since βit is the parameter of interest.

We use only total residential installations to deduce the LC for each country in Table 3. However, utility installations can also be viewed as a factor that contributes to learning within the residential sector and vice versa. Hence, to deduce the LC for the solar industry in a country it may be more indicative to consider total cumulative installation. The latter is performed in Table 4. As can be seen, when total installations are used, the learning curve changes depending on the utility installations. Nonetheless, the general message does not change significantly: countries that are progressing from a BOS LC perspective still possess a reasonable learning parameter irrespective of the installations considered. In the rest of the paper, we will consider total installations for our analysis.

Table 3. The learning parameter of BOS for residential scale solar PV systems using the classical and enhanced methods. The associated LCs are calculated based on the learning parameter value. The quantity considered is the total cumulative residential installations.

	The Classical Model				**The Enhanced Model**		
	Method 1		**Method 2**		**Method 3**		
Country	**Learning parameter β estimated using OLS**	Corresponding LC (%)	**Learning parameter β estimated using SUR**	Corresponding LC (%)	**Learning parameter β_i (Y_i) estimated using SUR**	Corresponding LC (%)	Time Period
Australia	0.165**	89.2	0.194**	87.4	0.186**	87.9	1992–2015
Austria	0.148**	90.3	0.153**	89.9	0.145**	90.4	1998–2014
Belgium	0.330**	79.6	0.308**	80.8	0.301**	81.2	2007–2013
Bulgaria	0.330**	79.6	0.274**	82.7	0.273**	82.8	
Canada	0.073**	95.1	0.069	95.3	0.063	95.7	1992–2014
China	0.084	94.3	0.353**	78.3	0.346**	78.7	2000–2015
Czech			0.274**	82.7	0.096**	93.6	2003
Denmark	0.138**	90.9	0.122**	91.9	0.117**	92.2	1993–2015
Europe	0.104	93.0	0.274**	82.7	0.267**	83.1	2001–2013
France	0.160**	89.5	0.132**	91.3	0.113**	92.5	1992–2013
Germany	0.316**	80.3	0.316**	80.3	0.256**	83.2	2004-2015
Greece			0.274**	82.7	0.273**	82.6	
India			0.274**	82.7	0.273**	82.6	
Italy	0.164**	89.3	0.145**	90.4	0.138**	90.9	1998-2014
Japan	0.245**	84.4	0.221**	85.8	0.221**	85.8	1992-2015
Malaysia	0.245**	84.4	0.274**	82.7	0.269**	83.0	
Mexico	1.070**	47.6	0.274**	82.7	0.270**	82.9	1992–2010
Netherlands	0.036	97.5	0.034	97.7	0.043	97.1	1992–2013
Norway	1.721**	30.3	0.274**	82.7	0.269**	83.0	1997–2014
Portugal	0.024	98.4	0.274**	82.7	0.271**	82.9	1992–2014
South Korea	–0.034	102.4	–0.034	102.4	–0.040	102.8	2004–2014
Spain	6.875**	0.85	0.274**	82.7	0.266**	83.2	2008–2013
Sweden	0.463**	72.5	0.432**	74.1	0.425**	74.5	2000–2014
Switzerland	–0.080	105.7	–0.045	103.2	–0.034	102.4	1992–2010
Thailand	0.076	94.9	–0.003	100.2	–0.006	100.4	2013–2014
U.K.	–0.082	105.8	–0.087	106.2	–0.061	104.3	2000–2008
USA	0.156**	89.8	0.174**	88.6	0.171**	88.8	2004–2014

Source: KAPSARC analysis.

Notes: **1.** Log likelihood for SUR: –697.8, and for SUR βi(Yi): –399.3. **2.** Total number of observations for SUR: 864, and for SUR $\beta_i(Y_i)$: 675. **3.** '**' is significant at 1%.

Table 4. The learning parameter of BOS for residential scale solar PV systems using the classical and enhanced methods. The associated LCs are calculated based on the learning parameter value. The quantity considered is the total cumulative installations.

	The Classical Model				**The Enhanced Model**	
	Method 1		**Method 2**		**Method 3**	
Country	**Learning parameter β estimated using OLS**	Corresponding LC (%)	**Learning parameter β estimated using SUR**	Corresponding LC (%)	**Learning parameter β_i (Y_i) estimated using SUR**	Corresponding LC (%)
Australia	0.208**	86.6	0.240**	84.7	0.096**	93.6
Austria	0.121**	92.0	0.123**	91.8	0.081**	94.5
Belgium	0.386**	76.5	0.302**	81.1	0.163**	89.3
Bulgaria			0.201**	87.0	0.127**	91.6
Canada	0.126**	91.6	0.094**	93.7	0.095**	93.6
China	0.107**	92.9	0.135**	91.1	0.047**	96.8
Czech		100.0	0.201**	87.0	0.095**	93.6
Denmark	0.188**	87.8	0.183**	88.1	0.171**	88.8
Europe	0.079	94.7	0.257**	83.7	0.130**	91.4
France	0.208**	86.6	0.173**	88.7	0.098**	93.4
Germany	0.156**	89.8	0.156**	89.8	0.095**	93.6
Greece			0.201**	87.0	0.127**	91.6
India			0.201**	87.0	0.132**	91.3
Italy	0.194**	87.4	0.176**	88.5	0.099**	93.4
Japan	0.218**	86.0	0.218**	86.0	0.194**	87.4
Malaysia	0.218**	86.0	0.201**	87.0	0.099**	93.4
Mexico	0.827**	56.4	0.201**	87.0	0.094**	93.7
Netherlands	0.216**	86.1	0.215**	86.2	0.089**	94.0
Norway	1.877**	27.2	0.201**	87.0	0.104**	93.0
Portugal	–0.024	101.7	0.201**	87.0	0.096**	93.6
South Korea	–0.028	102.0	–0.028	102.0	0.087	94.1
Spain	6.803**	0.9	0.201**	87.0	0.100**	93.3
Sweden	0.520**	69.7	0.486**	71.4	0.419**	74.8
Switzerland	0.053**	96.4	0.082**	94.5	0.042**	97.1
Thailand	0.642	64.1	0.353**	78.3	0.199**	87.1
U.K.	0.282**	82.2	0.281**	82.3	0.229**	85.3
USA	0.251**	84.0	0.204**	86.8	0.099**	93.4

Source: KAPSARC analysis.

Notes: **1.** Log likelihood for SUR: –947.8, and for SUR $\beta_i(Y_i)$: –635.4. **2.** Total number of observations for SUR: 1057, and for SUR $\beta_i(Y_i)$: 868. **3.** '**' is significant at 1%.

Time-specific BOS learning curve

Tables 3 and 4 quantify an aggregate LC for countries considering a single time period. However, as mentioned earlier, the policy support environment toward renewable energy in general changed drastically after the 2008 financial crisis. Hence, we divided the period of analysis: the first being before 2008 and the second after. In interest of brevity, we only include one set of results in this section relying on total installations within a country. We performed a Chow test and a likelihood ratio (LR) test to ascertain that there are significant estimation differences between the two periods. Both tests show that the difference in pre- and post- crisis coefficients is significant (in particular, the Chow test is 12.9 against a critical value of 1.46 and the likelihood ratio test is 405 against a critical value of 91.9).

The results in Table 5 show that the LC after 2008 was actually slightly higher compared with the LC before 2008. This result may seem counterintuitive, as there was generous policy support toward RES before the crisis, not after. This observation will be further analyzed in the next section.

Table 5. The learning parameters for residential BOS estimated before and after 2008. The quantity considered here is the total cumulative installations, including utilities.

Country	Learning Parameter β before 2008	Corresponding LC (%)	Learning Parameter β after 2008	Corresponding LC (%)
Australia	0.083	94.4	0.108	92.8
Austria	0.072	95.1	0.092	93.8
Belgium	0.089	94.0	0.172	88.8
Bulgaria			0.127	91.6
Canada	0.088	94.1	0.104	93.0
China	0.025	98.3	0.057	96.1
Czech	0.095	93.6	0.095	93.6
Denmark	0.158	89.6	0.185	88.0
Europe	0.120	92.0	0.139	90.8
France	0.082	94.5	0.108	92.8
Germany	0.077	94.8	0.106	92.9
Greece			0.127	91.6
India			0.132	91.3
Italy	0.088	94.1	0.106	92.9
Japan	0.182	88.1	0.209	86.5
Malaysia	0.086	94.2	0.114	92.4
Mexico	0.090	94.0	0.100	93.3
Netherlands	0.083	94.4	0.099	93.4
Norway	0.081	94.5	0.117	92.2
Portugal	0.093	93.8	0.107	92.9
South Korea	0.073	95.1	0.104	93.0
Spain	0.084	94.3	0.108	92.8
Sweden	0.408	75.4	0.430	74.2
Switzerland	0.036	97.5	0.053	96.4
Thailand	0.167	89.1	0.212	86.3
U.K.	0.221	85.8	0.248	84.2
USA	0.078	94.7	0.107	92.9

Source: KAPSARC analysis.

Notes: **1.** All parameters are significant at 1%.

2. Test for the structural break: Chow test = 12.9 (critical value = 1.46); LR test = 405 (critical value = 91.9).

Policy Implications and Discussion

The data compiled for this paper can be analyzed and studied in numerous ways and for different purposes. The intention of this section is to provide general observations based on the modeling results, while restricting the focus to the evolution of learning rates. We do not intend to perform detailed country-by-country analysis. Instead, we extract aggregate insights for the solar industry as a whole.

It is important here to distinguish between the value of the BOS cost itself and the LC of the BOS cost. For example, country 'A' may have been successful in bringing down the BOS costs from $4/W to $3/W within a specific timeframe, whereas the BOS in country 'B' was stable at $2/W. For this specific example, country 'A' is progressing well in terms of learning, yet country 'B' is considered more competitive despite having no learning progress.

Typically, the learning parameter is positive. However, a negative learning parameter could also be observed. A negative learning parameter means that there is 'negative' learning, i.e., the cost of the product is becoming more expensive as time passes. Such a result may be due to increased energy or raw material prices that dwarf any cost reductions achieved from learning. In Table 3, we see, for example, negative learning parameters for the U.K. and Switzerland. This is in part due to data scarcity. As an illustration, we note that residential installations data was only available up to 2010 for Switzerland. Hence, the drop that occurred in module prices was not fully captured, which resulted in the negative learning parameter.

On the other hand, some countries possessed a higher learning parameter value due to the timing of when they began their solar PV program. Belgium, for example, started installations around 2006/2007 with a high CAPEX, but quickly benefited from the drop in module prices that occurred in 2008. Similarly, Norway and Sweden possess aggressive LCs but installed a modest capacity (less than 100MW). With this in mind, interpreting the results provided in this table has to be done in the context of explicitly considering: (1) data availability, (2) when a country 'enters' or 'leaves' the installation pursuit and (3) capacity.

LC of modules versus LC of BOS

Recall that the LC of the solar modules followed an 80 percent (i.e., $\beta = 0.322$) path. Tables 3 and 4 show that the learning rate of the BOS component has not been developing as well as modules. Irrespective of the total installations chosen and method used to deduce the LCs, we see that only a few countries were able to achieve a learning rate that is better than 80 percent (i.e., LC lower in magnitude than 80, or equivalent β higher than 0.322). These results are in line with the studies that were conducted in some countries (as cited earlier in the paper), and they consolidate the view that the BOS is worthy of attention if more significant cost reductions in solar CAPEX are to be achieved. Tables B1 and B2 in Appendix B, which derive a LC for the overall CAPEX, also prove that the LC for modules and BOS are not the same. The analysis and conclusions of this paper generalizes this finding globally compared with a few previous studies that just analyzed a single country (for example, Strupeit and Neij 2017).

Attempting to forecast future solar PV CAPEX can now be performed with the LC figures provided in this paper. Countries can use the 80 percent LC for modules, and refer to their specific LC of the BOS. Once again, while referring to these deduced figures, it is important to keep in mind the caveats provided in the latter section while simultaneously considering the phase of adoption that the country is currently in. As with any numerical model, the results can be first interpreted qualitatively and used for directional analysis to help shape better policy decisions.

With the data at hand, it is possible to calculate a global average LC for the BOS. Providing such a value enables countries to compare their performance against a global benchmark. Consequently, countries can revisit their policies if they are not on par, and better plan for their future installations, or alternatively strive to maintain or even enhance their practices if they are performing well. The global LC of the BOS component is summarized in Table 6. As can be seen, the LC of the BOS for the residential PV sector is around 90 percent. Comparing this global LC of the BOS with that of the LC of modules (i.e., 80 percent) we note, once again, that the modules have performed better in terms of learning as expected. To the best of our knowledge, this is the first time that a global LC for the BOS is derived in the literature. The deduced global LC gives a reasonable indication, especially when realizing that the countries considered in this study are responsible for more than 85 percent of global solar installations.

Country-specific lessons

In the previous section, we deduced overall LCs, pre-2008 LCs and post-2008 LCs. The pre-2008 period was shaped generally by substantial global support for renewables compared with the post financial crisis years. Yet, the data also shows that some countries actually possess a higher LC post-2008 compared with pre-2008. This is an important observation that deserves further scrutiny. It is widely accepted that renewables will not be able to fully reach competitiveness with conventional generation, in terms of grid parity and socket parity, without various types of support and policy intervention. The analysis herein shows that this condition is not an absolute necessity.

The period before 2008 was mainly focused on reducing CAPEX by cutting module costs, though some BOS cost reductions were also achieved. Post-2008, given that less funding was available, more emphasis was directed toward BOS to achieve cost reductions through enhancing efficiencies in the soft costs (processes). In the following sections, we discuss briefly some of the steps taken by countries to reduce the BOS costs.

Germany: The case of Germany is one that has been researched and discussed widely. The country led the world with total solar installations of over 38 GW as of 2014. The expeditious installation rate was mainly driven by generous feed-in-tariffs.

Table 6. Deriving a global value for the BOS learning for residential solar PV systems. The estimation is simultaneous for all countries. ‘**’ is significant within 1%.

	Calculating β using SUR		**Calculating β using SUR**	
	β	**Corresponding LC (%)**	**β**	**CorrespondingLC (%)**
Deriving learning via total residential cumulative installations	0.133 **	91.2	0.161 **	89.4
Deriving learning via total cumulative installations	0.156 **	89.8	0.177 **	88.5

Source: KAPSARC analysis.

One implication of these high tariffs was that solar companies in Germany did not have to invest as much as companies elsewhere in marketing and advertising (Seel 2012). The generous feed-in-tariffs that homeowners received meant that they earn a high return at a low risk. Hence, there was little reason for solar companies to be involved in aggressive marketing activities. Coupled with the financial support, Germany also facilitated the permitting, inspection and interconnection (PII) requirements to make them more homogenous nationwide, which brought down the concomitant legal costs by reducing cycle time. Although the financial support resulted in companies requiring less marketing, the standardization of PII efforts – a nonfinancial endeavor – enabled soft costs of installations to be reduced substantially.

United Kingdom: The U.K. adopted an aggregate purchasing scheme whereby installers complete several installations for neighboring homes at the same time (Chase 2015). Such a model reduces down time and benefits from economies of scale given that, for example, labor, sales and transportation costs are shared across several homes.

United States: Innovative financing is one option that should not be overlooked, especially since CAPEX is the biggest hurdle in solar system acquisition. CPS, the largest municipally owned utility in the U.S., for example, adopted a novel model to aid homeowners to circumvent the upfront cost obstacle in solar systems. In essence, CPS borrows at rates that homeowners or installers cannot secure. Then solar companies install the system, maintain it and collect the tax credits, while the homeowner self-consumes or exports the excess electricity to the grid. With this model, homeowners reduce their monthly bill and do not bear the initial cost of purchasing the system (Gross 2015). Similar models have been implemented in Europe, indicating that inventive business models and financing schemes can help bring down CAPEX.

Italy: There have been several regulatory frameworks in Italy to promote RES since 1991, such as direct PPA between the government and IPP (1991–1998); green certificates (GC) (1999–2005); net metering and feed-in premium (2005–2007); all-inclusive feed-in since 2008. The initial share of RES, set at 2 percent in 1999 to promote the GC market, was increased by 0.75 percent annually, thus setting a moving target for the industry. The all-inclusive tariff was designed to promote small plants and was guaranteed for 15 years. For small plants, a simplified purchase and resale arrangement was designed in 2009 to allow producers to directly sell the power generated to the government agency instead of the market. The price is guaranteed at the average monthly price per hourly band (which is set on the Italian electricity market). Hence, the producer is sheltered from the risk of short-term market price fluctuations. The number of small producers under this scheme grew from 50,000 in 2008 to 580,000 in 2015. The total RES capacity (excluding hydro) increased from 6.2 GW in 2008 to 32.9 GW in 2015. The PV capacity increased in the same period from 0.4 GW to 18.9 GW (Bigerna et al. 2015).

The above observations are not region-specific and can generally be implemented in all countries with appropriate modifications. These practices do not require any financial commitment from the government, but only require cooperation between the different parties involved, including the government.

The argument of reducing BOS by enhancing module efficiency

It is often mentioned that using solar cells possessing high efficiency conversion ratios is one of the most effective ways for reducing BOS costs (Fraunhofer 2015b; Handleman 2015). By virtue of using cells with higher efficiencies, less area is required to generate the same amount of energy output, which translates to less racking, labor and cables – all translating to reduced BOS costs.

In principle, this efficiency argument is correct. However, there are a few considerations that may impede its practical acceptance. According to the Shockley-Queisser limit (Schockley and Queisser 1961), the maximum theoretical efficiency that a single junction solar cell can achieve is around 30 percent. Typical commercial silicon cells, which represent nearly 85 percent of the current market, have achieved laboratory efficiencies of 25 percent. As shown in Figure 5, the efficiencies of silicon cells (blue lines) have been mostly stagnant for more than a decade, underlining the challenge technologists face in seeking to enhance silicon cell efficiencies any further given that they are now close to reaching their theoretical limit. Attempts to achieve the same efficiency through a more cost effective route, however, should not be ignored.

Multijunction cells, on the other hand, are able to overcome the Shockley-Queisser ceiling. As shown in Figure 5, efficiencies reaching the mid-40s have already been demonstrated. Doubling the efficiency means halving the area required to erect the solar system (and we assume for simplicity that the BOS costs would also be halved as a result), but doubling the efficiency does not mean doubling the cost of manufacturing the cell – in fact, it is far from that. The cost of multijunction technology is deemed as prohibitively expensive, with costs reaching as high

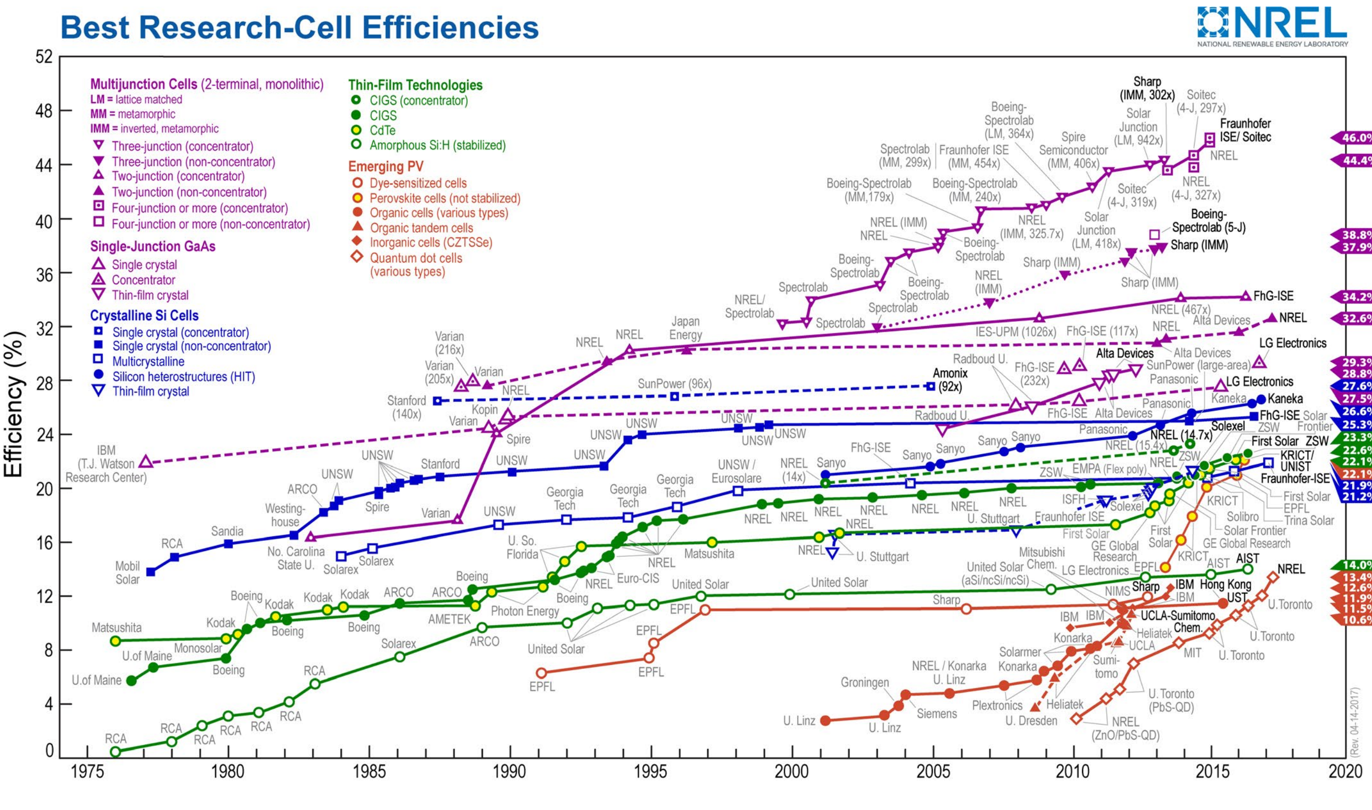

Figure 5. The efficiency of many types of solar cell technologies plotted against time measured in a laboratory setting. Note there is no single junction technology that possess efficiencies higher than 30 percent. Silicon technologies (blue) have generally witnessed little progress in the past 10 years.

Source: National Renewable Energy Laboratory, Golden, CO, U.S.

as \$5/cm2 compared with approximately \$0.02/cm2 for the typical silicon technology (PROMES 2015; MIT 2015). Consequently, and given current prices, the premium paid for using high efficiency cells will not be recovered from the reductions in the BOS. Solar concentrators can be used to reduce the overall area required, but the concentrators need to be purchased and a cooling system may be required to account for the heating that will result from using the concentrators. Using high efficiency cells may be justified if there are austere area constraints or if the site requires abnormally high preparation requirements such as brownfields. Generally, however, and based on the above, seeking to reduce the BOS by adopting high efficiency solar cells should be considered with caution, at least in the near term.

The way forward

Looking at the solar installation targets that countries have set for themselves, genuine efforts toward reducing the BOS costs would reap benefits. If a country's target is to install 1 GW of solar systems and succeeds in saving a mere one cent per watt, the savings will total \$10 million. Moving forward, and in addition to what some countries have done to lower the BOS, opportunities do exist. For example:

> Many governments, including Germany and the U.S., have initiated programs for more aggressive standardization efforts for residential systems. Within that framework, the solar system would be preconfigured, to the extent possible, for prevailing rooftop types. The intention behind such an initiative is to try and enable the homeowner to install the solar system without the need for a contractor. This initiative is literally called 'Plug and Play' by the U.S. government. Coupled with this standardization is an initiative for installers to automate the processes by utilizing an enterprise application software and online application functionality to achieve quicker approvals. The latter was adopted by Pacific Gas and Electric Company, one of the largest utilities in the U. S., which managed to reduce BOS cost considerably (Ardani & Margolis 2015).

> Although the cost of an inverter amounts to a small portion of capital costs in solar installations, new paradigms in inverter design and manufacturing are reducing costs in the inverter segment itself, and in the associated costs that stem from inverter installation including connection to the modules, connection to the grid, site preparation, etc. Interest in skid inverters is growing, in which the inverter, combiner box(es), transformer and monitoring equipment are preassembled and installed on to a skid (a combiner box is a device that combines the output of many modules before it is carried to the inverter). The skid configuration reduces on-site labor, transportation requirements, site preparation costs and grid connection costs. Note that in the case of skid inverters, the cost of the inverter itself may not be reduced. However, it lessens the system installation complexity.

> The BOS encompasses a number of activities that are governed by different entities, are different in nature and require different skills, products, components or materials. Vertical integration across these activities can bring down the BOS cost. Moreover, vertical integration across the entire solar PV system is also possible. Companies such as First Solar, which offers integrated solar solutions, have proven repeatedly that they can provide competitive bids compared with their rivals.

Conclusion

The costs of solar PV technology have dropped significantly over the past few decades, primarily driven by technological innovations and global policy support. The BOS component, however, did not decline as fast. Our analysis shows that the global LC of the BOS component for residential scale systems is 89 percent, compared with a LC of 80 percent for modules. To the best of our knowledge, this is the first study that creates a global 'benchmark' LC for the BOS. Though further cost reduction prospects can still be found within solar module manufacturing, there are greater cost reduction opportunities within the BOS segment, and if well exploited the capital cost impediment of solar PV systems can be overcome.

Compared with conventional energy generation technologies, renewable technologies are considered young. It is widely accepted that renewables still need financial support for further deployment and for them to reach grid and socket parity with conventionals. Based on our analysis, and after studying the learning curves of more than 20 countries that account for over 85 percent of global solar PV installations, it was shown that a number of cost reduction opportunities exist in the BOS segment and require no (or little) financial policy support or commitments. These include promoting market competition between solar installers, legal process standardization and adopting collective purchasing and installation schemes.

If these steps are taken, which are controllable and within the circle of influence of industry and government, the resulting cost reductions can serve as a catalyst to stimulate policymakers to make new financial commitments; thereby, contributing to further cost reduction in the BOS segment and beyond. These findings were a result of splitting the period of analysis into two: one that preceded the 2008 financial crisis and the other post-2008. We found that many countries were still able to achieve cost reductions after 2008 in the BOS component (some even better than the pre-2008 period) despite the decline in global monetary commitments to renewables.

The results obtained in this paper allow us to project future solar PV CAPEX. Countries can potentially use the 80 percent LC for modules, and simultaneously refer to their specific LC of the BOS cost evolution. However, it is important to be mindful that the results attained for each country were a function of data availability and when that country initiated its solar deployment program. Hence, putting these observations in context helps 'calibrate' the LC to be used. Finally, we note that although enhancing the efficiency of solar cells will reduce BOS costs, this option is deemed as challenging especially in the near term.

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Appendix A

We will deduce the learning parameter from the learning curve equation. The idea of the LC stems from empirical evidence. Cost reductions are observed with each doubling of cumulative production. In mathematical form, the LC can be expressed as:

$$C_Q = C_1 \cdot Q^{-\beta} \tag{1a}$$

where

C_Q is the cost of producing the Q-th unit,

C_1 is the cost of producing the first unit,

Q is the quantity produced, and

β is the learning coefficient.

To find the learning curve, we assume:

$$C_{QX} = C_1 \,.\, (Q_X)^{-\beta} \tag{2a}$$

$$C_{QY} = C_1 . (Q_Y)^{-\beta} \tag{3a}$$

where $Q_Y = 2Q_X$.

Then, the learning curve (Henderson's Law), LC is

$$LC = \frac{C_{Q_Y}}{C_{Q_X}} = \frac{C_1 . (Q_Y)^{-\beta}}{C_1 . (Q_X)^{-\beta}} = \frac{C_1 . (2Q_X)^{-\beta}}{C_1 . (Q_X)^{-\beta}}$$

$$LC = 2^{-\beta} \tag{4a}$$

Alternatively, we can write solve equation 4a for β in term of LC:

$$\beta = -3.3219 \times log_{10} (LC) \tag{5a}$$

Appendix B

Table B1. The learning parameter of CAPEX for residential scale solar PV systems using the classical and enhanced methods. The associated LCs are calculated based on the learning parameter value. The quantity considered is the total cumulative residential installations.

	The Classical Model				**The Enhanced Model**	
	Method 1		**Method 2**		**Method 3**	
Country	**Learning parameter β estimated using OLS**	Corresponding LC (%)	**Learning parameter β estimated using SUR**	Corresponding LC (%)	**Learning parameter β_i (Y_i) estimated using SUR**	Corresponding LC (%)
Australia	0.179**	88.3	0.210**	86.5	0.176**	88.5
Austria	0.178**	88.4	0.184**	88.0	0.154**	89.9
Belgium	0.293**	81.6	0.314**	80.4	0.286**	82.0
Bulgaria			0.283**	82.2	0.288**	81.9
Canada	0.103**	93.1	0.108**	92.8	0.096**	93.6
China	0.166**	89.1	0.326**	79.8	0.292**	81.7
Czech			0.283**	82.2	0.096**	93.6
Denmark	0.174**	88.6	0.168**	89.0	0.145**	90.4
Europe	0.053	96.4	0.283**	82.2	0.261**	83.5
France	0.186**	87.9	0.185**	88.0	0.119**	92.1
Germany	0.483**	71.5	0.483**	71.5	0.263**	83.3
Greece			0.283**	82.2	0.288**	81.9
India			0.283**	82.2	0.291**	81.7
Italy	0.173**	88.7	0.163**	89.3	0.139**	90.8
Japan	0.204**	86.8	0.203**	86.9	0.203**	86.9
Malaysia	0.204**	86.8	0.283**	82.2	0.270**	82.9
Mexico	1.106**	46.5	0.283**	82.2	0.270**	82.9
Netherlands	0.116**	92.3	0.114**	92.4	0.145**	90.4
Norway	1.762**	29.5	0.283**	82.2	0.272**	82.8
Portugal	0.068**	95.4	0.283**	82.2	0.275**	82.6
South Korea	-0.019	101.3	-0.019	101.3	-0.039**	102.7
Spain	5.726**	1.9	0.283**	82.2	0.263**	83.3
Sweden	0.495**	71.0	0.476**	71.9	0.441**	73.7
Switzerland	0.082**	94.5	0.110**	92.7	0.161**	89.4
Thailand	0.059	96.0	0.001	99.9	-0.019	101.3
U.K.	-0.080	105.7	-0.077	105.5	0.004	99.7
USA	0.233**	85.1	0.192**	87.5	0.180**	88.3

Source: KAPSARC analysis.

Notes: **1.** Log likelihood for SUR: –402.0, and for SUR $\beta_i(Y_i)$: –59.4. **2.** Total number of observations for SUR: 864, and for SUR $\beta_i(Y_i)$: 675. **3.** ‘**’ is significant at 1%.

Table B2. The learning parameter of CAPEX for residential scale solar PV systems using the classical and enhanced methods. The associated LCs are calculated based on the learning parameter value. The quantity considered is the total cumulative installations.

	The Classical Model				**The Enhanced Model**	
	Method 1		**Method 2**		**Method 3**	
Country	**Learning parameter β estimated using OLS**	Corresponding LC (%)	**Learning parameter β estimated using SUR**	Corresponding LC (%)	**Learning parameter β_i (Y_i) estimated using SUR**	Corresponding LC (%)
Australia	0.217**	86.0	0.251**	84.0	0.182**	88.1
Austria	0.146**	90.4	0.150**	90.1	0.090**	94.0
Belgium	0.319**	80.2	0.323**	79.9	0.179**	88.3
Bulgaria			0.257**	83.7	0.140**	90.8
Canada	0.165**	89.2	0.163**	89.3	0.107**	92.9
China	0.181**	88.2	0.197**	87.2	0.085**	94.3
Czech			0.257**	83.7	0.087**	94.1
Denmark	0.205**	86.8	0.203**	86.9	0.154**	89.9
Europe	0.042	97.1	0.287**	82.0	0.148**	90.3
France	0.223**	85.7	0.213**	86.3	0.113**	92.5
Germany	0.167**	89.1	0.167**	89.1	0.134**	91.1
Greece			0.257**	83.7	0.140**	90.8
India			0.257**	83.7	0.143**	90.6
Italy	0.194**	87.4	0.186**	87.9	0.127**	91.6
Japan	0.244**	84.4	0.244**	84.4	0.216**	86.1
Malaysia	0.244**	84.4	0.257**	83.7	0.108**	92.8
Mexico	0.899**	53.6	0.257**	83.7	0.104**	93.0
Netherlands	0.281**	82.3	0.282**	82.2	0.187**	87.8
Norway	1.874**	27.3	0.257**	83.7	0.113**	92.5
Portugal	0.016	98.9	0.257**	83.7	0.106**	92.9
South Korea	-0.021	101.5	-0.021	101.5	-0.045	103.2
Spain	5.674**	2.0	0.257**	83.7	0.102**	93.2
Sweden	0.537**	68.9	0.515**	70.0	0.442**	73.6
Switzerland	0.148**	90.3	0.175**	88.6	0.140**	90.8
Thailand	0.481	71.6	0.377**	77.0	0.221**	85.8
U.K.	0.254**	83.9	0.255**	83.8	0.200**	87.1
USA	0.295**	81.5	0.233**	85.1	0.113**	92.5

Source: KAPSARC analysis.

Notes: **1.** Log likelihood for SUR: –576.7, and for SUR $\beta_i(Y_i)$: –212.3. **2.** Total number of observations for SUR: 1057, and for SUR $\beta_i(Y_i)$: –870. **3.** ‘**’ is significant at 1%.

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About the Project

Although the costs of solar modules have fallen precipitously and have, thus far, followed an 80% learning curve, balance-of-system (BOS) costs have not declined at the same rate. Today, the BOS represents the majority of the capital costs for solar installations. The growing share of BOS in the total cost of solar systems has direct implications on its competitiveness.

For the first time, and with the aid of an extensive dataset, learning curves of the BOS component for residential systems have been deduced for over 20 countries. In addition to computing a global average for BOS learning at 89%, this modeling exercise showed that there are a number of cost reduction opportunities that exist in the BOS segment, and these require no (or little) financial policy support.

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